# Essays in Sustainable Finance

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# Abstract

Sustainability has grown to be a fundamental part of the finance landscape. Whether understanding through assets under management in sustainable funds, the breadth of firm sustainability reports, or the ever-increasing volume of academic literature on the topic, the centrality of sustainability is clear. This thesis presents three papers which contribute against this growth. Uniting the chapters is the desire to further our understanding of the economic relevance of companies' dynamically changing corporate social responsibility (CSR) attributes.

Chapter 2 evaluates the importance of the stakeholder dimensions of CSR to maximising corporate financial performance (CFP) across the CFP distribution using unconditional quantile regression. Results show that poor CFP firms should not use CSR as a short-term strategy, but may use external stakeholder dimensions such as community and environment, to improve long-term CFP. Good CFP firms should focus on sharing success with employees. Environment focused CSR is most effective for firms around the median of the CFP distribution. Each of these results emerge here for the first time and contribute important understanding to the CSR-CFP relationship. Managers should be guided by the results to optimise their CSR investment. Policymakers must design incentive structures for CSR improvements accordingly, for example subsidising only lesser profitable firms to increase support to employees.

Identifying true sustainability index listing effects has been hindered by challenges of parallel trend assumptions and a lack of robustness to shocks which only impact certain industries. In response, Chapter 3 considers listing to the Dow Jones Sustainability Index North America (DJSI). Formally, a generalised synthetic control approach that addresses both concerns is used. A counterfactual portfolio of industry peers is created for each listing firm such that returns to the portfolio match the control period. Absent of listing, the behaviour of this portfolio is how the listing stock would have been expected to behave. Listing effects are then the difference between observed returns on the listing stock and the counterfactual portfolio. Abnormal returns to listing are found to be more persistent than previously identified. Investors gain from these abnormal returns by identifying firms who will be listed ahead of the formal DJSI announcement.

High volumes of sustainable investment inspire an investigation of the possibilities to augment traditional strategies, such as the long-small-short-large firm size strategy, with information on firms' environment, social and governance (ESG) performance. Chapter 4 shows that abnormal returns to these ESG flavoured strategies are not significantly lower than the corresponding pure traditional strategies. Investors may use ESG flavoured strategies to increase ESG exposure without incurring any alpha cost. New evidence is contributed that having an ESG focus and having a return focus

need not be mutually exclusive.

Across the three chapters, it is shown how innovative econometric techniques and novel approaches to investors portfolio selection yield critical understanding of the links from CSR to CFP and stock returns. Learning therefrom can help firms and investors to leverage the benefits of CSR and also help policymakers to best incentivise progression to more sustainable practices. Meanwhile the contributions aid the academic community to best model and evaluate the role of sustainability in finance.

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# Contents

# List of Figures

# List of Tables

# Chapter 1

# Introduction

*[The] outperformance of ESG strategies is beyond doubt.*

- Financial Times, *November 2017*

When concluding that the outperformance of ESG strategies were beyond doubt in 2017, the Financial Times was undoubtedly making a statement far stronger than any empirical evidence could support[1]. However the conviction in the statement begs many important research questions. Today the assets under management in environment, social and governance (ESG) focused funds is pushing one third of the total assets under management (Bloomberg 2021). Begun in an environment where growth in sustainable investment was starting to accelerate, this thesis persents three related papers that target a fuller understanding of how the ESG behaviour of firms impacts on their financial outcomes.

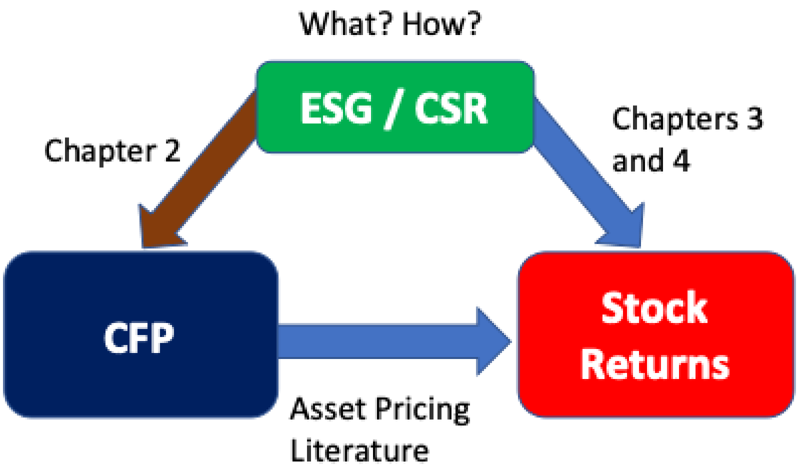
## 1.1 Research Background and Motivation

Before progressing further it is critical to note a change in the naming culture that has taken place in recent years. Increasingly studies refer to Corporate Social Responsibilty (CSR) under the acronym ESG. ESG stands for Environment, Social and Governance. There are some subtle differences between the common understanding of CSR and the prescribed three channels of ESG. However, as Gillan et al. (2021) explain, the terms CSR and ESG may be used interchangeably. In this thesis the same interchangeable approach is adopted. All three chapters build on literatures that have used both CSR and ESG in their descriptions.

In the finance literature, much is known about the relationship between corporate financial performance (CFP) and stock returns. CSR is a much less well understood

[1]The full article is available at http://www.ft.com/content/9254dfd2-8e48-11e7-a352-e46f43c5825d.

Figure 1.1: Research Framework




Notes: Stylised representation of the motivation for this thesis. Chapter numbers refer to the chapter numbers assigned to each of the papers. ESG and CSR may be used interchangably for the purposes of this thesis. Corporate Financial Performance (CFP) and its links to stock returns are understood through the literature. See for example Green et al. (2017). This Introduction begins to ask the what? and how? questions about ESG.

factor within that relationship. On one side the CSR performance of a firm can be associated with the CFP of the firm. In corporate finance CSR continues to be the most used term. On the other hand, the CSR activity of a firm can also be linked directly to the stock returns of the firm. Within the asset pricing literature most contemporary papers refer to ESG. Given the established link between CFP and stock returns, a comprehensive understanding of both the CSR-CFP and CSR-stock returns links is needed. This thesis is motivated as an intended contribution to a fuller picture.

Each of the three chapters represent a paper that speaks to a part of the overall picture. To motivate that connectivity, Figure 1.1 provides a visual representation of the relationship between the three key elements. These elements are CSR, CFP and Stock Returns. At the top, the ESG/CSR box gives the main theme of the thesis. To the left, we have Chapter 2, which focuses on the links from CSR to CFP. To the right are Chapters 3 and 4, which both focus on stock returns as the outcome of interest. Across the bottom of the diagram is the established link from CFP to stock returns. Linkage between CFP and stock returns cannot be ignored because CSR can impact stock returns through the CFP effect. Therefore the link from CFP to stock returns is used as a control in this thesis. A critical question in the evaluation is the definition of CSR. The next section addresses that fundamental question.

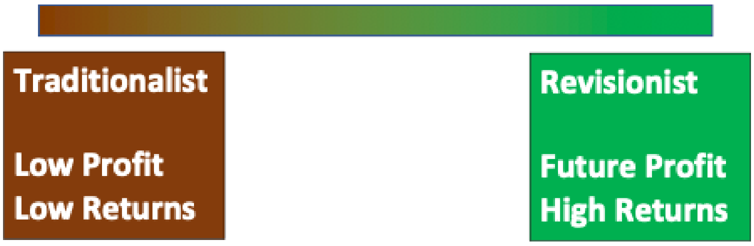
Although there is ready agreement on the basic structure of the relationships in Figure 1.1, there are still questions about the way in which these relationships behave through time. For example, would a firm with strong CFP be better placed to invest in ESG? If that firm did invest in ESG would that then have impacts on subsequent CFP? These questions are addressed in Chapter 2. Investment in ESG projects will take time to produce results. Is it right to assume that finanical impacts, and subsequent impacts on stock returns, take place at the same time? Is there a stock returns effect at the point of the ESG being recognised by external agencies? These are questions for Chapter 3. Finally, can the links between CFP and stock returns, and ESG and stock returns, be treated in isolation? Can investors use the combination of both the direct ESG to stock return and the CFP to stock return channels to obtain improved outcomes? These questions motivate Chapter 4.

To appreciate the tensions within the existing literature, Oberndorfer et al. (2013) defines two perspectives on the CSR-CFP literature[2]. Perspective 1 is the "traditionalist" perspective. Because CFP projects are costly and resources are limited, CFP improvements should only be made if their CFP impact is larger than other alternative projects that would have used the same resource. Traditionalists argue that the CFP benefits will not outweigh the costs. Revisionists, by contrast, believe that the efforts placed on CSR today will bring future benefits in CFP. To revisionists the present value of these future benefits outweighs the costs of investment today. In this way revisionists argue that CSR projects are optimal. Revisionists make a futher link to stock returns using these future cashflows. Future CFP benefits are also brought back into today's stock prices by investors who see today's ESG performance and believe in the future benefits (Oberndorfer et al., 2013).

Figure 1.2 gives a neat overview of the beliefs of the two perspectives on the two outcomes of interest. Traditionalists argue that the diversion of funds to CSR investment is inefficient. Profit suffers in the short term and long term. The lower cashflows from the CSR investment mean the firm can pay less dividends. Opportunities to invest in the future will also be limited by the lower returns to the firm from the CSR investment. At the other end of the scale revisionists see all of the impact of increasing CSR as positive. Higher profits and higher stock returns would make investment in

[2]Subsequently the debate has become wider ranging than just returns and profits. Because this thesis focuses on returns and profits, the Oberndorfer et al. (2013) split remains of high relevance, but the limitation of the narrower focus must be recognised. Grewal et al. (2020b) offers a useful review of the heterogeneity of profit and return responses to CSR activity. Moderating factors that emerge from the contemporary literature are identified and then linked into this thesis as relevant, but the theoretical framework is best motivated from the Oberndorfer et al. (2013) discussion.

Figure 1.2: Traditionalist and Revisionist Perspectives




Notes: Figure represents the traditionalist and revisionist perspectives discussed within Oberndorfer et al. (2013). Below each perspective the impacts on corporate financial performance and stock returns are summarised. In truth the impact will sit somewhere on the scale line between the two ends.

CSR natural. The truth will lie somewhere between these persepectives. In each of the chapters, this thesis asks where the evidence places the true impact of CSR on CFP and stock returns.

Figures 1.1 and 1.2 help us to appreciate the debates that are being had within the current literature. Necessarily both Figures 1.1 and 1.2 make simplifications and omit confounding factors that are identified in the literature. Of note is the heterogeneity of CSR projects and the importance of firm size. It follows naturally that some are of greater relevance to the firm. Investors react more favourably to CSR which is material to the firm (Khan et al., 2016; Grewal et al., 2020a; Serafeim and Yoon, 2021). Within this thesis the focus is on the broad positioning of CSR, CFP and stock returns and it is assumed that the particular projects within each dimension that firms choose to invest in are those which are most financially material to the firm. Firm size is a long considered moderator in the CSR-CFP literature (Orlitzky, 2001). However CSR databases draw primarily on large firms, meaning a qualifier that results apply for larger firms must be added in the observed CSR-CFP relationships. Chapter 2 asks whether firm size, or firm profitability, is really the dominant factor. Reflecting moderating factors, like materiality and size, this introduction will review those debates in more detail ahead of the specific coverage in the chapters.

## 1.2 Measuring CSR and ESG

Accurate identification of any CSR effect on CFP, or stock returns, requires a clear understanding of how CSR is actually measured. Since Anderson Jr and Cunningham (1972) identified the valuation of CSR by consumers, the need to understand how to use

CSR empirically has been strong. Today there are more metrics of CSR to scrutinise. Although all start from the same definitions of what CSR should be, the results can be very different. In this section thought is therefore given to the measurement types, and how they are useful to the respective chapters of this thesis.

ESG/CSR data comes in many forms. Behind each of the measures sits a wealth of research and assessment, but the ability to use the data depends on the final form. The MSCI KLD data used in Chapter 2 offers a unique opportunity to see the categorical assessment data that informs MSCI's continuous ESG score. Although weightings of each category are not provided, it is possible to get a detailed impression of how each item affects CFP or stock returns. Other datasets do not offer such depth. In Chapter 3 we use membership of the DJSI as a binary measure. Binary measures can also be created for membership of other ESG indices. Another binary measure, studied by Hong and Kacperczyk (2009), is a dummy for whether a firm operates in a sin industry[3]. A binary measure does not give any information on the relative performance of firms. For example, there is no differentiation between those who just meet the standard for index inclusion and those who far exceed it. Continuous measures, like the Refinitiv ESG scores used in Chapter 4, allow the assessment of rankings and relative performance, but require more interpretation.

### 1.2.1 MSCI KLD ESG Data

MSCI KLD data has been popular in the literature because of its ability to map to stakeholder theory (Freeman, 1984; Freeman et al., 2010). Mattingly and Berman (2006), Perrault and Quinn (2016) and Mattingly (2017) offer useful reviews of the strengths of the MSCI KLD database in this regard. The primary concern with the MSCI KLD data is availability. Data used in this thesis runs from 2005 to 2015 inclusive. Subsequent changes in the data methodology, coverage and availability make comparison across longer periods more difficult. Prior to 2004 the coverage of the MSCI KLD data was limited to around 650 firms. For our sample that number is around 1500 with the number further rising in 2019 to 3000 (Hatten et al., 2020). Being restricted to so few firms, and for such a short time period, does not outweigh the value of the granular data provided by MSCI.

Within the dataset, binary indicators are provided for an extensive set of 80 assessment points. These points are either strengths, or concerns, for the firm. Example strengths would be high levels of energy efficiency, community engagement and the shar-

[3]Sin industries include alcohol, tobacco, and gambling.

ing of profits with employees. Example weaknesses include pollution, anti-competitive practices and a lack of diversity on the board. Where a particular assessment point is not collected for a firm the database records NA. In this way aggregate and average measures can be easily constructed across multiple assessment points. Averages are valuable because a firm assessed on just two strengths, but which has both, would be seen as performing better than a firm assessed on eight assessment points with three strengths. The ability to split out strengths and concerns has contributed greatly to the popularity of MSCI KLD data in the literature (Mattingly and Berman, 2006; Mattingly, 2017; Hatten et al., 2020).

It is typical in the literature to group assessment points into stakeholders. Most studied are product, environment, community, diversity and employees. As Perrault and Quinn (2016) note, product has a useful link to consumers whilst environment, community, diversity and employees are all readily understood. The data also includes strengths and concerns for human rights and governance, but these are less studied as few firms have concerns in human rights and governance is better proxied from other sources (Mattingly, 2017). Combinations of the dimensions allow the study of the difference between internal and external stakeholders (Mattingly and Berman, 2006). Internal, or primary, stakeholders are product, diversity and employees. Motivation for not aggregating can be found in Perrault and Quinn (2016) conclusion that "firms do not exhibit an intrinsic or a strategic commitment simultaneously to *all* stakeholders, but that each firm may operate guided by intrinsic commitment to *some* stakeholders while managing others strategically" (Perrault and Quinn, 2016, p.899)[4]. Five stakeholder dimensions are used in this thesis to give clearer focus on which internal, or external, stakeholders strengths and concerns are associated with improved financial performance.

### 1.2.2 Dow Jones Sustainability Index

The DJSI gives a binary indicator of membership. However, the decision as to which firms gain membership is based upon an average of 600 ESG relevant data points per firm. Robecco SAM[5] as the assessors will gather the data from firms, both through public information and private questionnaire, and then produce a weighted average score. These scores may then be compared between companies and the members of the index selected. The data for this thesis is then a simple binary indicator of membership.

[4] Emphasis in the quotation is that provided by Perrault and Quinn (2016).

[5] Robecco SAM is now part of the Standard and Poors Global group, but the name Robecco SAM remains on the DJSI documentation.

Firms who get listed are seen as industry leaders for the listing year. Amongst the 600 firms invited each year for DJSI assessment around 150 will make the final list. Competition is therefore intense and the capacity of a firm to provide data to the assessors is pivotal. Data on the individual assessment points is not made public by Robecco SAM. Binary indicators are clear in giving the public an understanding that firms are leading in ESG activity. Indexes are also easy for funds to follow.

In the case of the DJSI, the weightings vary by industry. For instance, banks have particular focus on the economic aspects of the survey because their products are primarily financial. As another example, firms with major global supply chains are assessed more on their carbon emmissions and hence see bigger weightings within the environment dimension. Robecco SAM ESG assessment weightings encourage firms to direct their CSR activities accordingly, if they want to gain listing. For banks this means seeking out sustainable investment projects to fund. But for an electrical engineering company the focus would be on improving the health and safety of employees. In order for firms to understand if the efforts in these particular CSR activities are worthwhile the only measure is the impact of index membership. The more disaggregated measures, like the criterions offered in the MSCI KLD, offer more scope to analyse direction from a research persepective.

Indexes have value for event studies. Assessment is by an independent body and at a time which is exogenous to the firm. In the case of the DJSI this means an annual announcement in mid-September. All of the announced changes to the DJSI membership are made effective one week later. In every case for this thesis both announcement and effective date are before the 1st October. Deletions can take place at any time because mergers and firm failure can happen throughout the year. Listings only happen once per year. Firms are invited to submit for assessment in February, with the submission being complete by June. In this way listing is a reflection of historic activity and it is possible for observers to anticipate the outcome of the assessment panel. All of these features make the DJSI informative on industry leadership (Fowler and Hope, 2007), and a popular base for listing effects papers. Robinson et al. (2011), Hawn et al. (2018) and Durand et al. (2019) are all examples of listing effect studies using the DJSI. The strength of the Robecco SAM investigations means funds also make use of the assessment of the DJSI rather than conducting their own research (Consolandi et al., 2009). Chapters 3 and 4 use the DJSI.

### 1.2.3 Continuous Measures of ESG

Like the assessment process for the DJSI, the creation of ESG score data is based upon assessment against a large number of specific ESG criteria. The Refinitiv ESG scores used in Chapter 4 are one such example. Individual data points are collated first under the three pillars of E, S and G, and then into an overall score for the firm. This thesis uses the aggregate score to best align with the multiple dimensions considered in the DJSI assessment. The Refinitiv ESG scores were previously known as Thomson Reuters Asset 4, with the name changing in 2018. Contemporary applications of Asset 4 include Gasser et al. (2017) early work on portfolio construction with ESG and Kim et al. (2021) application to stock risk.

To understand the Refinitiv ESG scores we may make use of the extensive guide provided on the company website[6]. Refinitiv ESG scores are based on the analysis of more than 500 ESG relevant data points. These datapoints are then refined into 186 metrics, of which 68 concern the environment, 62 concern social and 56 are related to governance. The precise number of these which are considered for a given firm varies by industry. The lowest number of ESG metrics for an individual industry is 70 and the highest is 170. Again, the sources of information include annual reports, news reports, stock exchange filings, websites and firms' own CSR reports. Coverage in 2003 extended to the full S&P 500 and NASDAQ 100, growing to include the Rusell 1000 in 2011. Like other measures used in this thesis the emphasis is again on larger firms. Russell 2000 and most Russell 3000 firms were added in 2017, but this leaves a very limited time frame for analysis of the expanded universe. Our use of Refinitiv ESG scores in Chapter 4 only considers firms that are on the S&P 500 and therefore is complete from 2003.

### 1.2.4 Summary

Reconciling the wealth of available ESG measures is a big task. As well as the MSCI KLD, DJSI and Refinitiv ESG measures described there are many other ways proposed to capture ESG. Several other continuous scores have been used within the finance literature. Examples include the Vigeo score used in Becchetti et al. (2018) and the MSCI scores used by Pedersen et al. (2020). The uniting feature remains the creation of the scores from a diverse range of data points. The literature points to a lack

[6]The current guide at the time of writing is the February 2021 edition which may be viewed at: https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf. (Accessed 8th August 2021).

of correlation between measures (Dimson et al., 2020). Therefore it is hard to say definitively which is the best ESG dataset. This thesis employs each data set where its strengths can be best used.

## 1.3 Literature: ESG, CSR, CFP and Stock Returns

Bringing together the ESG measures with CFP and CSR can be done in many ways. Papers within the literature concentrate on either the CSR-CFP link, like in Chapter 2, or on the ESG-Stock Returns link, like Chapters 3 and 4. Here thought is given to the works that have sought to evaluate those links and the research questions that open up.

### 1.3.1 CSR and CFP

Initial impacts of CSR were presented in terms of consumer demand. McWilliams and Siegel (2001) and Sen and Bhattacharya (2001) both discuss the inevitable trade off between the costs of CSR projects and the benefits that they can bring through increased consumer demand. If, as Anderson Jr and Cunningham (1972) first suggested, consumer sentiment towards firms with strong CSR is a major demand driver, then investment in CSR will bring reward. The way in which consumers see the CSR activity of the firm then matters. There is a large literature which looks at hereterogeneity in consumer perception based upon the performance of firms including Öberseder et al. (2011), Green and Peloza (2014) and Gallardo-Vázquez et al. (2019). The value of a positive public image on CSR is seen in the extent to which firms promote their green credentials. Wu et al. (2020) is amongst many works that examines "greenwashing". Greenwashing is where firms overstate their efforts on CSR in order to present a more favourable image to external stakeholders and potential consumers. Costly effort that is placed into greenwashing confirms that there is value in being seen to practise CSR.

Whilst the demand argument makes a case for a positive CSR-CFP link, there are many papers which identify a negative relationship. Examples of works which find CSR can harm CFP include Friedman (1970), Aupperle et al. (1985) and McWilliams and Siegel (1997). Motivation for CSR harming CFP comes through the traditionalist persepective that the costs do not outweigh the benefits. Traditionalists do not believe that the additional demand from consumers will be sufficient to outweigh costs either.

Within the corporate finance literature, the dominant way to think about CSR is through stakeholders. Freeman (1984) and Freeman et al. (2010) put forward the idea that the way agents interact with the firm is important. Stakeholders are just individuals, or groups, with an interest in the activity of the firm. Clarkson (1995) proposes an internal-external split of stakeholders. Internal stakeholders are those with direct connection to the company and those whose happiness depends on the actions of the firm. Stakeholders such as the employees are obviously internal to the firm. Also under the direct control of the firm are the product offered and the diversity policies which are used. These three dimensions, product, diversity and employees, are therefore the internal stakeholders. Meanwhile, the environment, and the community are external stakeholders.

When analysing the effects of CSR it must be recognised that it is easy for the public to see the external actions of firms. Investors can similarly see how the firm they wish to invest in behaves. An investor would be able to see if a firm had a polluting factory, for example. By contrast, knowledge of problems with employees will only come once any scandal has happened. This makes the internal-external distinction natural. Studies supporting the internal-external split include Mattingly and Berman (2006) and Godfrey et al. (2009). Meanwhile, Orlitzky (2001) and others maintain the five dimensions. However defined splits in CSR allow the understanding of heterogeneity in the CSR-CFP link more than an aggregate CSR measure.

Another important econometric question is the way that the links from past CFP to present CFP are handled. There is a natural endogeneity in the performance of firms. Profits in one year can be re-invested to produce further profit in the following year. In Chapter 2 the endogeneity concerns are reduced by the inclusion of lagged CFP. Shahgholian (2019) notes that only a quarter of papers account for this intuitive concern. Secondly, theory talks about diminishing marginal returns to CSR investment (Wagner et al., 2002), and an inverted "U" shaped relationship with an optimal level of CSR (Sun et al., 2019; Meier et al., 2019). Both diminishing marginal returns and the "U" shaped relationship have been modelled with quadratic CSR as an explanatory variable. However a fuller picture comes from allowing some freedom to the shape. As Chapter 2 shows, unconditional quantile regression (UQR) supplies exactly the flexibiity missing in the literature to date.

For the study of CSR-CFP through stakeholders, the MSCI KLD data is ideal. Perrault and Quinn (2016) and Mattingly (2017) explore precisely the correspondence between Freeman (1984) orignal stakeholder dimensions and the specific criteria in the MSCI KLD data. The aggregation into product, environment, community, diversity and employees makes it easy for researchers to use the MSCI KLD data to apply stakeholder theory. Being able to disaggregate the CSR measure helps greatly with directing companies' investment strategies and showing where improvements to practice should be made. Such direction has been underexplored within the literature. Chapter 2 makes full use of the potential within the MSCI KLD dataset to help managers see the stakeholders in which investment will be most effective.

Two questions arise from the literature. Firstly, how does the relative importance of CSR as a driver of CFP change across the CFP distribution? The question of variation follows naturally from the inverted "U" relationship between CSR and CFP, and the theoretical arguments of diminishing marginal returns to CSR. Secondly, how does the relative importance of the five stakeholder dimensions as CFP determinants change over the CFP distribution? Here the focus becomes of more practical relevance and reflects Perrault and Quinn (2016)'s position on the changing focuses of firms within the set of stakeholders. In answering these questions it becomes possible to speak to the ambiguity in results within the present literature.

### 1.3.2 ESG and Stock Returns

On the other side of Figure 1.1, is the link from the CSR actions of firms to stock returns. Unlike other stakeholders, stock investors are not close to individual firms. In the ESG literature, there is a very important role for ratings agencies and indpendent assessments. Consequently, the literature may be split into those which use membership of ESG indexes, for example the DJSI, and those which use continuous ratings, for example the Refinitiv ESG scores. Central to the ability of ESG to impact stock returns is the way in which investors understand the signals coming from the ESG measure. Fowler and Hope (2007) identifies the benefits of sustainability index membership because of the comprehensive assessment that goes into selecting which firms are allowed to join the indexes. That a firm has been able to achieve listing is then sufficient to view that firm as an ESG leader. Continuous measures of ESG enable sorting from low ESG to high ESG. In the same way that other financial characteristics are sorted into portfolios for anomaly detection in the asset pricing literature, so ESG scores can be. Becchetti et al. (2018) is an example of a paper using a continuous ESG measure to create sorted portfolios in this way.

Derwall et al. (2011) defines two groups of investors. Those who are "values based" and those who are purely motivated by returns. In this thesis "values based" is replaced by "ESG driven" to avoid any confusion with the value factor of Fama and French (1993). An ESG driven investor gains utility from the CSR activities of the firms whose shares they hold. Such an investor would look to buy DJSI index members and hold firms with high Refinitiv ESG scores. Demand from ESG driven investors will drive up the stock price. Unless the volume of ESG driven investment increases further the initial rise will not continue. From the return perspective there is an initial jump of high returns, but then the stock continues to behave as it would have done absent of ESG. Support for the temporary response is found in the experimental work of Martin and Moser (2016) and the analysis of El Ghoul et al. (2011). Theoretical works see this temporary effect as a motivation for lower returns on all but the jump day. Evidence from listing effects studies such as Robinson et al. (2011), Hawn et al. (2018), Durand et al. (2019) and others is consistent with a temporary effect from CSR. Listing effect studies offer a direct means to assess persistence of return effects. Chapter 3 targets this purpose.

Focusing on ESG creates a screen on stocks. Firstly, the universe of stocks with ESG scores is smaller than the complete stock universe. Secondly, within those stocks that do have ESG assessments, the number that are confirmed as leaders is limited. Portfolio theory tells us that diversification is the key to obtaining strong returns. Screening to reduce the investment universe goes against the aim of maximum diversification. Renneboog et al. (2008), Ielasi et al. (2020) and Alessandrini and Jondeau (2020) all demonstrate that the screening costs associated with using ESG information to focus on a subset of stocks are small. Once an ESG driven investor is operating within the screened set they may then make selections based on other factors. This screening process is the motivation for the ESG flavoured strategies of Chapter 4.

Fama and French (2007), Pástor et al. (2020) and Pedersen et al. (2020) take the idea of ESG driven investors into adaptations of the utility function. An ESG driven investor gains utility from the activity of a firm and therefore will be willing to give up some returns in exchange. As the proportion of individuals who have this ESG component grows, so the demand for ESG stocks increases. Likewise, if the strength of feeling towards ESG increases so the demand grows. Pedersen et al. (2020) is the closest to a two-way split of investor types in the sense of Derwall et al. (2011). Importantly Pedersen et al. (2020) is the first to set out the minimal role that ESG preference plays on the efficient frontier. It is shown that introducing theoretical ESG screens has as limited an effect as was seen in the empirics of Renneboog et al. (2008) and others. On this theory and practice align.

Potential explanations for the demand for ESG stocks also include risk and resiliency to crisis. Where Lin et al. (2017) found high ESG stocks more resilient to the global financial crisis, Albuquerque et al. (2020) does not see the same resilience during the Covid-19 crash of March 2020. Evidence on risk is more conclusive. Oikonomou et al.

(2012) demonstrates that ESG stocks have lower risk. Cerqueti et al. (2021) confirm that the lower risk of firms with strong CSR continues. A further risk that faces stocks based upon their ESG performance comes from the potential for new regulations that increase the costs of poor ESG performance. An example of this is the increasing costs placed on firms with high greenhouse gas emissions. Empirical evidence on the requirement to report greenhouse gas emissions on stock returns is provided by Alessi et al. (2021). Hence those high ESG firms who do not face the regulatory risk are lower risk from the regulation perspective also. Because of the lower risk it becomes possible for investors to raise their Sharpe ratio, the ratio of return to risk, without losing returns. This result appears in the ESG efficient frontier model of Pedersen et al. (2020) also. Neither Chapter 3, nor Chapter 4 make direct reference to risk, but the importance of the risk-return relationship is not ignored.

Asset pricing studies focus on the ability of investment strategies to generate alpha. Pedersen et al. (2020) finds no alpha signal in ESG scores. Indeed it is shown that the sin stock premium of Hong and Kacperczyk (2009) persists. Hence the puzzle of high demand for ESG stocks, but low returns, continues. Notwithstanding the discussion of risk, there is still a contradiction between investor behaviour and the theoretical expectation of investor stock selections. Chapter 4 examines whether it is possible to increase exposure to ESG stocks without paying an alpha cost for so doing.

## 1.4 Summary of the Chapters

### 1.4.1 Stakeholder Dimensions and the Firm Performance Distribution

Chapter 2 asks whether the relative CFP of the firm impacts the strength of the CSR-CFP link. Motivation comes from the simultaneous punishment of profitable firms with poor CSR and reward for less profitable firms who have good CSR (Green and Peloza, 2014; Gallardo-Vázquez et al., 2019). Chapter 2 demonstrates that there are significant differences in the coefficients on CSR across the distribution of return on assets (ROA), Tobin's q (TOB) and for the total q (TOT) measure of Peters and Taylor (2016). CSR is defined in terms of the five stakeholder dimensions of Freeman (1984) and Freeman et al. (2010), as derived from the MSCI KLD database[7]. Hence it is shown that a firm's performance in the dimensions of product, environment, community, diversity and employees have a differential impact on CFP according to the position of the firm

[7]Mattingly (2017) provides an excellent review of the links between MSCI KLD data and the stakeholder dimensions as used in this paper.

on the CFP distribution. Where extant studies using OLS have found insignificance (Gillan et al., 2021), the UQR analysis of Chapter 2 identifies that there are significant CSR effects on CFP which have been previously hidden by the econometric approach used. Empirical evidence is added to the suggested differences in the role of CSR on CFP discussed in Gallardo-Vázquez et al. (2019).

The research gap for Chapter 2 lies in the void between the literature on the moderating effect of profit and size on the CSR-CFP relationship and the empirical CSR-CFP studies which have appeared to date. Perrault and Quinn (2016) identify a theoretical heterogeneity in the importance of stakeholders in the determination of profit, but the results of empirical investigations are dominated by insignificance. Despite the theoretical arguments of Gallardo-Vázquez et al. (2019) and others, there has been no attempt to account for the relative CFP of firms as a motivation for the observed heterogeneity identified by Perrault and Quinn (2016). The primary research question becomes how does the relative level of CFP affect the linkage between the five CSR stakeholder dimensions and CFP? Picking up the resilience discussion from Godfrey et al. (2009) and Lins et al. (2017), Chapter 2 also asks how the global financial crisis has impacted upon the answers to the primary research question.

To address the research gap, Chapter 2 uses UQR. Use of quantile regression versus standard OLS follows because quantile techniques allow the coefficient on the explanatory variables to change according to the quantile of the dependent variable at which estimation is made. Quantile regression (QR) gives coefficients for profitable firms and less profitable firms alike and allows the testing of the differences there between. Consequently, QR allows a direct answer to the question on the importance of relative CFP to determining which stakeholder dimensions economically impact CFP. Chapter 2 uses UQR rather than the standard QR of Koenker and Bassett (1978) because UQR offers robustness in cases where there is a moderating impact from control variables on the relationship of interest (Borah and Basu, 2013). Perrault and Quinn (2016) argue that there is extensive moderation of the CSR-CFP relationship by firm characteristics, such as size, which therefore make UQR the best methodological choice.

In the extant literature, Shawtari et al. (2016) uses QR on the corporate governance to profitability link and Kang and Liu (2014) link a simple CSR measure to CFP. Neither study has the detail offered by the stakeholder dimensions used in Chapter 2. Shawtari et al. (2016) and Kang and Liu (2014) also do not offer the range of CFP outcomes considered in Chapter 2. A recent study by Lin et al. (2021) considers a dynamic panel quantile approach for the link between CSR ratings and profitability in the automotive industry. Whilst the specific focus may not generalise and they do not use the stakeholder dimensions, the Lin et al. (2021) paper adds weight to the early evidence that there is value in considering the quantiles of the CFP distribution. Methodologically, panel quantile has an advantage where a particular unit has a tendency to consistently appear in part of the outcome distribution (Powell, 2010, 2022). Individual firms may consistently appear in the same part of the CFP distribution, for example Apple Inc will often be at the top end of the CFP distribution. In such cases, a firm's fixed effect in the regression will account for the consistency in CFP distribution positon. However, in Chapter 2 industry-year fixed effects are used and we would not expect all firms in a given industry to consistently appear at the same end of the CFP distribution. The fixed effect UQR specification used in Chapter 2 is therefore sufficient to capture the desired relationship under the arguments presented in Powell (2010) and Powell (2022). Borgen (2016) also addresses this argument in stating that his fixed effects UQR code, as used in Chapter 2, can be used in place of a panel structure. Chapter 2 then represents the first comprehensive appraisal of the link between the widely studied stakeholder dimensions and CFP across the CFP distribution.

Evidence in the chapter shows that there is at least one stakeholder dimension upon which firms may improve performance in order to improve their CFP. Formally, we show that increasing strengths in the PRO dimension can help those at the bottom of the CFP distribution to increase their CFP with CSR. For firms whose CFP places them near the middle of the overall CFP distribution, the increasing of ENV strength has significant CFP improving impact. Finally, for those whose CFP performance is near the top of the CFP distribution focusing on EMP strengths can further success. All of these insights apply for the short-term CFP measure return on assets, and the longer term focused measures like TOB and TOT. Only the very worst performers have no significant means to improve their short-term CFP through raising CSR strengths. Relative to improving strengths, reducing CSR concerns shows less significance. However, for the short term performance of the least profitable firms there is an opportunity to reduce product concerns to raise CSR. Existence of a means to raise CFP through CSR for all firms delivers an important contribution to advocating improved CSR performance, which has been missing in the inconclusive and insignificant results of past works.

### 1.4.2 Dow Jones Sustainability Index North America listing effects

Moving into the relationship between CSR and stock returns, Chapter 3 targets a clearer understanding of the effect of a firm listing to the DJSI. The DJSI is seen as an important indicator of CSR performance in the literature (Robinson et al., 2011; Lourenço et al., 2014; Hawn et al., 2018; Durand et al., 2019, amongst others). Despite criticisms of its ability to truly identify industry leaders (Scalet and Kelly, 2010; Venturelli et al., 2017), the DJSI remains something firms wish to be on (Carlos and Lewis, 2018), and which investment funds use as an ESG screening tool (Consolandi et al., 2009). Chapter 3 follows Hawn et al. (2018) and Durand et al. (2019) in being a contemporary reappraisal of DJSI listing effects.

Existing literature on listing effects first constructs abnormal returns using the CAPM. This is the method encouraged in MacKinlay (1997). Coefficients for the CAPM are estimated during a control period and then used, together with the market excess return, to form predicted excess returns around the time of listing. This assumes therefore that the stock continues on the same trend following listing. A positive listing effect appears where the listing stock is offering returns above its predicted return. Event studies estimate the CAPM coefficients for all stocks and then compare the difference between observed and predicted returns, the abnormal returns, using either t-tests, or specifications with dummies and financial controls (MacKinlay, 1997; Acemoglu et al., 2016). During the treatment, period only movements in the market affect the expected return, and hence the results are not robust to any shock which affects the listing stock and a related subset of the full stock universe. Not being able to account for shocks which affect only a subset of stocks that are related to the listed firm during the treatment period has been a key criticism of the existing index listing literature.

Formally, the gaps in understanding the listing effects for the DJSI stem from the empirical identification of listing effects. Gaps exist in the need for robustness to shocks which only impact a subset of firms and to work with the parallel trend assumption to best estimate a trend from the control firms to which it may be realistically assumed that the listing stock would have continued to be parallel in the absence of listing. Chapter 3 presents a new way of thinking about listing effects, which addresses the criticisms of existing methodologies. Using the generalised synthetic control (gsynth) method of Xu (2017), a synthetic portfolio is constructed that mirrors tightly the performance of the listing stock during the control period. The stocks within the portfolio are taken from a relevant peer group. In Chapter 3 the relevant peer group is industry. The choice of industry is made because of the critical role industry plays in the selection of firms for the DJSI, and because of the importance of product market competition to firms. During the treatment period, the weights of the portfolio are used to construct the returns that would have been achieved had the listed stock maintained its original path. The listing effect is the difference between the observed behaviour of the stock and the synthetic portfolio. No asset pricing models are used. Should a shock affect the industry then the synthetic portfolio and the listed stock will both be impacted. The difference between the two remains the listing effect. These benefits motivate the use of the original synthetic control of Abadie and Gardeazabal (2003); Abadie et al. (2010) in Acemoglu et al. (2016). Using gsynth means that multiple listings from the same industry can be accounted for.

Despite the advantages of synthetic control methods discussed, synthetic controls are underused in the finance literature. Most use of synthetic controls continues to be in the political economy literature. Acemoglu et al. (2016) is also joined by Acemoglu et al. (2017) study of the impact of the Arab Spring on financial markets in the Middle East. Amongst the citations of Acemoglu et al. (2016) we may also find work assessing the synthetic control for finance by Castro-Iragorri (2019), a paper on share price reaction to family business ownership transition by Zou et al. (2020) and most recently a look at bank deregulation and economic growth by Berger et al. (2021). None of these consider listing effects. Berger et al. (2021) also apply the gsynth approach, but amongst the citations to the Xu (2017) gsynth paper there are no other papers which either consider related finance topics, or study listing effects.

As with Hawn et al. (2018), Durand et al. (2019) and others, the primary research question is how listing to the DJSI affects stock returns in the period surrounding the listing. Within this we ask whether an improved empirical identification of the listing effect can be made through the use of the gsynth method. Recognising the discussions about the resilience of ESG stocks to the global financial crisis (Lins et al., 2017), the first robustness question asks how outcomes have changed since the global financial crisis. To understand whether sustainability index listing offers informational content, we ask whether splitting the sample into S&P 500 members and non-S&P 500 members will reveal stronger effects in the lesser covered non-S&P 500 set.

Using the synthetic control reveals that listings are more persistent than previously identified. This is more in-keeping with results from the S&P 500 listing literature (Chan et al., 2013). In robustness checks, it is found the persistence of the listing effect has got stronger since the global financial crisis. It is further shown that those firms who gain listing from outside the S&P 500 have far stronger listing, and de-listing, effects. The message to investors is clear; there is value in identifying likely listings and de-listings. This repayment to the research comes from improved cumulative abnormal returns from ahead of the announcement of the new year's DJSI listings. Persistence in the abnormal returns shows ESG driven investors can continue to hold the stock and make profit. A further important result is that the listing and de-listing effects are not symmetric. Because it is impossible to see how a listing firm would have behaved in the absence of listing, the focus must be on gaining the best counterfactual. Chapter 3 takes important steps in this regard.

### 1.4.3 ESG Flavoured Alpha?

Evidence on the link between ESG and stock returns has been more conclusive toward higher ESG exposure being linked to lower returns (Pedersen et al., 2020). Derwall et al. (2011) splits investors into those who are ESG driven and those who are profit driven. The evidence from Pedersen et al. (2020) shows that the split between the two types of investors continues. It follows that investment flows to ESG stocks come from a desire to minimise risk, or the utility investors get from longing stocks of firms who have high ESG. Derwall et al. (2011) contends that ESG stocks and the set of alpha generating stocks are mutually exclusive. Evidence continues to support that assumption (Becchetti et al., 2018; Pedersen et al., 2020). However, given the funds flowing into ESG stocks, there is a gap to explore more thoroughly any links between these new flows and the pursuit of abnormal returns. For Chapter 4, the primary question is to ask whether there exist investable strategies that allow investors to increase their ESG exposure without sacrificing their ability to generate abnormal returns. That is, we ask can investors with greater ESG exposure still achieve alpha?

In addressing this question we begin with four key considerations. Firstly, the investment universe is restricted to S&P 500 firms, which are the most liquid stocks. This will ensure that any strategies developed are investable with low implementation costs. Secondly, 18 anomalies documented for non-microcaps by Green et al. (2017) are used to create double sorts with ESG. Our double sorts also use the 6 core anomalies identified by Green et al. (2017), being size, book to market ratio, profitability, investment, momentum and return on equity. Thirdly, two measures of ESG are used, Refinitiv ESG scores and membership of the DSJI. Finally, value weighting of portfolios is used in the literature to avoid putting large weights on very small firms that are hard to trade. However, as focus is restricted to the S&P 500 members, liquidity of stocks is not a problem. We therefore use equal and value weighted portfolios in our main analysis.

Recognising the lack of an ESG alpha, confirmed again most recently in Pedersen et al. (2020), Chapter 4 instead seeks to identify ESG flavoured alphas. Long-short strategies are constructed which long only high ESG stocks in a given anomaly strategy. These strategies have obvious appeal to ESG driven investors. One possibility is to apply a screen based upon the traditional anomaly to take a long-short position based on ESG within only the end of the traditional distribution that offers high returns. For example, longing only high ESG stocks among the small stocks in the S&P 500 universe, we are intending to capitalise on the size premium while increasing the ESG exposure. Alternatively the screen may be applied to just select high ESG stocks and the long-short reflect the traditional anomaly strategy. A strategy is also proposed that takes a long position on the high ESG stocks for which the sort variable is also expected to produce high returns. The short position of this strategy is stocks that have low ESG and are at the end of the sort variable distribution associated with low returns. If these strategies outperform the traditional strategy with no conditioning on ESG, then there exists ESG flavoured alpha. Chapter 4 also considers further strategies and comparisons to verify any cases in which including ESG information increases returns relative to the unconditional strategy.

Like Mollet and Ziegler (2014), Becchetti et al. (2018), Pedersen et al. (2020) and many others, Chapter 4 does not identify meaningful significant positive alphas. What few are found are insufficient to conclude that the results are not just chance. Harvey et al. (2016) discusses that if enough tests are run then inevitably some come back as showing alpha. A solution is to impose a higher t-statistic requirement of 3, compared to the usual 1.96. At a cut off of three there are just 3 significant ESG alphas amongst the tests. Importantly, none of the strategies produce a significantly low alpha relative to the unconditional sort. The conclusion is that investors can increase their ESG exposure without incurring significant alpha cost by following the strategies suggested in Chapter 4.

## 1.5 Research Contributions

Within the academic literature there continues to be disagreement about the linkage between CSR-CFP, and between CSR and stock returns (Gillan et al., 2021). One of the reasons for the difference is a failure to account for moderating and mediating factors in the CSR-CFP and CSR-stock return relationships. Each of the chapters of this thesis extends understanding by methodologically exploring some of the moderators and mediators omitted from recent work. For example, Chapter 2 considers the CSR activities that help a profitable firm improve their financial performance will not necessarily help a less profitable firm. Chapter 3 recognises that there are heterogeneities in the link between CSR and firm valuation based on the industry in which a firm operates. Therefore Chapter 3 contributes an approximation of performance in the absence of listing which comes from a portfolio of industry peers with a similar performance prior to the listing. Motivating Chapter 4 is the ability to combine ESG information with common factor sorts. Chapter 4 reflects that adding ESG information to a sort on firm size will not necessarily produce the same impact as adding ESG information to a sort on volatility. In the three examples raised here lies a gap in understanding that the papers in this thesis contribute to.

Chapter 2 makes three contributions on the link between CSR and CFP. Firstly, the empirical work shows that the stakeholder dimensions which have positive significant impacts on CFP are different based upon the relative CFP of the firm in the overall CFP distribution. For the most profitable firms, sharing the success with their employees brings significant CFP improvement. For those whose CSR is near the median of the overall CFP distribution, enhancing environmental strengths offers significantly higher CFP. However, the poorest performing firms are recommended to reduce concerns in the short term and only increase stakeholder strengths in the longer term. Importantly, all of the identified affects do not apply for all firms. Benefits of improving engagement with employees are absent for the poorest performers, whilst increasing environmental stakeholder initiatives may reduce profits for those firms at the top and bottom of the overall CFP distribution. In past work, Edmans (2011) identifies employees as being significant through standard OLS regression and therefore does not demonstrate that the effect is stronger in the best performing firms, or that it is absent for low CFP firms. Berman et al. (1999) showed that product and environment performance raises return on assets, but again without reference to the position on the CFP distribution. Aside from Edmans (2011) and Berman et al. (1999), much of the extant work is missing significance on the stakeholder dimensions when studying CSR-CFP. By demonstrating that there are significant coefficients, Chapter 2 addresses the overall insignificance of the CSR-CFP relationship and shows that there are opportunities for all firms to raise CFP through CSR.

Secondly, Chapter 2 adds to a literature that discusses the changing role of CSR in the post global financial crisis period. Most work on CSR-CFP predates the crisis, with more recent studies finding little to add to the seminal CSR-CFP works. As with the full sample results, the use of UQR in Chapter 2 shows that there are significant differences in the post-crisis period when contrasted with the crisis period iteself. Those works which have considered economic crashes argue for CSR providing insurance against the worst CFP effects (Godfrey et al., 2009), or view CSR as aiding stock resilience (Lins et al., 2017, 2019). Whilst Godfrey et al. (2009) recongnises the importance of external stakeholders to resilience, there is no comprehensive study of the five stakeholder dimensions. Again demonstration of the significance on all stakeholder dimensions adds to the inconclusive effects of CSR on CFP documented in the Gillan et al. (2021) review.

Finally, given that there are significant CFP benefits to be realised from the increasing of CSR performance on some stakeholder dimensions, Chapter 2 directs policy into those areas were firms would need incentives to improve their CSR. Because the impact of raising strengths, or reducing concerns, is assessed based upon the relative CFP of the firm, policymakers can use the results of Chapter 2 to guide policy. For example, promotion of engagement with employees would not be necessary if the conclusions of Edmans (2011) applied for all firms. However we show that employee strengths does not raise CFP for the low profit firms. Therefore if the government targets improving employee strengths then there is a need to subsidise firms at the bottom of the CFP distribution. Meanwhile, the strength of the coefficients at the top end of the CFP distribution are much bigger than past work had suggested. For these firms highlighting the results would be sufficient; providing an incentive would be a waste of funds. Such detail on policy is only possible because of our use of UQR.

Past studies of listing to sustainable indexes have produced limited significance. Studying the DJSI North America, Chapter 3 finds a longer lasting valuation increase for listing firms than previously identified. Further, it is shown that the effect is much stronger for firms that had not been exposed to the analyst coverage afforded to S&P 500 members. Existing literature has identified abnormal returns through the CAPM followed by the application of treatment effects methods such as difference-in-difference or two-sample t-tests for abnormal return equality. Chapter 3 generates its abnormal returns using a gsynth approach which reflects relationships between groups of related stocks and does not have an underlying asset pricing model like the CAPM. As well as a methodological differential, the extant work does not allow for heterogeneities across industries or consider the S&P 500 membership split.

The first contribution of Chapter 3 is enabled by the application of a gsynth approach not previously used in finance event studies. Robinson et al. (2011), Oberndorfer et al. (2013), Kappou and Oikonomou (2016), Hawn et al. (2018) and Durand et al. (2019) all construct abnormal returns based on the CAPM in the traditional style exposited in MacKinlay (1997). The gsynth approach generates a counterfactual outcome for a treated firm in the absence of treatment, which is formed of a portfolio of stocks which had a similar return performance during the pre-event control period. Abnormal returns are calculated as the observed return minus the counterfactual portfolio return. Closest to the work of Chapter 3 are Acemoglu et al. (2016) and Acemoglu et al. (2017) who use the original synth method of Abadie and Gardeazabal (2003) and Abadie et al. (2010). Acemoglu et al. (2016) and Acemoglu et al. (2017) motivate their use of synth because it enables the resulting abnormal returns to be free from the problems of parallel trends which plague finance event studies[8]. Synthetic control approaches, both synth and gsynth, allow the specification of the control group from which the weighted portfolio is produced. Chapter 3 chooses industry peers such that any shock which affects the industry of the listed stock also affects the control. Use of the Xu (2017) gsynth in Chapter 3 is required because synth fails to allow for multiple treatments happening at the same time. In the case of DJSI listing there are often simultaneous treatments. Inference on the results contributes to the literature through the robustness the gsynth approach allows.

Second of the contributions in Chapter 3 is the demonstration of higher persistence of the listing effect. Once industry effects have been controlled for and parallel trends better accommodated, there is a value increasing effect of DJSI membership not previously identified in the literature. Likewise, the additional robustness of the gsynth abnormal returns allows the identification of a significant pre-announcement effect in US data which had not been previously seen. The pre-announcement effect echoes a similar effect found in European data by Oberndorfer et al. (2013). Given the drive towards sustainable investment, insights from Chapter 3 contribute timely evidence of abnormal returns to sustainability.

The third contribution of Chapter 3 arises from the testing of the sources of the newly identified valuation effects. We compare reuslts for stocks which are listed on the S&P 500 at the time of the DJSI reconstitution with those who are not S&P 500 members. Significantly larger listing and de-listing effects for the non-S&P 500 stocks confirm that the DJSI does provide value relevant information. Where the information about CSR is already priced into the stock, listing effects will be much smaller and less significant. As S&P 500 stocks receive greater analyst and press coverage, the resulting DJSI listing reveals little about the firm's sustainability practices that is not already known by the market. The extant literature has not considered this perspective and hence our results contribute new confirmation of the value relevance of sustainability.

Chapter 4 adds to a literature on the motivation of investors to hold stocks with

[8]All event studies require an estimate for what would have happened to the treated stock in the absence of treatment. A trend is estimated in the control period and it is then assumed that the path of the treated unit would have followed the same trend absent of the treatment. In the original finance event study literature is is assumed that the trend is captured by a CAPM model which fits the observed returns of the stock durung the control period. The parallel trend is formed by assuming that the performance of the listing stock absent of listing would be parallel to the abnormal returns on the control stocks.

strong ESG. The primary contribution is the demonstration that it is possible to increase ESG exposure without paying an alpha cost. Results stand against the traditionalist perspective that investors must trade abnormal returns for increased ESG performance as explained in Derwall et al. (2011). Contrast is also seen with the recent work of Becchetti et al. (2018) and Pedersen et al. (2020) whereby any difference in returns favoured the holding of portfolios with lower ESG performance. Holding an ESG exposed portfolio need not solely be the result of additional utility from the high ESG performance on top of the standard utility from financial returns. That is the utility function need not follow the two part structure as suggested in Pástor et al. (2020), Pedersen et al. (2020) and others. Rather, Chapter 3 contributes evidence consistent with the increased holdings of sustainable stocks being rational for purely alpha seeking investors.

Chapter 4 is novel in its use of double sorts and focus on the ESG flavoured alpha. The strategies produced suggest that it is possible to increase ESG exposure without an alpha cost. Previously consideration of ESG alpha had focused only on the univariate sort of firms based on their ESG performance (Mollet and Ziegler, 2014; Becchetti et al., 2018; Pedersen et al., 2020). When sorting only on ESG, the abnormal returns from longing high ESG firms and shorting low ESG firms were consistently negative and significant (Pedersen et al., 2020; Gillan et al., 2021). As Alessi et al. (2021) and others argue, the potential for new legislation which may hurt firms with poor ESG is high, particularly on the use of fossil fuels. The option to increase ESG exposure and avoid regulation risk through the ESG flavoured strategies is again something which the existing literature does not offer. Derwall et al. (2011) based the assertion that pursuing sustainable stocks and pursuing abnormal returns were mutually exclusive on those univariate sorts. Double sorts and the ESG flavoured alphas contributed by Chapter 4, suggest Derwall et al. (2011)'s conclusion to be incorrect.

Across the three chapters an increasing importance of ESG is found. Three very different datasets are used, but the message is the same. The chapters demonstrate that it is important to get the best empirical representation for a problem. All three chapters use regularly studied data in novel ways. Each chapter brings out messages that were not easily visible previously. Whether it is a company investing in a project, or an investor choosing stocks, each chapter guides investment decisons towards increased efficiency and returns.

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# Chapter 2

# Directing CSR Investment for Optimal CFP Improvement Using Unconditional Quantile Regression

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**Abstract**

Corporate Social Responsibility (CSR) investment is increasingly recognised as being valuable to improving Financial Performance (CFP), but non-linearities in this relationship are seldom explored. Embracing contemporary theoretical developments on the marginal returns to stakeholder satiation we adopt unconditional quantile regression to robustly study the true impact of strengthening CSR on CFP. For the most profitable firms scaling back CSR may be profit improving, whilst poorer performing firms are advised to focus on their fundamentals rather than assuming CSR can provide a short-term answer. Testing these results against the financial crisis our distributional analysis reveals the insurance effect of established CSR strategy and reaffirms the importance of primary stakeholders in normal times.

Keywords: Financial performance, stakeholder relations, social responsibility, unconditional quantile regression

## 2.1 Introduction

Since the first link between corporate social responsibility (CSR) and corporate financial performance (CFP) there has been a drive for firms to understand how best to target CSR (Orlitzky, 2001). The value of improved CSR performance is seen in resilience to crises (Lins et al., 2017; Albuquerque et al., 2019), reduced downside risk (Hoepner et al., 2018) and a potential for a reduced cost of capital (Baker et al. 2020;

Flammer 2021). However, the literature continues to be inconclusive about the overall effect of CSR on CFP (Gillan et al., 2021). Within this literature CSR may be usefully understood through stakeholders including the environment, community and employees, as well as the product and the diversity of the firm (Freeman, 1984; Freeman et al., 2010; Mattingly, 2017). Meanwhile, CFP may be understood in the short-term as return on assets (ROA), and in the long-term through measures like Tobin's q (TOB). A long-term versus short-term trade off exists (McWilliams and Siegel, 2001; Nguyen et al., 2020) and so the impact of the five stakeholder dimensions must be framed for both. However, the focus continues to be on the average impact of CSR on CFP. This paper asks whether firms can be better guided to focus CSR investment if they consider their own relative CFP.

Intuitively there are issues with the one-size-fits-all approach of the present literature. Theoretical consideration has already been given to the decreasing marginal returns to CSR investment (Garcia-Castro and Francoeur, 2016; Sun et al., 2019). Meanwhile, consumers are known to credit poorer performers more for their CSR improvement efforts (Green and Peloza, 2014; Pope and Waeraas, 2016). Empirical work has not kept pace with the developing arguments for non-linearity. Intuitively, a poorly performing firm needs to get the fundamentals right and not direct funds into activities that are unlikely to bring quick financial reward. From the CSR perspective this means the product and the external image. A highly profitable firm may gain more from investing in its workers, ensuring they are part of the success. Meanwhile only those average performing firms find benefit in environment. Such intuition is lost on the present modelling used within the CSR-CFP literature and a gap exists to empirically investigate CFP dependent stakeholder focuses. Obtaining empirical evidence can then provide more direction to the CSR activity of firms.

This paper recognises that the CSR investment that works for highly profitable firms may not be the best strategy for those with low profitability. By introducing unconditional quantile regression (UQR), we show empirically the best stakeholder dimensions for firms to target at different levels of the CFP distribution. Building on explanatory variables that are well studied in the CSR-CFP literature we may isolate the effect of the five stakeholder dimensions on CFP. We unlock the information within the data to better guide managers in selecting how best to improve their financial performance. We test hypotheses on the CSR-CFP relationship that had been previously untested because of empirical limitations.

Our research design takes the MSCI KLD stakeholder data to construct net strength measures for each firm. Regressing CFP on these net strengths, and with a full set of controls from past CSR-CFP studies we obtain the influence of each strength on CFP. Using UQR allows us to integrate industry and year fixed effects for further robustness. We also consider strengths and concerns separately in reflection of the arguments of Margolis et al. (2009), Mattingly (2017) and others on the asymmetry between responses to strengths and concerns. For example a firm with two strengths and a concern has a net strength of 1, the same as a firm which simply has a single strength. Where stakeholders place more value on strengths the former firm is stronger, whilst in the case that concerns invoke the bigger response the firm with just a single strength is better placed. Splitting into strengths and concerns allows the coefficients to show which perspective dominates on a particular dimension. Adoption of UQR here follows the lack of consensus on controls within the CSR-CFP relationship. The advantage of UQR stems from coefficients being independent of the choice of explanatory variables unlike traditional quantile regression after Koenker and Bassett (1978).

Through the novel approach used in this paper we are able to demonstrate that the impact of stakeholder net strengths on CFP does vary according to the level of the firms CFP. Environmental improvements are most effective for those whose performance is around the average. Increasing environmental strengths for the best performing firms will not bring benefits to match the investment cost. Increases in net strengths with respect to community stakeholders only offer short-term benefits to firms performing around the average. Little significance is seen for diversity. For the poorest CFP firms the product dimension offers the only means to improve in the short-term. Longer-term the environment offers a second route to higher CFP for those at the lower end of the CFP range. For the highest performing firms employees are the only dimension where significant CFP increases are predicted. Improving conditions for staff is shown to be beneficial in the short and long term. Critically we show that there are differences according to CFP and that therefore there is value in using UQR.

A large literature, including Lins (2017,2019) and Jia (2019), sees the Global Financial Crisis as a turning point in the understanding of CSR-CFP. The resilience of those firms who had strong CSR performance to the worst of the crisis is seen as an important lesson learned by investors. We use tests based on seemingly unrelated regressions to show the impact of the global financial crisis on the CSR-CFP relationship. We evidence that product has been the dimension most changed, with environmental concerns bringing stronger benefits to those performing around the median. Concerns in general, and particularly on diversity, reduce financial performance. Peters and Taylor (2016) total q measure is most notably impacted by these diversity changes. We thus evidence a broad robustness of our results, but given the increasing prominance of CSR there is time variance in the estimates.

Contributions of the papers are three-fold. Firstly, UQR demonstrates that the stakeholder focus for poorly performing firms should be very different from that of the best performers. Those at the lowest end of the CFP distribution should focus away from CSR for short-term gain and concentrate on external dimensions for longer term benefit. Secondly, we demonstrate how the importance of the five stakeholders changed after the global financial crisis. Clear evidence on the importance of relative financial performance to the impact of CSR on CFP is provided. Finally, we show how policy-makers and practitioners may target stakeholder dimensions according to the specific firm goal. For example, for environmental performance improvement those performing near the median do not need incentives, but the least profitable firms need much more support than an OLS model would suggest. Subsidies will help low profit firms overcome the lack of profitability. Top performing firms have similar negative coefficients but have the profitability to invest in environmental improvements if the penalty for not investing is high enough. Recognising the differences across the distribution, the government may target incentives at the low profitability and taxation on profitable firms who do not invest. A guide to policy is contributed from our movement away from the mean in estimation. This paper then represents an important step to empirically supporting the theoretical arguments for diminishing marginal returns to CSR investment, and the associated costs

The remainder of the paper is organised as follows. Section 2.2 reviews current research on CSR and CFP to motivate the approach of this paper. We exposit the dataset in Section 3.3 and the UQR methodology in Section 2.4. Results for the full time period are presented in Section 2.5, with the role of the global financial crisis explored in Section 2.6. Section 2.7 evaluates the lessons for management and wider stakeholders, discussing the ways in which the understanding of the CSR-CFP link has been advanced. Section 2.8 concludes.

## 2.2 Literature and Background

CSR-CFP research primarily targets the specific question of benefit to shareholders (Gillan et al., 2021) under the recognition that those making CSR investment decisions will be responsible to those providing the capital. Likewise, we focus on CFP as the outcome of interest rather than any wider measure of the benefit of CSR. Four critical focuses are then the definition of CSR and CFP, the channels through which CSR impacts CFP, moderating factors on those channels and the way that the impact is captured empirically.

Traditional ideas of shareholder wealth maximisation drive the corporate finance literature. When exploring the impact of CSR activity the way that profitability changes is the primary concern. Whether looking at the short-term return on assets (ROA), or the long-term Tobin's q (TOB) the aim is the same. ROA gives an instant picture of the performance of the firm relative to the assets that it has at its disposal. Larger firms have larger assets to invest in CSR, but then should expect larger returns as well. TOB is a valuation based measure that uses the stock market valuation of the firm. As valuation models are based on shareholder expectations for future cashflows, TOB captures the longer-term expected impact of firm's activities. These two measures are then used by most CSR-CFP studies. Presenting both also allows the discussion of the short-run versus long-run trade-off that goes with investing in increased CSR activities (McWilliams and Siegel, 2001; Nguyen et al., 2020).

Recognising CSR through stakeholder dimensions is commonplace, but there remains significant heterogeneity in how the stakeholders are studied empirically. We focus on the five primary areas of Product (PRO), Environment (ENV), Community (COM), Diversity (DIV) and Employees (EMP) identified readily in the MSCI KLD dataset adopted herein. MSCI KLD, like other ratings agencies, base their reports on the examination of specific criteria and so improvements in the score can be made by firms meeting those criteria. Estimating the coefficient on every strength or concern that MSCI raise about a firm is both impractical and unlikely to reflect the way that we think about firms. It is more realistic to consider a firm being judged on its product or environmental impact. Targetting improvement at the dimension level is then more sensible against the five stakeholder dimensions. Fuller options for doing so are detailed within single dimension works, such as those on environment (Goll and Rasheed, 2004; Trumpp and Guenther, 2017), and employees human capital (Kim et al., 2015), for example. Our focus, like much of the literature, is breaking down the effect of CSR on CFP into five stakeholder dimensions and the strengths and concerns thereupon.

Value in treating stakeholders differently is intuitive as firms engage with different stakeholders differently (Clarkson, 1995; Hillman and Keim, 2001). Amongst those papers which have studied all five dimensions EMP and PRO have been the most commonly linked to improved CFP. Berman et al. (1999) is amongst the earlier works to find the importance of what may be considered the primary stakeholders (Hillman and Keim, 2001). By contrast ENV considerations have less immediate impact because the environment does not interact directly with the firm. However, the secondary dimensions build reputation which is likely to impact on longer-term measures of CFP (Hoffman and Ventresca, 1999; Tetrault Sirsly and Lvina, 2019). Godfrey et al. (2009) suggests that secondary stakeholders only become important when the economy is performing badly as they help firms to be more resilient. We demonstrate that the primary stakeholders retain the biggest statistical significance, but that there are variations across the distribution of CFP.

Alternative positions include Perrault and Quinn (2016) who recognise a two-way internal-external stakeholder split after Clarkson (1995). Activities towards external stakeholders, such as ENV and COM are the most observable. Performance on PRO is also readily observable by those who interact with the firm's products. By seeing the way a firm is performing customers and investors may make their demand decisions. Increases in demand increase the profitability of the firm and therefore the long-term value. This is the demand channel from CSR to CFP. However, DIV and EMP are felt more by those inside the firm. For internal stakeholders the impact on CFP is likely to come through productivity, compared to the demand driven impact of external stakeholders. Such splits are intuitive from the channel perspective, but do not help greatly in saying which particular external, or internal, dimension is most linked to CFP. Here we present results on the external-internal split but primarily focus on the five stakeholders after Freeman (1984); Freeman et al. (2010).

Across these literatures, a common question is the way through which the strengths and concerns assessments in databases, like the KLD ESG set used here, should be best employed. Earlier studies took the net strength on each dimension summed over strengths and concerns (Margolis et al., 2007; Perrault and Quinn, 2016). Perrault and Quinn (2016) consequently argue that the actual performance of firms is masked by the aggregation. Separation into strengths and concerns gives more coeffficients, but allows strengths and concerns to impact performance differently. Splitting is advocated by Margolis et al. (2007), Mattingly (2017) and Perrault and Quinn (2016) amongst others. Here we provide both net strengths and the separation of strengths and concerns.

Anderson Jr and Cunningham (1972) is amongst the first works to evidence consumers responding positively to CSR. Increased consumer demand then has the ability to offset any additional costs of engaging with CSR activity (McWilliams and Siegel, 2001; Sen and Bhattacharya, 2001). The consumer demand channel works quickly; as soon as the consumers see the behaviour of the firm they can immediately respond Bhattacharya and Sen (2004); Peasley et al. (2020)[1]. Investor reaction is likewise quick in the event of CSR news (Groening and Kanuri, 2018; Capelle-Blancard and Petit, 2019; Serafeim and Yoon, 2021). Here it is important to see the difference between

[1]For a recent discussion of firm boycotts as an example of an instant response see He et al. (2021).

CSR news and the release of ratings, like those from MSCI, which only takes place anually. Both ROA and TOB will therefore react quickly to the events that change the strengths, or concerns, of firms on the stakeholder dimensions.

Moderation in the consumer demand relationship comes from three main sources. Firstly, CSR activity which is designed to bring corporate gains will be less well received than any CSR activity which appears to be benevolent (Öberseder et al., 2011; Skarmeas and Leonidou, 2013; Sahelices-Pinto et al., 2018). Secondly, consumers expect better corporate citizenship from large firms and those which are the most profitable (Green and Peloza, 2014; Gallardo-Vázquez et al., 2019). Smaller firms may be able to "piggy-back" on the back of the larger firms in their industry. Performance levels matter. Thirdly, the way in which the information is conveyed to the public matters; internal stakeholder activity requires disclosure and results on disclosure are inconclusive (Gallardo-Vázquez et al., 2019). The extent to which image matters to firms can be seen in the efforts they make to appear to have more, not less, CSR engagement (Pope and Wæraas, 2016)[2].

The global financial crisis sparked a change in the way the Finance community viewed CSR. Lins et al. (2017) documents how CSR served as an insurance against downside risk in the GFC. Further Lins et al. (2017) determines CSR as a means to create trust in the management of firms in the recovery from the GFC. Subsequently that trust creates more demand, sales, revenues and therefore stock market valuation. Lins et al. (2019) reaffirms the trust-higher stock returns link with data from within the crisis period itself. Although there are many arguments to improve CSR strengths in a recession, the associated lack of demand means any CSR investment must be handled very carefully.

Econometric concerns are typically downplayed in studies of the CSR-CFP relationship. However, it is intuitive that firms who are performing well are best placed to invest in CSR and hence to benefit from the "virtuous circle" of CFP (Hammond and Slocum, 1996; Makni et al., 2009). Our modelling addresses this by incorporating a lag of CFP. In this way we capture past performance being a key influence on current performance (Waddock and Graves, 1997; Nelling and Webb, 2009). Shahgholian (2019) review notes 22 of 80 leading works on the CSR-CFP link account for endogeneity in this way. Many studies are thus failing to recognise the statistical problems the two-way relationship presents. Following Grewatsch and Kleindienst (2017), Garcia-Castro et al. (2010), and others, we allow for unobserved heterogeneity in both industry and

[2] Overstating your own CSR status is referred to in the literature as "greenwashing". A useful discussion can be found in Wu et al. (2020).

time. Again Shahgholian (2019) highlights the absence of such concerns elsewhere. Important robustness is thus added to our results.

The main contribution of this paper empirically comes from the use of UQR. Early capturing of a non-linear relationship between CSR and CFP is provided by Sun et al. (2019). Evidence is provided of an "inverted-U" shaped relationship between CSR and next period shareholder value. Using one period ahead differs from the majority of the literature but is necessitated by their focus on investor reaction. Because of the strong correlation between CFP performance over time, and CSR performance over time, a similar relationship would emerge for the same period CFP. Given the significance of the quadratic term in Sun et al. (2019) using a simple linear model imposes important restrictions that newer work should avoid. The Sun et al. (2019) "inverted-U" shaped relationship is an important development of the theory in Wagner et al. (2002). Modelling this through quantile regression offers the easiest way to reflect upon the stronger expected coefficients atop the "U" around the median. We show that this inverted-U relationship does exist for longer-term CFP measures TOB and TOT on ENV, but for most dimensions the highest coefficient is at the highest quantiles.

Meier et al. (2019) demonstrates the inverted U for human resource management. Here it is argued that increasing the level of investment in CSR has diminishing marginal returns as in Garcia-Castro and Francoeur (2016). Accompanying this is an increased cost of raising strengths that will go up with every extra strength added. Combining the two means that for low levels of strength the extra profit outweighs the extra costs, but for higher levels of CSR costs rise faster then revenues and financial performance falls. Hence if we were to consider a quantile regression we would see low financial performance associated with high CSR performance. Higher CFP would emerge near the middle of the CSR range. Firms who had gone for higher than average CSR would then have the opportunity to raise profit by reducing CSR. These cost-benefit arguments can be found in Sun et al. (2019) also. Subsequent work to Sun et al. (2019) and Meier et al. (2019) has focused on non-linearities in the CSR-risk relationship rather than the CSR-CFP explored here. Non-linearity has also been evidenced for all dimensions by Garcia-Castro and Francoeur (2016) through a fuzzy set approach, although this does not provide the clarity offered by UQR.

Addressing multicollinearity and endogeneity alongside this call for distributional analysis, we study how firms may best target CSR stakeholder investment with respect to their performance levels using UQR after Fortin et al. (2009). Whilst sharing many characteristics with the quantile approach of Koenker and Bassett (1978), UQR offers greater robustness to covariate selection, parameter distributions not being dependent on the choice of explanatory variables (Borah and Basu, 2013). Given the identified divergence of covariates within the literature, having a methodology where the impact of the stakeholder dimensions is less affected by other controls is invaluable.

## 2.3 Data

Studies of the CFP-CSR relationship face three key decisions upon which little unity of direction has been derived. Firstly, and with the most commonality in the literature, the process of capturing CFP must be established. For this purpose return on assets (ROA) and Tobin's q (TOB) have been the mainstay of extant studies. Chosen for their ability to capture current and future expected performance succinctly they cover most of what CFP can be considered to be. However, the rationale that CSR encourages increased brand perception amongst consumers creates an opening for a third measure of CFP that reflects such intangible assets. In this paper the Total q (TOT) of Peters and Taylor (2016) is used to meet the challenge. Secondly, a measure for CSR is required and here there is less consistency. Increasingly studies are using disaggregate measures to run alongside the simple net strength approach; division into either strengths or weaknesses is growing in commonality. Finally, the degree of unobserved heterogeneity begs methodological and control variable questions. Here two-digit North American Industrial Classification System (NAICS) codes are used for industry effects but the results are robust to using three-digit codes or moving to an individual firm level[3]. Through the following three subsections we detail the response to these three key questions in introducing the data used in our analysis.

### 2.3.1 Measuring CFP

In keeping with the extant literature CFP is measured through ROA and TOB, with these calculated directly from Compustat data using:

$$\mathrm{ROA} = \frac{oibdp - dp - xint}{at} \tag{2.1}$$

$$\mathrm{TOB} = \frac{at + prcc_c \times csho + txdb + itcb - pref}{at} \tag{2.2}$$

In the top line of (2.1) *oibdp* is the operating income before depreciation, *dp* is the total depreciation and ammortisation for the year and *xint* is the sum of all interest and related expenses. For TOB the top line has the market value of the firm calculated as

[3] Results for these two cases are available on request.

the product of the year end price $prcc_c$ and the number of shares outstanding *csho*. To this the assets of the firm (*at*), deferred taxes (*txdb*), and investment tax credit (*itcb*) are added. Finally, a measure of the preferred stock of the firm is deducted. $pref$ here is constructed as the first available measure from the list *pstkrv*,*pstkl*,*pstk* and 0. In both (2.1) and (2.2) the values of these CFP measures are scaled according to the size of the firm by dividing by *at*, the total assets of the business. TOB can also be constructed using the market value of the firm as the denominator, but we maintain an asset focus in this paper. Results with the market based TOB are qualitatively similar.

In recognising the role of consumer perceptions, advertising, and CSR as a competition tool, we further adopt Peters and Taylor (2016) total q (TOT). Details of the calculation of TOT are provided with the Peters and Taylor (2016) paper and are omitted here for brevity; we use the values downloadable from WRDS for this analysis. Matching on the CUSIP stock code ensures no data is lost. In principle TOT is linked to TOB but with assets also including intangible assets. The numerator of TOT additionally captures accumulated knowledge capital from research and development activities.

### 2.3.2 Measuring CSR

Freeman (1984)'s stakeholder approach is the most commonly used way to empirically capture firm CSR. The MSCI KLD dataset is particularly well designed for the representation of CSR through stakeholders (Mattingly, 2017). The five considered stakeholder dimensions are product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). Of these PRO, DIV and EMP may be considered internal as they relate to that particular firm's business, whilst ENV and COM are external as they engage with the wider set of stakeholders. Independent MSCI observers examine firms to establish their practice on a number of CSR activities; the precise number varies per industry. If a given characteristic is present it is coded with a 1, if not then a 0 is used. These characteristics are classified as either being strengths from a CSR perspective, or as being concerns. For example a strength in the relationship with the community is providing donations to local charities, whilst a concern under the COM is failure to engage with nearby residents in production decisions. The five primary dimensions all feature strengths and weaknesses.

Whilst some CSR-CFP studies have used an aggregate measure, and others focus on internal and external stakeholders, we maintain the five dimensions. Whether using five dimensions, internal-external, or just the total, a second decision is required on how exactly to measure. Using total strengths, total weaknesses or the difference there between seems intuitive, but fails to recognise the fact that different firms have different strengths and weaknesses assessed. A higher number of strengths may not be reflective of better performance but simply being in an industry where more strengths are assessed. Overcoming this issue we divide the firms net strength by the number of MSCI ESG criteria upon which the firm was assessed. A firm with three strengths will then score higher if it was only assessed on three strengths compared to if it had been assessed on six but still only scored three.

Firm $i$ is assessed on $sikt$ strengths and $wikt$ concerns at time $t$ on each dimension $k$ from the five stakeholder dimensions, $k \in \{PRO, ENV, COM, DIV, EMP\}$. The indicator variable $s_{ipkt}$ takes the value 1 if a firm has particular strength $p$ from within dimension $k$ at time $t$ and is 0 otherwise. Likewise $w_{imkt}$ is 1 whenever firm $i$ has particular concern $m$ in dimension $k$ at time $t$. The measure of strengths, $S^k_{it}$, and concerns $W^k_{it}$ are then computed as:

$$S^k_{it} = \frac{1}{sikt} \sum_{p=0}^{sikt} s_{ipkt} \tag{2.3}$$

$$W^k_{it} = \frac{1}{wikt} \sum_{m=0}^{wikt} w_{imkt} \tag{2.4}$$

Following the adjustment for the numbers of strengths and concerns $S^k_{it} \in [0, 1]$ and $W^k_{it} \in [0, 1]$. Net strengths, $NS_{ikt}$ of firm $i$ in dimension $k$ at time $t$ are thus computed using:

$$NS_{ikt} = \frac{1}{sikt} \sum_{p=0}^{sikt} s_{ipkt} - \frac{1}{wikt} \sum_{m=0}^{wikt} w_{imkt} \tag{2.5}$$

Given the bounds on $S_{ikt}$ and $W_{ikt}$, $NS_{ikt}$ is bounded between 1 and -1. The former implies that the firm has complete strength and no negatives, whilst the latter displays all assessed weaknesses and none of the assessed strengths. Most firms will have values between these two bounds.

### 2.3.3 Financial Controls

Consistently within the CSR-CFP literature firm size and leverage are used as controls. Firm size is measured as the log of assets, whilst leverage is simply the ratio of debt to equity. Both measures are useful in understanding the ability of the firm to raise

Table 2.1: Firm numbers by year

| Year | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
|---|---|---|---|---|---|---|
| Firms | 1297 | 1311 | 1298 | 1403 | 1461 | 1479 |
| | | | | | | |
| Year | 2011 | 2012 | 2013 | 2014 | 2015 | Total |
| Firms | 1422 | 1428 | 1282 | 1277 | 1404 | 15,062 |

Notes: Firm numbers represent those with valid data within our matched MSCI and Compustat sample. Totals denote the total number of firm-years within the full sample.

capital and invest themselves. Any firms with negative assets or leverage are dropped from the dataset.

Berman et al. (1999) proposes four strategy variables that should be used in CSR-CFP regressions; these are applied here. Two intensity measures are suggested. First sales intensity (SI) measures the ratio of sales to assets, with firms seeking to get high values of sales for each asset investment. Capital intensity (CI) relates to the ratio of assets to employment, following from simple production models. Cost efficiency (EF) uses the cost of goods sold to establish how efficiently the firm is able to operate; more efficient firms may be able to maintain that efficiency when investing in CSR initiatives. Finally, capital expenditure (CE) provides a measure of the existing investment of the firm, revealing how much scope remains for the firm to invest further. With *emp* as the number of employees and *sale* being the total sales of the firm, *cogs* is the cost of goods sold and *capex* as capital expenditure we have the four ratios in equations (2.6) to (2.9).

$$SI = \frac{sale}{at} \tag{2.6}$$

$$CI = \frac{at}{emp} \tag{2.7}$$

$$EF = \frac{cogs}{sale} \tag{2.8}$$

$$CE = \frac{capex}{sale} \tag{2.9}$$

### 2.3.4 Summary Statistics

Our data spans the period 2005 to 2015 with Table 2.1 providing the breakdown by year. Following the definitions provided by Reinhart and Rogoff (2008) and Mishkin (2011) the financial crisis is considered as being 2007 to 2009 inclusive. When assessing the impact of the financial crisis, 2005 and 2006 are dropped leaving a sample of 12,453 firms. Over time the number of matched firms has increased. 2004 to 2005 saw a large number of firms added to the MSCI data. 2005 therefore represents a logical startpoint for the sample. Table 2.1 confirms numbers have remained similar since.

Table 2.2 shows that there is considerable variation amongst the firms in the sample on all of the financial controls. Primary interest lies in the five stakeholder dimensions where there are indeed firms who have only strengths (concerns) and where these cover all of the specific traits upon which they are assessed. One exception to this is ENV. No firms are assessed as having concerns in all of the concern criteria on which they are tested. The lowest concern score is 0.833. Given the lowest net strength is -0.750 we may then conclude that the firm scoring 0.833 for concerns has some strengths to offset. This is likely attributable to the importance environmental issues have had in the corporate psyche in recent years. In all cases the average scores are low, recognising that for many firms the score is 0.

## 2.4 Empirical Approach

Unconditional quantile regression (UQR) as developed by Fortin et al. (2009) is implemented with fixed effects following Borgen (2016) to recognise the unobserved heterogeneity between industries. Relative to Koenker and Bassett (1978) the UQR offers a removal of the conditionality of coefficient distributions on the choice of covariates. Such robustness to explanatory variable choice is particularly valuable in studies of CSR-CFP since the optimal choice of independent variables has not been defined (Borah and Basu, 2013). Such advantages have ensured that the methodology is widely adopted in health and labour economics in particular; recent examples being Broecke et al. (2017) and Pereira and Galego (2018). Each exploit UQR to gain new insights "away from the mean" of the type sought in this work. Wider use of quantile regression in finance is limited, amongst the few examples being Somers and Whittaker (2007) and Krüger and Rösch (2017) explorations of the link between profitability and defaults.

Data in this paper is organised as an unbalanced panel of firms observed over many time periods. Therefore, in any given year the position of a firm in the CFP distribution is defined by the CFP of all firms across all years. Powell (2010) and Powell (2022) argue that where individual units are more prone to appear consistently in the same part of the outcome distribution a panel quantile estimator should be used with fixed effects applied at the unit level. Within the dataset used in this paper there are many examples of firms who only appear at most three times and so firm level fixed effects are impractical. Rather we use industry year fixed effects to capture unobserved

Table 2.2: Summary statistics for full period

| Variable | Mean | s.d. | Min | Max |
|---|---|---|---|---|
| Corporate Financial Performance: | | | | |
| Return on assets (ROA) | 0.113 | 0.167 | -5.045 | 1.274 |
| Tobin's q (TOB) | 2.592 | 1.822 | 0.588 | 77.39 |
| Total q (TOT) | 1.698 | 11.01 | -224.5 | 435.2 |
| Controls: | | | | |
| Sales inensity (SI) | 0.937 | 0.678 | 0.024 | 4.075 |
| Capital intensity (CI) | 1223 | 2779 | 23.43 | 30291 |
| Cost efficiency (EF) | 0.678 | 0.609 | 0.032 | 8.382 |
| Capital Expenditure (CE) | 0.095 | 0.199 | 0.000 | 1.821 |
| Leverage | 1.739 | 3.847 | 0.000 | 31.96 |
| Size | 7.244 | 1.699 | 3.579 | 12.60 |
| Stakeholder Dimensions Net Strengths: | | | | |
| Product (PRO) | 0.004 | 0.217 | -1 | 1 |
| Environment (ENV) | 0.034 | 0.160 | -0.750 | 1 |
| Community (COM) | 0.011 | 0.205 | -1 | 1 |
| Diversity (DIV) | -0.139 | 0.350 | -1 | 1 |
| Employees (EMP) | -0.005 | 0.180 | -1 | 1 |
| Stakeholder Dimensions Strengths: | | | | |
| PRO | 0.050 | 0.192 | 0 | 1 |
| ENV | 0.063 | 0.159 | 0 | 1 |
| COM | 0.041 | 0.173 | 0 | 1 |
| DIV | 0.079 | 0.183 | 0 | 1 |
| EMP | 0.064 | 0.139 | 0 | 1 |
| Stakeholder Dimensions Concerns: | | | | |
| PRO | 0.046 | 0.126 | 0 | 1 |
| ENV | 0.029 | 0.091 | 0 | 0.833 |
| COM | 0.030 | 0.151 | 0 | 1 |
| DIV | 0.218 | 0.261 | 0 | 1 |
| EMP | 0.069 | 0.130 | 0 | 1 |

Notes: Firm size is measured using the natural log of assets. Capital intensity is divided by 10,000 and capital expenditure by 1,000 to ensure readability of coefficients. Data from MSCI ESG and Compustat. ($n = 15081$)

heterogeneity. Consequently it would not be the case that a given industry-year would only include observations in one part of the CFP distribution. Borgen (2016) presents a solution to the need for panel data using a wrapper for the Stata panel regression command xtreg and adapts it for use with UQR. It is Borgen (2016)'s approach which is used in this paper. Further, as our controls are at the firm level, the result is that there is a far reduced effect of not having a panel structure of the type used in Powell (2022)'s updated version of the Powell (2010) estimators. Solutions for panel data in QR are presented in Canay (2011) and Galvao Jr (2011). However, given the advantages of UQR over QR in the presence of moderation effects between covariates, we employ a UQR solution here.

Our interest lies in the impact of CSR, captured through the variables PRO, ENV, COM, DIV and EMP, on CFP as measured by ROA, TOB and TOT. For firm $i$ these performance measures may be referred to as $Y_i$, with $Y \in \{ROA, TOB, TOT\}$. Defining the distribution of $Y$ as $F_Y$ then gives the marginal distribution for $Y$ as $f_Y$. All other covariates are collected together in a matrix $X_i$, while the year dummies are collected in a single matrix $T$. Unobserved heterogeneity across industries enters via the fixed effect $\gamma_j$, where firm $i$ is in industry $j$. UQR then requires two phases of calculation, first focusing the inference function on 0 converts it to the recentered inference function (RIF). This transformation draws upon the distribution $F_Y$ to create $RIF(Y, q_\tau, F_Y)$, and then the regression on the net CSR strengths, controls and year dummies.

In phase 1 the $RIF$ function is generated using equation (2.10).

$$RIF\left(Y, q_\tau, F_Y\right) = q_\tau + \frac{\tau - \mathbb{1}\left(Y \leq q_\tau\right)}{f_Y(q_\tau)} \tag{2.10}$$

in which $q_\tau$ is the value of $Y$ at quantile $\tau$. Symmetric treatment observations either side of $\tau$ is generated through the indicator function $\mathbb{1}\left(Y \leq q_\tau\right)$, which takes the value 1 when the inequality is satisfied. By not including the covariates at this stage UQR offers the opportunity to obtain parameter distributions which are independent of the measurement of CSR employed and the variables selected as controls.

Using the RIF estimated in equation 2.10 it is then possible to perform a simple linear regression to obtain the impact of $NS_{it}^k$ at quantile $\tau$. We estimate:

$$\begin{aligned} RIF\left(Y, q_\tau, F_Y\right)_{it} = & \alpha + \phi_1 NS_{it}^{PRO} + \phi_2 NS_{it}^{ENV} + \phi_3 NS_{it}^{COM} + \phi_4 NS_{it}^{DIV} \\ & + \phi_5 NS_{it}^{EMP} + \beta X_{it} + \gamma_{mt} + \epsilon_{it} \end{aligned} \tag{2.11}$$

with our interest being in $\phi_1$ to $\phi_5$ as the coefficients on the stakeholder dimensions.

Note that for convenience the $\tau$ subscript associated with each coefficient is deprecated both in equation (2.11) and hence forth. $\gamma_{mt}$ here captures the industry-year fixed effects where firm $i$ is in industry $m$ at time $t$.

In this paper we also consider the strengths and concerns independently. In that case the regression model may be specified as:

$$\begin{aligned} RIF\left(Y, q_\tau, F_Y\right)_{it} =& \alpha + \phi_1 S_{it}^{PRO} + \phi_2 S_{it}^{ENV} + \phi_3 S_{it}^{COM} + \phi_4 S_{it}^{DIV} + \phi_5 S_{it}^{EMP} \\ &+ \phi_6 W_{it}^{PRO} + \phi_7 W_{it}^{ENV} + \phi_8 W_{it}^{COM} + \phi_9 W_{it}^{DIV} \\ &+ \phi_{10} W_{it}^{EMP} + \beta X_{it} + \gamma_{mt} + \epsilon_{it} \end{aligned} \tag{2.12}$$

with our interest being in how the coefficients on $\phi_1$ to $\phi_5$ differ from those on $\phi_6$ to $\phi_{10}$. To aid the notation we move the dimension to the superscript. Note again that the $\tau$ subscript associated with each coefficient is deprecated. In this paper we use two-digit NAICS codes for the industry year fixed effects. As a robustness check we consider three digit NAICS codes.

To evaluate the benefits of UQR, a test is required to establish whether there are significant differences in coefficients on the CSR stakeholder dimensions across quantiles. UQR uses a two stage process such that the regressions at stage two are performed on the same set of observations and control variables, but have different independent variables. To compare quantiles $\tau_1$ and $\tau_2$, the dependent variables are $RIF\left(Y, q_{\tau,1}, F_Y\right)$ and $RIF\left(Y, q_{\tau,2}, F_Y\right)$. As such the test of parameter equality must be based upon seemingly unrelated regressions. The test used follows Rios Avila (2019) and is as implemented in Stata using the package *rif* (Rios-Avila, 2020). As industry-year fixed effects are used in this paper all variables are centred by the code prior to estimating the seemingly unrelated regressions. Bootstrapping is used to allow for the industry-year cluster robust standard errors; 1000 repetitions are employed. We report a joint test that the parameters are equal across all five of the quantiles within the result tables and also conduct pairwise tests for the 10 combinations of the quantiles analysed in this paper[4]. Implementation of the test follows Rios Avila (2019) and uses code provided in the stata package rif (Rios-Avila, 2020).

[4]Pairwise tests for the CSR dimensions in the full sample results are available in the supplementary material. All other pairwise tests are available on request.

## 2.5 Results

Estimation of our model is performed across three measures of CFP at all quantiles from $\tau = 0.10$ to $\tau = 0.90$ at intervals of 0.01, however for brevity we report only $\tau = 0.10$, $\tau = 0.25$, $\tau = 0.50$, $\tau = 0.75$ and $\tau = 0.90$ within the paper. All quantiles are then used to plot graphs of the CSR coefficients to give a complete picture of the impact of increasing the net strengths of the firm in each stakeholder dimension. As this is the first exposition of UQR on the CSR-CFP link attention is given to the other controls and the information contained within the $\beta$ matrix.

### 2.5.1 Net Strengths

Table 2.3 reports the estimates of the stakeholder dimension coefficients for ROA, TOB and TOT. In all cases the models are estimated with the financial controls set out in Table 2.2. We also include a lag of the dependent variable to allow for endogeneity. In the OLS column we report the estimates under OLS regression with industry-year fixed effects and heteroskedasticity robust standard errors. Quantiles $\tau = 0.10$, $\tau = 0.25$, $\tau = 0.50$, $\tau = 0.75$ and $\tau = 0.90$ are reported to provide an impression of the variation over the distribution of the respective CFP measures.

Immediately Table 2.3 demonstrates that there are more significant coefficents from the unconditional quantile regression compared to the OLS. When considering ROA there are no significant coefficients in the OLS model, but all five dimensions are significant at $\tau = 0.75$. ROA is a short term measure and it is unsurprising that the poorer performing firms, $\tau = 0.10$ and $\tau = 0.25$, display negative coefficients on the stakeholder dimensions. For these firms stakeholders will look for improved performance, and this is likely to come from non-CSR projects. For the best performing firms, $\tau = 0.90$, ENV, COM and DIV all offer significant positive coefficients. These are the external stakeholders and show the value for the best firms engaging with CSR in a public way. We see also that the EMP coefficients are positive and significant. Employees are primary stakeholders and this result is in line with Hillman and Keim (2001) and others.

For TOB the OLS regression shows significant positive coefficients on PRO, DIV and EMP, representing again the primary stakeholders. However, there is no significance on either ENV or COM as suggested by Godfrey et al. (2009). Quantile coefficients reveal that ENV is in fact a significant benefit to those performing closer to the middle of the profit distribution. For $\tau = 0.90$ the coefficient is negative, but not significant.

Table 2.3: Stakeholder Dimension Net Strengths and Financial Performance

| | | OLS | Unconditional quantile regression | | | | | Equal |
|---|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ | |
| ROA | PRO | -0.003 | -0.006 | 0.009** | 0.004 | 0.010 | -0.007 | 14.31** |
| | | (0.002) | (0.008) | (0.003) | (0.003) | (0.006) | (0.011) | |
| | ENV | -0.002 | -0.023* | -0.005 | 0.016** | 0.021* | 0.021 | 13.06** |
| | | (0.004) | (0.011) | (0.005) | (0.005) | (0.009) | (0.012) | |
| | COM | -0.001 | -0.013 | -0.001 | 0.005 | 0.011* | 0.022* | 5.82 |
| | | (0.003) | (0.009) | (0.004) | (0.004) | (0.005) | (0.009) | |
| | DIV | -0.002 | -0.026*** | -0.004 | 0.002 | 0.006 | 0.017*** | 16.80** |
| | | (0.002) | (0.005) | (0.002) | (0.002) | (0.003) | (0.005) | |
| | EMP | 0.003 | -0.009 | 0.003 | 0.012** | 0.033*** | 0.049*** | 17.82** |
| | | (0.003) | (0.009) | (0.004) | (0.004) | (0.007) | (0.013) | |
| Tobins Q | PRO | 0.092 | 0.012 | 0.067* | 0.081* | 0.148 | 0.373 | 7.99 |
| | | (0.053) | (0.020) | (0.027) | (0.037) | (0.099) | (0.241) | |
| | ENV | 0.043 | 0.126*** | 0.165*** | 0.380*** | 0.390*** | -0.025 | 17.22** |
| | | (0.057) | (0.036) | (0.041) | (0.052) | (0.099) | (0.191) | |
| | COM | -0.004 | 0.060* | 0.029 | 0.039 | 0.004 | -0.042 | 1.94 |
| | | (0.022) | (0.023) | (0.026) | (0.034) | (0.048) | (0.134) | |
| | DIV | 0.127* | 0.080*** | 0.093*** | 0.110*** | 0.121* | 0.265 | 1.89 |
| | | (0.064) | (0.017) | (0.019) | (0.028) | (0.053) | (0.146) | |
| | EMP | 0.155* | 0.082** | 0.184*** | 0.385*** | 0.407*** | 0.393 | 21.60*** |
| | | (0.062) | (0.029) | (0.033) | (0.057) | (0.111) | (0.219) | |
| Total Q | PRO | -0.294 | 0.059 | 0.099** | 0.182*** | 0.375** | 0.746* | 10.55* |
| | | (0.236) | (0.044) | (0.031) | (0.039) | (0.129) | (0.339) | |
| | ENV | 0.048 | 0.010 | 0.076 | 0.238*** | 0.363** | 0.176 | 16.57** |
| | | (0.138) | (0.044) | (0.040) | (0.048) | (0.127) | (0.397) | |
| | COM | -0.146 | 0.019 | -0.004 | 0.056 | -0.014 | -0.047 | 5.80 |
| | | (0.122) | (0.027) | (0.022) | (0.032) | (0.073) | (0.202) | |
| | DIV | 0.185 | 0.030 | 0.039* | 0.041 | 0.051 | 0.375* | 3.42 |
| | | (0.102) | (0.020) | (0.018) | (0.022) | (0.046) | (0.159) | |
| | EMP | -0.389* | 0.042 | 0.164*** | 0.291*** | 0.764*** | 1.404*** | 43.26*** |
| | | (0.172) | (0.038) | (0.035) | (0.046) | (0.123) | (0.333) | |

Notes: Estimation of equation (2.11) with the re-centered inference function for return on assets (ROA) ,Tobin's q (TOB), and total q from Peters and Taylor (2016) (TOT) as the CFP measure of interest. The first column indicates which measure applies to which rows of coefficients. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code and year. Test reports a joint equality test on the parameters for the five estimated quantiles with a null hypothesis of no variation across quantiles. All models are estimated with sales intensity, capital intensity, cost efficiency, capital expenditure, leverage and size as financial controls. Equal is a test for parameter equality across the five stated quantiles following Rios-Avila (2020). Reported values are $\chi^2$ statistics with significance based upon 1000 bootstraps. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

PRO likewise is only significant for those performing closer to the median. Both DIV and EMP show increasing coefficients across the quantiles, the best performing firms gaining most from improving their scores in these dimensions. When we contrast these coefficients against the OLS estimates we note that the UQR has revealed significance in ENV that was not there in the OLS. The magnitude of the OLS coefficient on EMP is also much smaller than that for the upper quartile.

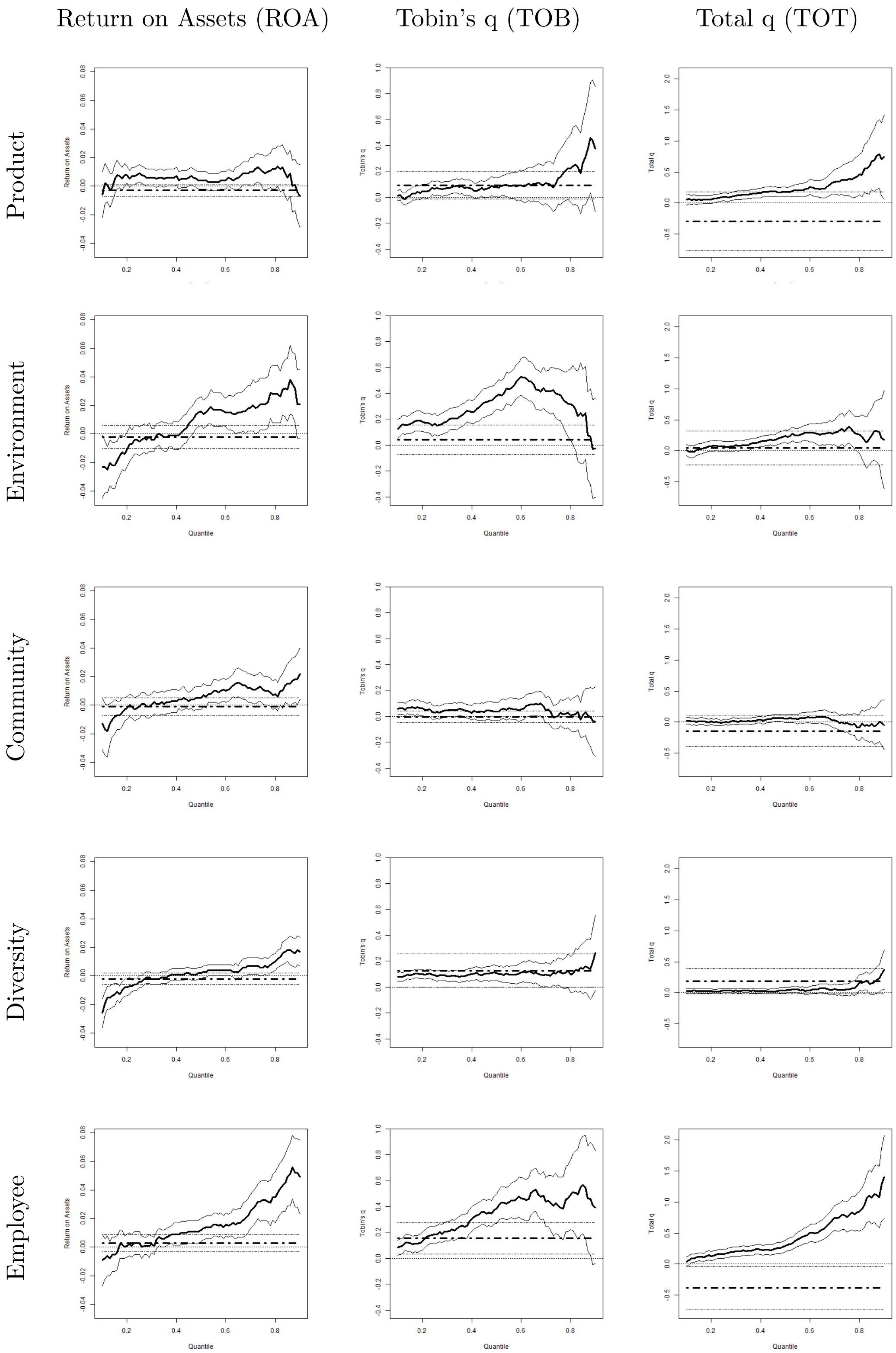
TOT displays similar patterns but here only DIV gives a significant positive coefficient from the OLS. EMP is estimated with a significant negative coefficient. For TOT there are no significant coefficients at $\tau = 0.10$, but very high benefits at $\tau = 0.75$ and $\tau = 0.90$. Long-term measures both point to the importance of primary stakeholders for the best firms and the secondary stakeholders as being only beneficial to those around the median. Contrast between UQR and OLS on EMP for TOT is marked and shows well the dangers of estimating only at the average. Firms may follow a strategy of moving funds away from EMP projects when actually they could have significant improvement to their performance.

UQR has value if we are able to demonstrate significantly different impact from the stakeholder net strengths on the overall CFP of the firm across CFP quantiles. Table 2.3 reports the results from joint tests of parameter equality across the five stated quantiles. These tests are based upon Rios Avila (2019) as implemented in Rios-Avila (2020). Because our models use clustered standard errors, 1000 bootstraps are used in the evaluation of statistical significance. We see that in 9 of the 15 cases there is statistical significance. From the pairwise comparisons we see 52 of the 150 tests conducted reject the null hypothesis of parameter equality at the 5% level[5]. We may therefore conclude that the impact on CFP of net strengths in the five stakeholder dimensions does depend upon the relative position of the firm in the overall CFP distribution.

To better illustrate the effect of the stakeholder dimensions on CFP across the distribution we plot the quantile estimates for $\tau \in [0.10, 0.90]$. Figure 2.1 presents the three CFP measures as the columns and the five stakeholder dimensions as the rows. Thick lines are used to plot coefficients and thinner lines to add a 95% confidence interval around the estimates. Solid lines are used to show the UQR coefficients, whilst the horizontal dot-dash lines are the OLS estimate and associated confidence interval. Three patterns can be seen. For many dimensions there is an upward slope to the

[5]Results may be found in the supplementary material. We have 10 combinations of the five quantiles studied in this paper. There are 5 stakeholder dimensions meaning a total of 50 tests per CFP measure. With three CFP measures there are therefore 150 tests performed

Figure 2.1: CSR-CFP Unconditional Quantile Regression Coefficients: Net Strengths




Notes: OLS and UQR estimated coefficients. Thick lines are used to plot coefficients, thinner lines the associated 95 per cent confidence intervals. Solid lines represent the UQR values and horizontal, quantile invariant, dot-dash lines the OLS.

UQR, representing a higher value of net strengths for the best CFP firms. In some cases, such as ENV and DIV for ROA there are negative significant ranges for the poorest performers. In the TOB and TOT plots there are cases where there is little variation across quantiles. For ENV there is a clear "inverted-U" shape for TOB, matching with Trumpp and Guenther (2017) and Sun et al. (2019). Unlike Sun et al. (2019) our CFP measure is contemporeneous, so here we are seeing further robustness to the existing literature. An "inverted-U" may also be seen for EMP, matching the Meier et al. (2019) uni-dimensional analysis.

### 2.5.2 Strengths and Concerns

Mattingly and Berman (2006), Perrault and Quinn (2016) and others argue for the separate consideration of the strengths and concerns when using the MSCI KLD data. As a second stage we use the $S_{it}^k$ and $W_{it}^k$ measures independently. From each regression we obtain 10 coefficients on the stakeholder dimensions and these are reported in Table 2.4. Once more OLS regression results are contrasted with $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$.

In the first six columns of coefficients there are many positive significant coefficients for all three of the CFP measures. Patterns have similarity to those from the net strengths in Table 2.3, with smaller and negative values at the lower quantiles. The OLS model identifies a negative significant coefficient on COM for ROA, driven by these lower quantiles. For the short term measure, ROA, increasing strengths is seen as a costly diversion of funds that lower ROA firms cannot afford. At $\tau = 0.75$ the same positive significant coefficients on primary stakeholders may be seen. Concerns, the last six columns, are seen to have less significance for ROA, with PRO the only dimension to show significant positive coefficients. This behaviour may be tail effects, but is also consistent with the traditionalist perspective that CSR projects divert funds away from more profitable non-CSR projects

In the long-term measures there is far greater positive signficant coefficients on strengths, and more negative significant coefficients on concerns. Primary stakeholder strengths are important to the highest performers. Firms at, and below, the median can also gain from strengths with secondary stakeholders. Godfrey et al. (2009) argues that for secondary stakeholders firms need to take time to build up reputation. Data here suggests this is true because of the longer-term benefits. We see too that concerns on DIV and EMP decrease CFP for all, including those poor performers. Addressing concerns, as well as working on strengths, can then be seen as a route to greater profitability from the bottom end of the distribution. PRO again has positive significant

Table 2.4: Coefficients of Stakeholder Dimension Strengths and Concerns on Financial Performance

| | Stakeholder Dimension Strengths | | | | | | | Stakeholder Dimension Concerns | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | OLS | Unconditional quantile regression | | | | | Equal | OLS | Unconditional quantile regression | | | | | Equal |
| | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ | |
| Panel (a): Return on Assets | | | | | | | | | | | | | | |
| PRO | -0.003 | -0.032*** | 0.006 | 0.008* | 0.026*** | 0.017 | 18.03** | 0.001 | -0.082*** | -0.020*** | 0.007 | 0.039*** | 0.087*** | 39.19*** |
| | (0.002) | (0.008) | (0.003) | (0.004) | (0.007) | (0.013) | | (0.005) | (0.011) | (0.006) | (0.005) | (0.010) | (0.018) | |
| ENV | -0.005 | -0.016 | -0.006 | 0.014* | 0.011 | 0.002 | 10.75* | -0.014 | -0.031 | -0.014 | -0.010 | -0.021 | -0.014 | 1.79 |
| | (0.004) | (0.013) | (0.006) | (0.006) | (0.010) | (0.013) | | (0.010) | (0.021) | (0.012) | (0.012) | (0.016) | (0.026) | |
| COM | -0.007* | -0.040*** | -0.009 | 0.005 | 0.012* | 0.031** | 16.75** | -0.003 | -0.018 | -0.008 | -0.006 | -0.004 | -0.004 | 1.07 |
| | (0.003) | (0.011) | (0.005) | (0.005) | (0.006) | (0.011) | | (0.004) | (0.011) | (0.006) | (0.005) | (0.007) | (0.013) | |
| DIV | 0.001 | -0.024* | -0.012* | 0.004 | 0.019* | 0.027* | 12.39* | 0.003 | 0.015 | -0.003 | -0.000 | 0.005 | -0.003 | 2.58 |
| | (0.005) | (0.010) | (0.005) | (0.006) | (0.008) | (0.014) | | (0.003) | (0.008) | (0.004) | (0.003) | (0.004) | (0.008) | |
| EMP | 0.001 | -0.052*** | -0.001 | 0.019*** | 0.047*** | 0.091*** | 34.43*** | -0.006 | -0.033* | -0.007 | -0.004 | -0.020 | -0.008 | 13.15* |
| | (0.006) | (0.014) | (0.006) | (0.005) | (0.009) | (0.016) | | (0.006) | (0.015) | (0.007) | (0.007) | (0.011) | (0.021) | |
| Panel (b): Tobin's q | | | | | | | | | | | | | | |
| PRO | 0.239** | 0.041 | 0.090** | 0.207*** | 0.427*** | 0.850** | 12.75* | 0.355*** | 0.063 | 0.009 | 0.299*** | 0.715*** | 1.096*** | 21.01*** |
| | (0.073) | (0.026) | (0.032) | (0.048) | (0.125) | (0.307) | | (0.083) | (0.050) | (0.065) | (0.088) | (0.174) | (0.299) | |
| ENV | 0.001 | 0.099** | 0.146** | 0.342*** | 0.286* | -0.273 | 16.01** | 0.079 | -0.165 | -0.149 | -0.286** | -0.182 | -0.004 | 1.43 |
| | (0.064) | (0.037) | (0.048) | (0.057) | (0.113) | (0.198) | | (0.071) | (0.102) | (0.080) | (0.110) | (0.157) | (0.306) | |
| COM | 0.016 | 0.154*** | 0.066 | 0.099* | 0.108 | -0.034 | 4.90 | 0.030 | 0.060 | 0.021 | 0.036 | 0.130 | 0.081 | 1.66 |
| | (0.034) | (0.032) | (0.040) | (0.042) | (0.069) | (0.204) | | (0.041) | (0.042) | (0.059) | (0.058) | (0.090) | (0.155) | |
| DIV | 0.117 | 0.081** | 0.102* | 0.121* | 0.095 | -0.012 | 1.09 | -0.099 | -0.066** | -0.075** | -0.073* | -0.061 | -0.326 | 3.58 |
| | (0.078) | (0.030) | (0.042) | (0.054) | (0.091) | (0.186) | | (0.056) | (0.022) | (0.025) | (0.037) | (0.079) | (0.176) | |
| EMP | 0.274** | 0.058 | 0.225*** | 0.446*** | 0.670*** | 0.950** | 30.92*** | -0.066 | -0.108* | -0.142** | -0.350*** | -0.192 | 0.082 | 13.15* |
| | (0.096) | (0.044) | (0.044) | (0.080) | (0.162) | (0.332) | | (0.068) | (0.046) | (0.052) | (0.069) | (0.127) | (0.256) | |
| Panel (c): Total q | | | | | | | | | | | | | | |
| PRO | -0.233 | 0.048 | 0.129** | 0.262*** | 0.677*** | 1.425*** | 27.37*** | 0.486 | -0.101* | -0.029 | 0.034 | 0.557** | 1.462** | 14.35** |
| | (0.225) | (0.056) | (0.042) | (0.051) | (0.164) | (0.411) | | (0.413) | (0.050) | (0.049) | (0.083) | (0.195) | (0.521) | |
| ENV | 0.129 | 0.035 | 0.087 | 0.196*** | 0.144 | -0.170 | 6.87 | 0.277 | 0.024 | -0.070 | -0.311** | -0.412* | 0.484 | 9.42 |
| | (0.205) | (0.055) | (0.049) | (0.058) | (0.154) | (0.509) | | (0.174) | (0.084) | (0.072) | (0.100) | (0.203) | (0.424) | |
| COM | -0.205 | 0.063 | -0.016 | 0.075 | 0.100 | 0.154 | 7.94 | 0.024 | 0.017 | -0.017 | -0.019 | 0.232* | 0.385* | 10.00* |
| | (0.186) | (0.032) | (0.028) | (0.039) | (0.108) | (0.305) | | (0.070) | (0.047) | (0.038) | (0.052) | (0.096) | (0.184) | |
| DIV | 0.144 | -0.007 | 0.042 | 0.064 | 0.153 | 0.552 | 2.92 | -0.203 | -0.052 | -0.043 | -0.019 | 0.094 | -0.039 | 5.58 |
| | (0.215) | (0.049) | (0.046) | (0.050) | (0.114) | (0.327) | | (0.169) | (0.032) | (0.023) | (0.029) | (0.064) | (0.218) | |
| EMP | -0.388 | -0.014 | 0.085 | 0.246*** | 1.077*** | 2.434*** | 31.14*** | 0.360 | -0.100 | -0.260*** | -0.354*** | -0.473** | -0.415 | 11.88* |
| | (0.214) | (0.057) | (0.046) | (0.066) | (0.195) | (0.497) | | (0.201) | (0.066) | (0.053) | (0.061) | (0.143) | (0.419) | |

Notes: Estimation of equation (2.12) with the re-centred inference function for ROA as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. Test reports a joint equality test on the parameters for the five estimated quantiles with a null hypothesis of no variation across quantiles. Equal is a test for parameter equality across the five stated quantiles following Rios-Avila (2020). Reported values are $\chi^2$ statistics with significance based upon 1000 bootstraps. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

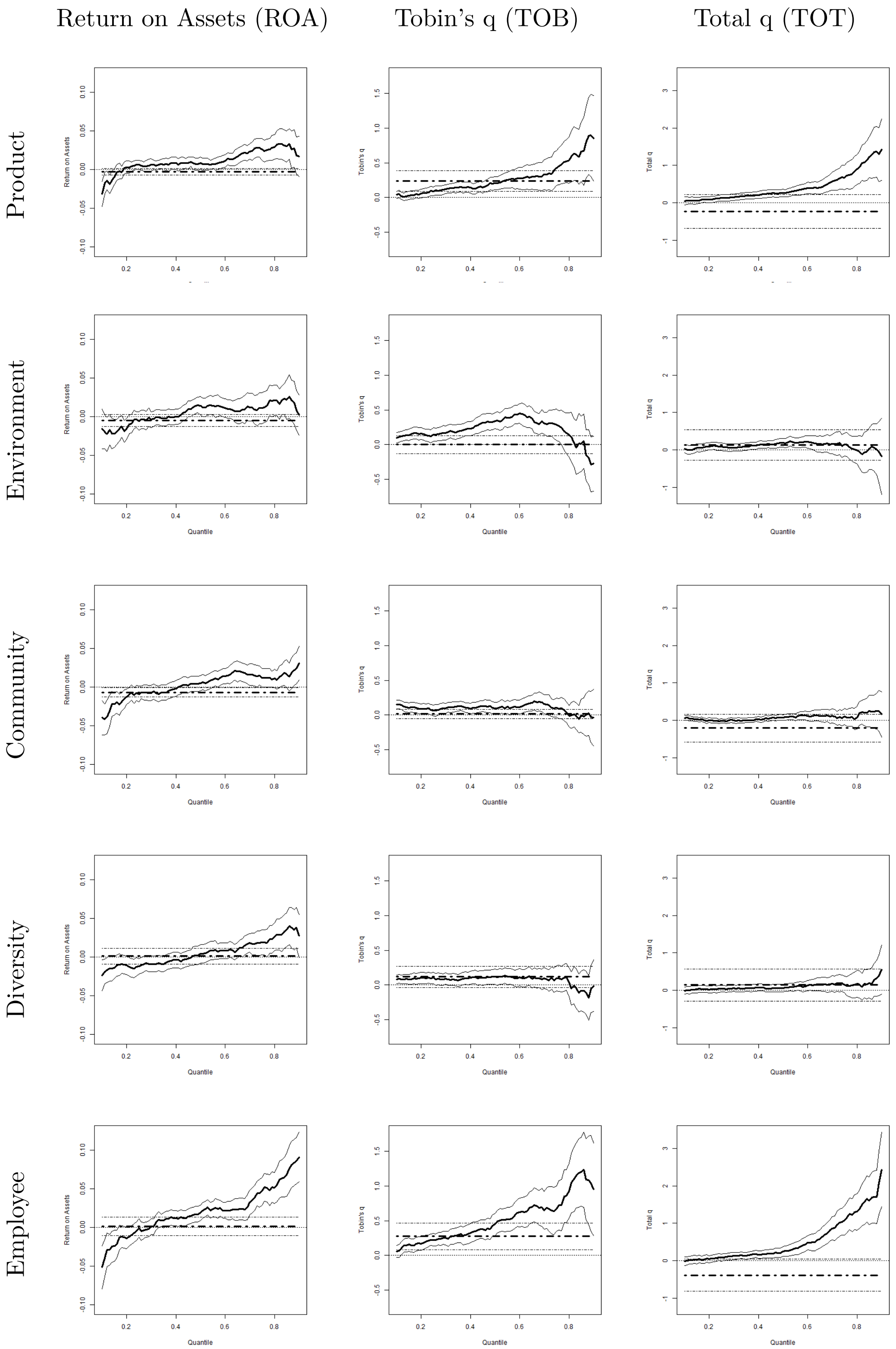
coefficients for the best performing firms. For TOB the OLS regression also picks up a positive coefficient on PRO. As with net strengths there are surprising coefficients from the OLS on EMP when measuring CFP through TOT. We see a negative significant coefficient on EMP strengths and a positive significant coefficient on EMP concerns. These results contrast directly with the quantile coefficients.

Of all the results in Table 2.4, the stand out message is on the positive significant coefficients for PRO concerns. The surface conclusion is that to increase profits firms should look to increase the number of PRO concerns that they have. Such positive coefficients are consistent with the traditionalist view of CSR as an unnecessary diversion from optimising business performance to benefit shareholders. In our results these are the only coefficients displaying full consistency with traditionalist perspectives. The majority of our estimates are consistent with the revisionist perspective that CSR brings CFP benefits. Within the MSCI database, PRO concerns include anti-competitive practice, misleading advertising or unfairly extracting rent from consumers. All of these would result in increased CFP in the short term and so there should be less surprise that it is PRO where concerns imply increased CFP. If the actions do not break other laws then there is no reason that the concerns would not continue to generate increased CFP going forwards either. A lack of significant negative coefficients on concerns does go against the overall result of the paper the firms should raise CSR to raise CFP, but can be rationalised in an environment where most strengths have significant positive coefficients and concerns have negative coefficients.

Within the estimates on strengths and concerns there is also statistical significance to reject the null hypothesis of parameter equality across the five quantiles. We see that PRO and EMP have significant differences between quantiles for both strengths and concerns. For ROA the parameters on all five of the stakeholder dimensions strengths have significant variation across quantiles. We also see significant coefficients on ENV strengths when TOB is the CFP measure. When considering pairwise comparisons between the quantile estimates we do note a large number of pairs for which the coefficients do vary. In total 113 of the 300 pairwise comparisons reject the null hypothesis of parameter equality at the 5% level. As in the case of net strengths, the evidence from the parameter equality tests confirms that there is value in using UQR compared to assuming that all stakeholder dimensions have equal impact on CFP across the CFP distribution.

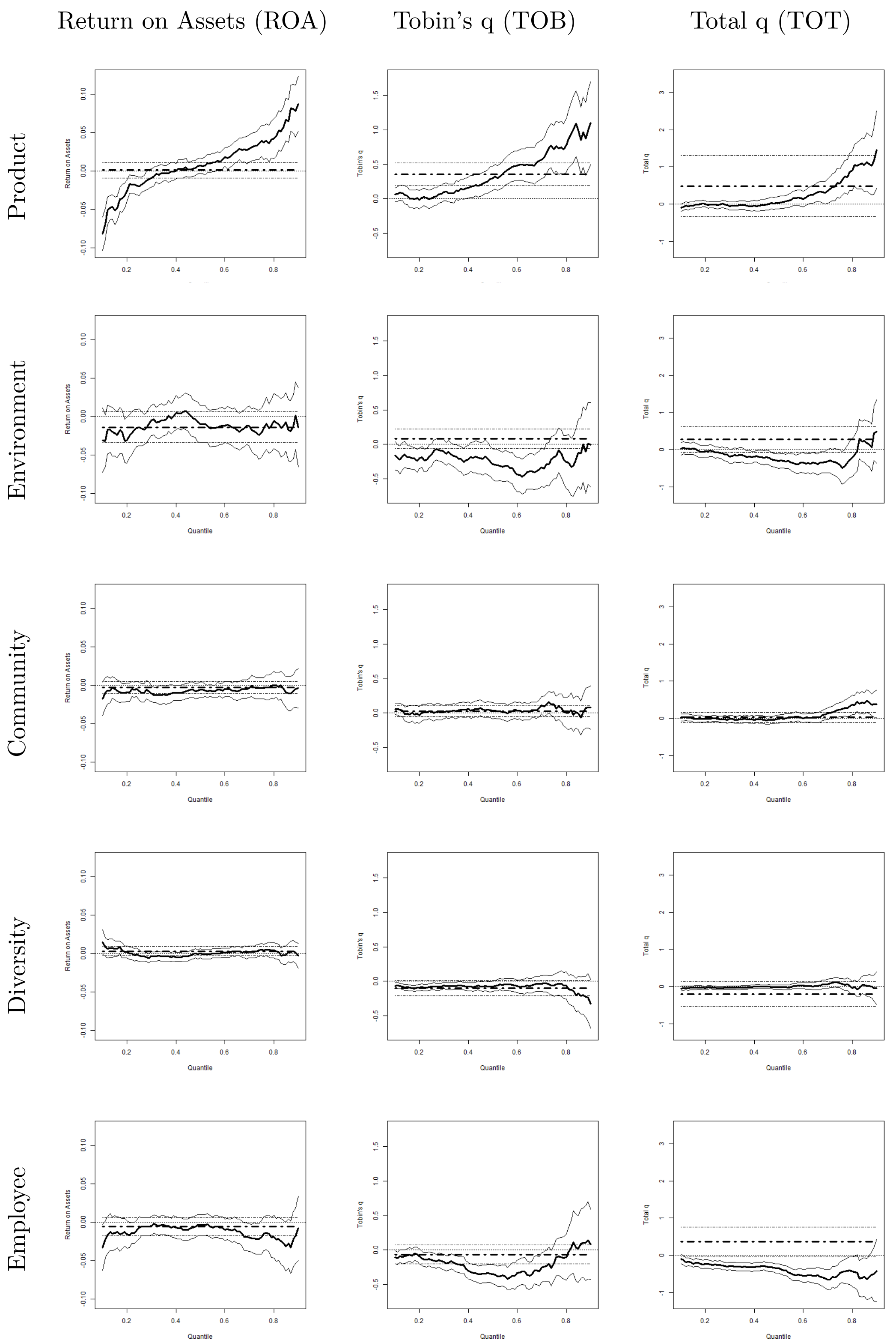
Figures 2.2 and 2.3 plot the estimates of equation (2.12) for $\tau \in [0.10, 0.90]$. To ease comparison between the two figures the same axes are used for all of the plots on any one of the dimensions. Hence the top three plots on Figure 2.2 and 2.3 have the

Figure 2.2: CSR-CFP Unconditional Quantile Regression Coefficients: Strengths




Notes: OLS and UQR estimated coefficients. Thick lines are used to plot coefficients, thinner lines the associated 95 per cent confidence intervals. Solid lines represent the UQR values and horizontal, quantile invariant, dot-dash lines the OLS.

Figure 2.3: CSR-CFP Unconditional Quantile Regression Coefficients: Concerns




Notes: OLS and UQR estimated coefficients. Thick lines are used to plot coefficients, thinner lines the associated 95 per cent confidence intervals. Solid lines represent the UQR values and horizontal, quantile invariant, dot-dash lines the OLS.

same scale on the vertical axis.

For PRO the strengths have increasing coefficients as the quantiles increase, becoming significantly higher than the OLS for all three CFP measures. However, as noted from Table 2.4, the concern coefficients also increase across the quantiles, especially for ROA. Only for ROA do we see any of the expected negative significant coefficients on concerns. Firms are therefore encouraged by the data to increase their strengths, but are suggested to do so by reducing efforts to control concerns. The implications of the message require further consideration.

ENV displays the familiar "inverted-U" shape of Sun et al. (2019) for TOB when strengths are taken independently of concerns. That "inverted-U" is also visible in the concern plot with those performing near the median having the strongest negative impact from environmental concerns[6]. The most profitable firms do not benefit from increasing their strengths, but equally do not gain from reducing their concerns. Coefficients at the higher quantiles are shown to be insignificant on all three of the concerns plots. Following Hoffman and Ventresca (1999) and other early works the advantage of being seen as environmentally friendly is well understood. Results from the UQR show that to be particularly true for those performing close to the middle of the profitability distribution.

Apart from the ROA strengths, neither COM nor DIV show much variation across the quantiles when strengths and concerns are split. DIV concerns have a negative impact on CFP, particularly TOB. Of the three primary stakeholder dimensions discussed for net strengths, DIV is the one shown to have least significance in our strengths and concerns analysis.

EMP was a major explanatory factor in the net strengths regressions. Here we see that EMP strengths can really support the best performing firms to achieve higher on all three of the CFP measures. Significance of the negative effect of EMP concerns is also clear in Figure 2.3. The UQR estimates on concerns often sit below the OLS for TOB and almost throughout for TOT. This evidence is again supportive of the importance of primary stakeholders and the need to get employee support to improve productivity.

### 2.5.3 Summary of Full Sample

Across the whole sample a separation between primary and secondary stakeholders is in evidence. Poorer performing firms have been suggested to focus on improving

[6]The theory of the "inverted-U" would make the plot for concerns "U" shaped as we see for TOB on net ENV concerns.

fundamentals in the short-term and then to use CSR in the long-term. Larger firms are shown to benefit from focus on internal stakeholders, whilst those at the median can gain from all CSR dimensions. Our results support the notion of a U shaped relationship between CSR and CFP, although this applies most for TOB and TOT. Results for both net strengths, as well as the separate strengths and concerns, show variation across quantiles that the OLS model does not pick up. Tests of parameter equality confirm that the variation seen in the analysis is statistically significant. Benefits from adopting UQR here are clear.

## 2.6 Financial Crisis

A particular innovation of this paper is the consideration of the role of the global financial crisis. Identification of the impact comes through the creation of a post-crisis dummy and interaction with the stakeholder dimensions. The global financial crisis period is defined as 2007, 2008 and 2009 following Reinhart and Rogoff (2008) and Mishkin (2011). In the regression we include a dummy for the post-crisis period to absorb much of the demand uplift from the recovery. Our industry-year fixed effects also pick up unobserved heterogeneity from the period. Therefore the coefficients on the interaction between the post-crisis dummy and the five dimensions identify how the importance of the stakeholder dimensions changed.

In order to assess the effect of the financial crisis on the estimated coefficients for net strengths we thus re-estimate equation (2.11) using slope dummies for the crisis and post-crisis period. These slope dummies are given the prefix $P$ such that the interaction between the post crisis dummy *post* and the net strengths on PRO, $NS_{it}^{PRO}$ becomes $PNS_{it}^{PRO}$. Equation (2.11) is updated to become:

$$\begin{aligned} RIF\left(Y, q_\tau, F_Y\right) = & \alpha + \phi_1 NS_{it}^{PRO} + \phi_2 NS_{it}^{ENV} + \phi_3 NS_{it}^{COM} + \phi_4 NS_{it}^{DIV} \\ & + \phi_5 NS_{it}^{EMP} + \phi_6 PNS_{it}^{PRO} + \phi_7 PNS_{it}^{ENV} + \phi_8 PNS_{it}^{COM} \\ & + \phi_9 PNS_{it}^{DIV} + \phi_{10} PNS_{it}^{EMP} + \beta X_i + \phi_{11} post + \gamma + \epsilon_i \end{aligned} \tag{2.13}$$

with our interest now being in two sets of coefficients. Firstly, $\phi_1$ to $\phi_5$ as the coefficients on the stakeholder dimensions inform of the main effect of the dimension across all time. Secondly, $\phi_6$ to $\phi_{10}$ provide information about the effect of the GFC on the roles of each of the CSR dimensions. Significance of this second set says that there has been a change in perception of CSR that makes it more, or less, profitable than it previously had been. Equation (2.13) is again estimated for $\tau \in [0.10, 0.90]$. We also perform the same interaction for the strengths and concerns regression from equation (2.12).

$$\begin{aligned} RIF\left(Y, q_\tau, F_Y\right)_{it} =& \alpha + \phi_1 S_{it}^{PRO} + \phi_2 S_{it}^{ENV} + \phi_3 S_{it}^{COM} + \phi_4 S_{it}^{DIV} + \phi_5 S_{it}^{EMP} \\ &+ \phi_6 W_{it}^{PRO} + \phi_7 W_{it}^{ENV} + \phi_8 W_{it}^{COM} + \phi_9 W_{it}^{DIV} \\ &+ \phi_{10} W_{it}^{EMP} + \phi_{11} PS_{it}^{PRO} + \phi_{12} PS_{it}^{ENV} + \phi_{13} PS_{it}^{COM} \\ &+ \phi_{14} PS_{it}^{DIV} + \phi_{15} PS_{it}^{EMP} + \phi_{16} PW_{it}^{PRO} + \phi_{17} PW_{it}^{ENV} \\ &+ \phi_{18} PW_{it}^{COM} + \phi_{19} PW_{it}^{DIV} + \phi_{20} PW_{it}^{EMP} \\ &+ \beta X_{it} + \gamma_{mt} + \epsilon_{it} \end{aligned} \tag{2.14}$$

Now we are focused on the coefficients $\phi_{11}$ to $\phi_{20}$. Again the strengths and concerns are given $P$ prefixes to denote the post-crisis period. For example, $S_{it}^{PRO}$ becomes $PS_{it}^{PRO}$.

### 2.6.1 Net Strengths

Initial evaluation of the effects of the GFC comes through the interaction coefficients between the post-crisis dummy and the net strengths on each of the five stakeholder dimensions. Estimates of coefficients $\phi_1$ to $\phi_{10}$ are provided in Table 2.5 for each of the three CFP outcomes.

When considering ROA the OLS models suggest a negative coefficient on DIV and EMP in the post crisis period. From this it would be assumed that these primary stakeholders have lost importance since the crisis. However, although the UQR produces negative coefficients, none are significant. It is also noted that EMP has a strong positive effect for the full period and therefore the net effect post-crisis is still positive at all quantiles except the very lowest. Aside from three coefficients on PRO there are no significant differences between the financial crisis and post-crisis periods. Here we confirm the additional performance from the improved economic conditions is being picked up by the post-crisis dummy.

For TOB there are more positive significant coefficients on the stakeholder dimensions. In the OLS regression the PRO estimate for the full period is negative, but the post-crisis interaction with PRO is significant and positive. PRO also shows similar behaviour in the better performing firms. Estimates for the full sample at $\tau = 0.75$ and $\tau = 0.90$ are negative and signficant for the whole period but then positive, significant, and larger in absolute value when interacted with the post-crisis dummy. Similar cancelling effects are seen for the lower quantiles, but these are not significant. ENV shows reduced significance compared to the full sample, but we do see a significant increase in the value of ENV net strengths to those performing around the median.

Table 2.5: Coefficients of Stakeholder Dimension Net Strengths on Financial Performance

| | Full Period Coefficients ($\phi_1 - \phi_5$) | | | | | | | Post Crisis Coefficients ($\phi_6 - \phi_{10}$) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | OLS | Unconditional quantile regression | | | | | Equal | OLS | Unconditional quantile regression | | | | | Equal |
| | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ | |
| Panel (a): Return on Assets | | | | | | | | | | | | | | |
| PRO | -0.006 | 0.072* | 0.001 | -0.006 | -0.031* | -0.066 | 11.11* | -0.000 | -0.104** | 0.002 | 0.008 | 0.048*** | 0.072* | 20.75*** |
| | (0.007) | (0.027) | (0.007) | (0.006) | (0.013) | (0.045) | | (0.007) | (0.033) | (0.010) | (0.008) | (0.013) | (0.032) | |
| ENV | 0.012 | -0.002 | -0.004 | -0.005 | 0.044 | 0.035 | 11.33 | -0.007 | -0.024 | 0.005 | 0.031 | -0.011 | 0.009 | 8.02 |
| | (0.009) | (0.030) | (0.008) | (0.021) | (0.028) | (0.058) | | (0.009) | (0.039) | (0.012) | (0.020) | (0.027) | (0.055) | |
| COM | 0.007 | 0.012 | -0.016 | 0.009 | 0.010 | 0.030 | 4.36 | -0.010 | -0.026 | 0.013 | -0.006 | 0.003 | -0.012 | 2.79 |
| | (0.013) | (0.057) | (0.029) | (0.021) | (0.032) | (0.054) | | (0.012) | (0.058) | (0.028) | (0.020) | (0.030) | (0.061) | |
| DIV | 0.003 | -0.026* | -0.007 | 0.003 | 0.005 | 0.012 | 8.40 | -0.013*** | -0.008 | -0.001 | -0.004 | -0.006 | -0.000 | 0.34 |
| | (0.004) | (0.011) | (0.004) | (0.005) | (0.008) | (0.016) | | (0.003) | (0.013) | (0.003) | (0.004) | (0.006) | (0.019) | |
| EMP | 0.006 | -0.005 | 0.002 | 0.009 | 0.040* | 0.075 | 10.12* | -0.018* | -0.020 | -0.004 | -0.003 | -0.030 | -0.058 | 4.83 |
| | (0.005) | (0.021) | (0.008) | (0.011) | (0.018) | (0.042) | | (0.007) | (0.022) | (0.010) | (0.011) | (0.026) | (0.046) | |
| Panel (b): Tobin's q | | | | | | | | | | | | | | |
| PRO | -0.341* | -0.082 | 0.089 | -0.181 | -0.597* | -1.009* | 7.16 | 0.539** | 0.097 | -0.041 | 0.322* | 0.916*** | 1.894*** | 13.87** |
| | (0.129) | (0.149) | (0.168) | (0.145) | (0.288) | (0.449) | | (0.174) | (0.182) | (0.172) | (0.149) | (0.176) | (0.447) | |
| ENV | 0.019 | 0.454* | 0.210 | 0.139 | 0.197 | -0.568 | 4.94 | 0.074 | -0.381* | -0.045 | 0.227 | 0.286 | 0.663 | 10.20* |
| | (0.235) | (0.161) | (0.141) | (0.147) | (0.192) | (0.660) | | (0.262) | (0.172) | (0.149) | (0.123) | (0.208) | (0.815) | |
| COM | 0.004 | -0.322* | -0.094 | 0.233 | 0.338 | 0.077 | 6.16 | 0.038 | 0.400** | 0.147 | -0.197 | -0.362 | -0.045 | 6.65 |
| | (0.085) | (0.123) | (0.214) | (0.164) | (0.197) | (0.458) | | (0.080) | (0.133) | (0.200) | (0.157) | (0.178) | (0.518) | |
| DIV | 0.088 | 0.079 | 0.128* | 0.145 | 0.106 | 0.273 | 2.57 | -0.004 | -0.006 | -0.054 | -0.074 | -0.028 | -0.206 | 3.41 |
| | (0.091) | (0.044) | (0.053) | (0.093) | (0.141) | (0.264) | | (0.034) | (0.040) | (0.045) | (0.071) | (0.082) | (0.141) | |
| EMP | 0.213* | 0.178* | 0.237** | 0.400*** | 0.491** | 0.396 | 6.88 | 0.045 | -0.103 | -0.038 | -0.032 | 0.051 | 0.409 | 1.48 |
| | (0.077) | (0.080) | (0.068) | (0.100) | (0.151) | (0.378) | | (0.132) | (0.056) | (0.091) | (0.133) | (0.358) | (0.348) | |
| Panel (c): Total q | | | | | | | | | | | | | | |
| PRO | -0.609 | 0.060 | 0.047 | 0.091 | -0.419 | -1.623* | 8.51 | 0.407 | -0.014 | 0.032 | 0.138 | 1.145** | 3.087*** | 11.02* |
| | (0.638) | (0.084) | (0.075) | (0.174) | (0.465) | (0.667) | | (0.398) | (0.107) | (0.083) | (0.160) | (0.368) | (0.767) | |
| ENV | -0.185 | 0.272 | 0.186 | 0.082 | 0.230 | 0.375 | 0.68 | 0.005 | -0.300 | -0.114 | 0.094 | 0.078 | -0.074 | 1.66 |
| | (0.489) | (0.197) | (0.148) | (0.164) | (0.422) | (1.289) | | (0.480) | (0.170) | (0.147) | (0.197) | (0.527) | (1.268) | |
| COM | -0.462 | -0.543 | -0.116 | 0.154 | 0.097 | 1.278 | 3.06 | 0.618 | 0.567 | 0.089 | -0.146 | -0.231 | -1.601 | 2.59 |
| | (0.331) | (0.281) | (0.177) | (0.183) | (0.390) | (0.755) | | (0.430) | (0.282) | (0.173) | (0.198) | (0.366) | (0.809) | |
| DIV | 0.240* | -0.023 | 0.006 | 0.037 | -0.085 | 0.076 | 3.03 | -0.174 | 0.066 | 0.038 | 0.026 | 0.218 | 0.440* | 4.72 |
| | (0.108) | (0.044) | (0.040) | (0.063) | (0.142) | (0.285) | | (0.194) | (0.039) | (0.042) | (0.067) | (0.131) | (0.183) | |
| EMP | -0.870 | 0.077 | 0.187 | 0.310** | 0.847*** | 1.584* | 7.29 | 0.984 | -0.015 | 0.014 | 0.045 | 0.162 | 0.062 | 0.21 |
| | (0.805) | (0.071) | (0.104) | (0.095) | (0.201) | (0.631) | | (0.790) | (0.103) | (0.085) | (0.113) | (0.420) | (0.791) | |

Notes: Estimation of equation (2.13) with the re-centred inference function for ROA, TOB and TOT as the CFP measures of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. Equal is a test for parameter equality across the five stated quantiles following Rios-Avila (2020). Reported values are $\chi^2$ statistics with significance based upon 1000 bootstraps. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

COM has a balance at the lower quantile, from significant negative in the whole period to significant positive in the post-crisis interaction. Employees were seen as the most significant determinant of TOB in the full period and that comes through in the significance in the left column. In the post-crisis interaction only a small negative coefficient at $\tau = 0.10$ is seen. Whilst PRO gains importance for the best performers, others do not see change in the TOB coefficients.

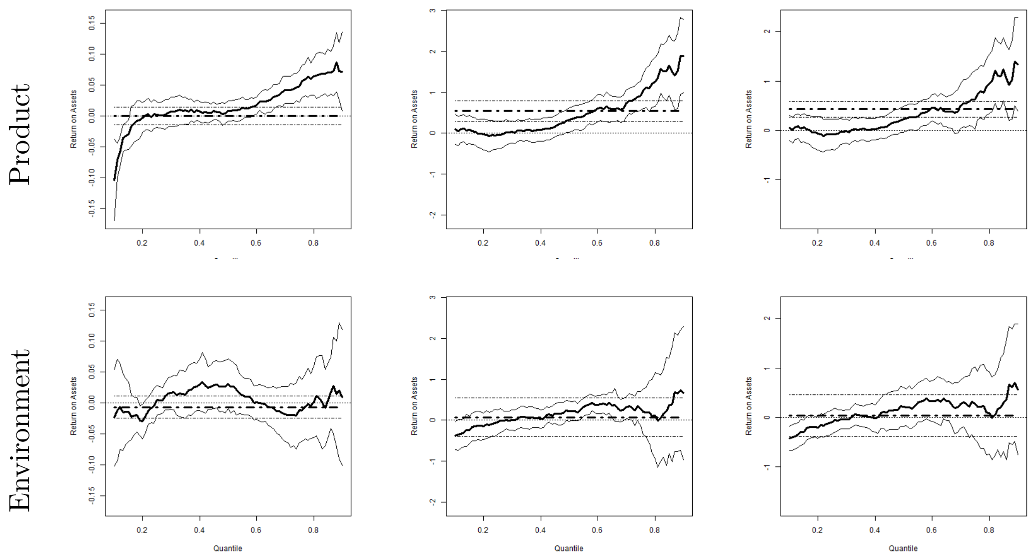
Consideration of the post-crisis split for TOT produces similar conclusions to TOB. The main difference is that for TOT there is a signficant role for DIV that was not seen in the TOB estimates. The OLS regression assigns a positive significant coefficient on DIV for the full period, and the UQR shows the best performing firms get a significant increase in the DIV coefficient for TOT post-crisis.

Value from using UQR is demonstrated where the tests for parameter equality reject the null hypothesis of identical coefficients across quantiles. Relative to the full results, the test statistics reported in the Equal column of Table 2.5 show reduced significance. PRO and EMP have significant variation in the full period coefficients when ROA is the CFP measure, but all other full period results do not show significance. In the post-crisis period there has been significant variation in the impact of PRO on CFP under all three CFP measures. We see that PRO has strong positive effects for the best performing firms post-crisis. ENV coefficients are also confirmed to have significant variation between quantiles when TOB is the CFP measure. Here again the best performers have a significant positive ENV post-crisis interaction coefficient whilst the corresponding coefficient for the poorest performers is negative. Results for the pairwise comparison reveal a similar reduction in the cross quantile variaton, but do continue to demonstrate that there is value in using UQR. In total 20% of the pairwise comparisions reject equality at the 5% level, far more than would be the case if the results were pure chance. Whilst not as strong as the overall results, there is evidence that UQR is capturing significant variation in the role of CSR on CFP across the CFP distribution.

To see the effects graphically, Figure 2.4 plots the post-crisis coefficients for PRO and ENV. We already saw the insignificance of COM, DIV and EMP and so these graphs are placed in the supplementary material for brevity. Within the PRO coefficients there is strong evidence of the upward sloping pattern observed in the full period. The plots show that PRO net strengths are neither more, nor less, important to the short-term profitability of the poorer performing firms. By contrast the best performers have significant positive coefficients. For ROA we see the post-crisis estimate go significantly above the OLS estimate to the point both confidence intervals no longer overlap. In

Figure 2.4: Net Strengths and Financial Crisis

Return on Assets (ROA) Tobin's q (TOB) Total q (TOT)




Notes: Estimates of differential between pre-crisis and the stated period for the product and environment stakeholder dimensions of Freeman (1984). Thick lines are used to plot coefficients, thinner lines the associated 95 per cent confidence intervals. Solid lines represent the financial crisis differential, coefficients $\phi_6$ to $\phi_{10}$ in equation (2.13). Dashed lines represent the post-crisis to pre-crisis differential, coefficients $\phi_{11}$ to $\phi_{15}$ in equation (2.13).

ENV there is some evidence of the "inverted-U" shape, but the variation is unlikely to be significant. On ROA, ENV is also producing an "inverted-U" shape near the middle of the plot, but then the upward slope to the right of the plot explains why this does not come through in the table. Figure 2.4 shows again benefit in seeing UQR coefficients graphically.

In all three cases the primary stakeholders continue to have the most importance to ROA. The mixed messages on COM and ENV suggest that the crisis did not change much on the impact of net strengths for secondary stakeholders.

### 2.6.2 Strengths and Concerns

As supported by Perrault and Quinn (2016) and others, the use of net strengths risks missing important distinctions between strengths and concerns. Results for the whole sample confirmed that to be the case in UQR also. To understand more of the message from the net strengths coefficients of Table 2.5, and plots of Figure 2.4, we again use disaggregated strength and concern measures. We estimate equation (2.14) for $\tau \in [0.10, 0.90]$. Results are again reported with the full coefficients in the left hand block and the post-crisis slope dummies in the right hand columns.

Table 2.6 shows similar benefits from CSR to those at the lower end of the CFP distribution, but many of the negative significant coefficients for ROA are absent in this case. For better performing firms there is an opportunity to use CSR strengths to improve ROA, especially EMP and COM. However, whilst COM is useful in the crisis the negative significant post-crisis coefficients remove any benefit. These coefficients are consistent with Godfrey et al. (2009) suggestion that external stakeholders are an insurance mechanism in times of crisis.

For TOB there are no signficant OLS coefficients, but again we see benefits from COM strengths in the crisis that are reveresed post-crisis. There are also benefits for those at the lower end of the distribution from PRO and DIV across the whole sample, but these too reverse post-crisis. Although EMP has large positive coefficients on TOB these are not significant in most cases. TOT has a similar lack of significance when including the post-crisis dummies. Of interest here is the reversal of the positive impact of ENV on the lower performers, and the negative significant coefficients on post-crisis COM for high performers. These negative significant coefficients at $\tau = 0.75$, mirroring that for ROA. Negative coefficients on COM in the TOT regressions are also in line with the insignificant, but strongly negative, coefficients on TOB. Again the evidence supports the notion of Godfrey et al. (2009) that COM can be an insurance in times of crisis.

When considering the change to concern coefficients post-crisis we again see a drop in significance relative to the whole sample. Nonetheless, there are some important patterns to be seen. Across the whole sample the poorest performing firms, $\tau = 0.10$, have negative coefficients on PRO and COM but positive coefficients on DIV. In the post-crisis period none of these reverse. Meanwhile the initial strength from EMP reduces as weaknesses also give positive ROA to the firm. An important result in the full sample is the positive significant coefficient on PRO concerns. In Table 2.7 we see significance for the 2007 to 2015 sample, but that the coefficients on the post-crisis PRO concern interaction term are negative and of similar value to the full sample coefficient. Therefore the net effect post-crisis is that the significance of PRO concerns goes away. Further investigation of the effects is needed, but would require more data on the specific PRO concerns than is available in the MSCI KLD database used in this paper.

For TOB and TOT the OLS has no significant coefficients across the whole sample,

Table 2.6: Coefficients of Stakeholder Dimension Strengths on Financial Performance

| | Full Period Coefficients ($\phi_1 - \phi_5$) | | | | | | | Post Crisis Coefficients ($\phi_6 - \phi_{10}$) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | OLS | Unconditional quantile regression | | | | | Equal | OLS | Unconditional quantile regression | | | | | Equal |
| | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ | |
| Panel (a): Return on Assets | | | | | | | | | | | | | | |
| PRO | 0.007 | -0.069 | 0.010 | 0.035* | 0.104 | 0.094 | 2.71 | -0.014 | 0.028 | -0.009 | -0.032** | -0.081 | -0.079 | 2.11 |
| | (0.014) | (0.103) | (0.018) | (0.013) | (0.079) | (0.110) | | (0.014) | (0.106) | (0.018) | (0.011) | (0.078) | (0.097) | |
| ENV | 0.000 | 0.045 | -0.027* | -0.022 | 0.039 | -0.001 | 6.91 | 0.002 | -0.058 | 0.029* | 0.046** | -0.015 | 0.024 | 8.71 |
| | (0.010) | (0.050) | (0.010) | (0.013) | (0.048) | (0.165) | | (0.010) | (0.035) | (0.011) | (0.014) | (0.048) | (0.163) | |
| COM | -0.009 | -0.183 | -0.010 | 0.045 | 0.127** | 0.158* | 12.26* | -0.004 | 0.142 | -0.001 | -0.047 | -0.116** | -0.142* | 7.96 |
| | (0.016) | (0.110) | (0.041) | (0.027) | (0.044) | (0.056) | | (0.015) | (0.111) | (0.042) | (0.027) | (0.038) | (0.052) | |
| DIV | 0.009 | -0.028 | -0.037 | -0.003 | 0.013 | 0.090 | 15.59** | -0.003 | 0.018 | 0.033 | 0.008 | 0.002 | -0.079 | 10.24* |
| | (0.011) | (0.050) | (0.023) | (0.026) | (0.035) | (0.066) | | (0.008) | (0.052) | (0.022) | (0.022) | (0.031) | (0.062) | |
| EMP | 0.009 | -0.045 | 0.002 | 0.023* | 0.043 | 0.091** | 5.76 | -0.018 | -0.019 | -0.011 | -0.010 | -0.016 | -0.027 | 0.70 |
| | (0.011) | (0.038) | (0.022) | (0.011) | (0.021) | (0.028) | | (0.015) | (0.047) | (0.018) | (0.016) | (0.036) | (0.038) | |
| Panel (b): Tobin's q | | | | | | | | | | | | | | |
| PRO | 0.233 | 0.312 | 0.476** | 0.392 | 0.932 | 1.240 | 2.62 | -0.005 | -0.295 | -0.422* | -0.215 | -0.536 | -0.261 | 1.46 |
| | (0.210) | (0.173) | (0.164) | (0.390) | (1.064) | (1.294) | | (0.166) | (0.177) | (0.171) | (0.347) | (0.915) | (1.001) | |
| ENV | 0.219 | 0.082 | 0.005 | 0.015 | 0.111 | -0.637 | 1.68 | -0.186 | 0.010 | 0.152 | 0.370* | 0.271 | 0.426 | 1.25 |
| | (0.398) | (0.163) | (0.116) | (0.149) | (0.594) | (1.695) | | (0.409) | (0.187) | (0.124) | (0.175) | (0.663) | (1.791) | |
| COM | 0.260 | -0.156 | -0.036 | 0.865* | 0.858 | 1.064 | 8.31 | -0.172 | 0.330 | 0.128 | -0.758 | -0.759 | -0.976 | 8.51 |
| | (0.200) | (0.354) | (0.255) | (0.404) | (0.489) | (0.880) | | (0.192) | (0.357) | (0.236) | (0.392) | (0.487) | (1.023) | |
| DIV | 0.235 | 0.245 | 0.390* | 0.329 | 0.446 | 0.142 | 4.00 | -0.232 | -0.243 | -0.400* | -0.333 | -0.588 | -0.433 | 4.84 |
| | (0.256) | (0.140) | (0.148) | (0.352) | (0.601) | (0.691) | | (0.237) | (0.146) | (0.146) | (0.339) | (0.625) | (0.806) | |
| EMP | 0.208 | 0.157 | 0.132 | 0.417 | 0.731* | 0.462 | 2.30 | 0.208 | -0.115 | 0.080 | -0.022 | 0.077 | 0.987 | 5.07 |
| | (0.156) | (0.130) | (0.096) | (0.257) | (0.346) | (0.703) | | (0.243) | (0.120) | (0.102) | (0.313) | (0.543) | (0.778) | |
| Panel (c): Total q | | | | | | | | | | | | | | |
| PRO | -0.278 | 0.050 | 0.407 | 0.787 | 1.182 | 0.758 | 6.57 | 0.094 | -0.016 | -0.322 | -0.541 | -0.379 | 0.806 | 5.58 |
| | (0.560) | (0.208) | (0.254) | (0.563) | (1.068) | (1.848) | | (0.435) | (0.165) | (0.233) | (0.544) | (1.008) | (1.842) | |
| ENV | 0.747 | 0.482* | 0.203 | 0.164 | -0.018 | 1.239 | 3.82 | -0.904 | -0.456* | -0.081 | 0.040 | 0.260 | -1.147 | 6.42 |
| | (0.644) | (0.183) | (0.274) | (0.430) | (1.181) | (2.994) | | (0.694) | (0.178) | (0.266) | (0.474) | (1.302) | (2.696) | |
| COM | -0.573 | -0.438 | -0.135 | 0.023 | 1.005 | 2.719 | 12.06* | 0.812 | 0.472 | 0.092 | -0.033 | -1.171* | -2.994 | 12.17* |
| | (0.306) | (0.479) | (0.371) | (0.278) | (0.589) | (1.707) | | (0.426) | (0.493) | (0.377) | (0.282) | (0.559) | (1.717) | |
| DIV | 1.017 | -0.148 | -0.002 | 0.157 | 0.448 | 0.276 | 7.65 | -0.987 | 0.124 | -0.006 | -0.210 | -0.562 | -0.283 | 7.55 |
| | (0.964) | (0.218) | (0.315) | (0.317) | (0.696) | (1.203) | | (0.859) | (0.209) | (0.274) | (0.277) | (0.635) | (1.150) | |
| EMP | -0.763 | 0.027 | -0.029 | 0.095 | 0.763 | 2.134 | 7.81 | 0.892 | -0.050 | 0.108 | 0.167 | 0.430 | 0.322 | 1.59 |
| | (0.941) | (0.115) | (0.193) | (0.200) | (0.469) | (1.164) | | (0.915) | (0.115) | (0.147) | (0.183) | (0.446) | (0.864) | |

Notes: Estimation of equation (2.14) with the re-centred inference function for all three CFP measures of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code and year. Equal is a test for parameter equality across the five stated quantiles following Rios-Avila (2020). Reported values are $\chi^2$ statistics with significance based upon 1000 bootstraps. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 2.7: Coefficients of Stakeholder Dimension Concerns on Financial Performance

| | Full Period Coefficients ($\phi_1 - \phi_5$) | | | | | | | Post Crisis Coefficients ($\phi_6 - \phi_{10}$) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | OLS | Unconditional quantile regression | | | | | | OLS | Unconditional quantile regression | | | | | |
| | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ | |
| Panel (a): Return on Assets | | | | | | | | | | | | | | |
| PRO | 0.008 | -0.091* | 0.002 | 0.011 | 0.040** | 0.076 | 16.05*** | -0.007 | 0.015 | -0.028* | 0.003 | -0.002 | 0.018 | 3.35 |
| | (0.007) | (0.034) | (0.009) | (0.008) | (0.014) | (0.044) | | (0.008) | (0.040) | (0.011) | (0.013) | (0.017) | (0.039) | |
| ENV | -0.020 | -0.006 | -0.024 | -0.002 | -0.025 | -0.009 | 1.75 | 0.012 | -0.014 | 0.003 | -0.012 | -0.017 | -0.043 | 1.35 |
| | (0.018) | (0.052) | (0.021) | (0.034) | (0.034) | (0.051) | | (0.011) | (0.056) | (0.014) | (0.028) | (0.037) | (0.030) | |
| COM | -0.012 | -0.106 | 0.021 | 0.007 | 0.036 | 0.029 | 9.50* | 0.006 | 0.090 | -0.028 | -0.017 | -0.046 | -0.041 | 7.68 |
| | (0.015) | (0.054) | (0.031) | (0.023) | (0.044) | (0.088) | | (0.014) | (0.058) | (0.027) | (0.021) | (0.047) | (0.099) | |
| DIV | -0.002 | 0.017 | -0.001 | -0.001 | 0.007 | 0.020 | 4.19 | 0.020** | 0.023 | 0.010 | 0.006 | 0.004 | -0.030 | 2.01 |
| | (0.003) | (0.009) | (0.006) | (0.005) | (0.006) | (0.020) | | (0.006) | (0.017) | (0.008) | (0.007) | (0.011) | (0.029) | |
| EMP | -0.005 | -0.025 | -0.004 | 0.001 | -0.030 | -0.054 | 7.78 | 0.021 | -0.006 | -0.003 | 0.006 | 0.041 | 0.114 | 7.60 |
| | (0.009) | (0.030) | (0.011) | (0.014) | (0.021) | (0.050) | | (0.017) | (0.041) | (0.018) | (0.015) | (0.022) | (0.066) | |
| Panel (b): Tobin's q | | | | | | | | | | | | | | |
| PRO | 0.399** | 0.149 | -0.045 | 0.223 | 0.814** | 1.396** | 14.91* | -0.258 | -0.195 | 0.039 | -0.011 | -0.308 | -1.107 | 8.33 |
| | (0.141) | (0.174) | (0.200) | (0.190) | (0.269) | (0.458) | | (0.130) | (0.192) | (0.141) | (0.216) | (0.218) | (0.701) | |
| ENV | 0.248 | -0.544 | -0.202 | -0.019 | 0.079 | 0.783 | 3.44 | -0.391* | 0.501* | -0.096 | -0.015 | -0.549 | -1.420* | 7.89 |
| | (0.149) | (0.276) | (0.201) | (0.218) | (0.277) | (0.551) | | (0.143) | (0.197) | (0.211) | (0.221) | (0.366) | (0.612) | |
| COM | 0.050 | 0.480** | 0.165 | 0.057 | -0.136 | 0.327 | 5.89 | -0.024 | -0.456** | -0.171 | -0.061 | 0.302 | -0.219 | 6.81 |
| | (0.177) | (0.127) | (0.293) | (0.219) | (0.390) | (0.954) | | (0.179) | (0.141) | (0.266) | (0.251) | (0.391) | (1.000) | |
| DIV | -0.010 | -0.033 | -0.050 | -0.056 | 0.062 | -0.228 | 2.00 | -0.113 | -0.074 | -0.077 | -0.055 | -0.252 | -0.007 | 1.32 |
| | (0.067) | (0.049) | (0.052) | (0.067) | (0.108) | (0.257) | | (0.129) | (0.065) | (0.056) | (0.089) | (0.175) | (0.369) | |
| EMP | -0.179 | -0.180 | -0.274* | -0.352* | -0.303 | -0.259 | 2.78 | 0.187 | 0.046 | 0.121 | -0.078 | 0.160 | 0.676 | 7.39 |
| | (0.091) | (0.096) | (0.101) | (0.133) | (0.193) | (0.454) | | (0.126) | (0.108) | (0.126) | (0.118) | (0.339) | (0.519) | |
| Panel (c): Total q | | | | | | | | | | | | | | |
| PRO | 0.457 | -0.092 | -0.002 | -0.008 | 0.555 | 1.858* | 12.11* | -0.110 | -0.090 | -0.084 | -0.120 | -0.435 | -1.804 | 1.25 |
| | (0.506) | (0.123) | (0.101) | (0.202) | (0.470) | (0.721) | | (0.242) | (0.201) | (0.143) | (0.171) | (0.464) | (1.532) | |
| ENV | 1.012 | -0.180 | -0.141 | 0.052 | -0.018 | 0.580 | 2.85 | -1.186 | 0.167 | 0.028 | -0.481* | -0.345 | -0.622 | 6.53 |
| | (0.851) | (0.278) | (0.186) | (0.146) | (0.398) | (0.978) | | (0.821) | (0.238) | (0.147) | (0.176) | (0.426) | (0.957) | |
| COM | 0.146 | 0.529* | 0.097 | -0.251 | 0.304 | -0.949 | 16.83*** | -0.155 | -0.560 | -0.116 | 0.210 | -0.250 | 1.269 | 14.54** |
| | (0.292) | (0.245) | (0.241) | (0.271) | (0.597) | (0.807) | | (0.300) | (0.286) | (0.243) | (0.305) | (0.551) | (0.817) | |
| DIV | 0.086 | 0.009 | 0.003 | 0.026 | 0.325 | 0.180 | 10.71* | -0.207 | -0.113 | -0.101 | -0.189* | -0.625** | -0.993* | 2.98 |
| | (0.325) | (0.068) | (0.064) | (0.073) | (0.173) | (0.403) | | (0.551) | (0.061) | (0.074) | (0.086) | (0.180) | (0.395) | |
| EMP | 0.976 | -0.100 | -0.287 | -0.398*** | -0.791** | -1.149 | 11.26* | -1.077 | -0.097 | -0.153 | -0.122 | 0.036 | 0.911 | 6.37 |
| | (0.801) | (0.096) | (0.143) | (0.102) | (0.258) | (0.829) | | (0.829) | (0.159) | (0.109) | (0.137) | (0.526) | (1.087) | |

Notes: Estimation of equation (2.14) with the re-centred inference function for all three CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code and year. Equal is a test for parameter equality across the five stated quantiles following Rios-Avila (2020). Reported values are $\chi^2$ statistics with significance based upon 1000 bootstraps. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

but does have negative signficant coefficents on PRO and ENV in the post-crisis interaction. Negative is the direction that would be associated with the increased awareness of environmental responsibility. Although not significant the coefficients from the quantiles are also mainly negative on TOB. For TOT there are only negative significant coefficients in concerns, including for DIV at almost all quantiles. We see here the increased importance of diversity to society. TOT shows a reversal from a significant benefit to COM at the lowest quantile in the whole sample to a negative coefficient post-crisis. Negative coefficients on EMP for the full sample are consistent with theory. For the post-crisis interaction there is no significant difference, but EMP concerns do still have a negative coefficient at the median.

Testing the equality of coefficients across quantiles again allows us to evaluate the benefit of UQR. Table 2.6 reports that when ROA is the CFP measure, COM and DIV have significantly different whole sample coefficients across the quantiles. When we consider TOT only COM is significant. Meanwhile, when testing the equality of the post-crisis interactions, we evidence significant variation in DIV on ROA and COM on TOT. Table 2.7 reports more variation amongst concerns, with 7 of the 15 whole sample estimates showing significant variation, including all three of the PRO concern estimates. Interaction between the post-crisis dummy and the stakeholders leads to just one case of significance, for COM concerns with TOT as the CFP measure. Whilst again significance is lower than the main results, there is still more variation identified than would be found by pure chance. From the pairwise comparisons there are 110 significant differences out of the 600 tests performed, that is approximately 18% of tests reject parameter equality at the 5% level. There is significant variation across quantiles, which justifies the use of quantile regression over the OLS approach employed in the literature to date.

### 2.6.3 Summary

The study of the financial crisis reveals that there have been changes, strengthening the effect of ENV and EMP. On net strengths PRO was most significant, but when splitting into strengths and concerns much of that impact is lost. We evidence significant variation between quantiles, well above that which would appear by change. Here in both the overall sample, and in the post-crisis adjustments, there are significant variations in the role of the stakeholder dimensions across the CFP distribution. Our results support the position that CSR is a valuable insurance tool against crises, but equally show that it continues to have importance throughout time.

## 2.7 Discussion

Motivated by the heterogeneity in the conclusions of past studies, this paper aims to understand why the variety of conclusions reached emerge. We investigated further using a UQR approach. Our results show three key features. Firstly, the dimensions that can bring most profit to firms does depend on where on the CFP distribution a firm is. For poorer performing firms the aim is to get the fundamentals right and make sure that the firm is in a position to grow. Those performing around the median can gain from improving their environmental performance. Our evidence here is consistent with the “inverted-U” of Sun et al. (2019). For the best performing firms there is little incentive to extend their environmental performance; motivation for such lies in the fact consumers are already treating those firms as having good CSR. The best performers are suggested to focus on their primary stakeholders, particularly their employees. The impact of employee strengths on CFP is far greater at the top end of the performance distribution.

Garcia-Castro and Francoeur (2016), Trumpp and Guenther (2017), Sun et al. (2019) all offer theoretical motivation for non-linearity in the CSR-CFP relationship. Meier et al. (2019) delivers the clearest theoretical motivation for the “inverted-U”. The idea that it becomes increasingly costly to enhance CSR strengths, as the number of strengths increases is intuitive. Once profitability passes the peak of the “inverted-U” further increasing the strengths will reduce profit. We see this in negative coefficients on strengths at higher quantiles in our regressions. However, we only see the inverted u clearly for the environment. In Sun et al. (2019) the role of public perception is discussed. Environment is an external stakeholder that can be readily observed so perception is important. For other dimensions stakeholders are very aware of what the firm is doing and so the cost-benefit arguments of Meier et al. (2019) appear stronger. UQR analysis does not produce such clear “inverted-U” shapes.

Many of our results point to an increase in the CSR coefficient as we rise up the CFP distribution. For better performing firms CSR becomes a way to increase CFP even further. This is evidence of the virtuous circle put forward by Hammond and Slocum (1996), Makni et al. (2009) and others. The lower coefficients for poorer performing firms would then be suggestive of the ability of these firms to piggyback their CSR reputation on better performers (Green and Peloza, 2014; Grewatsch and Kleindienst, 2017). Where poorer performers do indeed benefit from this second hand reputation, investment in CSR would not benefit profitability to the same extent. Here again we see value from using UQR.

Employees are a critical element of a firm's performance and they know this well; having a share in the success of the company goes hand-in-hand with supporting the company when times are tough. For the better performing firms the need to invest in their staff is intuitive. Analysis of strengths and weaknesses independently shows that employees are the only dimension for which there is statistically significant symmetry. As a primary stakeholder the arguments of Perrault and Quinn (2016) support focus on employees. Berman et al. (1999) identify employees as a dimension where CSR improves CFP and our results show this applies across the distribution. Moreover, the benefit of having employee buy-in has also been identified as an important moderator of CSR success in the reviews of Perrault and Quinn (2016) and Gillan et al. (2021).

Like Berman et al. (1999) we find that product is important to the CFP of firms. For customers the product is the point of interaction with the firm and so getting the right impression here is important. Indeed we see strengths of product being significant in almost all cases. In the short term only the best performers benefit from improving their product, but longer-term we see that having the right offering of responsible products is an advantage. The shape of the UQR coefficients against the consumer demand channel is understood here, but missed by OLS. Again we see the value of going beyond the mean to see these theories in the data.

Many studies have noted the ability of CSR to shield firms from the worst of financial crises (Godfrey et al., 2009; Lin et al., 2017, and others). Here we evidence that many dimensions which have positive significant coefficients in the whole sample have negative coefficients for the post-crisis interaction. The net effect is that post-crisis the benefits of having high CSR performance in these directions have reduced. Results for community strengths on ROA and TOT show this most clearly. Consistent with the message from our other regressions is that these effects are only statistically significant once relative position on the CFP distribution is considered.

Important insights for policy-makers are offered. With obvious incentives for governments to improve environmental performance under global climate agreements such as the Kyoto protocol, the promotion of ENV strengths amongst firms is vital[7]. Results from our UQR show that large incentives will need to be given to less profitable firms to overcome the significant negative coefficients on ENV. Meanwhile, those firms performing near the middle of the distribution have been shown to get stronger benefits from ENV and will not need incentives. Finally, at the top of the CFP distribution,

[7]Balachandran and Nguyen (2018) discusses the links from the Kyoto protocol to policy and the financial markets from the perspective of Australia. It is noted that the United States of America has not ratified the Kyoto protocol, but has committed to reducing carbon emissions.

those with high profits also have negative coefficients on ENV. However, here governments may prefer to impose penalties, rather than offer subsidies, since these highly profitable firms could afford such penalties. By way of a second example, we may also consider EMP. Here the most profitable firms already enjoy significant positive CFP impacts from improved EMP strength, but those at the lower end of the distribution do not. Helping less profitable firms to help their employees also offers improved CSR through targeted policy. In each case the value of UQR is that the policy-maker can only provide subsidy to a subgroup of firms, reducing the costs of subsidising all. From the OLS regressions there are no significant effects on ROA, so a subsidy would be needed to get all firms to engage. Costs of a blanket subsidy thus disappear because of the direction by UQR.

Across the three CFP measures and two means of capturing CSR a consistent message is provided. Firms must consider their priorities when investing in their stakeholders. There is no one-size-fits all piece of advice. This applies in the demand channel, where the heterogeneous attitudes of consumers towards the activities of firms relative to profits create variation across CFP. It also applies when considering how much capital firms divert from potentially more profitable non-CSR projects into CSR. There are many areas here where UQR brings new light. Agreement with the literature was found on many dimensions, particularly on the changing attitidues to environment and the insurance offered by CSR in the crisis. Policy-makers may also stand to improve efficiency with better targeting of incentives and punishments. These were evidenced here because of our use of UQR. However, not all was as expected and within the presented analysis there is still much for managers to learn. Taking the first steps from what is demonstrated here will be critical to leveraging maximum benefit from stakeholder investment.

## 2.8 Conclusion

Corporate social responsibility, and accountability for actions there against, dominate the evaluative landscape of firm performance. Investment is directed on CSR as a repsonse. Consumers increasingly favour those who are improving utility beyond the bottom line. Managers are incentivised to deliver demonstrable improvement in stakeholder engagement. However, they must generate this improvement whilst still delivering financial returns. Focus on the stakeholders of Freeman (1984) is well discussed, but is often misunderstood for its non-linear effects. Though work like Trumpp and Guenther (2017), Sun et al. (2019) and Meier et al. (2019) put forward a proposed "'inverted-U" shape, the full extent of the non-linearity is not well known. A call for deeper knowledge for managers is made. Policy-makers likewise seek to encourage wider CSR engagement from firms, but lack evidence to motivate. Showing that there is far more significance in CSR investment than the linear models suggest is an important first step. Firms understand stakeholders and recognise the value in looking past the bottom line. This paper gives the first solid empirical support to the opportunities in CSR.

Important new insights are delivered on three fronts. Firstly, empirical justification is given to the notion that poorer performers should direct their attentions on different stakeholders to the best performers. This is intuitive, but can only be seen through distributional analysis. Time variance in the role of the respective stakeholders may also be expected. We show as a second insight exactly how the focus on external stakeholders is most important in harder economic conditions. As firms rein in expenditure to respond to crises seeing which dimensions are relevant to their level of performance can help direct CSR choice. The third aspect to which contribution is made is the performance dependent direction we can offer from UQR. This extra layer is lacking in the empirical leadership of stakeholder investment. As managers are aware of their standing the results of this paper can then be used to effectively decide which strengths or concerns to improve. We also demonstrate how policy-makers may take the lessons from our analysis to better align subsidies and taxation incentives to encourage optimal CSR behaviour by firms.

Limitations to the findings of this paper may be found in the CSR data, in the full interpretation of the quantile regression coefficients and in the limited number of strengths and concerns recorded for those firms who are assessed by MSCI. Our data is from 2005 to 2015 inclusive based on accessibility and changes in the MSCI methodology which have subsequently followed. Having more contemporary data which reflected the MSCI changes would be beneficial. We necessarily impose a single overall CFP distribution when employing UQR. However, this requires a firm to consider location in a large distribution when using our results to guide CSR decisions. Provided firms have an intuition about their location the results become a guide rather than a definitive metric of impact. Improving the connection from decision making to the coefficients would represent an important piece of further work. Finally, like all studies using the MSCI KLD database there is a limitation imposed by the low proportion of firms who are recorded as having strengths or concerns for particular stakeholders. For many firms their CSR performance against at least one of the stakeholders will be 0. The consequence is that estimates get influenced by the large proportion of 0's. However, since this represents the reality assessed by MSCI KLD removing data to reduce the 0 proportion is not advocated in any of the literature, rather it is just acknowledged as a limitation. Notwithstanding these limitations the contributions of this paper are important to recognising that improved CSR performance can increase CFP for all firms, and that position on the relative CFP distribution matters.

Data for CSR-CFP analysis is evolving. As more new sources of CSR engagement become available there is further potential to enrich the evidence here. However, the MSCI data remains the gold standard for analyses like this paper. Firms are asked to understand their relative performance to know which quantile of results to follow. We argue this is reasonable as managers will be aware of their place against competitors. Those controlling firms' finances will have a feel for relative profitability overall. In such circumstances quantile regression still offers more insight to the manager than simply following the average. Extending understanding with exploitation of wider datasets and further linking the empirical evidence with managerial thinking, both offer fruitful further steps. To the appreciation of stakeholders, looking beyond the mean provides a critical depth that may motivate both increased profits and increased stakeholder engagement. Such delivers much for society and enriches the knowledge set of researchers, businesses and their stakeholders alike.

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# Appendices

## A2.1 Full Results

In the main paper we supress the coefficients on the control variables for brevity. However, coefficients on the control variables remain informative for the understanding of CFP across the distribution. This Appendix presents the full tables to allow further analysis of non-linearities in CFP determination. We also look at the impact of using 3-digit NAICS codes for the industry fixed effects and show that there are few differences with the 2-digit NAICS code fixed effects used elsewhere in this paper.

### A2.1.1 Empirical Strategy

To aid the understanding of this appendix it is useful to remind on the control variables used in our regressions. Berman et al. (1999) proposes four strategy variables that should be used in CSR-CFP regressions; these are applied here. Two intensity measures are suggested. First sales intensity (SI) measures the ratio of sales to assets, with firms seeking to get high values of sales for each asset investment. Capital intensity (CI) relates to the ratio of assets to employment, following from simple production models. Cost efficiency (EF) uses the cost of goods sold to establish how efficiently the firm is able to operate; more efficient firms may be able to maintain that efficiency when investing in CSR initiatives. Finally, capital expenditure (CE) provides a measure of the existing investment of the firm, revealing how much scope remains for the firm to invest further. With *emp* as the number of employees and *sale* being the total sales of the firm, *cogs* as the cost of goods sold and *capex* as capital expenditure we have the four ratios in equations (2.6) to (2.9).

$$SI = \frac{sale}{at} \tag{2.15}$$
$$CI = \frac{at}{emp} \tag{2.16}$$
$$EF = \frac{cogs}{sale} \tag{2.17}$$
$$CE = \frac{capex}{sale} \tag{2.18}$$

We also control for the firm leverage, which is the ratio of debt to equity, and the size of the firm measured in log assets. All estimation is performed with industry-year fixed effects. In the tables that follow we use the short form for the five stakeholder dimensions, the four strategy variables and the lag of the dependent variable.

When looking at the full tables, a common feature is that the constant is significant at all quantiles but not in the OLS. This confirms that there are variables explaining CFP that are not included within the regression set. Identification of these variables is left to future work. It should be noted that all applications of quantile regression, both UQR and the conditional form of Koenker and Bassett (1978), produce similar significance to the constants.

### A2.1.2 Full Sample Net Strengths

Our first measure of CFP is the return on assets (ROA). Table A2.1 shows that the lag is highly significant to the current value. Both the lag of ROA and the sales intensity have a U shaped relationship with ROA. CI, EF and CE all have coefficients that increase with the quantile. Size coefficients show diminishing marginal returns; the coefficients get smaller moving up the quantiles. This means that a larger firm will perform better than a small one when they are at the lower end of the distribution. However, as the size of the firm increases the effect is to make their performance worse than the smaller counterpart as the level of performance increases. This paper is not focused on the relationship of these controls with CFP, but the diversity of patterns is of interest. CSR coefficients are then as reported in the main paper.

Table A2.2 includes the full set of coefficients for the regressions on Tobin's q (TOB). Unlike the U shape of quantile coefficients on the lag with ROA, instead we see increasing coefficients as the quantile increases. Having a high TOB is therefore more important to having a high TOB in the next period than it is at the lower end of the distribution. Firm strategy variables do show the increasing coefficients, but there are

Table A2.1: Return on Assets Net Strengths

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | 0.004 | -0.309*** | -0.043*** | 0.067*** | 0.168*** | 0.289*** |
| | | (0.009) | (0.023) | (0.009) | (0.007) | (0.008) | (0.013) |
| Controls | Lag | 0.682*** | 0.598*** | 0.250*** | 0.233*** | 0.334*** | 0.544*** |
| | | (0.041) | (0.059) | (0.029) | (0.029) | (0.042) | (0.069) |
| | SI | 0.033*** | 0.038*** | 0.024*** | 0.020*** | 0.027*** | 0.042*** |
| | | (0.005) | (0.007) | (0.003) | (0.003) | (0.004) | (0.006) |
| | CI | -0.000 | -0.048*** | -0.057*** | -0.026*** | -0.007 | 0.014* |
| | | (0.006) | (0.012) | (0.005) | (0.003) | (0.004) | (0.006) |
| | EF | -0.053*** | -0.083*** | -0.013*** | -0.003 | 0.003 | 0.013* |
| | | (0.009) | (0.012) | (0.003) | (0.002) | (0.003) | (0.005) |
| | CE | -0.013 | -0.046* | 0.029*** | 0.030*** | 0.031*** | 0.019 |
| | | (0.009) | (0.021) | (0.008) | (0.006) | (0.008) | (0.017) |
| | Leverage | -0.042* | -0.057 | -0.116*** | -0.083*** | -0.163*** | -0.233*** |
| | | (0.017) | (0.066) | (0.027) | (0.020) | (0.031) | (0.057) |
| | Size | 0.005*** | 0.038*** | 0.011*** | 0.002* | -0.008*** | -0.021*** |
| | | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.002) |
| Net Strengths | PRO | -0.003 | -0.006 | 0.009** | 0.004 | 0.010 | -0.007 |
| | | (0.002) | (0.008) | (0.003) | (0.003) | (0.006) | (0.011) |
| | ENV | -0.002 | -0.023* | -0.005 | 0.016** | 0.021* | 0.021 |
| | | (0.004) | (0.011) | (0.005) | (0.005) | (0.009) | (0.012) |
| | COM | -0.001 | -0.013 | -0.001 | 0.005 | 0.011* | 0.022* |
| | | (0.003) | (0.009) | (0.004) | (0.004) | (0.005) | (0.009) |
| | DIV | -0.002 | -0.026*** | -0.004 | 0.002 | 0.006 | 0.017*** |
| | | (0.002) | (0.005) | (0.002) | (0.002) | (0.003) | (0.005) |
| | EMP | 0.003 | -0.009 | 0.003 | 0.012** | 0.033*** | 0.049*** |
| | | (0.003) | (0.009) | (0.004) | (0.004) | (0.007) | (0.013) |
| R-squared | | 0.704 | 0.374 | 0.301 | 0.247 | 0.223 | 0.189 |

Notes: Estimation of equation (2.11) with the re-centred inference function for ROA as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$, the net strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed, less the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A2.2: Tobin's Q Net Strengths

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | 1.301** | 1.568*** | 1.856*** | 2.305*** | 2.483*** | 1.515 |
| | | (0.474) | (0.049) | (0.072) | (0.173) | (0.451) | (1.012) |
| Controls | Lag | 0.706*** | 0.054*** | 0.098*** | 0.237*** | 0.646*** | 1.516*** |
| | | (0.080) | (0.009) | (0.015) | (0.033) | (0.086) | (0.190) |
| | SI | 0.036 | 0.053** | 0.027 | -0.006 | 0.047 | 0.223** |
| | | (0.025) | (0.017) | (0.017) | (0.021) | (0.036) | (0.078) |
| | CI | -0.067 | -0.409*** | -0.183*** | -0.050 | 0.061 | 0.188 |
| | | (0.045) | (0.049) | (0.028) | (0.027) | (0.054) | (0.109) |
| | EF | 0.044 | -0.066*** | -0.082*** | -0.127*** | -0.106* | 0.128 |
| | | (0.104) | (0.015) | (0.018) | (0.031) | (0.054) | (0.132) |
| | CE | 0.053 | 0.161** | 0.029 | -0.061 | -0.018 | 0.198 |
| | | (0.164) | (0.056) | (0.057) | (0.077) | (0.161) | (0.375) |
| | Leverage | -0.651* | -2.765*** | -2.341*** | -2.128*** | -0.885* | 1.877 |
| | | (0.268) | (0.333) | (0.222) | (0.218) | (0.398) | (1.115) |
| | Size | -0.086** | -0.035*** | -0.051*** | -0.095*** | -0.173*** | -0.224** |
| | | (0.030) | (0.005) | (0.006) | (0.013) | (0.031) | (0.069) |
| Net Strengths | PRO | 0.092 | 0.012 | 0.067* | 0.081* | 0.148 | 0.373 |
| | | (0.053) | (0.020) | (0.027) | (0.037) | (0.099) | (0.241) |
| | ENV | 0.043 | 0.126*** | 0.165*** | 0.380*** | 0.390*** | -0.025 |
| | | (0.057) | (0.036) | (0.041) | (0.052) | (0.099) | (0.191) |
| | COM | -0.004 | 0.060* | 0.029 | 0.039 | 0.004 | -0.042 |
| | | (0.022) | (0.023) | (0.026) | (0.034) | (0.048) | (0.134) |
| | DIV | 0.127* | 0.080*** | 0.093*** | 0.110*** | 0.121* | 0.265 |
| | | (0.064) | (0.017) | (0.019) | (0.028) | (0.053) | (0.146) |
| | EMP | 0.155* | 0.082** | 0.184*** | 0.385*** | 0.407*** | 0.393 |
| | | (0.062) | (0.029) | (0.033) | (0.057) | (0.111) | (0.219) |
| R-squared | | 0.552 | 0.121 | 0.148 | 0.248 | 0.346 | 0.353 |

Notes: Estimation of equation (2.11) with the re-centred inference function for TOB as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$, the net strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed, less the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

more negative values than seen for ROA. We see leverage producing positive coefficients at the higher quantiles and size producing negative coefficients at all quantiles. Taking TOB as a measure of expected future profitability, we see that smaller firms are expected to perform better. R-squared values can be seen to be high for quantile regressions; around 0.2 would be the norm.

The final CFP measure to be considered is Peters and Taylor (2016) total q (TOT). Results are in Table A2.3. Here the constant terms are again highly significant and increase greatly across the quantiles. The lag is also significant and increasing, but at a much slower rate than the constant. Other variables have similar signs to the TOB results from Table A2.2. Relative to the other measures of CFP, the R-squared values are much smaller. Combined with the constant, it is clear that more variables are needed to really understand the variation in TOT across the quantiles. As in the other cases the R-squared for the OLS model does not give any real sign of omitted variables.

In summary the three regressions inform that there is variation across the quantiles in the financial controls as well as the stakeholder dimensions. With the focus of the main paper being on the stakeholder dimensions, this discussion of the other coefficients is a useful consistency check.

### A2.1.3 Full Sample Strengths and Concerns

As in the main paper, following Perrault and Quinn (2016) and others, we now consider strengths and concerns separately. Tables A2.4 to A2.6 report the results.

The effect on the stakeholder dimension coefficients is reported in the main paper. When considering the other coefficients there are strong simiarlities between the estimates and those under net strengths. Comparing the R-squared values we see a very slight increase in explanatory power, but not by much. Hence, whilst there is interest in discussing the differentials in strengths and concerns from a theoretical perspective the econometric evidence is indecisive.

### A2.1.4 3 Digit Fixed Effects

Another useful robustness check is to think about the coefficients when we use three digit NAICS code fixed effects in place of the two-digit fixed effects of the main paper. Again we provide the full set of tables for comparison. These are Tables A2.7 to A2.9.

Table A2.7 shows that the coefficients have not changed greatly compared to Table A2.4. However, there are some changes in the significance of these coefficients after

Table A2.3: Total Q Net Strengths

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | 0.210 | 0.389*** | 0.732*** | 1.445*** | 3.608*** | 7.996*** |
| | | (0.580) | (0.067) | (0.038) | (0.048) | (0.145) | (0.535) |
| Controls | Lag | 0.870*** | 0.011*** | 0.008*** | 0.010*** | 0.034*** | 0.144*** |
| | | (0.098) | (0.002) | (0.001) | (0.002) | (0.006) | (0.023) |
| | SI | 0.092* | -0.141*** | -0.151*** | -0.128*** | -0.190*** | -0.411** |
| | | (0.042) | (0.025) | (0.016) | (0.020) | (0.045) | (0.132) |
| | CI | -0.453 | -0.547*** | -0.266*** | -0.166*** | -0.246** | -0.871** |
| | | (1.083) | (0.064) | (0.037) | (0.040) | (0.090) | (0.279) |
| | EF | -0.015 | -0.125*** | -0.094*** | -0.106*** | -0.161 | -0.281 |
| | | (0.091) | (0.029) | (0.022) | (0.032) | (0.084) | (0.245) |
| | CE | 0.043 | 0.383*** | 0.251*** | 0.202*** | 0.190 | 0.745 |
| | | (0.625) | (0.064) | (0.041) | (0.059) | (0.133) | (0.380) |
| | Leverage | -2.896 | -1.336*** | -0.912*** | -1.563*** | -2.536*** | -6.005*** |
| | | (1.980) | (0.258) | (0.183) | (0.190) | (0.486) | (1.512) |
| | Size | -0.020 | 0.008 | -0.002 | -0.051*** | -0.233*** | -0.595*** |
| | | (0.045) | (0.008) | (0.005) | (0.006) | (0.017) | (0.054) |
| Net Strengths | PRO | -0.294 | 0.059 | 0.099** | 0.182*** | 0.375** | 0.746* |
| | | (0.236) | (0.044) | (0.031) | (0.039) | (0.129) | (0.339) |
| | ENV | 0.048 | 0.010 | 0.076 | 0.238*** | 0.363** | 0.176 |
| | | (0.138) | (0.044) | (0.040) | (0.048) | (0.127) | (0.397) |
| | COM | -0.146 | 0.019 | -0.004 | 0.056 | -0.014 | -0.047 |
| | | (0.122) | (0.027) | (0.022) | (0.032) | (0.073) | (0.202) |
| | DIV | 0.185 | 0.030 | 0.039* | 0.041 | 0.051 | 0.375* |
| | | (0.102) | (0.020) | (0.018) | (0.022) | (0.046) | (0.159) |
| | EMP | -0.389* | 0.042 | 0.164*** | 0.291*** | 0.764*** | 1.404*** |
| | | (0.172) | (0.038) | (0.035) | (0.046) | (0.123) | (0.333) |
| R-squared | | 0.779 | 0.056 | 0.051 | 0.055 | 0.076 | 0.094 |

Notes: Estimation of equation (2.11) with the re-centred inference function for TOT as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$, the net strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed, less the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A2.4: Return on Assets Strengths and Concerns

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | -0.002 | -0.352*** | -0.051*** | 0.071*** | 0.179*** | 0.316*** |
| | | (0.011) | (0.025) | (0.011) | (0.008) | (0.008) | (0.013) |
| Controls | Lag | 0.682*** | 0.594*** | 0.249*** | 0.233*** | 0.336*** | 0.547*** |
| | | (0.041) | (0.059) | (0.029) | (0.028) | (0.042) | (0.069) |
| | SI | 0.033*** | 0.039*** | 0.025*** | 0.020*** | 0.027*** | 0.042*** |
| | | (0.005) | (0.007) | (0.003) | (0.003) | (0.004) | (0.006) |
| | CI | -0.001 | -0.053*** | -0.058*** | -0.025*** | -0.005 | 0.017** |
| | | (0.006) | (0.012) | (0.005) | (0.003) | (0.004) | (0.006) |
| | EF | -0.053*** | -0.083*** | -0.013*** | -0.003 | 0.003 | 0.013* |
| | | (0.009) | (0.012) | (0.003) | (0.002) | (0.003) | (0.005) |
| | CE | -0.013 | -0.050* | 0.028*** | 0.030*** | 0.031*** | 0.021 |
| | | (0.009) | (0.021) | (0.008) | (0.006) | (0.008) | (0.017) |
| | Leverage | -0.044* | -0.069 | -0.118*** | -0.082*** | -0.161*** | -0.226*** |
| | | (0.018) | (0.066) | (0.027) | (0.020) | (0.031) | (0.058) |
| | Size | 0.006*** | 0.046*** | 0.013*** | 0.001 | -0.010*** | -0.026*** |
| | | (0.001) | (0.003) | (0.002) | (0.001) | (0.001) | (0.002) |
| Strengths | PRO | -0.003 | -0.032*** | 0.006 | 0.008* | 0.026*** | 0.017 |
| | | (0.002) | (0.008) | (0.003) | (0.004) | (0.007) | (0.013) |
| | ENV | -0.005 | -0.016 | -0.006 | 0.014* | 0.011 | 0.002 |
| | | (0.004) | (0.013) | (0.006) | (0.006) | (0.010) | (0.013) |
| | COM | -0.007* | -0.040*** | -0.009 | 0.005 | 0.012* | 0.031** |
| | | (0.003) | (0.011) | (0.005) | (0.005) | (0.006) | (0.011) |
| | DIV | 0.001 | -0.024* | -0.012* | 0.004 | 0.019* | 0.027* |
| | | (0.005) | (0.010) | (0.005) | (0.006) | (0.008) | (0.014) |
| | EMP | 0.001 | -0.052*** | -0.001 | 0.019*** | 0.047*** | 0.091*** |
| | | (0.006) | (0.014) | (0.006) | (0.005) | (0.009) | (0.016) |
| Concerns | PRO | 0.001 | -0.082*** | -0.020*** | 0.007 | 0.039*** | 0.087*** |
| | | (0.005) | (0.011) | (0.006) | (0.005) | (0.010) | (0.018) |
| | ENV | -0.014 | -0.031 | -0.014 | -0.010 | -0.021 | -0.014 |
| | | (0.010) | (0.021) | (0.012) | (0.012) | (0.016) | (0.026) |
| | COM | -0.003 | -0.018 | -0.008 | -0.006 | -0.004 | -0.004 |
| | | (0.004) | (0.011) | (0.006) | (0.005) | (0.007) | (0.013) |
| | DIV | 0.003 | 0.015 | -0.003 | -0.000 | 0.005 | -0.003 |
| | | (0.003) | (0.008) | (0.004) | (0.003) | (0.004) | (0.008) |
| | EMP | -0.006 | -0.033* | -0.007 | -0.004 | -0.020 | -0.008 |
| | | (0.006) | (0.015) | (0.007) | (0.007) | (0.011) | (0.021) |
| | R-squared | 0.704 | 0.379 | 0.302 | 0.248 | 0.227 | 0.193 |

Notes: Estimation of equation (2.12) with the re-centred inference function for ROA as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$. Strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed. Concerns for firm $i$ are the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A2.5: Tobin's Q Strengths and Concerns

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | 1.456** | 1.606*** | 1.899*** | 2.440*** | 2.810*** | 1.978 |
| | | (0.506) | (0.061) | (0.082) | (0.194) | (0.502) | (1.108) |
| Controls | Lag | 0.701*** | 0.053*** | 0.096*** | 0.233*** | 0.637*** | 1.504*** |
| | | (0.081) | (0.009) | (0.015) | (0.033) | (0.086) | (0.191) |
| | SI | 0.032 | 0.053** | 0.025 | -0.009 | 0.040 | 0.216** |
| | | (0.025) | (0.017) | (0.017) | (0.021) | (0.036) | (0.075) |
| | CI | -0.052 | -0.407*** | -0.179*** | -0.038 | 0.092 | 0.231* |
| | | (0.044) | (0.048) | (0.027) | (0.027) | (0.054) | (0.111) |
| | EF | 0.045 | -0.065*** | -0.082*** | -0.126*** | -0.106* | 0.131 |
| | | (0.104) | (0.015) | (0.018) | (0.031) | (0.054) | (0.131) |
| | CE | 0.062 | 0.162** | 0.032 | -0.053 | 0.004 | 0.232 |
| | | (0.165) | (0.057) | (0.057) | (0.077) | (0.162) | (0.379) |
| | Leverage | -0.647* | -2.763*** | -2.335*** | -2.126*** | -0.868* | 1.893 |
| | | (0.267) | (0.331) | (0.222) | (0.218) | (0.391) | (1.104) |
| | Size | -0.113** | -0.041*** | -0.059*** | -0.119*** | -0.229*** | -0.299*** |
| | | (0.037) | (0.008) | (0.008) | (0.016) | (0.039) | (0.085) |
| Strengths | PRO | 0.239** | 0.041 | 0.090** | 0.207*** | 0.427*** | 0.850** |
| | | (0.073) | (0.026) | (0.032) | (0.048) | (0.125) | (0.307) |
| | ENV | 0.001 | 0.099** | 0.146** | 0.342*** | 0.286* | -0.273 |
| | | (0.064) | (0.037) | (0.048) | (0.057) | (0.113) | (0.198) |
| | COM | 0.016 | 0.154*** | 0.066 | 0.099* | 0.108 | -0.034 |
| | | (0.034) | (0.032) | (0.040) | (0.042) | (0.069) | (0.204) |
| | DIV | 0.117 | 0.081** | 0.102* | 0.121* | 0.095 | -0.012 |
| | | (0.078) | (0.030) | (0.042) | (0.054) | (0.091) | (0.186) |
| | EMP | 0.274** | 0.058 | 0.225*** | 0.446*** | 0.670*** | 0.950** |
| | | (0.096) | (0.044) | (0.044) | (0.080) | (0.162) | (0.332) |
| Concerns | PRO | 0.355*** | 0.063 | 0.009 | 0.299*** | 0.715*** | 1.096*** |
| | | (0.083) | (0.050) | (0.065) | (0.088) | (0.174) | (0.299) |
| | ENV | 0.079 | -0.165 | -0.149 | -0.286** | -0.182 | -0.004 |
| | | (0.071) | (0.102) | (0.080) | (0.110) | (0.157) | (0.306) |
| | COM | 0.030 | 0.060 | 0.021 | 0.036 | 0.130 | 0.081 |
| | | (0.041) | (0.042) | (0.059) | (0.058) | (0.090) | (0.155) |
| | DIV | -0.099 | -0.066** | -0.075** | -0.073* | -0.061 | -0.326 |
| | | (0.056) | (0.022) | (0.025) | (0.037) | (0.079) | (0.176) |
| | EMP | -0.066 | -0.108* | -0.142** | -0.350*** | -0.192 | 0.082 |
| | | (0.068) | (0.046) | (0.052) | (0.069) | (0.127) | (0.256) |
| | R-squared | 0.554 | 0.122 | 0.149 | 0.251 | 0.349 | 0.355 |

Notes: Estimation of equation (2.12) with the re-centred inference function for TOB as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$. Strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed. Concerns for firm $i$ are the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A2.6: Total Q Strengths and Concerns

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | 0.284 | 0.393*** | 0.723*** | 1.464*** | 3.862*** | 8.780*** |
| | | (0.650) | (0.076) | (0.046) | (0.057) | (0.151) | (0.583) |
| Controls | Lag | 0.870*** | 0.011*** | 0.008*** | 0.010*** | 0.034*** | 0.144*** |
| | | (0.098) | (0.002) | (0.001) | (0.002) | (0.006) | (0.023) |
| | SI | 0.089* | -0.141*** | -0.150*** | -0.127*** | -0.194*** | -0.433** |
| | | (0.041) | (0.025) | (0.016) | (0.020) | (0.045) | (0.133) |
| | CI | -0.444 | -0.548*** | -0.267*** | -0.164*** | -0.215* | -0.774** |
| | | (1.078) | (0.063) | (0.036) | (0.040) | (0.090) | (0.274) |
| | EF | -0.014 | -0.125*** | -0.092*** | -0.103** | -0.161 | -0.289 |
| | | (0.091) | (0.029) | (0.022) | (0.031) | (0.082) | (0.239) |
| | CE | 0.045 | 0.382*** | 0.248*** | 0.201*** | 0.206 | 0.800* |
| | | (0.625) | (0.064) | (0.042) | (0.059) | (0.131) | (0.375) |
| | Leverage | -2.891 | -1.336*** | -0.925*** | -1.572*** | -2.493*** | -5.841*** |
| | | (1.971) | (0.257) | (0.182) | (0.189) | (0.472) | (1.483) |
| | Size | -0.032 | 0.010 | 0.000 | -0.055*** | -0.287*** | -0.754*** |
| | | (0.061) | (0.011) | (0.007) | (0.008) | (0.020) | (0.065) |
| Strengths | PRO | -0.233 | 0.048 | 0.129** | 0.262*** | 0.677*** | 1.425*** |
| | | (0.225) | (0.056) | (0.042) | (0.051) | (0.164) | (0.411) |
| | ENV | 0.129 | 0.035 | 0.087 | 0.196*** | 0.144 | -0.170 |
| | | (0.205) | (0.055) | (0.049) | (0.058) | (0.154) | (0.509) |
| | COM | -0.205 | 0.063 | -0.016 | 0.075 | 0.100 | 0.154 |
| | | (0.186) | (0.032) | (0.028) | (0.039) | (0.108) | (0.305) |
| | DIV | 0.144 | -0.007 | 0.042 | 0.064 | 0.153 | 0.552 |
| | | (0.215) | (0.049) | (0.046) | (0.050) | (0.114) | (0.327) |
| | EMP | -0.388 | -0.014 | 0.085 | 0.246*** | 1.077*** | 2.434*** |
| | | (0.214) | (0.057) | (0.046) | (0.066) | (0.195) | (0.497) |
| Concerns | PRO | 0.486 | -0.101* | -0.029 | 0.034 | 0.557** | 1.462** |
| | | (0.413) | (0.050) | (0.049) | (0.083) | (0.195) | (0.521) |
| | ENV | 0.277 | 0.024 | -0.070 | -0.311** | -0.412* | 0.484 |
| | | (0.174) | (0.084) | (0.072) | (0.100) | (0.203) | (0.424) |
| | COM | 0.024 | 0.017 | -0.017 | -0.019 | 0.232* | 0.385* |
| | | (0.070) | (0.047) | (0.038) | (0.052) | (0.096) | (0.184) |
| | DIV | -0.203 | -0.052 | -0.043 | -0.019 | 0.094 | -0.039 |
| | | (0.169) | (0.032) | (0.023) | (0.029) | (0.064) | (0.218) |
| | EMP | 0.360 | -0.100 | -0.260*** | -0.354*** | -0.473** | -0.415 |
| | | (0.201) | (0.066) | (0.053) | (0.061) | (0.143) | (0.419) |
| R-squared | | 0.779 | 0.056 | 0.052 | 0.057 | 0.081 | 0.098 |

Notes: Estimation of equation (2.12) with the re-centred inference function for TOT as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$. Strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed. Concerns for firm $i$ are the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A2.7: Return on Assets Strengths and Concerns 3-Digit Fixed Effects

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | -0.002 | -0.331*** | -0.049*** | 0.071*** | 0.169*** | 0.290*** |
| | | (0.012) | (0.026) | (0.009) | (0.006) | (0.007) | (0.013) |
| Controls | Lag | 0.678*** | 0.578*** | 0.238*** | 0.221*** | 0.323*** | 0.534*** |
| | | (0.043) | (0.058) | (0.029) | (0.029) | (0.043) | (0.070) |
| | SI | 0.034*** | 0.035*** | 0.024*** | 0.018*** | 0.026*** | 0.048*** |
| | | (0.005) | (0.008) | (0.003) | (0.003) | (0.004) | (0.007) |
| | CI | 0.003 | -0.042*** | -0.058*** | -0.025*** | -0.009 | 0.014 |
| | | (0.007) | (0.011) | (0.005) | (0.003) | (0.005) | (0.007) |
| | EF | -0.054*** | -0.083*** | -0.013*** | -0.004 | 0.001 | 0.008 |
| | | (0.009) | (0.012) | (0.003) | (0.002) | (0.003) | (0.005) |
| | CE | -0.006 | -0.045* | 0.015* | 0.020*** | 0.025* | 0.045** |
| | | (0.009) | (0.022) | (0.008) | (0.005) | (0.010) | (0.016) |
| | Leverage | -0.057** | -0.127 | -0.141*** | -0.083*** | -0.151*** | -0.211*** |
| | | (0.019) | (0.074) | (0.026) | (0.021) | (0.032) | (0.060) |
| | Size | 0.006*** | 0.044*** | 0.013*** | 0.001 | -0.008*** | -0.023*** |
| | | (0.001) | (0.003) | (0.001) | (0.001) | (0.001) | (0.002) |
| Strengths | PRO | -0.001 | -0.022 | 0.010* | 0.011** | 0.023*** | 0.006 |
| | | (0.003) | (0.013) | (0.004) | (0.004) | (0.007) | (0.012) |
| | ENV | -0.006 | -0.012 | -0.001 | 0.019** | 0.015 | 0.005 |
| | | (0.004) | (0.014) | (0.006) | (0.006) | (0.009) | (0.014) |
| | COM | -0.006* | -0.036*** | -0.009* | 0.002 | 0.007 | 0.023* |
| | | (0.003) | (0.009) | (0.004) | (0.004) | (0.006) | (0.011) |
| | DIV | 0.001 | -0.017 | -0.012* | 0.004 | 0.015* | 0.019 |
| | | (0.005) | (0.009) | (0.005) | (0.005) | (0.007) | (0.013) |
| | EMP | 0.001 | -0.049*** | 0.001 | 0.018*** | 0.045*** | 0.097*** |
| | | (0.006) | (0.015) | (0.006) | (0.005) | (0.008) | (0.016) |
| Concerns | PRO | -0.004 | -0.064*** | -0.020** | 0.002 | 0.027** | 0.058** |
| | | (0.005) | (0.014) | (0.007) | (0.006) | (0.009) | (0.018) |
| | ENV | -0.011 | -0.040 | -0.021 | -0.009 | -0.025 | -0.018 |
| | | (0.007) | (0.027) | (0.011) | (0.010) | (0.017) | (0.037) |
| | COM | -0.001 | -0.013 | -0.008 | -0.005 | 0.003 | 0.002 |
| | | (0.004) | (0.012) | (0.006) | (0.005) | (0.007) | (0.013) |
| | DIV | 0.002 | 0.015* | -0.001 | 0.002 | 0.004 | -0.005 |
| | | (0.004) | (0.008) | (0.004) | (0.003) | (0.005) | (0.009) |
| | EMP | -0.008 | -0.052*** | -0.014* | -0.007 | -0.014 | 0.004 |
| | | (0.006) | (0.016) | (0.007) | (0.007) | (0.011) | (0.019) |
| R-squared | | 0.694 | 0.357 | 0.286 | 0.234 | 0.214 | 0.187 |

Notes: Estimation of equation (2.12) with the re-centred inference function for ROA as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to three-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$. Strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed. Concerns for firm $i$ are the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

adding the more detailed fixed effects. Where previously there was significance on the diversity strengths at $\tau = 0.90$ there is no longer any. Likewise there is no longer any significance on COM concerns at $\tau = 0.10$. EMP concerns take on greater significance and the coefficients are slightly larger than they were when using two-digit fixed effects. Overall there is a robustness of results in qualitative terms.

As with ROA, Table A2.8 shows strong similarities to Table A2.5. The main differences are in the smaller coefficient on PRO concerns and the significance of PRO strengths at $\tau = 0.10$. Table A2.9 also shows few contrasts to Table A2.6.

There are some small differences to the estimates when using more industry fixed effect groupings. However, the overall inference remains that presented in the main paper. The “inverted U” shaped relationship on ENV can be seen in the strengths, and the pattern of increasing coefficients across the quantiles remains within the PRO and EMP dimensions. This subsection has therefore demonstrated the robustness of the results to the use of three digit NAICS code fixed effects.

### A2.1.5 Summary of Full Period Robustness

The aim of this appendix is to present the full set of coefficients from our full-period regressions. In addition to the full tables we have also discussed robustness to changes in the number of digits for the industry fixed effects. As the results are similar there is no particular benefit to having the loss of degrees of freedom that comes with 3-digit NAICS code fixed effects.

## A2.2 Parameter Equality Tests

In the main paper we present evidence that there is significant variation in the coefficients on stakeholder dimensions in the regression of CFP on CSR and firm controls. In this appendix we present a full set of pairwise comparisons between coefficients to further evidence the extent of variation across quantiles. We focus on the same five quantiles, $\tau = 0.10$, $\tau = 0.25$, $\tau = 0.50$, $\tau = 0.75$ and $\tau = 0.90$ that are included in all of the tables reported in this paper. Because UQR involves a two stage process, the second stage sees the recentred influence function (RIF) values for different quantiles regressed on the same set of covariates. Hence two or more RIF regressions are seemingly unrelated regressions and may be analysed as such. Inclusion of fixed effects mean that all covariates must be centred prior to testing. The equality tests reported here follow Rios Avila (2019) and are performed using the Stata code from Rios-Avila

Table A2.8: Tobin's Q Strengths and Concerns 3-Digit Fixed Effects

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | 1.353** | 1.568*** | 1.798*** | 2.256*** | 2.606*** | 1.820 |
| | | (0.495) | (0.055) | (0.077) | (0.167) | (0.465) | (1.046) |
| Controls | Lag | 0.689*** | 0.045*** | 0.085*** | 0.213*** | 0.602*** | 1.460*** |
| | | (0.086) | (0.008) | (0.014) | (0.033) | (0.090) | (0.202) |
| | SI | 0.069** | 0.046** | 0.029 | 0.016 | 0.109*** | 0.368*** |
| | | (0.026) | (0.016) | (0.015) | (0.018) | (0.033) | (0.079) |
| | CI | -0.088* | -0.465*** | -0.216*** | -0.068* | 0.069 | 0.158 |
| | | (0.043) | (0.043) | (0.026) | (0.027) | (0.052) | (0.121) |
| | EF | 0.044 | -0.049*** | -0.066*** | -0.118*** | -0.112* | 0.105 |
| | | (0.110) | (0.012) | (0.016) | (0.028) | (0.050) | (0.140) |
| | CE | 0.125 | 0.087 | 0.047 | 0.086 | 0.254 | 0.315 |
| | | (0.220) | (0.053) | (0.050) | (0.077) | (0.188) | (0.523) |
| | Leverage | -0.492* | -2.614*** | -2.171*** | -1.912*** | -0.687* | 1.852 |
| | | (0.246) | (0.281) | (0.201) | (0.192) | (0.339) | (1.093) |
| | Size | -0.099** | -0.031*** | -0.042*** | -0.091*** | -0.197*** | -0.275*** |
| | | (0.034) | (0.006) | (0.007) | (0.013) | (0.034) | (0.077) |
| Strengths | PRO | 0.180** | 0.063* | 0.098*** | 0.177*** | 0.336** | 0.621* |
| | | (0.067) | (0.025) | (0.029) | (0.047) | (0.111) | (0.293) |
| | ENV | 0.018 | 0.106** | 0.141** | 0.319*** | 0.259* | -0.224 |
| | | (0.072) | (0.040) | (0.046) | (0.068) | (0.123) | (0.230) |
| | COM | -0.003 | 0.125*** | 0.014 | 0.053 | 0.097 | -0.047 |
| | | (0.039) | (0.034) | (0.036) | (0.044) | (0.082) | (0.209) |
| | DIV | 0.088 | 0.073* | 0.084* | 0.066 | -0.031 | -0.146 |
| | | (0.074) | (0.033) | (0.040) | (0.055) | (0.100) | (0.188) |
| | EMP | 0.261** | 0.040 | 0.183*** | 0.411*** | 0.590*** | 1.059** |
| | | (0.091) | (0.043) | (0.048) | (0.072) | (0.153) | (0.332) |
| Concerns | PRO | 0.260*** | 0.024 | -0.021 | 0.238** | 0.522** | 0.611* |
| | | (0.065) | (0.051) | (0.070) | (0.081) | (0.167) | (0.258) |
| | ENV | 0.066 | -0.262** | -0.183* | -0.206 | -0.035 | 0.000 |
| | | (0.074) | (0.092) | (0.081) | (0.119) | (0.219) | (0.299) |
| | COM | 0.037 | 0.019 | -0.006 | 0.022 | 0.178 | 0.071 |
| | | (0.039) | (0.041) | (0.058) | (0.064) | (0.099) | (0.156) |
| | DIV | -0.088 | -0.061* | -0.064* | -0.046 | -0.083 | -0.329 |
| | | (0.057) | (0.025) | (0.026) | (0.036) | (0.084) | (0.181) |
| | EMP | -0.041 | -0.082 | -0.100 | -0.302*** | -0.082 | 0.234 |
| | | (0.071) | (0.051) | (0.054) | (0.067) | (0.126) | (0.283) |
| R-squared | | 0.520 | 0.111 | 0.116 | 0.200 | 0.303 | 0.324 |

Notes: Estimation of equation (2.12) with the re-centred inference function for TOB as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to three-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$,
$x \in \{PRO, ENV, COM, DIV, EMP\}$. Strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed. Concerns for firm $i$ are the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A2.9: Total Q Strengths and Concerns 3-Digit Fixed Effects

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | 0.477 | 0.439*** | 0.679*** | 1.293*** | 3.518*** | 7.921*** |
| | | (0.504) | (0.072) | (0.048) | (0.063) | (0.150) | (0.529) |
| Controls | Lag | 0.871*** | 0.011*** | 0.008*** | 0.010*** | 0.033*** | 0.143*** |
| | | (0.079) | (0.001) | (0.001) | (0.001) | (0.005) | (0.018) |
| | SI | 0.096* | -0.164*** | -0.156*** | -0.118*** | -0.143*** | -0.289* |
| | | (0.040) | (0.021) | (0.014) | (0.016) | (0.042) | (0.144) |
| | CI | -0.460 | -0.579*** | -0.290*** | -0.176*** | -0.283** | -1.083*** |
| | | (1.151) | (0.064) | (0.038) | (0.043) | (0.090) | (0.270) |
| | EF | -0.057 | -0.124*** | -0.100*** | -0.120*** | -0.197* | -0.323 |
| | | (0.086) | (0.029) | (0.023) | (0.031) | (0.078) | (0.224) |
| | CE | 0.000 | 0.307*** | 0.279*** | 0.396*** | 0.521*** | 1.452** |
| | | (0.507) | (0.059) | (0.047) | (0.057) | (0.138) | (0.457) |
| | Leverage | -2.413 | -1.355*** | -0.850*** | -1.386*** | -2.108*** | -5.224*** |
| | | (1.688) | (0.259) | (0.182) | (0.197) | (0.485) | (1.543) |
| | Size | -0.058 | 0.009 | 0.008 | -0.033*** | -0.242*** | -0.644*** |
| | | (0.048) | (0.009) | (0.007) | (0.008) | (0.020) | (0.060) |
| Strengths | PRO | -0.220 | 0.060 | 0.140*** | 0.236*** | 0.552*** | 1.116* |
| | | (0.188) | (0.044) | (0.032) | (0.040) | (0.130) | (0.446) |
| | ENV | 0.150 | 0.059 | 0.127** | 0.199** | 0.099 | -0.339 |
| | | (0.195) | (0.052) | (0.044) | (0.064) | (0.159) | (0.510) |
| | COM | -0.192 | 0.031 | -0.059 | 0.019 | 0.055 | 0.034 |
| | | (0.215) | (0.044) | (0.034) | (0.042) | (0.105) | (0.310) |
| | DIV | 0.174 | -0.008 | 0.019 | 0.015 | -0.021 | 0.179 |
| | | (0.154) | (0.046) | (0.038) | (0.050) | (0.111) | (0.328) |
| | EMP | -0.318 | 0.003 | 0.100* | 0.230*** | 0.992*** | 2.234*** |
| | | (0.256) | (0.057) | (0.043) | (0.064) | (0.164) | (0.494) |
| Concerns | PRO | 0.279 | -0.136* | -0.077 | -0.069 | 0.291 | 0.931 |
| | | (0.438) | (0.068) | (0.054) | (0.087) | (0.207) | (0.527) |
| | ENV | 0.288 | -0.053 | -0.131 | -0.260* | -0.289 | 0.742 |
| | | (0.176) | (0.090) | (0.082) | (0.129) | (0.248) | (0.487) |
| | COM | 0.217 | 0.007 | -0.071 | -0.049 | 0.245** | 0.369 |
| | | (0.139) | (0.045) | (0.040) | (0.049) | (0.091) | (0.195) |
| | DIV | -0.179 | -0.068* | -0.041 | -0.013 | 0.082 | -0.095 |
| | | (0.158) | (0.031) | (0.023) | (0.031) | (0.080) | (0.226) |
| | EMP | 0.398 | -0.133* | -0.225*** | -0.306*** | -0.304 | -0.098 |
| | | (0.314) | (0.066) | (0.053) | (0.064) | (0.158) | (0.438) |
| R-squared | | 0.780 | 0.059 | 0.053 | 0.050 | 0.068 | 0.091 |

Notes: Estimation of equation (2.12) with the re-centred inference function for TOT as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to three-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$. Strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed. Concerns for firm $i$ are the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

(2020). The test function in Rios-Avila (2020) first centres the data, then estimates the coefficients at each quantile before performing a $\chi$-squared test of equality on each individual coefficient between the given set of quantiles. Full details of the test are provided in Rios Avila (2019) and Rios-Avila (2020).

As noted in the main paper, 9 of the 15 joint equality tests reject the equality of parameters on the stakeholder dimensions at the 5% level. Amongst the pairwise test statistics reported in Table A2.10, there are a total of 55 significant results from the 150 tests performed. Within the ROA estimates, the overall parameter equality on PRO rejects, but none of the pairwise comparisions pass the 5% significance threshold. PRO also displays limited pairwise significance when TOB and TOT are the CFP measures; the number of rejections being 1 and 4 respectively. More variation is seen for ENV, particularly between the lower quantiles and the mid to high quantiles. For ROA there is a significant difference between $\tau = 0.50$ and either $\tau = 0.75$ or $\tau = 0.90$, but for TOB there is significant variation evidenced for ENV also. Here we confirm that the lower coefficients on either side of the maximum coefficient in the "inverted-U" are significantly different from the high point of that "inverted-U". COM has the least significant variation with just 2 rejections on ROA, 1 on TOT and none on TOB. DIV shows significant differences in 9 of the 10 tests on ROA but not in any of the pairwise comparisions for TOB or TOT. Finally, we see the greatest number of rejections of parameter equality for EMP, with 6 of the 10 ROA, 5 of the 10 TOB and 9 of the 10 TOT, pairwise tests rejecting equality at the 5% level. In the main paper we show that EMP is particularly important for the best performers and that coefficients increase with quantiles. Such significance in the pairwise comparisons as evidenced in Table A2.10 is therefore consistent. Evidence from Table A2.10 thus fully supports the use of UQR over OLS.

Table A2.11 reports coefficient equality tests for the separation of strengths and concerns. 10 of the 15 joint equality tests for stengths reject at the 5% level, with 6 of the 15 concerns tests also rejecting joint equality at the 5% level. Looking at the individual pairwise comparisons, we see that PRO strengths display significant variation in most comparisons. When TOB or TOT are the CFP measure, only the comparison between $\tau = 0.75$ and $\tau = 0.90$ does not show significance. ENV strengths have significance in the fewest comparisons once more, with 4 of the 10 TOB comparisons being the highest proportion for any of the CFP measures. For TOB it is the tests involving $\tau = 0.50$ and the ends of the distribution which reject equality, consistent with the "inverted-U" shaped relationship seen in the main analysis of ENV and TOB. COM and DIV strengths provide significnace when ROA is the CFP measure, but not

Table A2.10: Equality Tests for Stakeholder Dimensions: Net Strengths

| CFP | Dim | | Pairwise Parameter Equality Tests ($\beta_{\tau_1} = \beta_{\tau_2}$) | | | | | | | | | | All Equal |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $\tau_1$ | 0.10 | 0.10 | 0.10 | 0.10 | 0.25 | 0.25 | 0.25 | 0.50 | 0.50 | 0.75 | |
| | | $\tau_2$ | 0.25 | 0.50 | 0.75 | 0.90 | 0.50 | 0.75 | 0.90 | 0.75 | 0.90 | 0.90 | |
| ROA | PRO | | 2.69 | 1.17 | 1.69 | 0.00 | 1.88 | 0.02 | 1.93 | 1.15 | 1.15 | 3.65 | 14.31** |
| | ENV | | 2.90 | 8.24** | 7.42** | 5.13* | 11.27*** | 7.53** | 3.71 | 0.64 | 0.25 | 0.00 | 13.06* |
| | COM | | 1.50 | 2.86 | 3.77 | 4.91* | 2.57 | 3.74 | 4.29* | 1.11 | 2.86 | 1.52 | 5.82 |
| | DIV | | 5.87* | 7.77** | 8.50** | 713.78*** | 5.71* | 6.37* | 13.25*** | 1.50 | 8.12** | 6.37* | 16.80** |
| | EMP | | 1.30 | 3.11 | 9.51** | 9.92** | 2.96 | 15.03*** | 12.89*** | 10.89** | 9.45** | 2.58 | 17.82** |
| TOB | PRO | | 5.62* | 3.19 | 1.62 | 2.35 | 0.13 | 0.60 | 1.68 | 0.59 | 1.69 | 1.52 | 7.99 |
| | ENV | | 1.09 | 14.63*** | 6.20* | 0.59 | 10.73** | 4.66* | 0.94 | 0.00 | 3.92* | 5.37* | 17.22** |
| | COM | | 1.18 | 0.23 | 0.90 | 0.54 | 0.05 | 0.19 | 0.26 | 0.48 | 0.33 | 0.13 | 1.94 |
| | DIV | | 0.41 | 0.98 | 0.50 | 1.32 | 0.43 | 0.22 | 1.14 | 0.04 | 1.02 | 1.17 | 1.89 |
| | EMP | | 7.43** | 20.33*** | 9.73** | 2.38 | 13.50*** | 4.81* | 1.03 | 0.04 | 0.00 | 0.00 | 21.60*** |
| TOT | PRO | | 1.24 | 6.76** | 5.65* | 3.30 | 7.97** | 5.52* | 3.16 | 3.07 | 2.48 | 1.56 | 10.55* |
| | ENV | | 2.46 | 14.01*** | 7.54** | 0.13 | 11.28*** | 5.49* | 0.04 | 1.14 | 0.03 | 0.24 | 16.57** |
| | COM | | 0.72 | 1.08 | 0.19 | 0.09 | 4.94* | 0.02 | 0.04 | 0.90 | 0.22 | 0.03 | 5.80 |
| | DIV | | 0.18 | 0.20 | 0.15 | 3.19 | 0.00 | 0.05 | 3.11 | 0.05 | 3.09 | 3.25 | 3.42 |
| | EMP | | 7.95** | 17.58*** | 42.04*** | 11.61*** | 8.64** | 37.99*** | 10.05** | 29.57*** | 8.35** | 3.29 | 43.26*** |

Notes: Figures report $\chi^2$ statistics for tests of parameter equality following Rios Avila (2019) as implemented in Rios-Avila (2020) with 1000 bootstraps. Corporate financial performance (CFP) measures are return on assets (ROA), Tobin's q (TOB) and the Total q (TOT) of Peters and Taylor (2016). Dim refers to the stakeholder dimension and is either product (PRO), environment (ENV), community (COM), diversity (DIV) or employees (EMP). Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table A2.11: Equality Tests for Stakeholder Dimensions: Strengths and Concerns

| CFP | | Dim | | Pairwise Parameter Equality Tests ($\beta_{\tau_1} = \beta_{\tau_2}$) | | | | | | | | | | All Equal |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $\tau_1$ | 0.10 | 0.10 | 0.10 | 0.10 | 0.25 | 0.25 | 0.25 | 0.50 | 0.50 | 0.75 | |
| | | | $\tau_2$ | 0.25 | 0.50 | 0.75 | 0.90 | 0.50 | 0.75 | 0.90 | 0.75 | 0.90 | 0.90 | |
| ROA | Strengths | PRO | | 7.22** | 6.92** | 10.89** | 4.38* | 0.16 | 7.12** | 0.62 | 9.95** | 0.51 | 0.73 | 18.03** |
| | | ENV | | 0.57 | 3.57 | 1.76 | 0.55 | 8.47** | 2.07 | 0.25 | 0.18 | 0.74 | 0.58 | 10.75* |
| | | COM | | 6.37* | 10.20** | 10.75** | 13.82*** | 6.96** | 7.38** | 9.06** | 1.23 | 3.98* | 2.26 | 16.75** |
| | | DIV | | 0.94 | 3.72 | 6.17* | 5.38* | 10.14** | 10.73** | 6.67** | 4.44* | 3.10 | 0.73 | 12.39* |
| | | EMP | | 6.20* | 9.46** | 15.70*** | 24.50*** | 7.62** | 18.50*** | 28.99*** | 10.29** | 22.25*** | 9.07** | 34.43*** |
| | Concerns | PRO | | 8.84** | 15.00*** | 21.59*** | 34.54*** | 15.89*** | 25.01*** | 27.62*** | 13.80*** | 19.27*** | 9.28** | 39.19*** |
| | | ENV | | 0.67 | 0.67 | 0.11 | 0.17 | 0.17 | 0.20 | 0.00 | 1.02 | 0.03 | 0.11 | 1.79 |
| | | COM | | 0.72 | 0.87 | 0.93 | 0.46 | 0.10 | 0.21 | 0.06 | 0.08 | 0.02 | 0.00 | 1.07 |
| | | DIV | | 3.99* | 2.50 | 0.90 | 2.21 | 0.47 | 2.37 | 0.00 | 1.83 | 0.13 | 1.41 | 8.51 |
| | | EMP | | 2.37 | 2.44 | 0.40 | 0.82 | 0.29 | 1.23 | 0.00 | 2.53 | 0.03 | 0.60 | 6.82 |
| TOB | Strengths | PRO | | 3.32 | 11.63*** | 7.93** | 6.86** | 7.97** | 6.37* | 6.17* | 3.84* | 5.01* | 3.75 | 12.75* |
| | | ENV | | 1.52 | 13.69*** | 2.31 | 2.73 | 9.50** | 1.15 | 3.25 | 0.36 | 6.63* | 6.88** | 16.01** |
| | | COM | | 3.61 | 0.92 | 0.38 | 0.87 | 0.40 | 0.26 | 0.23 | 0.02 | 0.39 | 0.52 | 4.90 |
| | | DIV | | 0.35 | 0.52 | 0.02 | 0.23 | 0.11 | 0.01 | 0.34 | 0.14 | 0.50 | 0.34 | 1.09 |
| | | EMP | | 12.46*** | 18.19*** | 14.13*** | 8.98** | 7.84** | 7.13** | 5.66* | 2.65 | 2.68 | 0.94 | 30.92*** |
| | Concerns | PRO | | 1.04 | 6.88** | 13.84*** | 9.12** | 12.23*** | 16.66*** | 10.60** | 8.31** | 6.43* | 1.68 | 21.01*** |
| | | ENV | | 0.02 | 0.72 | 0.00 | 0.17 | 0.79 | 0.03 | 0.15 | 0.35 | 0.61 | 0.33 | 1.43 |
| | | COM | | 0.61 | 0.16 | 0.43 | 0.01 | 0.04 | 0.96 | 0.11 | 0.98 | 0.07 | 0.10 | 1.66 |
| | | DIV | | 0.12 | 0.03 | 0.01 | 1.76 | 0.01 | 0.06 | 1.69 | 0.05 | 1.73 | 2.38 | 2.58 |
| | | EMP | | 0.48 | 9.32** | 0.41 | 0.45 | 10.33** | 0.15 | 0.65 | 2.17 | 2.48 | 1.05 | 13.15* |
| TOT | Strengths | PRO | | 3.87* | 18.50*** | 17.08*** | 8.72** | 16.02*** | 15.02*** | 7.97** | 9.76** | 6.60* | 3.82 | 27.37*** |
| | | ENV | | 1.34 | 6.24* | 0.55 | 0.16 | 4.53* | 0.16 | 0.25 | 0.14 | 0.49 | 0.42 | 6.87 |
| | | COM | | 4.49* | 0.06 | 0.12 | 0.09 | 5.03* | 1.14 | 0.28 | 0.06 | 0.06 | 0.03 | 7.94 |
| | | DIV | | 1.00 | 1.53 | 1.75 | 1.84 | 0.26 | 0.99 | 1.61 | 0.76 | 1.47 | 1.09 | 2.92 |
| | | EMP | | 3.96* | 11.33*** | 30.99*** | 13.41*** | 7.02** | 29.94*** | 12.60*** | 27.02*** | 11.40*** | 5.72* | 31.14*** |
| | Concerns | PRO | | 1.60 | 2.45 | 11.24*** | 8.82** | 0.82 | 9.43** | 8.11** | 10.65** | 7.97** | 4.05* | 14.35** |
| | | ENV | | 0.94 | 5.73* | 3.15 | 0.68 | 6.02* | 2.24 | 0.97 | 0.28 | 2.07 | 3.01 | 9.42 |
| | | COM | | 0.48 | 0.40 | 4.59* | 3.16 | 0.00 | 6.40* | 3.90* | 8.46** | 4.07* | 0.64 | 10.03* |
| | | DIV | | 0.10 | 1.09 | 4.64* | 0.00 | 0.89 | 4.51* | 0.00 | 3.64 | 0.01 | 0.48 | 5.58 |
| | | EMP | | 5.85* | 9.80** | 5.76* | 0.49 | 2.79 | 2.01 | 0.11 | 0.69 | 0.01 | 0.03 | 11.88* |

Notes: Figures report $\chi^2$ statistics for tests of parameter equality following Rios Avila (2019) as implemented in Rios-Avila (2020) with 1000 bootstraps. Corporate financial performance (CFP) measures are return on assets (ROA), Tobin's q (TOB) and the Total q (TOT) of Peters and Taylor (2016). Dim refers to the stakeholder dimension and is either product (PRO), environment (ENV), community (COM), diversity (DIV) or employees (EMP). Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

for TOB. There is one occasion when COM rejects equality when TOT is the CFP measure. EMP strengths have been shown to have significance for the best performers and so it is unsurprising we see most rejections of parameter equality for EMP strengths. The only insignificance is above the median on TOB. Overall there is a wide body of evidence that there is significant variation in the coefficients on stakeholder strengths in Table A2.11.

When considering the concerns on the stakeholder dimensions it is PRO which displays the most significance. In the main paper we show a surprising result whereby PRO concerns carry large significant positive coefficients at the top of the CFP measures. Parameter equality tests support this with the comparisons between $\tau = 0.10$ and $\tau = 0.25$, with $\tau = 0.75$ and $\tau = 0.90$ producing significance. Outwith PRO there is far less significance in the equality test statistics. ENV concerns have 2 rejections of equality when TOT is the CFP measure. COM concerns impact on TOT differentially with 5 of the 10 pairwise comparisons rejecting parameter equality at the 5% level. However, here again there is no significance on either ROA or TOB. DIV has the least significance with just 1 ROA comparison and 2 TOT pairs rejecting equality. Finally EMP concerns have 5 pairwise rejections, 2 from TOB and 3 from TOT. Evidence from the pairwise comparisons remains supportive of the use of UQR for both strengths and concerns, but the impact of strengths on CFP is far more differentiated.

Through the parameter equality tests on net strengths, as well as strengths and concerns, we have shown that there are differences across the quantiles. As such, moving from the imposition of a single parameter in OLS to the flexibility offered by UQR has obvious appeal for the estimation of the impact of CSR on CFP.

## A2.3 Impact of Global Financial Crisis

This second appendix is prepared to provide some additional robustness to our observations on the global financial crisis. We will again consider the net strengths and the split between strengths and concerns. The main innovation of this section relative to the full sample specification is the creation of post-crisis slope dummies. These dummies are used to capture the difference between the crisis period and post-crisis. To correctly identify the effect, the pre-crisis years are dropped. Hence for this appendix the sample runs from 2007 to 2015 inclusive.

### A2.3.1 Net Strengths

As discussed in the main paper we update the basic UQR RIF second stage specification to add slope dummies for the crisis and post-crisis period[8]. These slope dummies are given the prefix $P$ such that the interaction between the post crisis dummy *post* and the net strengths on PRO, $NS_{it}^{PRO}$ becomes $PNS_{it}^{PRO}$. Hence we have:

$$\begin{aligned} RIF\left(Y, q_{\tau}, F_Y\right) = &\alpha + \phi_1 NS_{it}^{PRO} + \phi_2 NS_{it}^{ENV} + \phi_3 NS_{it}^{COM} + \phi_4 NS_{it}^{DIV} \\ &+ \phi_5 NS_{it}^{EMP} + \phi_6 PNS_{it}^{PRO} + \phi_7 PNS_{it}^{ENV} + \phi_8 PNS_{it}^{COM} \\ &+ \phi_9 PNS_{it}^{DIV} + \phi_{10} PNS_{it}^{EMP} + \beta X_i + \phi_{11} post + \gamma + \epsilon_i \end{aligned} \tag{2.19}$$

with our interest now being in two sets of coefficients. Firstly, $\phi_1$ to $\phi_5$ as the coefficients on the stakeholder dimensions inform of the main effect of the dimension across all time. Secondly, $\phi_6$ to $\phi_{10}$ provide information about the effect of the GFC on the roles of each of the CSR dimensions. Significance of this second set says that there has been a change in perception of CSR that makes it more, or less, profitable than it previously had been.

Tables A2.12 to A2.14 are provided here for reference, since the coefficients on the stakeholder dimensions are all included within the main paper. Comparing the estimates of the coefficients on the financial controls with those in Tables A2.1 to A2.3 confirms that the changing of the specification, and time period, does not make a large difference to the values.

Figure A2.1 presents the full set of estimated net strength slope dummy coefficients. Within each measure of CFP the axis scales are identical and therefore the importance of each dimension may be assessed quickly. Recall all net strengths measures are between -1 and 1. We report the PRO and ENV results within the main paper, noting the additional significance for PRO in the tails of the distribution. Looking at the COM, DIV and EMP plots we see that the impact of these dimensions is much smaller. There is some positive significance in COM at the lower quantiles since the crisis, but this is very small. The overall message remains one of consistency, and that it has only been PRO where the biggest changes have emerged.

### A2.3.2 Strengths and Concerns

To analyse the impact of the financial crisis when strengths and concerns are introduced into the regression, we update the equation for the UQR RIF to include slope dummies

[8]In the main paper the equation being updated is (2.11).

Table A2.12: Return on Assets Net Strengths Financial Crisis

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | 0.001 | -0.360*** | -0.059 | 0.065** | 0.174*** | 0.302*** | |
| | | (0.025) | (0.070) | (0.032) | (0.022) | (0.018) | (0.033) |
| Controls | Lag | 0.661*** | 0.637*** | 0.244*** | 0.221** | 0.313** | 0.523** |
| | | (0.041) | (0.117) | (0.063) | (0.064) | (0.091) | (0.152) |
| | SI | 0.034*** | 0.044* | 0.027*** | 0.021*** | 0.026** | 0.044** |
| | | (0.008) | (0.020) | (0.007) | (0.005) | (0.008) | (0.013) |
| | CI | 0.000 | -0.034 | -0.057*** | -0.026*** | -0.009 | 0.018 |
| | | (0.016) | (0.017) | (0.014) | (0.004) | (0.005) | (0.013) |
| | EF | -0.060*** | -0.094*** | -0.015* | -0.006 | -0.002 | 0.005 |
| | | (0.010) | (0.022) | (0.006) | (0.003) | (0.003) | (0.005) |
| | CE | -0.015 | -0.066 | 0.029 | 0.029*** | 0.027 | 0.024 |
| | | (0.010) | (0.048) | (0.016) | (0.006) | (0.013) | (0.025) |
| | Leverage | -0.048** | -0.051 | -0.104 | -0.069 | -0.147* | -0.250** |
| | | (0.016) | (0.069) | (0.056) | (0.041) | (0.057) | (0.088) |
| | Size | 0.005* | 0.043*** | 0.012** | 0.002 | -0.008*** | -0.023*** |
| | | (0.002) | (0.007) | (0.004) | (0.002) | (0.002) | (0.004) |
| Net Strengths | PRO | -0.006 | 0.072* | 0.001 | -0.006 | -0.031* | -0.066 |
| | | (0.007) | (0.027) | (0.007) | (0.006) | (0.013) | (0.045) |
| | ENV | 0.012 | -0.002 | -0.004 | -0.005 | 0.044 | 0.035 |
| | | (0.009) | (0.030) | (0.008) | (0.021) | (0.028) | (0.058) |
| | COM | 0.007 | 0.012 | -0.016 | 0.009 | 0.010 | 0.030 |
| | | (0.013) | (0.057) | (0.029) | (0.021) | (0.032) | (0.054) |
| | DIV | 0.003 | -0.026* | -0.007 | 0.003 | 0.005 | 0.012 |
| | | (0.004) | (0.011) | (0.004) | (0.005) | (0.008) | (0.016) |
| | EMP | 0.006 | -0.005 | 0.002 | 0.009 | 0.040* | 0.075 |
| | | (0.005) | (0.021) | (0.008) | (0.011) | (0.018) | (0.042) |
| Post-Crisis | PRO | -0.000 | -0.104** | 0.002 | 0.008 | 0.048*** | 0.072* |
| | | (0.007) | (0.033) | (0.010) | (0.008) | (0.013) | (0.032) |
| | ENV | -0.007 | -0.024 | 0.005 | 0.031 | -0.011 | 0.009 |
| | | (0.009) | (0.039) | (0.012) | (0.020) | (0.027) | (0.055) |
| | COM | -0.010 | -0.026 | 0.013 | -0.006 | 0.003 | -0.012 |
| | | (0.012) | (0.058) | (0.028) | (0.020) | (0.030) | (0.061) |
| | DIV | -0.013*** | -0.008 | -0.001 | -0.004 | -0.006 | -0.000 |
| | | (0.003) | (0.013) | (0.003) | (0.004) | (0.006) | (0.019) |
| | EMP | -0.018* | -0.020 | -0.004 | -0.003 | -0.030 | -0.058 |
| | | (0.007) | (0.022) | (0.010) | (0.011) | (0.026) | (0.046) |
| Post | | 0.010** | 0.019 | 0.010* | 0.003 | -0.000 | 0.006 |
| | | (0.003) | (0.010) | (0.005) | (0.003) | (0.003) | (0.010) |
| R-squared | | 0.683 | 0.366 | 0.300 | 0.242 | 0.213 | 0.181 |

Notes: Estimation of equation (2.19) with the re-centered inference function for return on assets (ROA) as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$, the net strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed, less the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. Post is a dummy which takes the value 1 for 2010 onwards. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A2.13: Tobin's q Financial Crisis

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | 1.214* | 1.496*** | 1.753*** | 2.200*** | 2.516*** | 1.429 |
| | | (0.437) | (0.088) | (0.116) | (0.237) | (0.647) | (1.382) |
| Controls | Lag | 0.701*** | 0.050** | 0.093*** | 0.221*** | 0.610*** | 1.542*** |
| | | (0.058) | (0.014) | (0.021) | (0.045) | (0.108) | (0.198) |
| | SI | 0.007 | 0.039 | 0.016 | -0.020 | 0.052 | 0.201 |
| | | (0.042) | (0.044) | (0.049) | (0.060) | (0.084) | (0.124) |
| | CI | -0.073* | -0.385* | -0.196*** | -0.050 | 0.038 | 0.092 |
| | | (0.035) | (0.137) | (0.050) | (0.032) | (0.088) | (0.069) |
| | EF | 0.068 | -0.078 | -0.094 | -0.157 | -0.149 | 0.162 |
| | | (0.067) | (0.044) | (0.049) | (0.087) | (0.141) | (0.119) |
| | CE | 0.002 | 0.160 | 0.007 | -0.104 | -0.036 | 0.136 |
| | | (0.097) | (0.122) | (0.119) | (0.143) | (0.208) | (0.413) |
| | Leverage | -0.547*** | -2.541*** | -2.040*** | -1.958*** | -0.910* | 1.779* |
| | | (0.111) | (0.664) | (0.221) | (0.277) | (0.383) | (0.737) |
| | Size | -0.096* | -0.033* | -0.045** | -0.089*** | -0.188** | -0.277* |
| | | (0.044) | (0.013) | (0.012) | (0.021) | (0.058) | (0.129) |
| Net Strengths | PRO | -0.341* | -0.082 | 0.089 | -0.181 | -0.597* | -1.009* |
| | | (0.129) | (0.149) | (0.168) | (0.145) | (0.288) | (0.449) |
| | ENV | 0.019 | 0.454* | 0.210 | 0.139 | 0.197 | -0.568 |
| | | (0.235) | (0.161) | (0.141) | (0.147) | (0.192) | (0.660) |
| | COM | 0.004 | -0.322* | -0.094 | 0.233 | 0.338 | 0.077 |
| | | (0.085) | (0.123) | (0.214) | (0.164) | (0.197) | (0.458) |
| | DIV | 0.088 | 0.079 | 0.128* | 0.145 | 0.106 | 0.273 |
| | | (0.091) | (0.044) | (0.053) | (0.093) | (0.141) | (0.264) |
| | EMP | 0.213* | 0.178* | 0.237** | 0.400*** | 0.491** | 0.396 |
| | | (0.077) | (0.080) | (0.068) | (0.100) | (0.151) | (0.378) |
| Post-crisis | PRO | 0.539** | 0.097 | -0.041 | 0.322* | 0.916*** | 1.894*** |
| | | (0.174) | (0.182) | (0.172) | (0.149) | (0.176) | (0.447) |
| | ENV | 0.074 | -0.381* | -0.045 | 0.227 | 0.286 | 0.663 |
| | | (0.262) | (0.172) | (0.149) | (0.123) | (0.208) | (0.815) |
| | COM | 0.038 | 0.400** | 0.147 | -0.197 | -0.362 | -0.045 |
| | | (0.080) | (0.133) | (0.200) | (0.157) | (0.178) | (0.518) |
| | DIV | -0.004 | -0.006 | -0.054 | -0.074 | -0.028 | -0.206 |
| | | (0.034) | (0.040) | (0.045) | (0.071) | (0.082) | (0.141) |
| | EMP | 0.045 | -0.103 | -0.038 | -0.032 | 0.051 | 0.409 |
| | | (0.132) | (0.056) | (0.091) | (0.133) | (0.358) | (0.348) |
| Post | | 0.244*** | 0.104*** | 0.100*** | 0.123*** | 0.194** | 0.551*** |
| | | (0.047) | (0.019) | (0.020) | (0.024) | (0.068) | (0.124) |
| | R-squared | 0.535 | 0.122 | 0.148 | 0.238 | 0.334 | 0.352 |

Notes: Estimation of equation (2.19) with the re-centered inference function for Tobin's q (TOB) as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$, the net strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed, less the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. Slope dummies for the post-financial crisis are prefixed with P. Post is a dummy which takes the value 1 for 2010 onwards. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

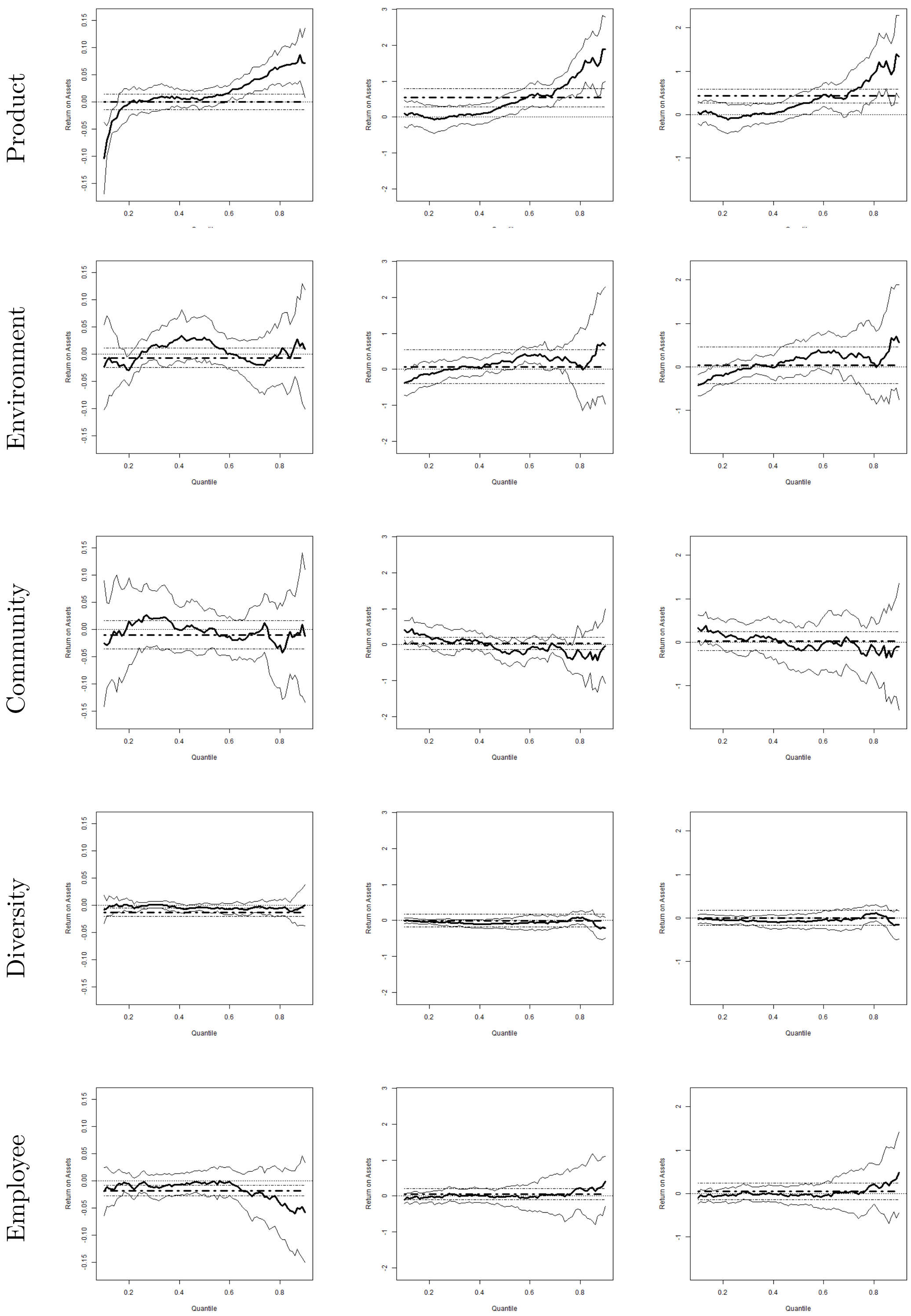
Table A2.14: Total q Net Strengths Financial Crisis

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | -0.237 | 0.210 | 0.525*** | 1.168*** | 3.257*** | 7.066*** |
| | | (0.148) | (0.131) | (0.094) | (0.100) | (0.296) | (1.209) |
| Controls | Lag | 0.851*** | 0.011*** | 0.008*** | 0.010* | 0.033* | 0.129** |
| | | (0.011) | (0.001) | (0.002) | (0.004) | (0.014) | (0.043) |
| | SI | 0.059 | -0.141 | -0.154** | -0.133* | -0.211 | -0.363 |
| | | (0.053) | (0.071) | (0.045) | (0.057) | (0.136) | (0.338) |
| | CI | -1.054 | -0.558** | -0.286* | -0.166 | -0.288* | -0.915* |
| | | (0.710) | (0.174) | (0.102) | (0.105) | (0.125) | (0.359) |
| | EF | -0.046 | -0.123* | -0.097 | -0.107 | -0.133 | -0.004 |
| | | (0.082) | (0.059) | (0.057) | (0.071) | (0.161) | (0.306) |
| | CE | 0.430 | 0.373* | 0.271** | 0.238 | 0.140 | 0.658 |
| | | (0.528) | (0.150) | (0.080) | (0.122) | (0.249) | (0.560) |
| | Leverage | -3.147 | -1.271* | -0.781* | -1.394*** | -2.416*** | -6.139* |
| | | (2.413) | (0.595) | (0.341) | (0.223) | (0.586) | (2.289) |
| | Size | -0.019 | 0.017 | 0.012 | -0.031* | -0.220*** | -0.560*** |
| | | (0.041) | (0.014) | (0.013) | (0.015) | (0.034) | (0.117) |
| Net Strengths | PRO | -0.609 | 0.060 | 0.047 | 0.091 | -0.419 | -1.623* |
| | | (0.638) | (0.084) | (0.075) | (0.174) | (0.465) | (0.667) |
| | ENV | -0.185 | 0.272 | 0.186 | 0.082 | 0.230 | 0.375 |
| | | (0.489) | (0.197) | (0.148) | (0.164) | (0.422) | (1.289) |
| | COM | -0.462 | -0.543 | -0.116 | 0.154 | 0.097 | 1.278 |
| | | (0.331) | (0.281) | (0.177) | (0.183) | (0.390) | (0.755) |
| | DIV | 0.240* | -0.023 | 0.006 | 0.037 | -0.085 | 0.076 |
| | | (0.108) | (0.044) | (0.040) | (0.063) | (0.142) | (0.285) |
| | EMP | -0.870 | 0.077 | 0.187 | 0.310** | 0.847*** | 1.584* |
| | | (0.805) | (0.071) | (0.104) | (0.095) | (0.201) | (0.631) |
| Post-Crisis | PRO | 0.407 | -0.014 | 0.032 | 0.138 | 1.145** | 3.087*** |
| | | (0.398) | (0.107) | (0.083) | (0.160) | (0.368) | (0.767) |
| | ENV | 0.005 | -0.300 | -0.114 | 0.094 | 0.078 | -0.074 |
| | | (0.480) | (0.170) | (0.147) | (0.197) | (0.527) | (1.268) |
| | COM | 0.618 | 0.567 | 0.089 | -0.146 | -0.231 | -1.601 |
| | | (0.430) | (0.282) | (0.173) | (0.198) | (0.366) | (0.809) |
| | DIV | -0.174 | 0.066 | 0.038 | 0.026 | 0.218 | 0.440* |
| | | (0.194) | (0.039) | (0.042) | (0.067) | (0.131) | (0.183) |
| | EMP | 0.984 | -0.015 | 0.014 | 0.045 | 0.162 | 0.062 |
| | | (0.790) | (0.103) | (0.085) | (0.113) | (0.420) | (0.791) |
| Post | | 0.763 | 0.125** | 0.101** | 0.131*** | 0.250** | 0.495* |
| | | (0.496) | (0.034) | (0.029) | (0.027) | (0.069) | (0.221) |
| R-squared | | 0.802 | 0.065 | 0.063 | 0.064 | 0.078 | 0.092 |

Notes: Estimation of equation (2.19) with the re-centered inference function for Peters and Taylor (2017) total q (TOT) as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$, the net strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed, less the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. Post is a dummy which takes the value 1 for 2010 onwards. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Figure A2.1: Net Strengths and Financial Crisis

Return on Assets (ROA) Tobin's q (TOB) Total q (TOT)




Notes: Estimates of differential between pre-crisis and the stated period for the five stakeholder dimensions of Freeman (1984). Thick lines are used to plot coefficients, thinner lines the associated 95 per cent confidence intervals. Solid lines represent the financial crisis differential, coefficients $\phi_6$ to $\phi_{10}$ in equation (2.13). Dashed lines represent the post-crisis to pre-crisis differential, coefficients $\phi_{11}$ to $\phi_{15}$ in equation (2.13).

on both strengths and concerns[9]. The updated equation is:

$$
\begin{aligned}
RIF\left(Y, q_\tau, F_Y\right)_{it} =& \alpha + \phi_1 S_{it}^{PRO} + \phi_2 S_{it}^{ENV} + \phi_3 S_{it}^{COM} + \phi_4 S_{it}^{DIV} + \phi_5 S_{it}^{EMP} \\
& + \phi_6 W_{it}^{PRO} + \phi_7 W_{it}^{ENV} + \phi_8 W_{it}^{COM} + \phi_9 W_{it}^{DIV} \\
& + \phi_{10} W_{it}^{EMP} + \phi_{11} PS_{it}^{PRO} + \phi_{12} PS_{it}^{ENV} + \phi_{13} PS_{it}^{COM} \\
& + \phi_{14} PS_{it}^{DIV} + \phi_{15} PS_{it}^{EMP} + \phi_{16} PW_{it}^{PRO} + \phi_{17} PW_{it}^{ENV} \\
& + \phi_{18} PW_{it}^{COM} + \phi_{19} PW_{it}^{DIV} + \phi_{20} PW_{it}^{EMP} \\
& + \beta X_{it} + \gamma_{mt} + \epsilon_{it}
\end{aligned} \tag{2.20}
$$

Now we are focused on the coefficients $\phi_{11}$ to $\phi_{20}$. Again the strengths and concerns are given $P$ prefixes to denote the post-crisis period. For example, $S_{it}^{PRO}$ becomes $PS_{it}^{PRO}$.

Once again the estimates for the coefficients on stakeholder dimensions are also discussed within the main paper. Tables A2.15 to A2.17 are therefore to allow the comparison of the coefficients on the financial controls. As with the net strengths the coefficients do not change greatly as a result of reducing the sample and introducing the post-crisis slope dummies. There is now an increase in the R-squared relative to the model without the post-crisis interaction. Although these are the adjusted R-squared values that account for the extra coefficients, the difference is small.

### A2.3.3 Summary

This appendix has presented a short confirmation of the consistency of the financial control coefficient estimates following two important changes to the modelling. Firstly, to isolate the effect of the financial crisis, a series of slope dummies are created which interact the net strengths, or strengths and concerns, with a post-crisis dummy. Secondly, to correctly identify the financial crisis effect, the pre-crisis period is dropped. What we have then shown is that there are no major effects on the coefficients on either the financial controls or the inference emerging for the CSR stakeholder dimensions.

[9] In the main paper this is equation (2.12).

Table A2.15: Return on Assets Financial Crisis Strengths and Concerns

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | -0.004 | -0.397*** | -0.066 | 0.068* | 0.185*** | 0.320*** |
| | | (0.029) | (0.071) | (0.037) | (0.025) | (0.018) | (0.027) |
| Controls | Lag | 0.661*** | 0.635*** | 0.243*** | 0.221** | 0.314** | 0.524** |
| | | (0.041) | (0.117) | (0.063) | (0.064) | (0.091) | (0.152) |
| | SI | 0.034*** | 0.045* | 0.028*** | 0.020** | 0.025** | 0.043** |
| | | (0.008) | (0.020) | (0.007) | (0.005) | (0.008) | (0.013) |
| | CI | 0.000 | -0.038* | -0.058*** | -0.025*** | -0.007 | 0.022 |
| | | (0.015) | (0.017) | (0.014) | (0.004) | (0.005) | (0.012) |
| | EF | -0.060*** | -0.094*** | -0.015* | -0.006 | -0.002 | 0.005 |
| | | (0.010) | (0.023) | (0.006) | (0.003) | (0.003) | (0.005) |
| | CE | -0.015 | -0.070 | 0.028 | 0.029*** | 0.029* | 0.027 |
| | | (0.010) | (0.048) | (0.017) | (0.006) | (0.013) | (0.024) |
| | Leverage | -0.050** | -0.064 | -0.107 | -0.068 | -0.144* | -0.242* |
| | | (0.015) | (0.066) | (0.055) | (0.041) | (0.057) | (0.089) |
| | Size | 0.006 | 0.050*** | 0.014** | 0.001 | -0.011*** | -0.028*** |
| | | (0.003) | (0.007) | (0.005) | (0.003) | (0.002) | (0.004) |
| Strengths | PRO | 0.007 | -0.069 | 0.010 | 0.035* | 0.104 | 0.094 |
| | | (0.014) | (0.103) | (0.018) | (0.013) | (0.079) | (0.110) |
| | ENV | 0.000 | 0.045 | -0.027* | -0.022 | 0.039 | -0.001 |
| | | (0.010) | (0.050) | (0.010) | (0.013) | (0.048) | (0.165) |
| | COM | -0.009 | -0.183 | -0.010 | 0.045 | 0.127** | 0.158* |
| | | (0.016) | (0.110) | (0.041) | (0.027) | (0.044) | (0.056) |
| | DIV | 0.009 | -0.028 | -0.037 | -0.003 | 0.013 | 0.090 |
| | | (0.011) | (0.050) | (0.023) | (0.026) | (0.035) | (0.066) |
| | EMP | 0.009 | -0.045 | 0.002 | 0.023* | 0.043 | 0.091** |
| | | (0.011) | (0.038) | (0.022) | (0.011) | (0.021) | (0.028) |
| Concerns | PRO | 0.008 | -0.091* | 0.002 | 0.011 | 0.040** | 0.076 |
| | | (0.007) | (0.034) | (0.009) | (0.008) | (0.014) | (0.044) |
| | ENV | -0.020 | -0.006 | -0.024 | -0.002 | -0.025 | -0.009 |
| | | (0.018) | (0.052) | (0.021) | (0.034) | (0.034) | (0.051) |
| | COM | -0.012 | -0.106 | 0.021 | 0.007 | 0.036 | 0.029 |
| | | (0.015) | (0.054) | (0.031) | (0.023) | (0.044) | (0.088) |
| | DIV | -0.002 | 0.017 | -0.001 | -0.001 | 0.007 | 0.020 |
| | | (0.003) | (0.009) | (0.006) | (0.005) | (0.006) | (0.020) |
| | EMP | -0.005 | -0.025 | -0.004 | 0.001 | -0.030 | -0.054 |
| | | (0.009) | (0.030) | (0.011) | (0.014) | (0.021) | (0.050) |
| Post Strengths | PRO | -0.014 | 0.028 | -0.009 | -0.032** | -0.081 | -0.079 |
| | | (0.014) | (0.106) | (0.018) | (0.011) | (0.078) | (0.097) |
| | ENV | 0.002 | -0.058 | 0.029* | 0.046** | -0.015 | 0.024 |
| | | (0.010) | (0.035) | (0.011) | (0.014) | (0.048) | (0.163) |
| | COM | -0.004 | 0.142 | -0.001 | -0.047 | -0.116** | -0.142* |
| | | (0.015) | (0.111) | (0.042) | (0.027) | (0.038) | (0.052) |
| | DIV | -0.003 | 0.018 | 0.033 | 0.008 | 0.002 | -0.079 |
| | | (0.008) | (0.052) | (0.022) | (0.022) | (0.031) | (0.062) |
| | EMP | -0.018 | -0.019 | -0.011 | -0.010 | -0.016 | -0.027 |
| | | (0.015) | (0.047) | (0.018) | (0.016) | (0.036) | (0.038) |
| Post Concerns | PRO | -0.007 | 0.015 | -0.028* | 0.003 | -0.002 | 0.018 |
| | | (0.008) | (0.040) | (0.011) | (0.013) | (0.017) | (0.039) |
| | ENV | 0.012 | -0.014 | 0.003 | -0.012 | -0.017 | -0.043 |
| | | (0.011) | (0.056) | (0.014) | (0.028) | (0.037) | (0.030) |
| | COM | 0.006 | 0.090 | -0.028 | -0.017 | -0.046 | -0.041 |
| | | (0.014) | (0.058) | (0.027) | (0.021) | (0.047) | (0.099) |
| | DIV | 0.020** | 0.023 | 0.010 | 0.006 | 0.004 | -0.030 |
| | | (0.006) | (0.017) | (0.008) | (0.007) | (0.011) | (0.029) |
| | EMP | 0.021 | -0.006 | -0.003 | 0.006 | 0.041 | 0.114 |
| | | (0.017) | (0.041) | (0.018) | (0.015) | (0.022) | (0.066) |
| Post | | 0.008* | 0.010 | 0.006 | 0.004 | 0.004 | 0.022 |
| | | (0.004) | (0.013) | (0.004) | (0.003) | (0.005) | (0.014) |
| R-squared | | 0.683 | 0.370 | 0.302 | 0.244 | 0.219 | 0.186 |

Notes: Estimation of equation (2.20) with the re-centered inference function for ROA as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$. Strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed. Concerns for firm $i$ are the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A2.16: Tobin's q Financial Crisis Strengths and Concerns

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | 1.323** | 1.513*** | 1.753*** | 2.300*** | 2.732*** | 1.782 |
| | | (0.453) | (0.106) | (0.131) | (0.274) | (0.638) | (1.381) |
| Controls | Lag | 0.698*** | 0.050** | 0.092*** | 0.218*** | 0.603*** | 1.533*** |
| | | (0.059) | (0.014) | (0.022) | (0.046) | (0.109) | (0.199) |
| | SI | 0.002 | 0.037 | 0.015 | -0.025 | 0.042 | 0.190 |
| | | (0.042) | (0.042) | (0.048) | (0.061) | (0.084) | (0.121) |
| | CI | -0.057 | -0.384** | -0.194*** | -0.038 | 0.068 | 0.133 |
| | | (0.035) | (0.134) | (0.049) | (0.032) | (0.090) | (0.069) |
| | EF | 0.067 | -0.077 | -0.094 | -0.156 | -0.150 | 0.156 |
| | | (0.067) | (0.044) | (0.050) | (0.087) | (0.140) | (0.121) |
| | CE | 0.014 | 0.163 | 0.008 | -0.093 | -0.007 | 0.176 |
| | | (0.097) | (0.126) | (0.120) | (0.143) | (0.205) | (0.413) |
| | Leverage | -0.532*** | -2.529*** | -2.040*** | -1.927*** | -0.866* | 1.792* |
| | | (0.119) | (0.659) | (0.226) | (0.278) | (0.406) | (0.760) |
| | Size | -0.120* | -0.038 | -0.050** | -0.111** | -0.238** | -0.338* |
| | | (0.049) | (0.020) | (0.017) | (0.030) | (0.065) | (0.133) |
| Strengths | PRO | 0.233 | 0.312 | 0.476** | 0.392 | 0.932 | 1.240 |
| | | (0.210) | (0.173) | (0.164) | (0.390) | (1.064) | (1.294) |
| | ENV | 0.219 | 0.082 | 0.005 | 0.015 | 0.111 | -0.637 |
| | | (0.398) | (0.163) | (0.116) | (0.149) | (0.594) | (1.695) |
| | COM | 0.260 | -0.156 | -0.036 | 0.865* | 0.858 | 1.064 |
| | | (0.200) | (0.354) | (0.255) | (0.404) | (0.489) | (0.880) |
| | DIV | 0.235 | 0.245 | 0.390* | 0.329 | 0.446 | 0.142 |
| | | (0.256) | (0.140) | (0.148) | (0.352) | (0.601) | (0.691) |
| | EMP | 0.208 | 0.157 | 0.132 | 0.417 | 0.731* | 0.462 |
| | | (0.156) | (0.130) | (0.096) | (0.257) | (0.346) | (0.703) |
| Concerns | PRO | 0.399** | 0.149 | -0.045 | 0.223 | 0.814** | 1.396** |
| | | (0.141) | (0.174) | (0.200) | (0.190) | (0.269) | (0.458) |
| | ENV | 0.248 | -0.544 | -0.202 | -0.019 | 0.079 | 0.783 |
| | | (0.149) | (0.276) | (0.201) | (0.218) | (0.277) | (0.551) |
| | COM | 0.050 | 0.480** | 0.165 | 0.057 | -0.136 | 0.327 |
| | | (0.177) | (0.127) | (0.293) | (0.219) | (0.390) | (0.954) |
| | DIV | -0.010 | -0.033 | -0.050 | -0.056 | 0.062 | -0.228 |
| | | (0.067) | (0.049) | (0.052) | (0.067) | (0.108) | (0.257) |
| | EMP | -0.179 | -0.180 | -0.274* | -0.352* | -0.303 | -0.259 |
| | | (0.091) | (0.096) | (0.101) | (0.133) | (0.193) | (0.454) |
| Post-Strengths | PRO | -0.005 | -0.295 | -0.422* | -0.215 | -0.536 | -0.261 |
| | | (0.166) | (0.177) | (0.171) | (0.347) | (0.915) | (1.001) |
| | ENV | -0.186 | 0.010 | 0.152 | 0.370* | 0.271 | 0.426 |
| | | (0.409) | (0.187) | (0.124) | (0.175) | (0.663) | (1.791) |
| | COM | -0.172 | 0.330 | 0.128 | -0.758 | -0.759 | -0.976 |
| | | (0.192) | (0.357) | (0.236) | (0.392) | (0.487) | (1.023) |
| | DIV | -0.232 | -0.243 | -0.400* | -0.333 | -0.588 | -0.433 |
| | | (0.237) | (0.146) | (0.146) | (0.339) | (0.625) | (0.806) |
| | EMP | 0.208 | -0.115 | 0.080 | -0.022 | 0.077 | 0.987 |
| | | (0.243) | (0.120) | (0.102) | (0.313) | (0.543) | (0.778) |
| Post-Concerns | PRO | -0.258 | -0.195 | 0.039 | -0.011 | -0.308 | -1.107 |
| | | (0.130) | (0.192) | (0.141) | (0.216) | (0.218) | (0.701) |
| | ENV | -0.391* | 0.501* | -0.096 | -0.015 | -0.549 | -1.420* |
| | | (0.143) | (0.197) | (0.211) | (0.221) | (0.366) | (0.612) |
| | COM | -0.024 | -0.456** | -0.171 | -0.061 | 0.302 | -0.219 |
| | | (0.179) | (0.141) | (0.266) | (0.251) | (0.391) | (1.000) |
| | DIV | -0.113 | -0.074 | -0.077 | -0.055 | -0.252 | -0.007 |
| | | (0.129) | (0.065) | (0.056) | (0.089) | (0.175) | (0.369) |
| | EMP | 0.187 | 0.046 | 0.121 | -0.078 | 0.160 | 0.676 |
| | | (0.126) | (0.108) | (0.126) | (0.118) | (0.339) | (0.519) |
| Post | | 0.300*** | 0.134*** | 0.147*** | 0.183*** | 0.338** | 0.643*** |
| | | (0.076) | (0.033) | (0.030) | (0.044) | (0.105) | (0.168) |
| R-squared | | 0.536 | 0.125 | 0.150 | 0.241 | 0.338 | 0.354 |

Notes: Estimation of equation (2.20) with the re-centered inference function for TOB as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$. Strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed. Concerns for firm $i$ are the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A2.17: Total q Financial Crisis Strengths and Concerns

| | | OLS | Unconditional quantile regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\tau = 0.10$ | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.90$ |
| Constant | | -0.244 | 0.192 | 0.488*** | 1.124*** | 3.347*** | 7.511*** |
| | | (0.178) | (0.152) | (0.109) | (0.115) | (0.308) | (1.236) |
| Controls | Lag | 0.851*** | 0.011*** | 0.008*** | 0.010* | 0.033* | 0.128** |
| | | (0.011) | (0.001) | (0.002) | (0.004) | (0.014) | (0.043) |
| | SI | 0.054 | -0.141 | -0.153** | -0.132* | -0.217 | -0.385 |
| | | (0.049) | (0.070) | (0.043) | (0.055) | (0.135) | (0.347) |
| | CI | -1.031 | -0.560** | -0.291** | -0.166 | -0.263* | -0.835* |
| | | (0.691) | (0.173) | (0.101) | (0.105) | (0.124) | (0.340) |
| | EF | -0.046 | -0.122 | -0.094 | -0.104 | -0.132 | -0.013 |
| | | (0.079) | (0.060) | (0.059) | (0.071) | (0.161) | (0.304) |
| | CE | 0.434 | 0.367* | 0.262** | 0.230 | 0.151 | 0.706 |
| | | (0.527) | (0.152) | (0.082) | (0.120) | (0.243) | (0.548) |
| | Leverage | -3.100 | -1.272* | -0.800* | -1.415*** | -2.383*** | -6.004* |
| | | (2.355) | (0.590) | (0.346) | (0.223) | (0.563) | (2.164) |
| | Size | -0.045 | 0.021 | 0.019 | -0.028 | -0.253*** | -0.663*** |
| | | (0.059) | (0.020) | (0.017) | (0.018) | (0.034) | (0.133) |
| Strengths | PRO | -0.278 | 0.050 | 0.407 | 0.787 | 1.182 | 0.758 |
| | | (0.560) | (0.208) | (0.254) | (0.563) | (1.068) | (1.848) |
| | ENV | 0.747 | 0.482* | 0.203 | 0.164 | -0.018 | 1.239 |
| | | (0.644) | (0.183) | (0.274) | (0.430) | (1.181) | (2.994) |
| | COM | -0.573 | -0.438 | -0.135 | 0.023 | 1.005 | 2.719 |
| | | (0.306) | (0.479) | (0.371) | (0.278) | (0.589) | (1.707) |
| | DIV | 1.017 | -0.148 | -0.002 | 0.157 | 0.448 | 0.276 |
| | | (0.964) | (0.218) | (0.315) | (0.317) | (0.696) | (1.203) |
| | EMP | -0.763 | 0.027 | -0.029 | 0.095 | 0.763 | 2.134 |
| | | (0.941) | (0.115) | (0.193) | (0.200) | (0.469) | (1.164) |
| Concerns | PRO | 0.457 | -0.092 | -0.002 | -0.008 | 0.555 | 1.858* |
| | | (0.506) | (0.123) | (0.101) | (0.202) | (0.470) | (0.721) |
| | ENV | 1.012 | -0.180 | -0.141 | 0.052 | -0.018 | 0.580 |
| | | (0.851) | (0.278) | (0.186) | (0.146) | (0.398) | (0.978) |
| | COM | 0.146 | 0.529* | 0.097 | -0.251 | 0.304 | -0.949 |
| | | (0.292) | (0.245) | (0.241) | (0.271) | (0.597) | (0.807) |
| | DIV | 0.086 | 0.009 | 0.003 | 0.026 | 0.325 | 0.180 |
| | | (0.325) | (0.068) | (0.064) | (0.073) | (0.173) | (0.403) |
| | EMP | 0.976 | -0.100 | -0.287 | -0.398*** | -0.791** | -1.149 |
| | | (0.801) | (0.096) | (0.143) | (0.102) | (0.258) | (0.829) |
| Post-Strengths | PRO | 0.094 | -0.016 | -0.322 | -0.541 | -0.379 | 0.806 |
| | | (0.435) | (0.165) | (0.233) | (0.544) | (1.008) | (1.842) |
| | ENV | -0.904 | -0.456* | -0.081 | 0.040 | 0.260 | -1.147 |
| | | (0.694) | (0.178) | (0.266) | (0.474) | (1.302) | (2.696) |
| | COM | 0.812 | 0.472 | 0.092 | -0.033 | -1.171* | -2.994 |
| | | (0.426) | (0.493) | (0.377) | (0.282) | (0.559) | (1.717) |
| | DIV | -0.987 | 0.124 | -0.006 | -0.210 | -0.562 | -0.283 |
| | | (0.859) | (0.209) | (0.274) | (0.277) | (0.635) | (1.150) |
| | EMP | 0.892 | -0.050 | 0.108 | 0.167 | 0.430 | 0.322 |
| | | (0.915) | (0.115) | (0.147) | (0.183) | (0.446) | (0.864) |
| Post-Concerns | PRO | -0.110 | -0.090 | -0.084 | -0.120 | -0.435 | -1.804 |
| | | (0.242) | (0.201) | (0.143) | (0.171) | (0.464) | (1.532) |
| | ENV | -1.186 | 0.167 | 0.028 | -0.481* | -0.345 | -0.622 |
| | | (0.821) | (0.238) | (0.147) | (0.176) | (0.426) | (0.957) |
| | COM | -0.155 | -0.560 | -0.116 | 0.210 | -0.250 | 1.269 |
| | | (0.300) | (0.286) | (0.243) | (0.305) | (0.551) | (0.817) |
| | DIV | -0.207 | -0.113 | -0.101 | -0.189* | -0.625** | -0.993* |
| | | (0.551) | (0.061) | (0.074) | (0.086) | (0.180) | (0.395) |
| | EMP | -1.077 | -0.097 | -0.153 | -0.122 | 0.036 | 0.911 |
| | | (0.829) | (0.159) | (0.109) | (0.137) | (0.526) | (1.087) |
| Post | | 0.967 | 0.144*** | 0.117** | 0.194*** | 0.424*** | 0.775* |
| | | (0.665) | (0.024) | (0.036) | (0.046) | (0.090) | (0.320) |
| R-squared | | 0.803 | 0.067 | 0.066 | 0.068 | 0.081 | 0.094 |

Notes: Estimation of equation (2.20) with the re-centered inference function for TOT as CFP measure of interest. Figures in parentheses represent cluster-robust standard errors according to two-digit NAICS code. OLS reports the OLS estimate, with unconditional quantile regressions reported for quantile $\tau$, $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Stakeholder dimensions are included as product (PRO), environment (ENV), community (COM), diversity (DIV) and employees (EMP). All stakeholder dimension coefficients are based upon net strengths. For dimension $X$, $x \in \{PRO, ENV, COM, DIV, EMP\}$. Strengths for firm $i$ are calculated as the sum of strengths for firm $i$ divided by the number of strengths upon which firm $i$ is assessed. Concerns for firm $i$ are the number of concerns for firm $i$ divided by the number of concerns upon which firm $i$ is assessed. To improve readability of coefficients capital intensity is divided by 10000 and capital expenditure is divided by 1000. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

# Chapter 3

# Reaction Asymmetries to Social Responsibility Index Recomposition: A Matching Portfolio Approach

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**Abstract**

Listing to the Dow Jones Sustainability Index conveys a signal of leadership in corporate social responsibility that may be readily interpreted by the market. Utilising a synthetic portfolio of industry peers for each new listing to the index, we demonstrate that there is a significant pre-announcement effect that yields positive abnormal returns. Further, a high persistence is shown to these abnormal returns that is critically missing under less robust means of listing effect estimation. Through comparisons between firms who are members of the S&P 500 index with those who are not we reveal a far greater short-term magnitude of impact for non-S&P 500 firms. Contrary to existing literature our adoption of the generalised synthetic control approach makes no assumptions of parallel trend, is robust to industry shocks and is not reliant on any subsetting of potential matched firms. Rather we create a portfolio which mimics the performance of the listing share during the control period, and compare the observed behaviour of the share under treatment with that of the mimicking portfolio. In so doing we overcome common criticisms of past studies of the Dow Jones Sustainability Index listing effects to cast new light on the true value of being an ESG leader.

Keywords: Listing effects, synthetic control, sustainability indexes, CSR, firm value

## 3.1 Introduction

Investor attention on corporate social responsibility (CSR) has never been higher. It is now 20 years since the formation of the first ever stock index of sustainability leaders, the Dow Jones Sustainability Index. Today there are many international and regional indices produced by MSCI, Bloomberg and S&P Global amongst others. The Dow Jones Sustainability Index now has regional indices such as the Dow Jones Sustainability Index Europe and the Dow Jones Sustainability Index North America (DJSI) studied here[1]. Each index has its own measurement criteria and means of assessing whether stocks qualify for admission. Such growth of assessment signals a market demand for sustainability. This demand appears in the ever increasing volume of assets under management in mutual funds with environmental, social and governance (ESG) concerns as their primary objective[2]. There are two explanations given for this growth. Firstly, that there is seen to be profit in firms that act sustainably[3]. Secondly, there is an investor beliefs channel. Pástor et al. (2020) and Pedersen et al. (2020) motivate their demand for ESG as coming from investors caring more about sustainability compared to returns. Both of these channels create additional investor demand for the stocks of firms who gain listing to the DJSI. Additional demand means increased stock prices and hence a positive return at the time of the demand increase. Demand channels from the ESG literature are very helpful to understanding the likely DJSI listing effects. Here we ask to what extent changes in the DJSI membership create abnormal returns. Our answers represent important new insight on the information effect of DJSI listing and the persistence of listing effects.

Decisions on DJSI membership are exogenous from the joining firms, and there is a clear event date each year. DJSI list changes therefore fit the natural experiment definition in MacKinlay (1997). Many papers have used this opportunity to isolate listing effects to indices where membership is determined by the ESG performance of the firm (Oberndorfer et al., 2013; Hawn et al., 2018; Durand et al., 2019). Abnormal returns are identified by comparing the performance of a listing stock with the forecast from a capital asset pricing model (CAPM) which is fitted to the stock during a control period. Comparing the abnormal returns of listed firms with others is done using either a t-test, or a regression approach with a dummy for listing. However, currently employed approaches make two important assumptions that are unrealistic in stock markets. Firstly, it is assumed that returns will follow a parallel trend post-listing. Callaway and Sant'Anna (2021) define the parallel trend as requiring that "in

[1]We use the short form DJSI for the North America index throughout this paper. This is consistent with other studies based on the US market.

[2]ESG assets may hit $53 trillion by 2025, a third of global AUM — Bloomberg Professional Services https://www.bloomberg.com/professional/blog/esg-assets-may-hit-53-trillion-by-2025-a-third-of-global-aum/ Accessed: 2021-07-20.

[3]See Gillan et al. (2021) for a review of the literature on ESG and firm profitability in the short and long term.

the absence of treatment the average outcomes for treated units and comparison groups would have followed parallel paths over time"(p.200). For studies using the CAPM to calculate abnormal returns, the assumption is that those abnormal returns would continue on trend parallel to the non-treated stocks. Whilst it must be assumed that there is a trend to which the return series would have been parallel, it is for the researcher to ensure the trend constructed from the control units by their study design is consistent with what would have happened to the treated units absent of the treatment. We argue that by constructing a portfolio of stocks with similar return paths in the control period, the gsynth approach provides such a trend. Secondly, we highlight an important industry specific element that other methods miss. Industry is understood as a relevant control for stock returns (Hou and Robinson, 2006) and is highlighted as a necessary consideration for ESG studies in Hoepner and Yu (2010). ESG is important in product market competition (Sen and Bhattacharya, 2001), and determines the precise dimensions upon which firms are assessed (Mattingly, 2017). Failure to consider industry is a recurring criticism of work on ESG (Gillan et al., 2021). Using the market for the control means existing approaches cannot capture the size of any industry specific shock in full. A research gap exists to consider identification of listing effects in a way which is robust to industry shocks and makes optimal use of the available controls.

We meet the challenge using the generalised synthetic control (gsynth) approach of Xu (2017). Use of synthetic controls follows Abadie and Gardeazabal (2003) and Abadie et al. (2010) construction of artificial treated units from untreated units. For a specified outcome the untreated units are weighted such that their weighted average outcome matches the outcome for the treated unit during the control period. The weights can then be used to map the outcomes of the non-treated units into a weighted average during the treatment period. This weighted average is synthetic because it is not actually the behaviour of any one untreated unit. Synthetic controls have natural interpretation as behaving in exactly the way that the treated unit would have done in the absence of treatment. In the context of this paper, the treated unit is a stock that gets listed to the DJSI. The untreated units are all of the stocks from the same industry as the listed stock that did not get listed. Through a control period of almost one year a weighted portfolio of untreated units is created so that the daily time series of portfolio returns matches the daily time series of returns on the listed stock as closely as possible. In the treatment period we can then calculate the return for the synthetic portfolio using the returns on the untreated stocks in the treatment period. The listing effect is then evaluated as the difference between the observed returns and the synthetic portfolio. This synthetic control is then a counterfactual for the firm's behaviour under the alternative that it was not listed. Acemoglu et al. (2016) and Acemoglu et al. (2017) are amongst the first to use synthetic controls in Finance. However, Abadie and Gardeazabal (2003) and Abadie et al. (2010) can only produce a synthetic control for one treated unit at a time. By contrast, gsynth allows multiple units to be treated at the same time. The DJSI often has multiple listings from the same industry and so needs the robustness to multiple listings offered by gsynth. As all stocks in the counterfactual portfolio are from the same industry as the listed firm, any industry shock affects the control portfolio and stock equally. The difference between the returns of the listing stock and the returns of its synthetic control is unaltered by the industry shock. A proportionate response to industry specific shocks creates confidence that gsynth delivers a suitable control from which to estimate abnormal returns. The additional robustness to multiple listings and industry shocks means our results may get much closer to identifying true listing effects than the existing literature has done so far.

Our sample begins with the formation of the DJSI in 2005[4]. The final membership change considered is 2018. DJSI membership changes take place once each year in late September. Construction of the synthetic portfolio uses the return time series from the 1st of November in the previous year. The control period ends three weeks before the announcement of the changes is made. Our treatment period runs from three weeks before the announcement until three weeks after the changes become effective. Our sample runs from November 2004 to October 2018. We consider all stocks listed on the New York Stock Exchange, the American Stock Exchange and NASDAQ. We require that the stocks have non-missing returns data for the full period. Stocks in 2-digit NAICS codes where there are no listed firms in a given year are not included within the sample for that year. In this way we provide relevant control stocks and ensure robustness to industry shocks as discussed.

Strong positive returns to listing are identified. Much of the gain comes prior to the announcement of the listed firm to the public. Here we provide the first evidence that the pre-listing effect seen in Oberndorfer et al. (2013) for European CSR index additions exists for the DJSI. Comparison methods used in the existing literature have not found the pre-listing effect in the United States. Across the whole sample, the gsynth effect begins earlier, and produces more long-lasting price effects, than identified elsewhere. Our immediate listings results are broadly complementary to past findings, including most recently by Hawn et al. (2018) and Durand et al. (2019). However, a persistence

[4]The Dow Jones Sustainability Index Global Index began in 1999 but it was only in 2005 when the Dow Jones Sustainability Index North America (DJSI) was formed.

to the positive returns to listing is found that had not been seen in recent works. When considering de-listing we identify significant differences between observed stock returns and the synthetic benchmark. These differences are far above what had been seen in existing work. Our effects have the same sign as those identified in Hawn et al. (2018), but the significance identified in this paper is an important result.

A helpful classification is to refer to the belief that CSR can bring positive returns as a "revisionist perspective". The longer held belief that CSR requires the diversion of funds from more profitable alternatives may be described as a "traditionalist perspective" (Oberndorfer et al., 2013). Our listing results align with revisionist beliefs, but the postive returns on de-listing are consistent with a traditionalist perspective. Relative to the wider literature on listing effects, the temproary nature of the DJSI listing effect is consistent only with the price-pressure hypothesis of Shleifer (1986)[5]. Although there are funds acting on the DJSI, there is no evidence of the increased trading volumes associated with the price-pressure hypothesis. A positive de-listing effect is consistent with traditionalist theory, but does not provide symmetry to the positive listing effect. In the S&P 500 literature most de-listing is found to be symmetric to the listing effect (Chan et al., 2013)[6]. Asymmetry in the DJSI suggests different perspectives dominate listing compared to de-listing and is made more possible by the comparatively low volume of funds trading on the announcements in our data.

Splitting out members of the S&P 500 from all other DJSI listed firms, we show that S&P 500 members' reaction to DJSI listing is small but persistent. Meanwhile, S&P 500 stocks display a higher positive return relative to their synthetic control on de-listing. Positive returns on de-listing support the traditionalist viewpoint that achieving high ranking for CSR comes at the expense of more profitable alternative uses of funds (Oberndorfer et al., 2013). Non-S&P 500 members show strong pre-announcement effects but there is an equally strong correction effect post listing. Here the stronger benefit for non-S&P 500 stocks arises because investors receive information about the activity of the firms from the announcement rather than ongoing analyst coverage. Gains to researching the ESG activities of non-S&P 500 stocks are thus

[5] There it is stated that demand from funds which track the S&P 500 index encourages investors to buy the newly listing stock to then sell to the funds at a higher price. Once the funds have acted the demand falls again. Many investors then return to the market to buy back the shares at a lower price. The effect is therefore only short-term.

[6] It follows, for example, that if the price pressure hypothesis holds then the listing effect comes from the extra demand for stocks placed by funds. When there is a de-listing those funds go into reverse and sell their stocks. The excess supply of stocks to the market reduces the price of the stock. There is a negative return to de-listing. The exception is the investor recognition hypothesis where there is evidence that investors continue to have more information about de-listed stocks than those firms that had never been listed.

identified. Subsequent correction effects come because the listing does not change investors valuation of these smaller stocks. Our results are consistent with the investor recognition hypothesis for S&P 500 listing effects (Denis et al., 2003; Chen et al., 2004). To evaluate time variance in the model a post crisis period is used as a second robustness check. Magnitudes of impact rise consistent with the growing importance of CSR. There is a persistence to the listing effect post-crisis which is not seen for the whole sample. Our robustness work further emphasises that it is the information effect that comes from S&P 500 membership that sits behind the gsynth DJSI results.

Three key contributions to the analysis of stock returns upon listing to, or de-listing from, social indexes are made. Our first contribution derives from the adoption of gsynth. By employing a methodology that compares stocks with a synthetic version of themselves we show more robustly how changes in DJSI status affect stocks. We do this without requiring the assumption that firms continue on a parallel trend relative to the market. Selection of candidate stocks for the synthetic portfolio comes from the same industry as the listed firm. We further strengthen the contribution of the new return calculation with robustness to industry shocks. Secondly, we demonstrate higher persistence of the listing and de-listing effects than had been identified in previous studies. We show this for listing to the DJSI and additionally show this persistence was made stronger by the global financial crisis. There exists a strength to the de-listing results that was not brought out in earlier work. By splitting out the S&P 500 stocks from the listing, and de-listing, our third contribution is to show that results in the existing literature are driven by infomation asymmetry. Specifically, there is a lack of information in the market about the CSR activities of firms outside the S&P 500. Consequently, to achieve the positive abnormal returns around the time of DJSI reconstitution, investors must undertake research to identify which stocks are likely to gain listing. Post-listing the correction effect on non-S&P 500 stocks confirms the listing impacts come from information rather than a long-term change in investor valuation due to the DJSI listing.

The remainder of the paper is organised as follows. An evaluation of the background to the study is presented through Section 3.2. Data, abnormal return construction and financial controls are introduced in Section 3.3. Section 3.4 details the generalised synthetic control method employed to evaluate the robustness of the initial findings. Results from the comparisons between listed shares and counterfactual alternatives from the synthetic control are reviewed in Section 3.5. Revealing more of the information and investor sentiment issues, Section 3.6 explores how S&P 500 membership and post-crisis attitudes affect the gsynth results. Section 3.7 discusses the results before Section

3.8 concludes.

## 3.2 Literature and Background

Recognition of the channels through which DJSI listing, and de-listing, impacts stock returns requires consideration of five important elements. First, we must consider the process through which reconstitution of the DJSI is undertaken. Because selection is exogenous we may use an event study to evaluate its effect. Secondly, we must consider the signals that DJSI listing, and de-listing, send to the market. Thirdly, we must learn from the competing hypotheses on S&P 500 listing. By looking at established channels we may evaluate which may be relevant to the DJSI. Fourthly, we must take lessons from existing studies of DJSI listing. Finally, our results come from a new methodology so we must understand the precise contribution against existing work.

### 3.2.1 The Dow Jones Sustainability Index

Of all the social indexes available it is the DJSI that has received greatest attention (Cheung, 2011; Robinson et al., 2011; Oberndorfer et al., 2013; Hawn et al., 2018, amongst others)[7]. As the first global index, the DJSI is an established part of the SRI landscape (Hawn et al., 2018). Of DJSI global index members, 40% of firms are headquartered in the United States. It is understandable that the first regional index covered North America. In this paper DJSI membership will be used to refer to all firms listed on either the New York Stock Exchange, Amex or NASDAQ who appear on the DJSI North America[8]. To gain listing firms must be evaluated on a stringent set of criteria by independent assessors. Assessments are performed by Robecco SAM, now an arm of S&P Global.

In any given year 2500 firms on the Dow Jones Global index of the world's largest firms are invited to apply for assessment. A bias of membership towards large firms is therefore introduced by design. Despite the invitations, the DJSI assessment is costly to firms. However, since the inception of the original index in 1999, firms have been happy to pay (Carlos and Lewis, 2018). Carlos and Lewis (2018) provide a survey into executives' motivations for wanting their firm listed on the DJSI. Carlos and Lewis (2018) identify a belief in long term competitive benefits of membership and the po-

[7]We include within this the original DJSI global index and the DJSI North America index studied in this paper.

[8]All firms who appear on the DJSI Global from North America also appear on the DJSI North America.

tential for short-term stock price increases. Results in this paper support the short term impact. The persistence of the listing effects suggests investors also believe in the long term benefits of CSR activity by firms. However, the positive returns associated with de-listing also derived in our results indicate the market is not in total agreement. Many investors do not believe DJSI membership is essential for generating longer term cash flows. Our robustness check with only listings from 2010 onwards, indicates attitudes may be evolving. Since the global financial crisis period we evidence much more belief that DJSI membership will create the future profitability for firms that makes their stocks more valuable.

Assessments by Robecco SAM vary according to industry. The aim is to identify industry leaders, not just which firms have the best CSR practice across the whole market. Focus on industry leadership adds competition to the listing process. Firms may assess their rivals and design ESG strategies accordingly. There are common core elements of assessment for all firms, but there is also a large variation in the weightings assigned to specific criteria across industries. Differences in DJSI assessment provides another motivation for splitting the sample into different industries in this paper.

There are challenges in assuming that the DJSI can be a direct signal of CSR leadership. Complexities in the listing evaluation make it harder for investors to identify which firms are likely to enter the list before the announcement[9]. Those researching companies' sustainability statements, news releases, and broader ESG trends would be able to make informed guesses on which stocks may gain listing. Getting all of these sources has a high information acquisition cost. We evidence strong pre-announcement effects, especially for firms outside of the S&P 500. In these results we are showing that investors are taking steps to identify likely listings. For de-listing the evidence of pre-announcement effects is also strong. Investors are trying to identify likely candidates for removal from the DJSI also. Our analysis supports the idea that investors research, and act, before the announcement. Although some studies question whether the DJSI does identify industry leaders (Scalet and Kelly, 2010; Venturelli et al., 2017) the DJSI remains valuable to finance research. The binary split between members, and non-members, of the DJSI makes communication to investors simple. As an exogenous binary signal of leadership, the DJSI is perfect for event studies and treatment analyses.

[9]Compare this to one of the most recognised global indexes, the S&P 500. The S&P 500 does represent the largest market capitalisations of US firms but does not list exclusively based upon size. Instead, membership of the S&P 500 is determined by a committee based on an undisclosed weighting of performance metrics. Using size would serve as a strong predictor of impending membership.

#### 3.2.2 Listing Effects

Listing studies for the S&P 500, provide important suggestions about potential listing effects for the DJSI. Four principal hypotheses about the value of S&P 500 membership have emerged. Firstly the "information hypothesis", advocated by Chen et al. (2004) and Denis et al. (2003), states that investors believe that the S&P membership panel uses information which is not available to investors. When investors see a firm is added to the S&P 500 they buy the firm. Investors buy because they expect that the information seen by the S&P panel evidences that the firm would experience better future performance than the market price of the stock suggests. A second hypothesis, based upon the downward sloping demand arguments of Shleifer (1986), argues that there will be "price pressure" on stocks as funds move to buy new listings and divest firms which de-list. Knowing there will be this demand, other investors may move quickly to gain arbitrage on selling to funds. Harris and Gurel (1986) presents early evidence of price pressure. An increased trading volume inspires the "liquidity hypothesis" (Mikkelson and Partch, 1985; Amihud and Mendelson, 1986). Additional demand for shares of S&P 500 firms means higher market value of equity. Firms may use this equity to invest in new projects that will bring increased future cash flows. More cash flow means a higher value of the stock and a long-lasting price impact. Finally the analyst coverage of S&P 500 stocks is significantly larger than others. Firms' activities are more transparent. Knowing that shareholders see their actions clearly, managers are incentivised to act more in the interests of shareholders. This is the "investor recognition" hypothesis seen in Merton et al. (1987) and Jain (1987). Three of the four effects suggest positive returns to joining the S&P 500 and a long-lasting price effect. Only the price pressure hypothesis implies a shorter term effect. True S&P 500 effects are shown by many studies to be a combination of all four hypotheses.

When recomposition of the DJSI is undertaken in the annual review it is based upon the research of Robecco SAM. This research combines many variables that would be hard for general investors to access. However, unlike the information hypothesis, which utilises the direct link between future cash flow and current valuation (Gordon, 1962), the information used by the DJSI surrounds CSR practice. It requires another step to appreciate how such practice translates into future cash flows. The definitive link between CSR and profit is one on which no consensus has been reached[10]. Firms

[10] A wide literature studies the CSR to corporate financial performance (CFP) relationship with inconclusive results. Some advocate a virtuous circle through which improved CSR leads to greater consumer demand and hence profit to invest back into CSR, whilst others continue to hold that CSR directs investment funds away from more profitable projects. Margolis et al. (2009) meta analysis

that join the DJSI will often be members of the S&P 500. Those who are already members will have strong coverage of past investment decisions. If the firm has been moving towards more sustainable practice then that will have already been observed by the market. These observations on changing practice will immdiately be evaluated by investors and incorporated into stock prices well ahead of the DJSI announcement. We hypothesise that any CSR listing effects would be smaller for S&P 500 members as a result. Therefore the information hypothesis would only apply to firms where investors were less aware of activity prior to the DJSI verification. Results in this paper are consistent with the information hypothesis.

By contrast the downward sloping demand hypothesis requires increased demand for stocks post listing to explain increased stock returns. For the stocks of firm $i$ demand comes from two sources. Firstly, investors who choose firm $i$ based upon its accounting and market fundamentals. Secondly, demand for firm $i$ comes from those funds which track the index of firms to which $i$ has just been admitted. For listing on the DJSI the analogy is with demand from funds following ESG. It is also seen that recognition for CSR practice attracts a further group of investors who base decisions on the corporate social repsonsibility of the listing firm (Derwall et al., 2011; Hawn et al., 2018; Durand et al., 2019). Evidence of increased fund activity and associated consideration of ESG is found in the literature (Nofsinger and Varma, 2014; Hartzmark and Sussman, 2019). These investor attitude and fund activity literatures give potential for the price pressure hypothesis to DJSI listing. The price pressure hypothesis suggests only short term effects on prices. Once the actions of the funds cease the market will normalise and any price effect will disappear (Harris and Gurel, 1986). However, there is growing evidence of improved performance long after S&P 500 listing (Denis et al., 2003; Hrazdil and Scott, 2009). Such persistence in the S&P 500 literature suggests the price pressure hypothesis does not hold. Unlike the S&P 500 listing, there is likely to be a long-lasting demand from investors coming to the market and making decisions based upon a firms CSR leadership (Derwall et al., 2011). Such "values based" investors do not purchase to obtain arbitrage from the funds in the way the price pressure hypothesis describes[11]. Evidence presented in this paper does not suggest strong support for the price pressure hypothesis on DJSI listings.

Liquidity and investment opportunities are promoted by Mikkelson and Partch (1985) and Amihud and Mendelson (1986). Increased market capitalisation gives firms

explores these arguments with CSR often not preceding CFP. Lins et al. (2017) gives contemporary evidence on the growing importance of CSR to CFP.

[11]The term values-based should not be confused with the pursuit of value stocks defined by the book-to-market ratio.

a platform to raise funds. These funds can then be used in investment projects that generate higher future profits. With investors understanding this long term effect, demand, prices, and hence market value, remain high. Subsequent work by Becker-Blease and Paul (2006) offers further support to the liquidity hypothesis. However, Cheung (2011) did not identify significant effects from additional investment opportunities that open from higher market capitalisation. For DJSI listings there is limited evidence to suggest that there will be greater investment opportunities from demonstrating sustainability leadership[12]. Trading volumes around DJSI recompositions do not spike in the way they do for S&P 500 stocks. Kappou and Oikonomou (2016) suggest some volume effect and in unreported results we also find evidence of more trading on DJSI announcement and effective dates in recent years. The liquidity hypothesis is likely to take on more relevance for DJSI listings in future.

Under the efficient market hypothesis information is critical for the proper functionality of the market. Chen et al. (2004) argues the cost of obtaining information, the "shadow cost", is an important component of investor demand. Information about firms is often asymmetric as a result. Agencies like S&P and Robecco SAM have more information than investors. Elliott et al. (2006) and Chan et al. (2013) both evidence how S&P 500 listing reduces shadow costs. Chan et al. (2013) further shows that the cost of asymmetric information continues to fall longer term. Consequently, information is more accessible the incentives for managers to act in the interests of profitability are higher. Transparency then allows shareholders to keep those running the business acting in shareholders' interests. This is in agreement with the investor recognition hypothesis. Investor recognition and the cost of information remain important to S&P 500 listing (Zhou, 2011).

Studies of the S&P 500 listing effects consistently point to longer term impacts. The DJSI may be expected to have the greatest listing effect on those stocks which are not well covered by analysts or are relatively illiquid. Hence we may hypothesise that membership of the S&P 500 matters. Stocks with lower recognition would be expected to display large short term gains from the exposure of DJSI membership. By contrast well regarded S&P 500 members will be guided primarily by the demand side because information on their CSR activities is already understood by the market. Any listing effect for S&P 500 firms must be responding to investor beliefs about the impact of DJSI membership on future cash flows. For both S&P 500 members, and

[12] Access to green finance products is producing a channel through which a liquidity effect may emerge (Goss and Roberts, 2011; Bae et al., 2019). Such fund raising opportunities are independent of membership of the DJSI. Instead they relate to the conduct of the firm itself rather than the assessment of that conduct by Robecco SAM.

non-members, listing to the DJSI may be expected to have longer lasting increases in returns. This persistence comes from the additional value placed on sociable stocks by investors. Analysis in this paper confirms the information asymmetry, persistence and increasing awareness of the value of social stocks. All are evident in the gsynth estimates of listing effects.

### 3.2.3 Sustainability Index Listings

Evaluations of the effect of joining the DJSI have applied event studies on listing, and de-listing, announcements (Cheung, 2011; Robinson et al., 2011; Lourenço et al., 2014; Joshi et al., 2017; Hawn et al., 2018; Durand et al., 2019). Event studies have an advantage when timings are known and exogenous to the units being considered MacKinlay (1997). Listing on a social responsibility index, such as the DJSI, is completely exogenous from the share price of a particular firm. Likewise, although the inclusion of a firm into the index is a result of the firm's efforts, timing is dictated by the ratings agency. For social indexes assessments are undertaken, and decisions made, far ahead of the announcement. As a consequence, there will be no changes close to the listing announcements that provide any information about the likelihood of a firm listing. Index listing, or de-listing, are perfect candidates for event studies.

As noted in MacKinlay (1997), event study design requires three key components. Firstly identification of the natural experiment to be assessed. For the DJSI this is eased by having just a single reconstitution event every year. Secondly, the period over which assessment of impact will be made needs to be determined. Finally, there must be identification of which controls will be used to ensure that the estimated effect is indeed representative of the phenomenon being investigated. Only through consistency in these elements can meaningful understanding of the event be reached.

There is a lack of consenus in existing work on timing. Hawn et al. (2018) takes a longer term look at listing effects to the DJSI world index, considering abnormal returns from as much as 40 days before, and after, the announcement. However Hawn et al. (2018) finds little evidence of significant abnormal returns outside of the immediate event window. The main analysis of Hawn et al. (2018) therefore focuses on the days either side of the DJSI reconstitution announcement. Earlier work by Cheung (2011) and Cheung and Roca (2013) had used 15 days ahead of the announcement, whilst Lackmann et al. (2012) and Consolandi et al. (2009) use 10 days ahead. Durand et al. (2019), based on Hawn et al. (2018), also uses just the immediate event window. After the listing there is a wider spread range of dates used. Cheung and Roca (2013) and

Robinson et al. (2011) consider up to 60 days after the effective date. Consolandi et al. (2009) and Lackmann et al. (2012) use just 10 days after the effective date. Here we extend a further week and use 15 days after the effective date. We therefore have a symmetry of 15 days either side of the key announcement and effective dates.

This paper makes a significant contribution to the consideration of control variables. Prior work has focused on established event study methodologies from the finance literature after MacKinlay (1997). Each paper constructs abnormal returns from a specific asset pricing model, typically the market model as in Hawn et al. (2018). Many also use a simple option, including comparsion with a benchmark like the S&P 500 index (Durand et al., 2019). Barber and Lyon (1997) notes advantages to using firm characteristics to create a matching between listed stocks and non-listing stocks from the control set. Comparing outcomes between the DJSI listed stock and its match would give the listing effect. Hawn et al. (2018) argues against matching and advocates the market model. Constructing matches also requires knowing the right set of characteristics to match on. The sustainability index listing literature has not reached agreement on this. Because gsynth matches on outcomes we maintain the benefits Hawn et al. (2018) sees in not restricting the control set. Because control variables are not used for matching the importance they are given in past works is reduced.

Evidence of the impact of DJSI listings and de-listings remains as varied as the empirical approaches used to study them. Robinson et al. (2011) is most relevant to our results on North America. Robinson et al. (2011) shows positive impacts seen for listings, and the associated insignificance of de-listing. Hawn et al. (2018) and Durand et al. (2019) are amongst the few to capture changes in investor perception over time. With a more contemporary sample, Hawn et al. (2018) is able to identify the trend that says investors are reacting more strongly to CSR than before. Hawn et al. (2018) and Durand et al. (2019) both point to persistent listing effects. Where Oberndorfer et al. (2013) argues price gains will disappear in a correction effect. Neither listing, nor de-listing show a correction effect. We show there are significant positive returns to listing ahead of the announcement and that CARs persist once the listing becomes public and the effective date passes. For de-listings the pre-announcement effects are also present. We further show that, as with Hawn et al. (2018), there is evidence that some investors reward firms for de-listing. Our results thus demonstrate robustness for some, but not all, results of each of the past studies. Our framework further allows important new results to emerge. Because we employ a more robust approach to the identification each confirmation, or reconsideration, is a contribution.

Motivation for the results in the existing literature can be summarised by the traditionalist and revisionist perspectives offered in Oberndorfer et al. (2013). Traditionalists believe that projects targetting CSR divert funds away from more optimal uses of captital. For traditionalists, being on the DJSI is evidence of a misuse of captial. Investors holding the traditionalist perspective would demand more de-listing stocks and force the price upwards. By contrast revisionists believe that CSR has the ability to generate future cash flows far in excess of the firm's initial investment costs. For revisionists listing to the DJSI is a signal that these higher cash flows are going to materialise. Demand from revisionists will increase upon announcement. Both groups move in the opposite direction and so the overall evidence will indicate which view dominates the market. Hawn et al. (2018) urges caution in the context of the DJSI because de-listing does not necessarily mean the firm being de-listed has bad CSR. Hawn et al. (2018) notes instead that de-listing simply means the firm is no longer leading the industry. Investors believing in the revisionist arguments may therefore continue to hold a de-listing stock. Combined with the traditionlist investors, the reduction in demand, reduction in returns and reduction in the firm's valuation may be smaller. Our high levels of persistence of positive returns to listing suggests revisionists dominate the market. The way in which persistence in de-listing effects fades after the financial crisis gives further support to revisionists dominating. That support is made stronger by the leadership argument of Hawn et al. (2018).

Choice of the DJSI is made because it has a long history, has accepted independence and sees widespread use in the sustainable investment literature. However, other studies consider alternative indices such as the Newsweek Green Rankings[13] (Cordeiro and Tewari, 2015) and the World's Most Ethical Companies list (Karim et al., 2016). As these are created by media organisations they have naturally higher coverage. Cordeiro and Tewari (2015) hypothesised higher rankings in the 2009 listing would correspond to positive returns in both the short-term and long-term. Evidence of such effects is found. For works dependent on such single-year orderings there is an inevitable problem of repeatability. However, our gsynth results demonstrate that the impact of DJSI listing is similarly positive and persistent during the period studied by Cordeiro and Tewari (2015).

[13] The Newsweek Green Rankings were first released in 2009 and gained wide interest in the USA. Scores are constructed as a combination of environmental impact score (45%) using emissions data, green policies (45%) which are obtained in part from the KLD database, and a green reputation score (10%) based on a survey of relevant stakeholders and academics (Cordeiro and Tewari, 2015). They are thus more environmentally focused than the DJSI index.

### 3.2.4 Evaluating Listing Effects

The major contribution in this paper stems from the use of a portfolio matching approach to create a counterfactual version of each firm that changes listing status. The counterfactual portfolio is a weighted combination of firms from the same industry as the listing, or delisting firm. The portfiolio is weighted such that its return matches the performance of the listing firm consistently through the control period. The value of using a counterfactual portfolio from the same industry comes from three sources. Firstly, the recognition of the importance of the industry to selection for the DJSI. Secondly, the use of a benchmark portfolio unique to the stock itself rather than a common benchmark for all stocks. Thirdly, the matching of outcomes through a weighted portfolio adds realism to the assumption that the behaviour of the stock post-listing in the absence of treatment would have followed a parallel trend to the control group.

An additional complexity to the parallel trend assumption is created by the potential for the beta coefficient used in abnormal return calculation to change over time. Patton and Verardo (2012) presents evidence that good news announcements impact not only stock returns, but also their market betas. Beta is therefore likely to change as a result of other events which change perception of future performance. It is intuitive that an indicator of improved future performance would lower the perceived riskiness of the firm. In the context of DJSI recognition, improved future performance is likely (Anderson Jr and Cunningham, 1972; McWilliams and Siegel, 2001; Sen and Bhattacharya, 2001)[14]. The use of beta coefficients from the pre-treatment period in the estimation of abnormal returns assumes no change to beta from the event. Any change in beta thus renders CAPM abnormal returns based upon a parallel trend a poor identifier of listing effects. Here models of changes to beta are a potential solution (Yin et al., 2018), but synthetic controls offer further robustness. We note that the parallel trend is not a problem of the asset pricing model used to construct abnormal returns. Parallel trends are complicated by the assumption that risk exposures do not change as a result of the event.

Industry is of great importance to stock returns because it informs of the competitve environment of the firm. Further industry dictates the likely behaviour of the stock over the economic cycle (Hou and Robinson, 2006). Industry shocks are viewed as important controls alongside market and firm level exogenous movements (Hoberg and Phillips, 2010). The desire of investors to avoid exposure to specific industry shocks is a common motivation for diversifying investment (Lamont and Polk, 2002). Given

[14] Also see the results from Chapter 2

how often we see industry shocks it is critical that event studies have robustness to such shocks. It follows that were there to be a parallel trend, it should be parallel to an industry relevant portfolio rather than the whole market. Our contribution is to use portfolios which only take from the same industry as the firm which changes DJSI status. Any shock at the industry level affects the stock being analysed and the benchmark portfolio at the same time. The diference between the two is therefore robust to the shock. It is reasonable to assume the trend is parallel to that generated by the gsynth approach.

By using the industry as part of its criteria the Robecco SAM assessment process also assigns importance to industry effects. Focusing on the market as a benchmark neglects the role of industry in DJSI assessments. Further only using the market means that stocks which are not subjected to the same assessment criteria are impacting upon the derived listing effect. For investors market level news is easiest to see, but industry level news is an important second[15]. This lack of attention to firm level news is a motivation for stronger co-movement in stocks at the industry level. Investor access to news is a further argument for an industry based control to identify index reconstitution effects. A potential alternative to the industry effect is to consider firms with similar ESG scores as controls. Identification of a listing effect against a portfolio of ESG peers can inform on the importance of DJSI membership as a signal of ESG. If there is no effect then we may conclude there is no additional informational content in DJSI membership over and above the ESG score. Because of the importance of consumer demand to the determination of the CSR impact on CFP (Anderson Jr and Cunningham, 1972; McWilliams and Siegel, 2001; Sen and Bhattacharya, 2001), focus on industry level remains the optimal approach to selecting peers that are relevant to the listing firm's financial performance. Firms are not necessarily in competition with their ESG score peers. Where gsynth allows the consideration of peer level shocks, it is rational to regard industry group membership as more relevant than ESG scores. Industry peers are used in this paper.

To consider the advantages of the industry approach over the market level benchmark from a methodological perspective, consider the listing of a technology stock and a shock which affects a different industry, say food and beverages. A large shock, for example legislation such as a sugar tax that significantly affects activity in the food and beverage sector, will impact on the market portfolio. Any change to the market portfolio would then feature in the claculation of abnormal returns for the listing technology

[15]Huang et al. (2019) use experimental evidence from Taiwan to validate hypotheses that when distracted, investors look only at market and industry news to make stock holding decisions.

stock. such effects would be spurious since the specific shock was not relevant to the technology firm. Comovement in stocks within industries is strong, but is not constant, and is not present in all stocks (Barberis et al., 2005). Any comovement with stocks from other industries would thus impact on our conterfactual portfolio by an industry appropriate amount. Similarly, any effect of the market on stocks which does impact the gsynth counterfactual portfolio will have exactly the same impact as it would in the market model. Losing the market portfolio does not create a cost, but the focus on industry is an important advantage.

Barber and Lyon (1997) outlines the value of propensity score matching as a way to align each stock which lists, or de-lists, with an unaffected stock of near identical characteristics. It is assumed that if the control is done correctly then the difference in returns of the two stocks may be attributed to the event. Formally, the propensity score estimates the probability that a unit will be treated and therefore matches treated and untreated units for which the probability of treatment is similar. Across all affected stocks there is then an average estimate of the change in returns for listing and de-listing. Consequently, there is still a large emphasis on the researcher to choose the right characteristics for matching. Hawn et al. (2018) provides strong criticism of matching methods and recent ESG listing effects literature has not made use of propensity score matching. Popularity of matching methods comes from the fact that for most stock return event studies the set of control stocks is far broader than the narrow set of treated stocks. Propensity score matching assumes that by finding stocks with similar characteristics the returns on those stocks are more likely to continue on a parallel trend. However, the low model fit of studies on firm characteristics and stock returns (Green et al., 2017) reminds that using a characteristics match is potentially misleading. Gsynth allows us to match firms on their historic return performance rather than any characteristics. In propensity score matching a stated number of matches for each treated firm is targetted[16]. Gsynth by contrast is an algorithm which assigns weights to all control group members. Hence, where propensity score matching is impacted by researcher choice, gsynth is data driven. As we never see the counterfactual of a treated unit in the absence of treatment, the ability of gsynth to optimise use of the known data has clear appeal. Both gsynth and propensity score matching allow for focus on a single industry, albeit that the weights used in synthetic portfolio construction allow

[16] The researcher may choose to create a balanced sample by having one non-treated firm for each treated firm. Alternatively, the choice may be made to have multiple non-treated firms to represent the smaller proportion of treated firms in the overall population. Provided the number of control firms selected is a reduction on the full set of control firms the target number is a researcher choice parameter of propensity score matching.

gsynth to be more flexible with the reduced sample than the necessarily poorer firm characteristic matches that will be found from any reduced sample by propensity score matching. However, it is the gsynth use of outcomes, rather than the assumption about links between characteristics and outctomes, which gives gsynth its strongest edge over propensity score matching.

It is clear that the calculation of the abnormal return to listing needs consider industry and must avoid overfitting. Synthetic control approaches after Abadie and Gardeazabal (2003) and Abadie et al. (2010) have the advantage of drawing from a selected pool of candidate stocks to produce a counterfactual that matches the behaviour of the treated stock in the control period. The natural synergy of this synthetic control with finance has seen the approach used by Acemoglu et al. (2016) in the study of political connections to the Obama administration in the global financial crisis. Acemoglu et al. (2017) uses synthetic controls to extract the effect of the Arab Spring on the Egyptian stock market. However, the Abadie et al. (2010) approach only creates a counterfactual for a single stock at any given running of the method. This is problematic in cases where multiple stocks are treated from within the same sample. In this paper, our sample are the firms from a given industry and there are often more than one firm which lists to the DJSI. Therefore we do see multiple treatments and require a statistical approach that can account for multiple listings.

To overcome this limitation we use gsynth (Xu, 2017) which has all the advantages of the synthetic control approach but also has the ability to cope with multiple treatments. Gsynth maintains co-integrating relationships between the stocks that receive the treatment. Keeping cointegrating relationships is important to produce accurate effects given the evidence in Barberis et al. (2005). The motivation to produce a counterfactual portfolio remains exactly the same. The final choice of gsynth, rather than the Abadie and Gardeazabal (2003); Abadie et al. (2010) synthetic control, is made to address the fact that there are times when more than one firm in an industry is listed in the same year. Because of its ability to deal with multiple treatments, gsynth has also been brought to the finance literature by Berger et al. (2021) in an exploration of banking deregulation and economic growth. There is yet to be an application on stock returns.

Figure 3.1: Listing Timeline


Notes: Control refers to the period over which models are trained, beginning at time $T_{start}$ and ending 16 days prior to the announcement at time $T_{end}$. The length of the control period is defined as $T_c$ and represents the difference in trading days between $T_{start}$ and $T_{end}$. The subsequent day, $T_{end}+1$, is the first in the treatment period over which models are assessed. This treatment period ends after $T_0$ periods at time $T_{end}+T_0$. Within the treatment period there are two key dates $T_{Ann}$ when the announcement of changes to the constituents is made and $T_{Eff}$, one week later, when those changes become effective. Announcement periods vary by year, but in all cases $T_{start}$ is the 1st November in the year prior to the announcement being studied.

## 3.3 Data

### 3.3.1 Sample Construction

Our focus is on changes in the constituents of the DJSI as a result of the annual review. There are four possible combinations of before, and after, status. Some firms are listed on the DJSI before and after the announcement. These are the firms which continue to be recognised for their CSR leadership. Likewise there are those firms for whom standards did not, and still do not, meet DJSI inclusion criteria. In this paper focus is on those firms who change status. Previously unlisted firms who meet the assessment criteria gain listing. Those whose standards do not keep pace with their industry rivals will lose their place. These two are our listing and de-listing treated firms.

All control samples are taken from the same industry as the listed firm being evaluated. This decision recognises industry differentials in the assessment criteria used for DJSI listing. We also ensure that the results are robust to industry shocks because all controls are from the same industry as the listed, or de-listed, firm. Given that not all industries will have a listed, or de-listed, firm in a given announcement it follows that the samples used to study the listing and de-listing effects will differ.

Figure 3.1 depicts the periods discussed in the exposition that follows. In all cases the specific time (trading day) being considered is referred to as $t$. A control period, $t \in [T_{start}, T_{end}]$ is defined as the period over which all models are trained. Model performance is then evaluated in the treatment period, which begins on day $T_{end}+1$

and ends on day $T_{end} + T_0$, $T_0$ days later. Following past works the treatment period extends 15 trading days before the index composition announcement and ends 15 days after the effective date. This represents a change from many studies who only base their period around a single treatment day. There are 5 trading days, 1 week, between the announcement and effective dates such that the total period is 36 days. Henceforth we can think of the treatment period as capturing $t \in [1, 36]$ as the time frame for which we are evaluating listing and de-listing effects. Thus we have $T_0 = 36$. The announcement day becomes day 16 and the effective day is day 21. Labelling convention is to set the announcement day to day 0 and hence our treatment period is $t \in [-15, 20]$. For comparability we use this labelling in the remainder of the article.

From a practical perspective, the treatment period for DJSI listing extends through October, ending on a different date each time. To ensure that there is no overlap the control period for the subsequent year does not begin until 1st November. Waiting until the next calendar month also reduces the chance that there is impact from the previous year's membership announcements. This pattern repeats for each year between the formation of the DJSI North America in 2005 and 2018. 2018 is the final year for which we have the data completed. Our share data covers the period from 1st November 2004 to 16th October 2018, 15 trading days after the 24th September 2018 effective date. De-listing requires that a firm first be on the DJSI North America; the first delistings are only found in the 2006 announcements.

In any given year the number of treated observations can vary, and many industries will not feature amongst either the newly listed set or the delisted set. Results for listing and de-listing are presented in the same tables and figures for comparison but will be based upon different samples. A firm observation only appears in the listing sample for a given year if there is at least one firm being listed to the DJSI within that year for the NAICS 2 industry in which the firm operates. Likewise the same is true for de-listing. Table 3.1 provides details of the sample sizes for each year, including the number of firms listing to the DJSI from the NAICS2 code with the most listing firms in the given year[17]. In almost all cases the highest number of firms changing DJSI status in an industry-year, Max, is larger than 1. Abadie and Gardeazabal (2003) allows for only one treated unit and is therefore not suitable for this study. We instead use the gsynth method (Xu, 2017), which does allow for multiple treated units.

Data on constituents of the DJSI is constructed using listings from Robecco SAM,

[17] In a supplementary appendix we provide the full break down of listings and de-listings by industry-year pair.

Table 3.1: Sample Size for DJSI Listing and De-Listing Analysis

| Year | Listing | | | De-Listing | | | Year | Listing | | | De-Listing | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | T | C | Max | T | C | Max | | T | C | Max | T | C | Max |
| 2005 | 49 | 2625 | 9 | | | | 2012 | 14 | 2007 | 3 | 15 | 1849 | 4 |
| 2006 | 16 | 2286 | 4 | 9 | 1738 | 2 | 2013 | 23 | 2350 | 4 | 13 | 1618 | 5 |
| 2007 | 11 | 2012 | 3 | 3 | 836 | 2 | 2014 | 15 | 2442 | 3 | 3 | 730 | 1 |
| 2008 | 14 | 2141 | 2 | 3 | 1112 | 1 | 2015 | 10 | 2037 | 3 | 8 | 1555 | 4 |
| 2009 | 20 | 1832 | 4 | 3 | 1010 | 1 | 2016 | 13 | 2296 | 3 | 6 | 1616 | 2 |
| 2010 | 16 | 1498 | 4 | 8 | 1141 | 4 | 2017 | 21 | 2812 | 3 | 10 | 2358 | 3 |
| 2011 | 17 | 1996 | 4 | 2 | 513 | 1 | 2018 | 8 | 1182 | 2 | 6 | 707 | 2 |

Notes: Numbers represent the total number of firms being treated (T) or appearing as controls for those treated firms (C) in a given year. Samples are constructed by industry-year pair where industry is based upon the North America Industrial Classification System two-digit (NAICS2) code. Max reports the highest number of firms being listed, or de-listed, from any one NAICS2 code within that year. Controls here are firms from within an industry-year pair who do not change DJSI status. Control firmst are only included if they are in the same industry as a firm which does either list, or de-list, within the given year. To be included firms must have no missing observations for their daily stock return.

with entries recorded for each year[18]. For each listing, or de-listing, the NAICS code is obtained at the two-digit level. Utilising unambiguous industry definitions allows the formation of a control sample from the same industry. Share price data is taken from CRSP and is gathered daily for the period beginning 1st November in the year prior to the announcement being studied and ending 20 days after that announcement. Data on firm assets, profitability and leverage is taken from Compustat such that the reported values of accounting data relate to the year prior to the announcement[19].

### 3.3.2 Descriptive Statistics

Descriptive statistics in Table 3.2 show how few firms change their DJSI status in any given year. Just 0.8% of all observations used in listing effect measurement actually represent listings. For de-listings the proportion of the de-listing sample that is actually de-listing firms is 0.6%. Such small samples pose challenges for statistical analysis.

[18] De-listing may be the result of mergers or acquisitions. Therefore all firms identified as leaving the index are checked. Firms which exit because of de-listing from the US Stock markets will not feature in the sample because of the requirement for no missing stock returns within the control and treatment periods.

[19] Accounting data is only used as controls in the regression approach for stock data in the treatment period. In studies of stock returns and firm characteristics it is usually assumed that past year accounting data is available for all firms from 1st July. Because our treatment period begins in late August, at the earliest, it follows that the previous year's accounting data would be the most recent. Because the treatment period ends before November it follows that no new Compustat accounting data would be released during the treatment period.

Table 3.2: Summary Statistics

| | | Summary Statistics | | | | Two-Sample t-Test | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean | s.d | Min | Max | Treat | Control | Diff | t-stat |
| List | DJSIE | 0.008 | 0.089 | 0 | 1 | | | | |
| | Size | 7.392 | 1.850 | 1.548 | 14.76 | 10.02 | 7.370 | 2.650 | 24.32*** |
| | Profitability | 0.088 | 7.003 | -11.71 | 13.65 | 0.196 | 0.087 | 0.109 | 7.999*** |
| | Leverage | 0.432 | 0.536 | 0 | 11.55 | 0.524 | 0.431 | 0.093 | 4.724*** |
| De-List | DJSIX | 0.006 | 0.078 | 0 | 1 | | | | |
| | Size | 7.502 | 1.854 | 1.748 | 14.46 | 10.83 | 7.500 | 3.329 | 19.94*** |
| | Profitability | 0.073 | 0.371 | -21.62 | 7.003 | 0.157 | 0.073 | 0.084 | 1.596 |
| | Leverage | 0.432 | 0.293 | 0 | 0.999 | 0.565 | 0.432 | 0.133 | 2.595* |
| | Listing Correlations | | | | | De-Listing Correlations | | | |
| | DJSIE | Size | Profit | Leverage | | DJSIX | Size | Profit | Leverage |
| DJSIE | 1 | | | | DJSIX | 1 | | | |
| Size | 0.131 | 1 | | | Size | 0.119 | 1 | | |
| Profitability | 0.034 | 0.149 | 1 | | Profitability | 0.025 | 0.146 | 1 | |
| Leverage | 0.027 | 0.504 | 0.056 | 1 | Leverage | 0.026 | 0.503 | 0.045 | 1 |

Notes: Descriptive statistics for variables used in main analyses. Samples are restricted by two-digit North American Industrial Classification System (NAICS) code to those industry-year pairs with at least one firm joining, or being de-listed from, the Dow Jones Sustainability Index North America (DJSI). DJSIE is a dummy which takes the value 1 for firms joining the DJSI in a given year, whilst DJSIX is a dummy which takes the value 1 for firms being de-listed from the DJSI. Size (log assets), profitability (return on equity) and leverage (ratio of total debt to total capital) are sourced from Compustat. Two-sample t-tests for equality of means between the listing, or de-listing, firms and those firms in the industry whose status does not change are reported in the final columns of the upper panel.

Because of these small proportions there is support for the use of matching techniques to reduce the control set (Barber and Lyon, 1997). Following Acemoglu et al. (2016), our abnormal return regressions control for three key financial characteristics. We use size, measured as log assets, profitability, measured as the return on equity, and finally leverage which provides the ratio of total debt to total capital. Table 3.2 also includes columns which report a test of the equality of the given variable between those firms who list (de-list) from the DJSI and those firms which feature as controls. It is confirmed that firms who gain listing are larger, more profitable and more highly leveraged than their peers. These t-tests are consistent with the fact that only large firms are eligible for consideration for listing. We see higher profitability amongst listing, but not de-listing, firms. Firms must be profitable to invest in CSR and there are positive profit benefits from CSR (Gillan et al., 2021). The descriptive statistics indicate that the market rewards CSR (Margolis et al., 2009; Lins et al., 2017).

Relative to the listing sample the de-listing sample is much smaller, there are just 16746 firm-years instead of the 23592 for listing. Many listings in 2005 came from the creation of the DJSI North America. No similar large change exists on the de-listing side. Consequently the average value of the DJSIE dummy is higher than DJSIX. Summary statistics for size, profitability and leverage are very similar to the listing sample. The primary differential is in the profitability, the listing firms having an average profit 20% higher than the de-listing. When conducting the two-sample t-tests for de-listing, only the size comes back as highly significant. Differences in leverage are only marginally significant. Firms who de-list have higher profitability than the controls but the difference is not significant. In summary DJSI firms are larger, more profitable and able to borrow to fund future investment. We may not assign this to DJSI membership, however.

Correlations between the variables in the lower panel of Table 3.2 show that broadly there is only low correlation between any given pair. In both listing and de-listing cases the correlation between profitability and leverage is high. No pairwise correlations are sufficiently high to stop us using all of the controls in the regression models with which we compare our results. For our gsynth work these correlations present no problems as we only use the stock returns.

## 3.4 Empirical Approach

Synthetic control methodologies (Abadie and Gardeazabal, 2003; Abadie et al., 2010) seek to construct a counterfactual for a treated unit. Using information from all other units, synthetic controls work under the assumption that the treatment was not administered. The counterfactual they create is unobservable and is used purely for identifying the treatment effect. The synthetic control treatment effect is the difference between the observed unit and the observed unit's counterfactual. In the assessment of excess stock returns from DJSI listing, the unit is the firm that gains listing and the treatment is the listing. This paper departs from the Abadie and Gardeazabal (2003) family of models by introducing the generalised approach of Xu (2017). We move to gsynth because in many instances there are multiple firms gaining listing within the same industry. There is a strong likelihood of co-integrating relationships amongst these listing stocks. Only gsynth can capture this and preserve it within the estimation results. Relative to other papers in the listing effects literature, a major advantage of the gsynth approach is to abandon the parallel trends assumption. Gsynth allows the average return for treated firms to no longer be a fixed distance from the average non-treated firm.

Industry effects are central to the consideration of abnormal returns. In this paper, we construct separate synthetic portfolios for each industry in each year. Following Acemoglu et al. (2016) consideration is made of all stocks within the firms two-digit NAICS code. As discussed, the portfolio is assembled using observations from the first trading date in November of the previous year, to 16 trading days ahead of the formal listing announcement. Our training set typically has 230 days[20]. The synthetic control is then analysed for the period between three weeks in advance of the listing announcement and three weeks after the effective date. In total this gives a 36 trading day long period.

### 3.4.1 Generalised Synthetic Control

To ease the exposition in this section we refer to listing. In the case of de-listing we may simply substitute the word de-listing for listing as appropriate. In any given industry firms are split into a treatment group, $\mathcal{T}$, and a control group, $\mathcal{C}$. Treated firms are those who gain listing to the DJSI and the controls are all other firms in the same NAICS two-digit code. Of the $N$ firms with sufficient data in a year, $N_{tr}$ are treated and the remaining $N_{co}$ are controls, such that $N_{co} + N_{tr} = N$. Each firm, $i$, is observed for $T$ periods, covering the $T_{0,i}$ control periods prior to listing, and the $q_i = T - T_{0,i}$ evaluation periods following the listing. As outlined data runs from the 1st November of the year prior to the recomposition under consideration to 15 days after the effective

[20] Because of the annual cycle of the DJSI listings we do not include a full year of training data.

date.

We consider only firms for which there are no missing returns data. Hence we have $T_{0,i} = T_0$ and $q_i = q$. It is thus assumed that the outcome of interest, excess returns for firm $i$ at time $t$, $R_{it}$, are given by a linear factor model, equation (3.1).

$$R_{it} = \delta_{it} D_{it} + x'_{it}\beta + \lambda'_i f_t + \epsilon_{it} \tag{3.1}$$

The treatment dummy, $D_{it}$, takes the value 1 for firms obtaining listing on the DJSI, that is $i \in \mathcal{T}$ and $t > T_0$. Focus is then on the coefficient on the treatment dummy, $\delta_{it}$ as this represents the treatment effect. For our purposes there are no controls and so we can simplify the exposition to remove $x'_{it}\beta$. The final term, the factor model, is the innovation within Xu (2017).

The $\lambda'_i f_t$ factor model may be expanded to (3.2). This expansion assumes that there are $r$ factors that have value $f_{rt}$ at time $t$. This takes a linear additive form that covers conventional additive unit and time fixed effects as special cases. Many further common financial models are also permissable, including autoregressive components[21]. In generalised form the factor model is:

$$\lambda'_i f_t = \lambda_{i1} f_{1t} + \lambda_{i2} f_{2t} + ... + \lambda_{ir} f_{rt} \tag{3.2}$$

Stacking over all firms equation (3.1) may be updated to:

$$R_i = D_i \odot \delta_i + F\lambda_i + \epsilon_i, i \in \{1, 2, ..., N_{co}, N_{co} + 1, N\} \tag{3.3}$$

in which $R_i = |R_{i1}, R_{i2}, ..., R_{iT}|; D_i = |D_{i1}, D_{i2}, ..., D_{iT}|'$, $\delta_i = |\delta_{i1}, \delta_{i2}, ..., \delta_{iT}|$, and $\epsilon_i = |\epsilon_{i1}, \epsilon_{i2}, ..., \epsilon_{iT}|'$ are $T \times 1$ vectors. The factors $F = |f_1, f_2, ..., f_T|'$ is a $(T \times r)$ matrix. Determination of the optimal number of factors, $r$, is discussed subsequently.

Further stacking all $N_{co}$ control units together produces $R_{co} = [R_1, R_2, ..., R_{N_{co}}]$ and $\epsilon_{co} = [\epsilon_1, \epsilon_2, ..., \epsilon_{N_co}]$, the factor matrix, $\Lambda_{co} = [\lambda_1, \lambda_2, ..., \lambda_{N_{co}}]$, is $(N_{co} \times r)$, whilst $R_{co}$ and $\epsilon_{co}$ are both $(T \times N_{co})$. The stacked model is stated as equation (3.4):

$$R_{co} = F\Lambda'_{co} + \epsilon_{co} \tag{3.4}$$

[21] See discussion in Xu (2017) and Gobillon and Magnac (2016). The specific case of time and firms fixed effects requires just two factors, $r = 2$ and setting $f_{1t} = 1$ and $\lambda_{i2} = 1$ to produce $\lambda'_i f_t = \lambda_{i1} + f_{2t}$. Now the factor model is the sum of a first term which varies by firm and a second constant which varies by time; fixed effects for firm and year respectively.

Identification of the parameters is constrained by a requirement that $F'F/T = I_r$ and $\Lambda'_{co}\Lambda_{co}$ =diagonal. It is at this point that $\lambda_j$, $j \in \{1, ..., N_{co}\}$ gives each control firm its own weighting on each factor, $\lambda_{jr}$ that determines the return of a firm gaining DJSI listing. Hence $\lambda_j$, $j \in \{1, ..., N_{co}\}$ gives each control firm its own weighting on each factor, $\lambda_{jr}$ that determines the return of the synthetic control of a firm which gains DJSI listing.

Average listing effects for those who are listed on the DJSI, are then the average effects of treatment on the treated ($ATT$). At time $t$, $t > T_0$ the ATT, $ATT_{t,t>T_0}$ is estimated as per equation (3.5)[22], the treatment being $R_{it}(1) - R_{it}(0)$.

$$ATT_{t,t>T_0} = 1/N_{tr} \sum_{i \in \tau} [R_{it}(1) - R_{it}(0)] = \frac{1}{N_{tr}} \sum_{i \in \tau} \delta_{it} \tag{3.5}$$

Xu (2017), like Abadie et al. (2010), treat the treatment effects $\delta_{it}$ as conditional on the sample data. Identification of treatment effects necessitates an appropriate measure of $R_{it}(0)$ when $t > T_0$ and $i \in \mathcal{T}$[23]. That is we require a means of identifying the returns that would have been generated by firm $i$ in the event that it had not been given listing. Estimation of the parameters of the model proceeds using three steps. Firstly estimates for $\hat{F}\hat{\Lambda}_{co}$ are obtained through:

$$(\hat{F}, \hat{\Lambda_{co}}) = \underset{\tilde{\beta}, \tilde{F}\tilde{\Lambda}_{co}}{argmin} \sum_{i \in \mathcal{C}} (R_i - \tilde{F}\tilde{\Lambda}_i)'(R_i - \tilde{F}\tilde{\Lambda}_i) \tag{3.6}$$

Recalling that this minimisation is performed subject to the twin constraints that $\tilde{F}'\tilde{F}/T = I_r$ and that $\tilde{\Lambda}'_{co}\tilde{\Lambda}_{co}$ is a diagonal matrix.

Following Xu (2017) the factor loadings are calculated. Values restricted to the pre-announcement period gain subscript 0. Hats denote estimates from (3.6). Step 2 is thus:

$$\begin{aligned} \hat{\lambda}_i &= \underset{\hat{\lambda}_i}{argmin} (R_i^0 - \hat{F}^0\tilde{\lambda}_i)'(R_i^0 - \hat{F}^0\tilde{\lambda}_i) \\ &= (\hat{F}^{0\prime}\hat{F}^0)^{-1}\hat{F}^{0\prime}R_i^0, i \in \mathcal{T} \end{aligned} \tag{3.7}$$

Step 3 calculates treated counterfactuals based on the estimated $\hat{F}$ and $\hat{\lambda_{co}}$ noting that

[22] For more on the social economic interpretation of this see Blackwell and Glynn (2018).

[23] A discussion of the requirements for causal inference in the generalised synthetic control framework is provided as a supplementary appendix to Xu (2017).

this is equation 3.1 with $x_{it} = 0$ and $D_{it} = 0$. Hence we calculate:

$$\hat{R}_{it}(0) = \hat{\lambda}_i{}' \hat{f}_t, i \in \mathcal{T}, t > T_0 \tag{3.8}$$

$R_{it}$ is substituted into (3.5) such that estimates for the average treatment effect on the treated, $ATT_t$ are provided as:

$$A\hat{T}T_t = (1/N_{tr}) \sum_{i \in \mathcal{T}} [R_{it}(1) - \hat{R}_{it}(0)] \text{ for } t > T_0 \tag{3.9}$$

In order to obtain convergence in the estimated factor loadings it is required that there be sufficiently large numbers of controls and a sufficiently long control period. As we have more than 200 days of data, and a large number of firms in each two digit NAICS code, there would not be expected to be any concerns about convergence. In every case the reported tests of convergence reveal that the model does converge.

Within Xu (2017), the number of factors to be included is determined using a five step procedure. Firstly a given $r$ is selected and an interactive fixed effects (IFE) model is estimated for the control group data to obtain an estimate of $F$, $\hat{F}$. A cross-validation loop is run at step 2. This loop first works systematically through the control period omitting one period and obtaining factor loadings for each treated unit, $i$, according to the formula:

$$\hat{\lambda}_{i,-s} = (F^{0\prime}_{-s} F^{0}_{-s})^{-1} F^{0\prime}_{-s} R^{0}_{i-s}, i \in \mathcal{T} \tag{3.10}$$

where the use of $-s$ in the subscripts denotes the ommision of period $s$ from the estimation. Predicted outcomes for the missing period are saved and compared with the observed period $s$ return to construct a prediction error $e_{is} = R_{is}(0) - \hat{R}_{is}(0)$. Step 3 sees the calculation of the mean square predicted error (MSPE) given the selected number of factors. Given $r$ the MSPE is:

$$MSPE(r) = \sum_{s=1}^{T_0} \sum_{i \in \mathcal{T}} e^2_{is} / T_0 \tag{3.11}$$

Repeating the process over further possible $r$ enables the identification of $r^*$ as that number of factors which minimises the MSPE from equation (3.11). Xu (2017) demonstrates through Monte Carlo simulation that this simplistic procedure performs well in factor number selection[24].

In order to obtain inference from the estimated ATT we need a conditional variance of the ATT estimator, i.e. $Var_{\epsilon}(\hat{ATT}_t|D_t, \Lambda F)$. Although $\epsilon$ should be the only random variable not being conditioned upon, it may be correlated with $\hat{\lambda}_i$ from the estimation loop above. Nonetheless, $\epsilon$ remains a measurement of the variations in returns that we cannot explain and which is unrelated to treatment assignment.

In this paper the focus is on the average listing (de-listing) effect across all of the industry-year pairs which contain a listed (de-listed) firm. At the individual level there is a procedure to obtain confidence intervals incorporated within the Xu and Liu (2018) code. Details of the estimation of confidence intervals for gsynth treatments are available in Xu (2017). Acemoglu et al. (2016) proposes an approach to handle multiple firms being treated simultaneously. However, Acemoglu et al. (2016) considers only a single event and a single time period. The weighted approach used by Acemoglu et al. (2016) does not provide a natural means to generate confidence intervals for the average estimates across industry-years. In what follows we use t-tests that the estimated listing effects for each firm have an average of 0. Therefore, we do not present confidence intervals, but may use the standard errors and t-statistics from the t-tests for inference.

### 3.4.2 Measurement of Listing Effects

Focus in this paper is on the listing effect. For an individual firm, $i$, we may view the treatment effect as the difference between the observed return and that of the synthetic control portfolio. Identifying abnormal returns in this way is consistent with the standard asset pricing position that the abnormal return should be the difference between observed and expected returns. The expectation in the gsynth model is that the stock return would have continued to follow the weighted average of other stocks from the same industry. Hence for firm $i$ on day $t$ in the treatment period, $t \in [T_0, T]$, the abnormal return from gsynth, $AR^G$, may be written as:

$$AR^G_{it} = R_{it}(1) - R_{it}(0) \tag{3.12}$$

[24]It is also shown to perform well in small datasets, but this is not a concern for our daily financial data (Xu, 2017).

such that the cumulative abnormal return (CAR) from the gsynth model in the period $[from, to]$, $CAR^G_{i,from,to}$ are given as:

$$CAR^G_{i,from,to} = \sum_{k=from}^{to} AR^G_{ik} \tag{3.13}$$

These CARs are dependent only on the performance of firms within the same industry as the firm which gains listing. Any influence from the overall performance of the market enters through its effect on returns of stocks within the industry.

Alternative means of evaluating listing effects require us to also seek to identify the difference between the listed stock and how that would have performed without the listing. This objective may be achieved by comparing new entrants with similar firms that are not joining the DJSI that year. In the case of de-listing, comparison would be between de-listing firms with others who are not exiting the DJSI that year. In traditional models the listing effect may also be considered as the difference between the observed returns and those returns that would have been realised had the listed firms share continued to follow its control period path. This is the parallel trend assumption. The aim of event studies must be to ensure that the control produces a trend to which it is reasonably assumed the counterfactual would be parallel.

The simplest model used to study the cross section of stock returns is the capital asset pricing model (CAPM) (Lintner, 1965; Sharpe, 1964; Treynor, 1962). Subsequent factor models are able to generate a better fit in the sample, but it is widely accepted that the CAPM is the most parsimonious solution for out-of-sample prediction (Campbell et al., 1997; Acemoglu et al., 2016). Here all abnormal return calculations follow the approach in Campbell et al. (1997) and MacKinlay (1997). For the control period, $t \in [T_{start}, T_{end}]$, we estimate equation (3.14) using ordinary least squares (OLS) regression. This is done for all firms in the sample individually.

$$R_{it} = \alpha_i + \beta_i MKT_t \tag{3.14}$$

In equation (3.14) $R_{it}$ is the excess return on share $i$ at time $t$, $MKT_t$ is the Fama-French excess return for the market at time $t$, and $\alpha_i$ and $\beta_i$ are the coefficients of interest[25]. Estimated values $\hat{\alpha}_i$ and $\hat{\beta}_i$ are then used to compute the fitted excess returns for share $i$, $\hat{R}_{it}$. The market model abnormal return, $AR^M_{it}$, is then defined as

[25] Note that we do not need to use robust standard errors here as we are only interested in the coefficient and not its signficance.

the difference between fitted and observed values:

$$AR^M_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i MKT_t \tag{3.15}$$

Consequently a subperiod $t \in [from, to]$ has CAR, $CAR^M_{i,from,to}$ of:

$$CAR^M_{i,from,to} = \sum_{k=from}^{to} AR^M_{ik} \tag{3.16}$$

Rational investors, with no preference for ESG, seek abnormal returns. Higher absolute values will therefore grab investor attention. If correctly priced the CAR would be zero. Here it is the relationship between CARs and DJSI status which becomes of interest.

Relative to (3.13) equation (3.16) has a clear reliance on the value of the market factor. Equation (3.16) also gives no recognition to industry heterogeneity. The calculation of $AR^M_{it}$ requires the estimation of an OLS model. Implicitly this OLS model assumes the performance of the stock would have remained on a parallel trend to its control period performance in the absence of listing. Further the model assumes that the slope coefficient $\beta_i$ is constant following the treatment. These assumptions have stronger limitations than the assumption made in gsynth that the firm would have preserved its relationships with other firms through the counterfactual portfolio.

Once the $CAR^M$ are generated there are two approaches to their use for the estimation of listing effects. First we may simply perform two-sample t-tests to compare abnormal returns amongst listing, and non-listing stocks. T-tests offer simplicity and are widely used, Hawn et al. (2018) and Durand et al. (2019) being recent examples. Secondly we may regress the CARs on firm level characteristics and a DJSI listing dummy. Significance and the sign of the coefficient on this listing dummy informs on the direction and magnitude of the listing effect. Following Acemoglu et al. (2016) the specification of our regression approach is given in equation (3.17).

$$\begin{aligned} CAR^M_{i,from,to} = &\alpha + \omega DJSIE + \beta_1 size_i + \beta_2 size_i^2 + \beta_3 size_i^3 + \beta_4 roe_i + \beta_5 roe_i^2 \\ &+ \beta_6 roe_i^3 + \beta_7 leverage_i + \beta_8 leverage_i^2 + \beta_9 leverage_i^3 + \gamma + \delta + \epsilon_{it} \end{aligned} \tag{3.17}$$

with $\omega$ being the coefficient of interest. Estimation of (3.17) is performed with industry and time fixed effects, $\gamma$ and $\delta$ resepectively. The inclusion of all of the three firm financial controls in quadratic and cubic form is also advocated by Acemoglu et al. (2016). Including cubic terms is a parsimonious means of limiting the number of variables in the regression. In all that follows only $\omega$ will be reported. A discussion of other coefficients is made in the supplementary material. Note that the impact of DJSI membership enters linearly and is additively separable from other variables. When studying de-listing the $DJSIE$ listing dummy would be replaced with the de-listing dummy $DJISX$. Specifying the model in this way ensures that the stock continues to follow a parallel trend to the line it was following in the control period. The difference between the two trends is simply $\omega$. As Acemoglu et al. (2016) argues, stocks rarely follow parallel trends, especially when they undergo an event.

Both the two-sample t-tests and regression models suffer potential bias because the DJSI firms must come from the largest firms within the US. Consequently within the CRSP database there are many smaller firms which lack the assets to be eligible for listing. To overcome this limitation studies may use matching algorithms to create a control sample similar in as many ways as desired to the listing sample. However, there are concerns that this removes important control firms and does not identify the true listing effect (Hawn et al., 2018). A second way to restrict the control group is to only use observations of large firms. In this paper we only include stocks whose assets are at least 80% of that from the smallest firm that changes status on the DJSI in the given year. So restricting creates a base sample to contrast with the full sample and gsynth results[26].

For clarity of expression all of the above has referred to firms gaining listing on the DJSI. In this paper we also consider those firms who are de-listed in a particular announcement.

## 3.5 Results

### 3.5.1 Control Period Fit

Motivation for the adoption of gsynth comes from the ability to maintain robustness to industry shocks. As a first step to evaluating the benefits of using gsynth, we may perform an analysis of how well the model fits during the control period. As well as a straight comparison between the gsynth and market model MSPE, we also count how many times the difference is greater than 0.1% in favour of each approach. Results are reported in Table 3.3.

Table 3.3 shows that gsynth has a better control period fit in 62 of the 117 industry-year pairs. Of those industry years where the difference in the MSPE is 0.1% or more

[26]Summary statistics for the base sample are included within the supplementary appendix

Table 3.3: Control Period Fit Comparison

| | $MSPE^M$ | $MSPE^G$ | Difference | t-stat | $MSPE^M > MSPE^G$ | $MSPE^M - 0.1 > MSPE^G$ | $MSPE^G - 0.1 > MSPE^M$ | Industry – Years |
|---|---|---|---|---|---|---|---|---|
| Listing | 2.058 | 1.854 | 0.202 | 3.606 | 62 | 38 | 13 | 117 |
| De-Listing | 1.941 | 1.763 | 0.178 | 1.041 | 31 | 29 | 24 | 55 |

Notes: Table reports average mean squared prediction error (MSPE) for the fitting of the market model (M) and generalised synthetic control (G) during the control period to firms who list, or de-list, from the Dow Jones Sustainability Index North America (DJSI) during the period 2005 to 2018. A paired two-sample t-test is performed to test equality of accuracy for the G and M models. In column t-stat we report the t-statistic of the test that the two MSPE are equal. Columns 5 to 7 report numbers of industry-years for which the stated condition holds. Column 8 informs on how many industry-year pairs data is available.

gsynth has 38 better fits compared to just 13 for the market model. Overall the average MSPE from the market model is 2.058 whilst the gsynth has an average MSPE of 1.854. A paired two-sample t-test reveals that the gsynth model has significantly better fit at the 0.01% level. For listing the control period fit is therefore much better when gsynth is used.

For the de-listing case the gsynth has a lower MSPE than the market model in 31 of the 55 cases. Further gsynth has a lower MSPE than the market model by a margin of more than 0.1% in 29 of the 52 cases where the difference is greater than 0.1%. Again we perform a paired two-sample t-test for the equality of effects under gsynth and the market model. Average MSPE for the market model is 1.941 and for the gsynth is just 1.763. However, the difference is not significant with the t-statistic for the paired test being 1.041. Although we cannot conclude in favour of the gsynth offering better fit in the de-listing data, we can also not conclude that it has a worse fit.

Accross both listing and de-listing we find many cases the MSPE is less than half that of the market model[27]. Overall the improved fit in the sample period is a guide to potential improved fit through the treatment periods also. However, it is the applied motivation of industry robustness which gives gsynth its advantage for studies of listings.

### 3.5.2 Listing and De-Listing Effects

We generate abnormal returns as the difference between the observed stock return of a listing firm and the synthetic control portfolio of firms from the same industry. Computations are performed using the *gsynth* package (Xu and Liu, 2018). We do this for each industry-year and for both listings and de-listings. In total there are 630 combinations of start and end dates for the consideration of CARs. Focus here is placed only on those seen to have relevance in past studies such as Hawn et al. (2018) and Durand et al. (2019). Particular attention is paid to effects around the announcement and effective dates. To capture the pre-listing effects evidenced in Oberndorfer et al. (2013) we consider three weeks prior to the announcement date. To check for lasting effects of the type seen in S&P 500 listing studies, such as the more recent work of Chan et al. (2013), we also use three weeks after the effective date.

Table 3.4 reports the estimated CARs over a series of windows defined by the past literature as being of interest in the study of DJSI listing effects. In every case the t-statistic in parentheses informs whether the average estimate of the CAR is statistically

[27] A full comparison of fit is available in the supplementary material.

Table 3.4: DJSI Listing/De-listing Effects

| | From<br>To | -15<br>ANN | -10<br>ANN | -5<br>-1 | -1<br>1 | ANN<br>1 | ANN<br>2 | ANN<br>3 | ANN<br>4 | ANN<br>EFF | EFF<br>10 | EFF<br>15 | EFF<br>20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel (a): Listing | | | | | | | | | | | | | |
| gsynth | F | 0.572 | 0.401 | -0.160 | 0.280 | 0.252 | 0.359 | 0.534 | 0.386 | 0.358 | -0.231 | -0.412 | -0.301 |
| | | (1.765) | (1.552) | (0.824) | (2.294) | (2.471) | (2.809) | (3.260) | (2.117) | (1.704) | (1.076) | (1.163) | (0.710) |
| t-test | F | -0.832 | -0.540 | -0.643 | 0.369 | 0.387 | 0.643 | 0.936 | 0.622 | 0.646 | 0.064 | -0.147 | 0.183 |
| | | (2.261) | (1.712) | (2.573) | (2.513) | (3.320) | (4.215) | (4.993) | (2.656) | (2.781) | (0.261) | (0.382) | (0.422) |
| t-test | B | -0.433 | -0.380 | -0.399 | 0.398 | 0.375 | 0.596 | 0.868 | 0.812 | 0.770 | 0.267 | 0.180 | 0.738 |
| | | (1.147) | (1.176) | (1.561) | (2.637) | (3.128) | (3.802) | (4.514) | (3.397) | (3.237) | (1.062) | (0.459) | (1.663) |
| Regression | F | -0.569 | -0.373 | -0.291 | 0.085 | -0.050 | 0.117 | 0.328 | 0.521 | 0.370 | -0.037 | -0.198 | -0.034 |
| | | (0.950) | (0.739) | (0.799) | (0344) | (0.244) | (0.467) | (1.142) | (1.539) | (1.120) | (0.096) | (0.386) | (0.054) |
| Regression | B | -0.830 | -0.501 | -0.474 | 0.077 | 0.079 | 0.288 | 0.358 | 0.466 | 0.307 | -0.014 | -0.012 | 0.139 |
| | | (1.630) | (1.121) | (1.456) | (0.375) | (0.480) | (1.370) | (1.445) | (1.632) | (1.022) | (0.046) | (0.026) | (0.254) |
| Panel (b): De-listing | | | | | | | | | | | | | |
| gsynth | F | 0.605 | 0.881 | 0.040 | 0.143 | 0.214 | 0.246 | 0.304 | 0.036 | -0.278 | -0.314 | -0.223 | -0.317 |
| | | (1.465) | (2.407) | (0.163) | (1.001) | (1.573) | (1.508) | (1.533) | (0.143) | (0.646) | (0.939) | (0.502) | (0.647) |
| t-test | F | -0.185 | 0.331 | -0.081 | 0.197 | 0.373 | 0.529 | 0.659 | 0.178 | 0.303 | 0.274 | 0.459 | 0.809 |
| | | (0.341) | (0.839) | (0.278) | (1.007) | (2.025) | (2.371) | (2.496) | (0.604) | (0.868) | (0.986) | (1.486) | (2.033) |
| t-test | B | 0.799 | 0.986 | 0.455 | 0.222 | 0.186 | 0.207 | 0.369 | 0.268 | 0.250 | 0.389 | 0.506 | 0.827 |
| | | (1.451) | (2.441) | (1.533) | (1.109) | (0.996) | (0.913) | (1.374) | (0.894) | (0.707) | (1.376) | (1.587) | (1.983) |
| Regression | F | 0.048 | 0.106 | 0.076 | -0.053 | 0.013 | 0.002 | 0.063 | -0.024 | -0.038 | 0.216 | 0.352 | 0.487 |
| | | (0.057) | (0.150) | (0.149) | (0.155) | (0.047) | (0.006) | (0.157) | (0.051) | (0.076) | (0.397) | (0.494) | (0.558) |
| Regression | B | -0.079 | 0.211 | 0.247 | 0.100 | 0.065 | 0.102 | 0.224 | -0.004 | 0.038 | 0.159 | 0.505 | 0.647 |
| | | (0.116) | (0.356) | (0.568) | (0.369) | (0.307) | (0.362) | (0.660) | (0.010) | (0.092) | (0.395) | (0.918) | (0.931) |

Notes: Table presents estimated listing effects for firms joining the DJSI as estimated by the generalised synthetic control (gsynth) approach of Xu (2017). Portfolio weights are constructed for the control period, 1st November in the year prior to the considered recomposition through to 16 days before the announcement of the new DJSI list. For comparison the market model, $r_{it} = \alpha_i + \beta_i MKT_t$, is again estimated for the control period. Abnormal returns are defined as $AR^M_{it} = r_{it} - \hat{\alpha_i} - \hat{\beta_i} MKT_t$, where $t$ is in the treatment period. Models are estimated for the full sample (F) and for a base sample (B) in which only firms whose size is at least 80% of the smallest listing firm in the same industry are included. Control firms are only included if there is a DJSI listing from their industry in the given year. Industries are defined by two digit NAICS codes. t-test denotes a t-test that the mean abnormal return for listing firms is equal to that for non-listing firms with the figure reported being the difference. Regression refers to the regression of the cumulative abnormal return on a listing dummy and a set of controls identified in Acemoglu et al. (2016) under time and industry fixed effects. Formally we report $\delta$ from the regression of abnormal returns on size (log assets), profit (return on equity, roe) and leverage with each entering up to cubically. We estimate this for the listing dummy $DJSIE$ and the delisting $DJSIX$ under year, $\gamma$ and industry, $\delta$, fixed effects.
$CAR^M_{i,from,to} = \alpha + \omega DJSI_{it} + \beta_1 size_i + \beta_2 size_i^2 + \beta_3 size_i^3 + \beta_4 roe_i + \beta_5 roe_i^2 + \beta_6 roe_i^3 + \beta_7 leverage_i + \beta_8 leverage_i^2 + \beta_9 leverage_i^3 + \gamma + \delta + \epsilon_{it}$.
Figures are the coefficient on the listing dummy and associated t-statistic from a test that the true coefficient is equal to zero. Newey et al. (1987) adjusted standard errors are used throughout.

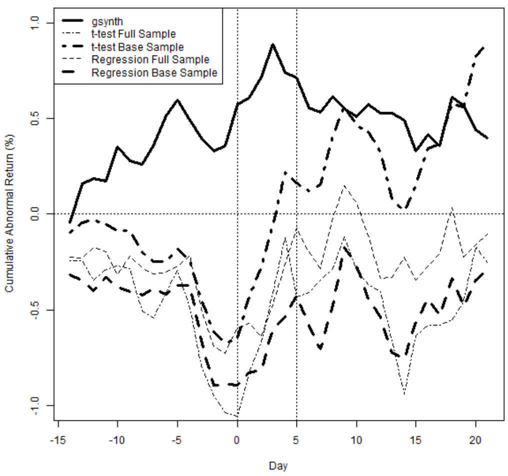
significantly different from 0. For the gsynth listing results the only significant effects occur between the day before the announcement date, day -1, and the day prior to the effective date. The same periods of positive CAR are also found to be significant for the two-sample t-tests on the base sample. When using the full sample there are significant negative CARs between day -15 and day 0, as well as between day -5 and -1. None of the considered post effective date windows produce CAR estimates which are significantly different from zero. Amongst the magnitudes of the listing effects there is a strong differential pre-announcement between the gsynth and the other approaches. Where the gsynth suggests positive CARs all other methods are negative. During the period most commonly studied by event studies, namely between day -1 and the effective date, all models agree on positive CARs. However, the largest magnitude come from the t-tests. Our gsynth estimates sit between the two other methods in this period but do show positive effects.

Evidence on de-listing effects in panel (b) of Table 3.4 shows far lower amounts of significance. Lower significance is unsurprising given the lower number of firms de-listing from the DJSI. When comparing across methodologies, the larger values from the gsynth in the pre-announcement period are matched only by the two-sample t-tests on the base sample. In the post effective date period our gsynth CARs indicate a correction effect whilst the comparator approaches point to increased returns through this time. Indeed over the three week period to day 20 the CAR from the t-tests on both base and full samples are statistically significant and more than 0.8%. Unlike the listing effects, very few of the CAR estimates between the announcement and effective dates are significantly different from 0. The greatest estimated CARs still come from the two-sample t-tests, and the smallest still come from the regression models.

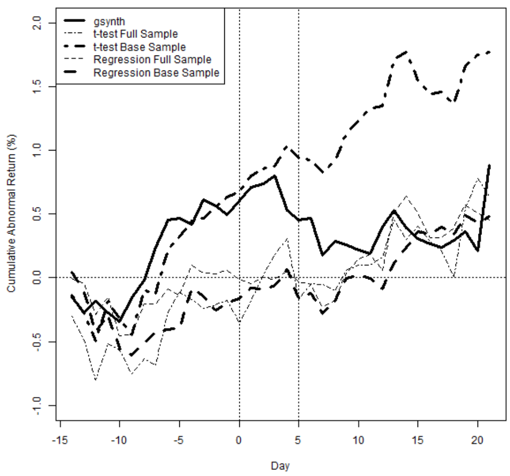
Figure 3.2 visualises the results from Table 3.4. We plot the CAR between day -15 and the given date on the horizontal axis from the gsynth specification. We then add the CARs from the two-sample t-tests and regression analyses. A solid black line is used for the gsynth CAR. Dot-dash lines are used for the t-tests and dashed lines for the regression coefficient. For the comparator methods a thicker line represents the results from the reduced sample. Immediately it is seen that there are important differences in the results, especially in the pre-announcement period.

Panel (a) shows how prior to the announcement of new stocks on day 0, the gsynth is already producing strong positive abnormal returns. Meanwhile, those methods based on the market model are all suggesting negative CAR of similar magnitude. Only between the announcement and the effective dates do the other approaches CARs climb to catch up with the gsynth estimates. Post effective date the gsynth and t-test results

Figure 3.2: DJSI Listing and Delisting Effects




(a) Listing




(b) De-listing

Notes: Plots show cumulative abnormal returns (CARs) gained between the first day of the treatment period, -15, and the date given on the horizontal axis, $x$. Vertical lines indicate the announcement on day 0 and the effective date on day 5. A solid line plots $CAR^{G}_{-15,x}$ as the estimate of the listing effect. For the market model CARs dot-dash lines are used for the two-sample t-tests. Dashed lines report the regression coefficients $\omega$ from the estimation of $CAR^{M}_{i,-15,x} = \alpha + \omega DJSI_{it} + \beta_1 size_i + \beta_2 size_i^2 + \beta_3 size_i^3 + \beta_4 roe_i + \beta_5 roe_i^2 + \beta_6 roe_i^3 + \beta_7 leverage_i + \beta_8 leverage_i^2 + \beta_9 leverage_i^3 + \gamma + \delta + \epsilon_{it}$ under year, $\gamma$, and industry, $\delta$, fixed effects. A base sample of firms with log assets at least 80% of those of the smallest DJSI listing, or de-listing, firm from the given industry year is created to better reflect the large size of DJSI members. Base sample market model effects are shown as thicker lines to contrast with thinner lines for the full sample.

show persistence of the positive CAR, though the latter estimates cycle back to 0 before climbing again in the final week of the treatment period. CARs from the gsynth model remain persistently positive. The large sample regression estimates remain negative throughout the treatment period. The full sample thinner lines are more erratic post-effective date. All comparator models pick up positive returns between announcement and effective dates.

Panel (b) of Figure 3.2 shows how de-listing effects also have a notable differential in the pre-announcement period. However, the movement in all CARs only takes place around day -10, with the gsynth showing most pre-announcement effect. By day 0 the t-test and gsynth are both showing strong positive CARs. The t-test results follow a steady rise in the final week. For the other measures we see steady rises through the period, resulting in very similar estimates to the gsynth from day 10 onwards. No notable deviation from that trend is picked up between announcement and effective dates. In the de-listing case positive CARs are associated with the traditionalist perspective. The persistence seen does suggest longer term rewards to being de-listed are perceived by investors. Our gsynth measure has higher CARs continuing through the post effective date period than all other measures except the two-sample t-tests on the size restricted sample.

Our listing results have strong similarity with those in Hawn et al. (2018), particularly in the strong effect between announcement and effective dates. However, gsynth CARs evidence a pre-announcement effect of the type identified by Oberndorfer et al. (2013). There is limited suggestion of a pre-announcement effect from the other approaches. No pre-announcement effect is consistent with the results in the more recent study of Hawn et al. (2018). Likewise the strength of the pre-announcement movements in the de-listing case is also much stronger than all but the two-sample t-tests on the base sample. Here again the negative values are consistent with Hawn et al. (2018). The movement in the gsynth is the only consistent evidence of learning about the announcement ahead of the date for both listing and de-listing. It is not unreasonable to assume that information about CSR projects for firms be in the public domain well ahead of the announcement. Our results here show gsynth to be more consistent with the observability of CSR projects.

By focusing on CARs from the first date of the treatment period it is possible to see the impact of daily abnormal returns throughout the event window. As Table 3.4 informed, only a small proportion of the results shown are statistically significant. Limited significance in the results is the consequence of the small sample size, and wide variation in daily stock returns. The graphical representations in this paper do not consider the significance of the estimates to allow clarity of the inference. However, the intuition taken from the graphs is useful to extend the discussion of listing, and de-listing, effects with respect to the DJSI.

### 3.5.3 Comparison with Listing Effects Hypotheses

Persistence of the CARs post event in both cases aligns with the information hypothesis. Kappou and Oikonomou (2016) also identifies the information hypothesis as most relevant of those discussed in the S&P 500 listing literature. However, Kappou and Oikonomou (2016) also note the inconsistency of both listing and de-listing both producing positive CARs. However, persistence is also consistent with the liquidity hypothesis (Mikkelson and Partch, 1985; Amihud and Mendelson, 1986). Kappou and Oikonomou (2016) find limited difference in the abnormal trading volumes for listing and de-listing stocks. Hence although the return results are consistent, the overall evidence does not support the liquidity hypothesis. Our data also does not support significance in the trading volumes around the listing dates. However, in recent years there are notable increases on the effective data that do fit with the theories of Mikkelson and Partch (1985), Amihud and Mendelson (1986) and others. Finally, there is the investor recognition hypothesis of Chen et al. (2004). Similarity between the listing and de-listing effects here suggests greater support for recognition than Kappou and Oikonomou (2016) find. Listing effects support investors becoming aware of the CSR activity of the firm. De-listing effects are consistent with the investors still being aware despite the de-listing. On investor recognition more investigation is needed because of the heterogeneity in investor attitudes to DJSI membership. Of those hypotheses for S&P 500 listing effects the price-pressure hypothesis was the only one which commanded temporary change. Although there is evidence of such from the regressions on the market model, the gsynth does not show mean reversion. Like Kappou and Oikonomou (2016) we also argue that there is limited evidence of price pressure in the abnormal returns.

From our analysis it is clear that there is something unique about social indexes that contrasts from the S&P 500. In keeping with Hawn et al. (2018), Durand et al. (2019), and the earlier work of Kappou and Oikonomou (2016), there is much to suggest that the way investors treat social investment index membership is very different from other indexes. As a consistent picture of return effects of listing and de-listing emerges, so a stronger underlining of the uniqueness of social indexes is made. In each case it is the attitudes of investors to the information conveyed by membership which determines returns. Our adoption of gsynth enables us to reveal the magnitude of these information effects in a way which is robust to industry shocks. Therefore, we give a far more accurate and reliable indication of the DJSI recomposition effects. The open challenge is then to understand the story behind those returns. The growing volume of data is helping to answer those questions but remains too limited in volume to give definitive answers.

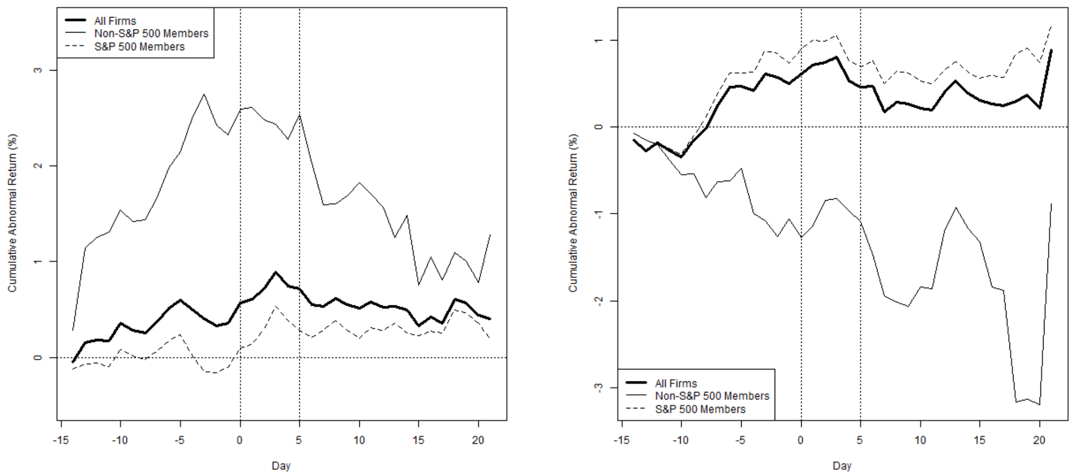
## 3.6 Robustness Checks

Strong support in the results was found for listing to the DJSI having a strong informational content for investors. However DJSI announcements having informational content is inconsistent with the fact that most firms are already members of the S&P 500. S&P 500 members are subject to the high analyst coverage. It was this coverage that Chen et al. (2004) cited as the reason for an information effect. Our first robustness check asks whether those firms who do not receive that high analyst coverage display stronger abnormal returns on listing to, or de-listing from the DJSI. Secondly, much is documented about the role of the global financial crisis in increasing awareness of the importance of CSR (Lins et al., 2017). Following Durand et al. (2019), we consider the listing effects from 2010 to 2018 to identify the extent to which consistency with the information hypothesis continues to hold in times when investor attention on CSR is stronger.

### 3.6.1 S&P 500 Membership

Membership of the DJSI requires that firms be leaders in CSR. Membership also requires that they are of a sufficiently large size. The invited universe in 2018 comprised just over 800 firms from the United States. However, it does not follow that all members are also members of the S&P 500 index of America's top firms. In the listings literature much is made of the impact of joining that top index (Harris and Gurel, 1986; Chen et al., 2004; Chan et al., 2013, amongst others). Analysis of any differential between those firms joining the DJSI who were members of the S&P500 at the point of listing is warranted. Further, we know there is a differential in information about S&P 500 firms through analyst coverage and news content. We perform the analysis of any S&P 500 differential using two sample t-tests of the gsynth CARs for S&P 500 members and non-S&P 500 members. Further we consider a fixed effect regression specification that

Figure 3.3: Cumulative Abnormal Returns and S&P 500 Membership




(a) Listings to DJSI (b) De-listings from DJSI

Notes: Figures plot estimated average cumulative abnormal returns of holding stocks which gain listing on, or were de-listed from, the Dow Jones Sustainability Index (DJSI) between 2005 and 2018. Abnormal returns are estimated as the difference between the observed returns for a given share and a portfolio of shares constructed using the generalised synthetic control approach to match the control period returns of the given share. Cumulative abnormal returns are calculated as the sum of these abnormal returns from 15 days prior to the announcement of DJSI constituents to the date indicated on the horizontal axis inclusive. A thick solid line is used to denote the average across all firms, a thinner dashed line the average amongst firms who were members of the S&P 500 one month prior to listing and a thin solid line for firms which were not members of the S&P 500 one month prior to the listing/de-listing date. Vertical lines are added on the announcement date (0) and the effective date (5) for reference. There are 89 de-listing firms of which 17 are non-S&P 500 members.

contains year and industry fixed effects.

$$CAR^G_{i,from,to} = \alpha + \beta sp500_i + \gamma + \delta + \epsilon_i \tag{3.18}$$

in which $CAR^G_{i,from,to}$ is the cumulative abnormal return of firm $i$ between the from date and to date inclusive. $sp500_i$ is a dummy which takes the value 1 if the firm is listed on the S&P 500 index at the time of listing/de-listing. We add fixed effects $\gamma$ for year and $\delta$ for two digit NAICS code. Within our data there are 247 listings and 89 de-listings. Of these the number of non-S&P 500 members is 46 and 17 respectively. Table 3.5 presents our results for both listing and delisting.

Figure 3.3 plots CARs based upon the gsynth estimations as a thick solid line. We use dashed lines for firms which were members of the S&P 500 one month prior to the

Table 3.5: S&P 500 Membership and DJSI Listing/De-listing Effects

| | From | -15 | -11 | -6 | -1 | ANN | ANN | ANN | ANN | ANN | EFF | EFF | EFF |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | To | ANN | ANN | -1 | 1 | 1 | 2 | 3 | 4 | EFF | 10 | 15 | 20 |
| Panel (a): Listing t-tests | | | | | | | | | | | | | |
| S&P 500 | | 0.099 | 0.194 | -0.279 | 0.302 | 0.244 | 0.408 | 0.633 | 0.489 | 0.310 | -0.179 | -0.152 | -0.022 |
| | | (0.335) | (0.793) | (1.396) | (2.274) | (2.287) | (2.998) | (3.503) | (2.471) | (1.696) | (0.877) | (0.431) | (0.052) |
| Non-S&P 500 | | 2.594 | 1.286 | 0.346 | 0.187 | 0.285 | 0.154 | 0.109 | -0.052 | 0.210 | -0.449 | -1.526 | -1.494 |
| | | (2.340) | (1.477) | (0.608) | (0.610) | (0.992) | (0.446) | (0.283) | (0.112) | (0.417) | (0.612) | (1.384) | (1.160) |
| Diff | | -2.495 | 1.092 | 0.825 | 0.115 | -0.041 | 0.254 | 0.524 | 0.541 | 0.100 | 0.270 | 1.374 | 1.472 |
| | | (2.174) | (1.208) | (1.036) | (0.342) | (0.132) | (0.683) | (1.237) | (1.080) | (0.805) | (0.354) | (1.187) | (1.085) |
| Panel (b): Listing fixed effect regressions | | | | | | | | | | | | | |
| S&P 500 | $\beta$ | -2.224 | -1.267 | -0.991 | -0.200 | -0.025 | 0.324 | 0.944 | 0.728 | 0.386 | 0.174 | 1.594 | 1.384 |
| | | (3.060) | (1.801) | (1.922) | (0.631) | (0.049) | (0.510) | (1.591) | (1.451) | (0.623) | (0.271) | (1.580) | (1.559) |
| R-squared | $R^2$ | 0.142 | 0.096 | 0.074 | 0.084 | 0.070 | 0.061 | 0.075 | 0.067 | 0.057 | 0.047 | 0.071 | 0.107 |
| Panel (c): De-listing t-tests | | | | | | | | | | | | | |
| S&P 500 | | 0.894 | 1.153 | 0.115 | 0.146 | 0.259 | 0.251 | 0.315 | 0.027 | -0.045 | -0.228 | -0.203 | -0.023 |
| | | (2.006) | (2.905) | (0.422) | (0.980) | (1.730) | (1.427) | (1.471) | (0.096) | (0.137) | (0.608) | (0.415) | (0.046) |
| Non-S&P500 | | -1.272 | -0.884 | -0.445 | 0.122 | -0.081 | 0.216 | 0.234 | 0.098 | -0.022 | -0.874 | -0.255 | -2.233 |
| | | (1.247) | (1.209) | (0.762) | (0.261) | (0.270) | (0.478) | (0.431) | (0.165) | (0.033) | (1.467) | (0.341) | (1.273) |
| Diff | | 2.166 | 2.037 | 0.560 | 0.268 | 0.340 | 0.035 | 0.081 | 0.071 | -0.023 | 0.646 | 0.052 | 2.210 |
| | | (1.946) | (2.449) | (0.871) | (0.048) | (1.014) | (0.071) | (0.137) | (0.109) | (0.031) | (0.915) | (0.131) | (1.213) |
| Panel (d): De-listing fixed effect regressions | | | | | | | | | | | | | |
| S&P 500 | | 2.002 | 1.882 | 0.795 | -0.022 | 0.360 | -0.210 | -0.097 | 0.003 | 0.208 | 1.411 | 1.251 | 3.158 |
| | | (1.761) | (1.511) | (0.969) | (0.042) | (0.791) | (0.384) | (0.152) | (0.000) | (0.221) | (2.522) | (1.222) | (1.387) |
| R-squared | $R^2$ | 0.116 | 0.092 | 0.070 | 0.231 | 0.147 | 0.136 | 0.203 | 0.152 | 0.223 | 0.236 | 0.296 | 0.187 |

Notes: Table presents results from t-tests that the cumulative abnormal returns (CAR) from the generalised synthetic control model are equal to zero for members, and non-members, of the Standard and Poor 500 (S&P 500) index as well as a test for the joint equality of cumulative abnormal returns between S&P 500 members and non-members. CAR represents sum of returns between the from and to day inclusive. ANN is the announcement day (0) and EFF is the day changes become effective. Regressions are estimated using $CAR^G_{i,from,to} = \alpha + \beta sp500_i + \gamma + \delta + \epsilon_i$ in which $CAR_{i,from,to}$ is the cumulative abnormal return of firm $i$ between the from date and to date inclusive, $sp500_i$ is a dummy which takes the value 1 if the firm is listed on the S&P 500 index at the time of listing/de-listing, $\gamma$ are year fixed effects and $\delta$ are two digit NAICS code fixed effects. Figures in parentheses report absolute t-statistics for joint equality of the mean CAR to zero, or $\beta = 0$, for t-test and regressions under heteroskedasticity robust standard errors panels respectively. $\alpha$ estimates for the fixed effects regressions are surpressed for brevity. There are 247 listing firms of which 46 are non-S&P 500 members. There are 89 de-listing firms of which 17 are non-S&P 500 members.

listing announcement. For those which were not members of the S&P 500 one month prior to the announcement we use a thin solid line. In both cases the performance of the S&P 500 members tracks closer to the overall average, whilst the other firms diverge greatly. Panel (a) helps visualise the importance of the non-S&P 500 in shaping the overall response. We see the overall average suggests larger effects than the S&P 500 members. However, this higher average is not statistically significant. Similar patterns are observed in the de-listing case. For those firms on the S&P 500 the effect is larger and the non-S&P500 is pulling the overall effect down. Three inferences may be taken from these plots. Firstly, investors in the S&P 500 are consistent with the traditionalist perspective on de-listing. However, in Table 3.5 the listing results for S&P 500 members show that being recognised for focus on sustainability brings a small and persistent increase in firm value, rather than the short-lived increase seen for non-S&P 500 stocks. Secondly, the non-S&P 500 firm increase pre-announcement and subsequent correction suggests that much of the effect is not due to DJSI listing. Three weeks after the announcement there is little separating non-S&P 500 firms from S&P 500 firms in their reactions. Finally, lower effects are more consistent with investors already being informed about the activities that lead to listing, or de-listing. The greater analyst coverage of S&P 500 firms supports this (Chen et al., 2004). These are important consistencies that were not previously picked out in the literature.

### 3.6.2 Post-Crisis Period

Reviewing the impact of the global financial crisis on DJSI recomposition effects, we now focus attention on a sub-sample of data from 2010 to 2018. The first observation in the control period is 1st November 2009 and the last observation in the final control period is mid-October 2018. These dates follow those used in Durand et al. (2019). For the reduced sample we then perform the same analysis of the gsynth results alongside two-sample t-tests and regressions on the CARs generated by the market model.

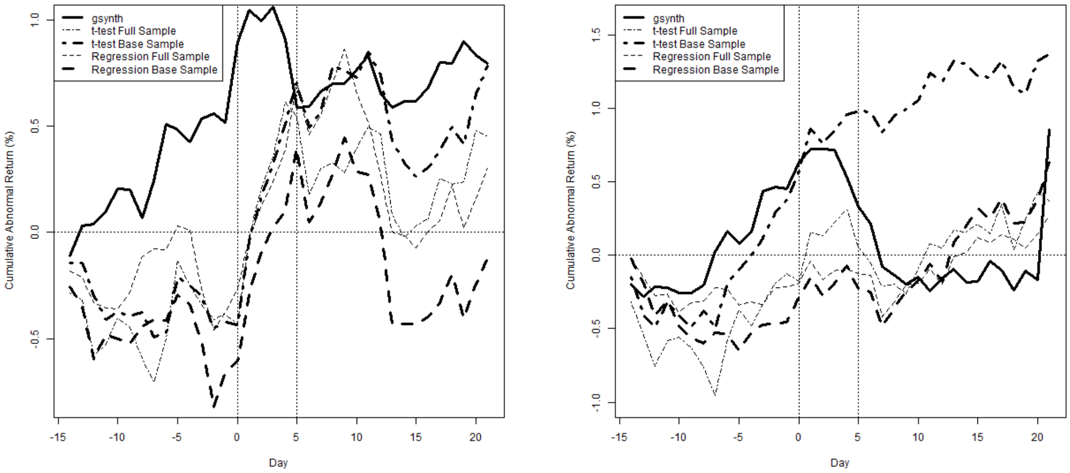
Figure 3.4 possesses many similarities with Figure 3.2. Panel (a) shows the strongest alignment to the main results. Prior to the announcement there is a stronger positive CAR than is seen over the full sample. The magnitude of the persistent CAR is around 3 basis points higher. Estimates from the other approaches also reveal stronger positive returns from the announcement date onwards. In the graph this appears as more positive CARs from around day 2 onwards. Although no other methods show the persistence of the gsynth result, the two-sample t-test does yield consistently positive CARs in the post-crisis period.

Table 3.6: DJSI Listing/De-listing Effects

| | From | -15 | -11 | -6 | -1 | ANN | ANN | ANN | ANN | ANN | EFF | EFF | EFF |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | To | ANN | ANN | -1 | 1 | 1 | 2 | 3 | 4 | EFF | 10 | 15 | 20 |
| Panel (a): Listing | | | | | | | | | | | | | |
| gsynth | F | 0.896 | 0.796 | 0.010 | 0.488 | 0.528 | 0.477 | 0.546 | 0.393 | 0.071 | -0.141 | -0.293 | -0.078 |
| | | (2.061) | (2.592) | (0.049) | (0.871) | (3.747) | (3.030) | (2.885) | (1.647) | (0.273) | (0.530) | (0.293) | (0.185) |
| t-test | F | -0.021 | 0.507 | 0.071 | 0.597 | 0.642 | 0.786 | 1.041 | 0.979 | 0.606 | -0.053 | -0.485 | -0.099 |
| | | (0.047) | (1.301) | (0.229) | (3.009) | (4.342) | (4.086) | (4.638) | (3.496) | (1.965) | (0.158) | (0.140) | (01.96) |
| t-test | B | -0.040 | 0.372 | 0.039 | 0.590 | 0.601 | 0.757 | 0.947 | 1.138 | 0.926 | 0.146 | -0.397 | 0.080 |
| | | (0.294) | (0.930) | (0.124) | (2.921) | (3.979) | (3.868) | (4.135) | (3.993) | (2.949) | (0.428) | (0.921) | (0.157) |
| Regression | F | -0.033 | 0.322 | -0.182 | 0.504 | 0.391 | 0.504 | 0.648 | 0.978 | 0.722 | -0.191 | -0.707 | -0.411 |
| | | (0.046) | (0.516) | (0.400) | (1.596) | (1.488) | (1.541) | (1.739) | (2.258) | (1.555) | (0.407) | (1.152) | (0.532) |
| Regression | B | -0.294 | 0.186 | -0.190 | 0.560 | 0.511 | 0.629 | 0.706 | 1.002 | 0.654 | -0.128 | -0.795 | -0.517 |
| | | (0.450) | (0.314) | (0.433) | (2.153) | (2.358) | (2.317) | (2.238) | (2.675) | (1.640) | (0.347) | (1.590) | (0.800) |
| Panel (b): De-listing | | | | | | | | | | | | | |
| gsynth | F | 0.631 | 0.852 | 0.286 | 0.257 | 0.270 | 0.271 | 0.267 | 0.079 | -0.118 | -0.679 | -0.707 | -0.699 |
| | | (1.607) | (2.390) | (1.104) | (1.579) | (1.852) | (1.627) | (1.255) | (0.310) | (0.388) | (1.754) | (1.389) | (1.224) |
| t-test | F | 0.157 | 0.737 | 0.396 | 0.261 | 0.316 | 0.404 | 0.494 | 0.237 | 0.129 | 0.023 | 0.092 | 0.309 |
| | | (0.327) | (1.684) | (1.272) | (1.226) | (1.654) | (1.894) | (2.047) | (0.860) | (0.387) | (0.076) | (0.259) | (0.718) |
| t-test | B | 0.858 | 1.177 | 0.755 | 0.384 | 0.183 | 0.273 | 0.383 | 0.405 | 0.404 | 0.260 | 0.229 | 0.385 |
| | | (1.732) | (2.621) | (2.361) | (1.764) | (0.944) | (1.254) | (1.547) | (1.430) | (1.184) | (0.043) | (0.631) | (0.867) |
| Regression | F | -0.039 | 0.226 | 0.041 | 0.050 | 0.026 | 0.089 | 0.097 | 0.067 | 0.057 | 0.031 | 0.211 | 0.401 |
| | | (0.047) | (0.316) | (0.078) | (0.136) | (0.086) | (0.237) | (0.225) | (0.135) | (0.107) | (0.059) | (0.299) | (0.452) |
| Regression | B | -0.150 | 0.153 | 0.254 | 0.174 | 0.004 | 0.095 | 0.216 | 0.052 | 0.032 | 0.175 | 0.481 | 0.868 |
| | | (0.202) | (0.241) | (0.533) | (0.589) | (0.018) | (0.309) | (0.574) | (0.122) | (0.068) | (0.420) | (0.834) | (1.181) |

Notes: Table presents estimated listing effects for firms joining the DJSI as estimated by the generalised synthetic control (gsynth) approach of Xu (2017). Portfolio weights are constructed for the control period, 1st November in the year prior to the considered recomposition through to 16 days before the announcement of the new DJSI list. For comparison the market model, $r_{it} = \alpha_i + \beta_i MKT_t$, is again estimated for the control period. Abnormal returns are defined as $AR_{it} = r_{it} - \hat{\alpha_i} - \hat{\beta_i} MKT_t$, where $t$ is in the treatment period. Models are estimated for the full sample (F) and for a base sample (B) in which only firms whose size is at least 80% of the smallest listing firm in the same industry are included. Control firms are only included if there is a DJSI listing from their industry in the given year. Industries are defined by two digit NAICS codes. t-test denotes a t-test that the mean abnormal return for listing firms is equal to that for non-listing firms with the figure reported being the difference. Regression refers to the regression of the cumulative abnormal return on a listing dummy and a set of controls identified in Acemoglu et al. (2016). Formally we report $\delta$ from the regression of abnormal returns on size (log assets), profit (return on equity, roe) and leverage, with each entering up to cubically, under fixed effects on year, $\gamma$ and industry, $\delta$:
$CAR_{i,from,to} = \alpha + \delta DJSI_{it} + \beta_1 size_i + \beta_2 size_i^2 + \beta_3 size_i^3 + \beta_4 roe_i + \beta_5 roe_i^2 + \beta_6 roe_i^3 + \beta_7 leverage_i + \beta_8 leverage_i^2 + \beta_9 leverage_i^3 + \gamma + \delta + \epsilon_{it}$.
Figures are the coefficient on the listing dummy and associated t-statistic from a test that the true coefficient is equal to zero.

Figure 3.4: DJSI Listing and Delisting Effects




(a) Listing (b) De-listing

Notes: Plots show cumulative abnormal returns (CARs) gained between the first day of the treatment period, -15, and the date given on the horizontal axis, $x$. Vertical lines indicate the announcement on day 0 and the effective date on day 5. A solid line plots $CAR^G_{-15,x}$ as the estimate of the listing effect. For the market model CARs dot-dash lines are used for the two-sample t-tests, and dashed lines report the regression coefficients $\omega$ from the estimation of $CAR_{i,-15,x} = \alpha + \omega DJSI_{it} + \beta_1 size_i + \beta_2 size_i^2 + \beta_3 size_i^3 + \beta_4 roe_i + \beta_5 roe_i^2 + \beta_6 roe_i^3 + \beta_7 leverage_i + \beta_8 leverage_i^2 + \beta_9 leverage_i^3 + \gamma + \delta + \epsilon_{it}$ under year, $\gamma$, and industry fixed effects $\delta$. A base sample of firms with log assets at least 80% of those of the smallest DJSI listing, or de-listing, firm from the given industry year is created to better reflect the large size of DJSI members. Base sample market model effects are shown as thicker lines to contrast with thinner lines for the full sample. The plot only considers industry-year pairs relating to the 2010 announcement or later as a post-crisis period.

In the de-listing results we see that the persistence of CARs from the gsynth model has gone, $CAR_{1,x}$ values being negative from day 10 onwards. Positive returns follow because increased future cashflow post de-listing means a higher valuation for the share. Since 2010 it can be seen that this traditionalist perspective no longer dominates. The post 2010 results imply that a growing proportion of investors see DJSI membership as being a better indicator of future revenue for the firm.

In the literature on S&P 500 listing, persistent higher returns were seen as the result of a combination of information, liquidity and analyst coverage. Whilst undoubtedly the CSR actions of the firm require coverage, there is little additional analyst time associated with social stocks. Any correlation between DJSI membership and analyst coverage is more likely to be from the high correlation between DJSI firms and S&P 500 membership. Liquidity is a plausible channel for persistence given the increase in green credit, but the market value link to liquidity is liable to come from the increased trading in the stock. Therefore we argue that the results on persistence are the consequence of the increased informational content of the message that the firm is an industry leader on CSR. This evaluation of the post-crisis period has shown that both the persistence of price effects, and returns to sustainable conduct, have increased.

## 3.7 Discussion

This paper has showcased how generating benchmark portfolios from a firm's industry casts stronger light on the impact of changing status on the DJSI North America. Our contribution is made to a literature where results had been inconclusive. The literature also features heterogeneity on the best way to capture listing effects. Inspired by insights from studies of the S&P 500 listing and de-listing, we set out to evaluate which of the competing listing hypotheses best explains DJSI changes. We have shown strong pre-announcement upward movements in stock returns that are consistent with interested investors acquiring information on likely listings ahead of the formal announcement of new members. These effects are far stronger for firms not listed on the S&P 500. Further, since the global financial crisis ended in 2009, the renewed importance of CSR may be evidenced in stronger DJSI listing effects. All of these results were derived in a way which is robust to industry shocks and preserves the advantages of the past approaches to which our results are compared.

Denis et al. (2003) and Chen et al. (2004) are proponents of the belief that listing to the S&P 500 conveys information about the likely improved financial performance of the joining firm. It is argued that the panel that determines membership would not admit a firm if it was not felt its ongoing performance would be worthy of a place. Accounting data and stock performance are publically accessible, but forecasting accurately from that data is difficult. Investors would like to see any guide to help predict the future performance of the stock. Information on social responsibility is different because there is a lag between the firm investing capital and that capital producing impact on the CSR performance of the firm. There is then a further lag before that impact on CSR appears as returns to the capital originally employed by the firm. As such any investor interested could find out about what steps firms are taking to improve their CSR performance well in advance of DJSI recognition. This timeline makes pre-announcement effects very possible. However, the timeline does not rule out the information hypothesis since many investors would also await the announcement. By waiting for the announcement investors avoid the costs of checking for genuine CSR activities amongst the general activity of the firm. Kappou and Oikonomou (2016) thus continue to see the information hypothesis as being the driving factor of DJSI listing effect results.

In our analysis we evidence an additional interpretation for the first time. We are able to align our results more clearly with the shadow cost hypothesis of Chen et al. (2004). Shadow costs represent the costs of obtaining additional information about firms. Greater analyst coverage means lower shadow costs. For firms on the S&P 500 there is strong analyst coverage meaning listing to the S&P 500 creates greater scrutiny for managers and incenitivises firms to act in the best interest of shareholders (Chen et al., 2004). When an S&P 500 company is being rewarded for their CSR activity through DJSI recognition, that listing would come long after analysts had covered the initial CSR investment and impact. Listings would not surprise most investors. Listing effects would therefore be much smaller. We show that this holds in our gsynth effects. Persistence in the listing effects evidence that there is still a value improving impact of DJSI recognition. However, for non S&P 500 firms there would not have been the same coverage of the CSR investment. Many investors may not be aware of the CSR performance of these firms until seeking out opportunities to profit from DJSI reconstitution. Large CARs are short-lived with a correction effect post-listing that is consistent with a reaction to information, rather than a change in the valuation of the smaller firms. Our evidence provides strong support to this information interpretation.

Shleifer (1986) proposes the price pressure hypothesis to argue that investors would look to buy firms listing to the S&P 500 ahead of the many funds which track the index. These investors add demand to the market. Although there are fewer funds tracking the DJSI than the S&P 500, that additional demand from funds when changes become effective remains. With analyst coverage giving low shadow costs, investors have the ability to take advantage of any price pressure from the ESG funds. The small positive abnormal returns shown for S&P 500 firms are entirely consistent with past listing effect results. The higher shadow costs associated with finding information about non-S&P 500 firms suggests high rewards to those investors who can identify which stocks will gain DJSI listing. As investors identify likely listing firms, pre-announcement effects come through in the stock returns. Likewise, for those stocks which de-list, investors would look to identify which firms would exit the DJSI to minimise the loss when fund demand is withdrawn. Pre-announcement effects would therefore be stronger for non-S&P 500 stocks. Although interest in ESG funds is rising, the price pressure hypothesis is not yet driving DJSI listing, and de-listing, effects.

Our work contradicts Hawn et al. (2018) and Durand et al. (2019) in showing that there are strong effects outside of the immediate event window. We show the strength of those effects are confined to the gsynth results, pre-announcement in particular. The market model based measures do not produce such persistence. Persistence has clear implications for our understanding of investor behaviour around DJSI recompositions. As the evidence base grows it will be possible to extract more on the factors behind the differentials. Durand et al. (2019) takes steps in this direction with an analysis of analyst coverage as well as stock returns. Our evidence suggests that extending beyond the market model is also useful to understand the true role analyst coverage plays. Given the strong advantages of gsynth, the new insight from this paper casts important light on the channels from the existing listing effects literature through which DJSI listing effects operate.

Sustainable investment is becoming more integral to the market landscape. Trends towards increased listing effects are identified in the time trends of Hawn et al. (2018). Durand et al. (2019) also find increasing effects over time of the kind seen here. That importance brings increased coverage, further indexes and more public data reporting. Though such may not be evidenced in the data it is instructive to note that the market is increasingly recognising the importance of CSR to firms' longer term performance. There is a stronger persistence to the positive abnormal returns to being a DJSI member. Our results extend the appreciation of how listing effects, and DJSI listing effects in particular, may be captured and better appraised under industry robustness.

## 3.8 Conclusion

Despite the growing importance of CSR in the financial landscape, little is truly understood about the channels through which recognition as an industry leader affects stock returns. Employing a novel synthetic control approach we compare how the performance of a stock which gains, or loses, recognition performs relative to its peers. Those control stocks are taken from the same industry and are weighted into a portfolio that matches as closely as possible the returns of the listing, or de-listing, firm during a control period. Ours is the first study with such a portfolio approach to allow multiple listings or de-listings from the same industry in the same year. We add this multi-listing capability by taking advantage of the evolution from the synthetic control method of Abadie and Gardeazabal (2003) and Abadie et al. (2010) into the gsynth approach of Xu (2017). In synthetic control methods the listing effect is then simply the observed return less the return to the synthetic portfolio. The synthetic portfilio represents how the stock would have continued to perform if its DJSI status did not change. With any industry shocks impacting the treated stock and the synthetic portfolio in similar ways, calculating the abnormal returns in this way has important robustness to industry shocks.

We show longer persistence of effects than would be identified under previously employed empirical approaches on the same data. Over time this persistence is increasing and the returns to understanding which firms will be recognised for CSR leadership are growing. This is our second contribution and is made possible by the synthetic control. Under the industry shock robustness, we show strong pre-announcement effects, particularly for firms outside the S&P 500. It is these firms, outside of the S&P 500 for whom information is given less scrutiny. That reduced scrutiny creates opportunities for investors do to their own research and profit ahead of the listing. We show the value of researching which stocks may enter the DJSI is increasing in line with the ever growing magnitude of positive DJSI listing effects. Although there are strong pre-announcement effects in non-S&P 500 stocks, these gains are short-lived and there is an almost equally large correction effect post-listing. Following the correction there is little long-term valuation change for smaller firms. Overall, our results indicate small positive and persistent rewards to listing, and short-term opportunities for investors who research the CSR activities of non-S&P 500 firms.

Natural limitations in our work stem from the still comparatively low number of listings and de-listings, and the inability to extract investor sentiment from observed market demand. Our work may thus not assign the factors behind observed differences between the results of the different event study methodologies. Regressions and t-test approaches offer a ready estimate of statisical significance. However, the gsynth estimates do not have a natural uncertainty estimate when computed for different event times and control sets. Overcoming this limitation in the reporting will add economic weight to the gsynth estimates. Through our analysis of the post-crisis period, we take steps to capture time variation in the abnormal returns to DJSI listing. However, the limited number of listings and de-listings limit the amount of statistical significance to be taken from the estimates once again. The gsynth approach allows for the consideration of covariates in the matching process. However, any covariates must have time variance and the controls typically used by the event study literature do not, accounting data being annual. Obtaining time varying controls offers potentially useful extension to our work. The limitations discussed herein highlight that there is much which additional data could offer to advance our work. Useful extensions to global sustainability listings, or exploration of listing effects to other non sustainability indexes using gsynth may be made. Robustness to industry shocks in this paper comes from the limitation of control firms to be in the same industry as the listing firm. However, the control set can be limited in other ways; the same advantage of being able to control for any shock which disproportionately affects the listing firm and the selected controls remains. A question of interest here would be to use firms with similar ESG performance as the controls and then use the identified listing effects as also capturing the investor recognition effect of the DJSI. Notwithstanding these challenges, this paper does take significant strides in providing robust estimation of the DJSI listing effects. We produce results that provide a consistent narrative on the events surrounding listing.

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# Appendices

## A3.1 Numbers of Listings and De-Listings

Exposition in the main paper is necessarily brief on the numbers of firms listing to, or being de-listed from, the DJSI in each industry-year combination. However, to understand more of what the models we apply are doing it is helpful to see a full listing of all of the numbers of firms that do list, or de-list, and the number of other firms in that industry year that are candidate stocks for the synthetic portfolio.

In any given year the number of treated observations can vary, and many industries will not feature amongst either the newly listed set, or the de-listed set. Two digit NAICS codes, and the number of entering firms therefrom, are reported in Tables A3.1 and A3.2. Table A3.1 reports the numbers for listings (L), whilst Table A3.2 provides numbers for de-listings (D). In each case the number of control firms is given by C. For the univariate and regression approaches these numbers do not present a challenge, but for the generation of counterfactual versions of listed shares the numbers in $L$, or $D$ are important. The original synthetic control method of Abadie et al. (2010) allows for only one treated unit. It is clear from Tables A3.1 and A3.2 that many year-industry pairs have more than one entrant or exiting firm. In this case we cannot ignore the potential impact that the other newly listed firm might have upon any other firm gaining DJSI listed status. Likewise effects of other de-listed firms also require control. Hence there is a call for a methodology that is robust to such diversity of treated unit profiles; Xu (2017) employed in the main paper meets this call.

## A3.2 Comparison with Event Studies

Within the main paper we contrast the gsynth results with traditional event study approaches. For brevity the details of these established means of assessing listing effects are moved to this appendix. Here we work systematically through both the t-test and regression approaches for identifying listing effects. We first look at the full

Table A3.1: Treatment and Control Numbers for Listing

| | | NAICS 2-Digit Industry Code | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 21 | 22 | 23 | 31 | 32 | 33 | 42 | 44 | 45 | 48 | 51 | 52 | 53 | 54 | 56 | 62 | 72 | Total |
| Panel A: Listings | | | | | | | | | | | | | | | | | | | |
| 2005 | L | 1 | 6 | 1 | 3 | 8 | 9 | | 4 | 1 | 1 | 4 | 7 | | 2 | 1 | | 1 | 49 |
| | C | 129 | 99 | 31 | 105 | 318 | 661 | | 89 | 53 | 89 | 285 | 535 | | 112 | 57 | | 62 | 2625 |
| 2006 | L | 2 | 4 | | 1 | 3 | 1 | 1 | | | | 1 | 3 | | | | | | 16 |
| | C | 140 | 104 | | 109 | 327 | 683 | 82 | | | | 301 | 540 | | | | | | 2286 |
| 2007 | L | 1 | 1 | | | | 2 | | | 1 | | 1 | 3 | | 1 | | 1 | | 11 |
| | C | 162 | 106 | | | | 694 | | | 49 | | 318 | 517 | | 114 | | 52 | | 2012 |
| 2008 | L | 1 | 2 | | 1 | 1 | 2 | | | 1 | | 1 | 2 | 2 | | 1 | | | 14 |
| | C | 145 | 100 | | 104 | 282 | 573 | | | 34 | | 256 | 440 | 156 | | 51 | | | 2141 |
| 2009 | L | 1 | 2 | | 1 | 4 | 2 | 2 | 1 | 1 | 1 | 1 | 3 | | 1 | | | | 20 |
| | C | 119 | 100 | | 88 | 221 | 430 | 60 | 60 | 26 | 84 | 204 | 353 | | 87 | | | | 1832 |
| 2010 | L | 3 | 2 | | | 4 | 3 | | | | | 1 | | | 2 | 1 | | | 16 |
| | C | 141 | 106 | | | 274 | 572 | | | | | 248 | | | 111 | 46 | | | 1498 |
| 2011 | L | | 1 | | 1 | 1 | 4 | | 1 | 1 | 2 | | 3 | 1 | | 1 | | 1 | 17 |
| | C | | 105 | | 104 | 273 | 577 | | 80 | 33 | 88 | | 462 | 178 | | 49 | | 47 | 1996 |
| 2012 | L | | 1 | | 2 | 2 | 2 | | | 1 | | 3 | 1 | | 1 | 1 | | | 14 |
| | C | | 98 | | 107 | 275 | 574 | | | 36 | | 263 | 499 | | 107 | 48 | | | 2007 |
| 2013 | L | 2 | | | 2 | 4 | 4 | | 2 | | | 3 | 2 | 3 | 1 | | | | 23 |
| | C | 152 | | | 112 | 293 | 587 | | 83 | | | 287 | 542 | 191 | 103 | | | | 2350 |
| 2014 | L | | 2 | 2 | | 1 | 3 | | | | 1 | 2 | 2 | 1 | | | | 1 | 15 |
| | C | | 100 | 46 | | 349 | 637 | | | | 119 | 322 | 591 | 220 | | | | 58 | 2442 |
| 2015 | L | | | 1 | | 3 | 1 | | | | | 1 | 1 | 2 | | | | 1 | 10 |
| | C | | | 43 | | 392 | 599 | | | | | 333 | 392 | 217 | | | | 61 | 2037 |
| 2016 | L | | | | 2 | 1 | 2 | | 1 | | | 1 | 3 | 2 | | 1 | | | 13 |
| | C | | | | 105 | 381 | 560 | | 81 | | | 329 | 564 | 223 | | 53 | | | 2296 |
| 2017 | L | 2 | 1 | | 2 | 2 | 3 | 1 | | | 1 | 2 | 2 | 2 | 1 | | | 2 | 21 |
| | C | 121 | 99 | | 106 | 388 | 576 | 95 | | | 115 | 330 | 608 | 224 | 88 | | | 62 | 2812 |
| 2018 | L | 1 | | | | 2 | 2 | | | | | | 2 | | | 1 | | | 8 |
| | C | 103 | | | | 221 | 401 | | | | | | 429 | | | 28 | | | 1182 |

Notes: Numbers represent the number of firms included in the full sample for the estimation of cumulative abnormal returns. L is used in Panel A to denote the number of firms joining the DJSI in the given year. C denotes the numbers of controls. Totals are provided for each year. 2005 has more joining firms because this was the year that the DJSI North America was formed and numbers of listed firms in North America thus increased to populate the regional list. Numbers reflect those industry-years for which there is sufficient share price data, and for which assets are listed for the preceding financial year.

Table A3.2: Treatment and Control Numbers for De-Listing

| | | NAICS 2-Digit Industry Code | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 21 | 22 | 23 | 31 | 32 | 33 | 42 | 44 | 45 | 48 | 51 | 52 | 53 | 54 | 56 | 62 | 72 | Total |
| 2006 | D | | 2 | | 1 | | 2 | | | | | 2 | 2 | | | | | | 9 |
| | C | | 106 | | 109 | | 682 | | | | | 300 | 541 | | | | | | 1738 |
| 2007 | D | | | | | | | | | | | 1 | 2 | | | | | | 3 |
| | C | | | | | | | | | | | 318 | 518 | | | | | | 836 |
| 2008 | D | | | | | 1 | 1 | | | | | 1 | | | | | | | 3 |
| | C | | | | | 282 | 574 | | | | | 256 | | | | | | | 1112 |
| 2009 | D | | | | | 1 | 1 | | | | | | 1 | | | | | | 3 |
| | C | | | | | 224 | 431 | | | | | | 355 | | | | | | 1010 |
| 2010 | D | | | | | 4 | 2 | | | | | 1 | | | | 1 | | | 8 |
| | C | | | | | 274 | 573 | | | | | 248 | | | | 46 | | | 1141 |
| 2011 | D | | | | | | | | | | | | 1 | | | 1 | | | 2 |
| | C | | | | | | | | | | | | 464 | | | 49 | | | 513 |
| 2012 | D | | 2 | | | 2 | 4 | | | 2 | | 2 | 1 | | 2 | | | | 15 |
| | C | | 97 | | | 275 | 573 | | | 35 | | 264 | 499 | | 106 | | | | 1849 |
| 2013 | D | | | | 1 | 5 | 3 | | 1 | | | | 3 | | | | | | 13 |
| | C | | | | 113 | 292 | 588 | | 84 | | | | 541 | | | | | | 1618 |
| 2014 | D | | | | | 1 | | | | | | 1 | | | | | | 1 | 3 |
| | C | | | | | 349 | | | | | | 323 | | | | | | 58 | 730 |
| 2015 | D | | | 1 | 1 | | 4 | | | | | | 1 | 1 | | | | | 8 |
| | C | | | 43 | 106 | | 596 | | | | | | 592 | 218 | | | | | 1555 |
| 2016 | D | | | | 1 | 1 | 2 | | | | | | 1 | | | 1 | | | 6 |
| | C | | | | 106 | 381 | 560 | | | | | | 516 | | | 53 | | | 1616 |
| 2017 | D | 3 | | | 2 | 1 | 1 | | | | | 1 | 1 | 1 | | | | | 10 |
| | C | 120 | | | 106 | 389 | 578 | | | | | 331 | 609 | 225 | | | | | 2358 |
| 2018 | D | | | | 2 | 2 | | | | | | | 2 | | | | | | 6 |
| | C | | | | 57 | 221 | | | | | | | 429 | | | | | | 707 |

Notes: Numbers represent the number of firms included in the full sample for the estimation of cumulative abnormal returns. D is used to denote the number of de-listings in a given year. C denotes the numbers of controls. Totals are provided for each year. 2006 is the first year for de-listing because the Dow Jones Sustainability Index began in 2005 and therefore no firms could be de-listed any earlier than 2006. Numbers reflect those industry-years for which there is sufficient share price data, and for which assets are listed for the preceding financial year.

dataset in more detail. Next, we explain the sample that features only larger firms. Construction of the abnormal returns and evaluation of the model are then the focus of the third section. A first means of identifying the listing effect is to perform t-tests of returns between listing firms and others. We present results of these t-tests in the fourth subsection. Acemoglu et al. (2016) proposes a regression specification through which listing effects may be accurately defined. Our fifth subsection discusses this.

### A3.2.1 Full Dataset

Descriptive statistics in Table A3.3 remind just how few firms obtain listing within any given year; just 0.8% of all observations represent listings. Focusing only on larger firms in Panel B that figure rises to 4.7%, but this is still low relative to the overall volume of data. Rows (2) to (4) provide some statistics for three key firm characteristics. Size, measured as the log of total assets, does indeed have a wide distribution in the full sample as log assets range from 2 to 15. Controlling for this diversity is the motivation for the adoption of a base sample which has a much higher average and a minimum value close to the median of the full sample. Row (14) of Panel C confirms the DJSI firms are indeed much larger than the average non-DJSI firm. Profitability, captured as the return on equity, in rows (3) and (12), is also wide ranging with a number of firms reporting losses in both samples. Once the requirement that non-listing firms have a log asset value at least 80% of that of the smallest listing firm is imposed the minimum ROE is much larger. Leverage also has a smaller range amongst the largest firms. Comparison of means on rows (4) and (13) verify this pattern.

Focus in this paper is on the abnormal returns, if any, gained when entering the DJSI. For this purpose CAR are used, calculated using (3.21). For the full sample, rows (5) to (9) give values for five periods of interest. From the start of the treatment period to announcement date, days 1 to 16, we note a small positive abnormal return of 0.115% amongst the whole sample. From the first day to the effective day this average has increased to 0.144%. Within the week from announcement date to the effective date there are thus positive abnormal returns to be had. Row (7) shows these to be 0.083%. Looking at periods beginning on the two key listing dates, announcement on day 16 and effective on day 21, to the end of the sample the CARs are -0.047% and -0.180% on average. From the positive pre-announcement and negative post effective date in particular we see much of the pre-announcement and correction effects discussed within the literature. As these figures contain all firms they remind that there will be many more stories behind the results, and that it is not possible to attribute all of these

Table A3.3: Descriptive Statistics

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Summary Statistics for Full Sample (Listing) | | | | | | | | | |
| | | Mean | Min | 25th pctile | Median | 75th pctile | Max | St. dev. | *N* |
| (1) | DJSIE | 0.008 | 0.000 | 0.000 | 0.000 | 0.000 | 1 | 0.089 | 23952 |
| (2) | Size | 7.392 | 1.548 | 6.053 | 7.284 | 8.535 | 14.76 | 1.850 | 23592 |
| (3) | Profitability | 0.088 | -11.71 | 0.045 | 0.101 | 0.167 | 13.65 | 7.003 | 22458 |
| (4) | Leverage | 0.432 | -24.78 | 0.150 | 0.391 | 0.651 | 11.55 | 0.536 | 23291 |
| (5) | CAR[1,16] | 0.115 | -89.18 | -4.146 | -0.324 | 3.743 | 128.1 | 8.795 | 23592 |
| (6) | CAR[1,21] | 0.144 | -81.00 | -4.735 | -0.261 | 4.422 | 120.0 | 9.963 | 23592 |
| (7) | CAR[16,21] | 0.083 | -94.76 | -2.252 | -0.025 | 2.331 | 126.2 | 5.182 | 23592 |
| (8) | CAR[16,36] | -0.047 | -112.1 | -4.823 | 0.060 | 4.906 | 151.7 | 10.42 | 23592 |
| (9) | CAR[21,36] | -0.180 | -97.76 | -4.218 | -0.027 | 4.053 | 165.4 | 9.073 | 23592 |
| Panel B: Summary Statistics for Base Sample (Listing) | | | | | | | | | |
| (10) | DJSIE | 0.047 | 0.000 | 0.000 | 0.000 | 0.000 | 1 | 0.197 | 4020 |
| (11) | Size | 9.728 | 6.617 | 8.678 | 9.556 | 10.54 | 14.76 | 1.552 | 4020 |
| (12) | Profitability | 0.142 | -2.115 | 0.068 | 0.123 | 0.196 | 5.279 | 0.228 | 3888 |
| (13) | Leverage | -0.180 | -13.38 | 0.352 | 0.504 | 0.724 | 8.369 | 0.405 | 3949 |
| Panel C: Univariate sample comparisons (Listing) | | | | | | | | | |
| | | Full Sample | | | | | Base Sample | | |
| | | List | Other | Diff. | | | List | Other | Diff. |
| (14) | Size | 10.02 | 7.370 | 2.650*** | | Size | 10.02 | 9.713 | 0.307** |
| (15) | Profitability | 0.196 | 0.087 | 0.109*** | | Profitability | 0.196 | 0.139 | 0.057 |
| (16) | Leverage | 0.524 | 0.431 | 0.093*** | | Leverage | 0.524 | 0.434 | 0.090 |
| Panel D: Correlations (Listing) | | | | | | | | | |
| | | Full Sample | | | | Base Sample | | | |
| | | DJSIE | Size | Profit | Leverage | DJSIE | Size | Profit | Leverage |
| (17) | DJSIE | 1 | | | | 1 | | | |
| (18) | Size | 0.131 | 1 | | | 0.045 | 1 | | |
| (19) | Profit | 0.031 | 0.149 | 1 | | 0.060 | 0.042 | 1 | |
| (20) | Leverage | 0.027 | 0.504 | 0.056 | 1 | -0.013 | 0.274 | 0.041 | 1 |
| Panel E: Summary Statistics for Full Sample (De-Listing) | | | | | | | | | |
| | | Mean | Min | 25th pctile | Median | 75th pctile | Max | St. dev. | *N* |
| (21) | DJSIX | 0.006 | 0.000 | 0.000 | 0.000 | 0.000 | 1 | 0.078 | 16746 |
| (22) | Size | 7.502 | 1.748 | 6.160 | 7.400 | 8.649 | 14.76 | 1.854 | 16746 |
| (23) | Profitability | 0.073 | -21.62 | 0.036 | 0.093 | 0.159 | 7.003 | 0.371 | 16746 |
| (24) | Leverage | 0.432 | 0.000 | 0.172 | 0.411 | 0.654 | 0.999 | 0.293 | 16746 |
| (25) | CAR[1,16] | 0.336 | -68.41 | -4.110 | -0.161 | 3.993 | 140.9 | 8.943 | 16746 |
| (26) | CAR[1,21] | 0.269 | -66.69 | -4.621 | -0.137 | 4.560 | 124.0 | 10.00 | 16746 |
| (27) | CAR[16,21] | -0.095 | -68.43 | -2.490 | -0.067 | 2.341 | 111.6 | 5.232 | 16746 |
| (28) | CAR[16,36] | -0.190 | -112.7 | -4.816 | 0.139 | 4.867 | 152.7 | 10.59 | 16746 |
| (29) | CAR[21,36] | -0.219 | -98.53 | -4.074 | 0.209 | 4.167 | 167.6 | 9.411 | 16746 |
| Panel F: Summary Statistics for Base Sample (De-Listing) | | | | | | | | | |
| (30) | DJSIX | 0.040 | 0.000 | 0.000 | 0.000 | 0.000 | 1 | 0.195 | 2612 |
| (31) | Size | 10.05 | 7.245 | 9.057 | 9.924 | 10.82 | 14.76 | 1.367 | 2612 |
| (32) | Profitability | 0.135 | -1.235 | 0.062 | 0.114 | 0.193 | 5.279 | 0.239 | 2612 |
| (33) | Leverage | 0.536 | 0.006 | 0.363 | 0.517 | 0.726 | 0.995 | 0.079 | 2612 |
| Panel G: Univariate sample comparisons (De-Listing) | | | | | | | | | |
| | | Full Sample | | | | | Base Sample | | |
| | | List | Other | Diff. | | | List | Other | Diff. |
| (34) | Size | 10.83 | 7.500 | 3.329*** | | Size | 10.83 | 10.05 | 0.784* |
| (35) | Profitability | 0.157 | 0.073 | 0.084 | | Profitability | 0.157 | 0.153 | 0.022 |
| (36) | Leverage | 0.565 | 0.432 | 0.133* | | Leverage | 0.565 | 0.536 | 0.029 |
| Panel H: Correlations (De-Listing) | | | | | | | | | |
| | | Full Sample | | | | Base Sample | | | |
| | | DJSIX | Size | Profit | Leverage | DJSIX | Size | Profit | Leverage |
| (37) | DJSIX | 1 | | | | 1 | | | |
| (38) | Size | 0.119 | 1 | | | 0.037 | 1 | | |
| (39) | Profit | 0.025 | 0.146 | 1 | | 0.047 | 0.005 | 1 | |
| (40) | Leverage | 0.026 | 0.503 | 0.045 | 1 | -0.006 | 0.235 | 0.009 | 1 |

Notes: Descriptive statistics for variables used in main analyses. Samples are restricted by two digit NAICS code to those industries with one or more firm joining, or leaving, the DJSI within a given year. DJSIE is a dummy which takes the value 1 for a firm listing to the DJSI. DJSIX is a dummy which takes the value 1 for firms de-listing from the DJSI. Full sample includes all firms listed on the major American stock exchanges with sufficient data, with the base sample considering only those with assets at least 80% as large as the smallest joining firm in their industry. All stock data is sourced from CRSP. DJSI listing data is taken from Robecco SAM. Size (log assets), profitability(return on equity) and leverage (ratio of total debt to total capital) are sourced from Compustat. Significance given by * = 10%, ** = 5%, *** = 1%.

changes to the DJSI listings.

Univariate tests in Panel C inform on the differences between those firms who join the DJSI and the control groups for that given year. These are aggregated into a large list and tested for equality of mean between the joining and non-joining samples. In both the full sample and the base sample the firms joining the list are significantly larger, this result remains even when the restriction based on size has been imposed. Looking at profitability the joining firms have a significantly higher ROE than the non-joiners; this would be consistent with the broad observation that improving CSR is costly and therefore typically only practised by firms who have the profitability to support such measures. After reducing the sample to the base, the average ROE for control firms rises but the gap between treatment and control is no longer significant. Finally, we see that amongst the whole sample firms joining the DJSI have a higher debt to capital ratio, but in the base sample it is the non-joining firms who have the higher leverage. The latter difference is also not significant however. It is therefore suggested that the largest firms with the greater profitability and ability to raise their leverage to fund investment in projects which will raise sustainability performance, are most likely to join.

Panel D addresses the correlations between the data. Leverage and size are the most correlated, but fall short of the 0.7 threshold usually assumed to be a concern for multicollinearity. For the base sample the correlations between the three financial variables drop significantly. Correlations between DJSI listing and all three controls are low in both the full, and base, samples. Thus in any regression contexts where these variables feature we can have confidence in the inference gained.

Relative to the listing sample the de-listing sample is much smaller, there are just 16746 firm-years instead of the previous 23592. A de-listing proportion of just 0.6% is lower than the 0.8% joining proportion. Since its inception in 2005 the DJSI North America has been growing in numbers; a larger proportion of joining firms is therefore to be expected. Summary statistics for firm characteristics in rows (22) to (24) are very similar to those in Panel A, the de-listing sample being slightly larger, slightly less profitable but being of identical leverage on average. Comparing the CARs for the periods summarised in lines (25) to (29), shows that those firms which are to leave the market return an average of 0.336% prior to the announcement compared to just 0.115% for those destined to gain listing. Negative effects post listing are also larger in absolute value for the de-listing group. The biggest contrast comes in the period between announcement day and the day the changes become effective. Returns between announcement and effective dates in the listing case were 0.083% whilst the de-listing set showed losses at 0.095%. Because there is great variation across years and firms it is not instructive to read deeply into this, but there is a suggestion of listing and de-listing moving in the opposite directions as intuition would suggest. Reducing the sample to consider only those control firms with assets of at least 80% of those of the smallest firm that gets de-listed in their industry-year produces a set of just 2612 observations. Summary statistics for this base sample, lines (30) to (33), have similar properties to those for the listing case (lines 10-13).

T-tests of firm characteristics between de-listed firms and their respective controls indicate that those leaving the DJSI were larger and more highly leveraged than others. Unlike the listing case there is no significance to the profitability differential. Combined with the lower average, 0.157 for de-listing firms versus 0.196 for those joining, there is indication towards the greater profitability of being seen as a CSR leader through the recognition afforded by remaining a DJSI member. Such is only indicative since it relies on consumers knowing in the previous financial year that the de-listed firms were not performing as strongly as those who were to gain listing[28]. Panel G further shows that even after reduction to the Base Sample size differentials are still significant. Correlation statistics in Panel H again urge caution on the relationship between size and leverage. In all tests performed on the regressions this is not seen as a problem to the reliability of the results that follow; maximum correlation is again shy of the 0.7 that would be problematic, for example.

### A3.2.2 Base Sample

Amongst the full sample are a number of firms who are significantly smaller than any of those who are members of the DJSI. This creates a potential bias in the comparison due to the well studied size anomaly[29]. Consequently a further control is placed upon firms that ensures the control set is more directly comparable with the treated set. Here a reduced sample is constructed using only those firms who have assets of at least 80% of those of the smallest firm that joins the DJSI in that year. By imposing this restriction we significantly reduce the number of shares available to serve as comparators, but are

[28]Consider the chronological ordering required. CSR reputation is observed by consumers who then make purchasing decisions accordingly. These purchasing decisions affect sales, and hence profits. To be recognised within the data here such changes would have to be seen in the financial variables more than nine months before the announcement is made. Such is not unreasonable since in many industries it is possible to know who the likely listees will be, or who the de-listed firms are likely to be, well ahead. Such a chronology may thus not be universal and so the temptation to generalise the motivation for the varied profitability is left as an intuition.

[29]See Keim (1983) for a review of the work that established this anomaly within the asset pricing literature.

able to minimise the impact of size. Alternative thresholds could be considered, but with the contribution of this paper stemming from an approach that does not require sample size reduction, robustness of the results in the main paper to minimum size is taken as given from the papers advocating those approaches. This set of larger firms is referred to as the base sample.

In the discussion of established modelling methodologies we present both the base sample and full sample, but do not use the base sample for the generalised synthetic control approach.

### A3.2.3 Cumulative Abnormal Returns

Evaluation of the effect of changes in a firm's DJSI listing status is based upon the ability of membership to generate returns which differ from those that might have been expected in the event that the firm did not receive the listing. This may be achieved either by comparing new entrants with similar firms that are not joining the DJSI that year, or by comparing de-listing firms with others who are not exiting the DJSI that year. However, it is more usefully considered as the difference between the observed returns and those that would have been realised had pricing behaviour of the listed firms share continued in the same way as it had been doing during the control period.

Simplest of the models to study the cross section of stock returns is the capital asset pricing model (CAPM) as introduced through the works of Lintner (1965); Sharpe (1964) and Treynor (1962). Although subsequent advancements of the CAPM are able to generate better fit for future returns predictions it is widely accepted that the CAPM is the most parsimonious solution for out-of-sample prediction (Campbell et al., 1997; Acemoglu et al., 2016). Here all abnormal return calculations follow the approach in Campbell et al. (1997). Before proceeding note that in all that follows we could add an additional $y$ subscript to recognise that all estimation and prediction applies to a specific year and that there are multiple years in the dataset. For the control period, $t \in [T_{start}, T_{end}]$, we estimate equation (3.19) using ordinary least squares (OLS) regression. This is done for all firms in the sample individually.

$$R_{it} = \alpha_i + \beta_i MKT_t \tag{3.19}$$

In equation (3.19) $R_{it}$ is the excess return on share $i$ at time $t$, $MKT_t$ is the Fama-French excess return for the market at time $t$, and $\alpha_i$ and $\beta_i$ are the coefficients of interest. Estimated values $\hat{\alpha}_i$ and $\hat{\beta}_i$ are then used to compute the fitted excess returns for share $i$, $\hat{R}_{it}$. The abnormal return, $AR_{it}$, is then defined as the difference between fitted and observed values:

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i MKT_t \tag{3.20}$$

Consequently a subperiod $t \in [\underline{t}, \bar{t}]$ has cumulative abnormal returns (CAR)s of:

$$CAR_i[\underline{t}, \bar{t}] = \sum_{t=\underline{t}}^{\bar{t}} AR_{it} \tag{3.21}$$

Investors have natural interest in obtaining abnormal returns, with higher absolute values being most attention grabbing. If correctly priced the CAR would be zero and hence the relationship between CARs and DJSI status becomes of interest.

This paper contrasts these simple abnormal returns with those generated by the synthetic control family. For this purpose we employ the mean square predicted error (MSPE) within the control period as a measure of model fit. For any given share $i$ the MSPE over the $T_c$ trading day interval $[T_{start}, T_{end}]$ is given by equation (3.22).

$$MSPE_i = \frac{1}{T_c} \sum_{t=T_{start}}^{T_{end}} AR_{it}^2 \tag{3.22}$$

Construction of the abnormal returns for the generalised synthetic control involves taking the difference between observed returns and those of the counterfactual version of that share. Consequently comparison can only be done on those shares considered “treated” by listing to, or being de-listed from, the DJSI. In the subsequent sections we report the CAPM CARs at an aggregate level and broken down by industry-year for those joining firms. Note further that because those announced as either gaining listing on, or being de-listed from, the DJSI are included in both the full and base samples there is no distinction between samples in the later reporting.

### A3.2.4 Two-Sample Approach

Identifying listing effects by comparing samples of firms entering the DJSI with their peers reveals many of the already identified phenomenon. Table A3.4 provides the t-tests in support of this section. First we consider the posted excess returns for the share sample. Whilst not accounting for past performance these do deliver the most direct outward impression of the performance of the shares of the new entrants to the DJSI. Compared to larger firms new entrants deliver significantly lower returns on day 9, 5 trading days prior to the announcement. On the announcement day listed firms offer a return 0.3% higher than non-listed and 0.2% higher than the largest control firms. Only a lower abnormal return on days 20 and 36 for newly listed firms compared to all others is significant. Such a lack of impact is suggestive that the CAPM model is pricing the DJSI listed firms with reasonable accuracy. Prior event studies on DJSI membership, such as Hawn et al. (2018), have spoken of the positive pre-announcement effect from social index listing. For those firms who are to gain listing we do see evidence of such here in Table A3.4, although many of the positive differences are not significant.

In the delisting effect there is more significance particular further away from the key announcement and effective dates. Attributing this to the DJSI is harder, but this is a difference between de-listed firms and others. That the effect is of a similar magnitude when comparing with large firms as it is when comparing with the full sample means it is not a size related effect. Moving into the period a week before the announcement there are no significant differentials between those who will be dropped from the index and any of the control groups. A positive effect here can be aligned to the traditionalist perspective that CSR is an expensive luxury for firms that is better reduced. Higher profitability would be expected from de-listing and therefore this uptick is consistent with expectation of better future performance post delisting. There is some evidence of a correction effect moving against these positive returns; values are similar in the delisting columns as they are in the listing case. Contrasts between the two change directions are stark but should not be viewed as demonstrative of a lack of appreciation of the role of DJSI membership. Heterogeneities in investor attitude are manifesting through revisionists driving returns on listed firms up and others who favour the traditionalist perspective being behind the boost to de-listing firms. Coexistence of the two effects is in line with Oberndorfer et al. (2013).

CARs, discussed in Table A3.5 recognise the trend in the stocks performance prior to the listing; they offer a measure of how listing creates deviation from that pre-announcement path. For the stated start and end dates we test whether the CARs of a pooled sample of listed firms are equal to that of a pooled sample of non-listed firms over the whole fourteen years of data. Positive values signify that the recently DJSI listed firms are offering higher CARs. Dates in the table range from day one of the treatment period through to the day after changes become effective, whilst the end dates range from day 11 to the final day of the treatment period. Table A3.5 shows that there are some positive CARs for samples starting a week before the announcement. Between announcement date and the date that changes become effective, CARs are significant and positive. Herein an opportunity for investors to profit is found. Around the effective date there is a correction. CARs that start on day 20, one day prior to

Table A3.4: Univariate Tests of Return Equality

| Day | Listing $DJSIE$ Return | All firms Return | Diff | Base Sample Return | Diff | Delisting $DJSIX$ Return | All firms Return | Diff | Base Sample Return | Diff |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | -0.010 | 0.145 | -0.155 | 0.031 | -0.041 | -0.129 | 0.188 | -0.316*** | 0.011 | -0.139 |
| 2 | 0.086 | -0.03 | 0.115 | -0.019 | 0.105 | -0.214 | -0.012 | -0.202* | -0.068 | -0.146 |
| 3 | 0.012 | 0.077 | -0.065 | -0.071 | 0.083 | -0.160 | 0.095 | -0.256** | -0.014 | -0.146 |
| 4 | -0.049 | -0.113 | 0.064 | -0.074 | 0.025 | 0.039 | -0.201 | 0.239** | -0.217 | 0.255** |
| 5 | -0.078 | -0.016 | -0.062 | -0.019 | -0.058 | -0.085 | -0.035 | -0.049 | 0.036 | -0.120 |
| 6 | 0.049 | 0.061 | -0.012 | -0.009 | 0.058 | -0.073 | 0.079 | -0.152 | 0.011 | -0.084 |
| 7 | -0.110 | 0.022 | -0.132 | -0.087 | -0.023 | 0.189 | 0.091 | 0.098 | -0.154 | 0.342*** |
| 8 | -0.011 | -0.002 | -0.008 | -0.013 | 0.002 | 0.044 | 0.073 | -0.029 | 0.047 | -0.003 |
| 9 | 0.129 | -0.111 | 0.239* | 0.011 | 0.118 | 0.230 | -0.161 | 0.392*** | -0.096 | 0.327** |
| 10 | 0.066 | -0.034 | 0.099 | 0.029 | 0.036 | 0.180 | -0.001 | 0.182 | 0.044 | 0.136 |
| 11 | 0.095 | 0.114 | -0.019 | -0.001 | 0.096 | 0.071 | 0.170 | -0.099 | -0.044 | 0.115 |
| 12 | -0.195 | -0.050 | -0.145 | -0.103 | -0.092 | 0.017 | -0.028 | 0.044 | -0.135 | 0.152 |
| 13 | -0.040 | 0.057 | -0.096 | 0.073 | -0.113 | 0.048 | 0.183 | -0.135 | -0.036 | 0.084 |
| 14 | -0.198 | -0.095 | -0.104 | -0.114 | -0.085 | -0.120 | -0.098 | -0.022 | -0.182 | 0.061 |
| 15 | 0.077 | 0.070 | 0.007 | 0.076 | 0.001 | -0.121 | 0.024 | -0.145 | -0.139 | 0.018 |
| ANN | 0.236 | -0.064 | 0.299*** | 0.010 | 0.226** | 0.033 | -0.147 | 0.180 | -0.104 | 0.137 |
| 17 | -0.046 | -0.133 | 0.087 | -0.145 | 0.099 | 0.226 | -0.068 | 0.184 | 0.106 | 0.010 |
| 18 | 0.086 | -0.003 | 0.090 | 0.091 | -0.004 | -0.043 | -0.133 | 0.090 | -0.016 | -0.026 |
| 19 | 0.095 | -0.064 | 0.159 | -0.035 | 0.131 | -0.091 | -0.050 | -0.041 | -0.108 | 0.016 |
| 20 | 0.010 | 0.268 | -0.258* | 0.050 | -0.041 | -0.006 | 0.426 | -0.432** | 0.053 | -0.058 |
| 21 | -0.075 | -0.086 | 0.010 | -0.055 | -0.020 | 0.017 | -0.125 | 0.142 | -0.002 | 0.019 |
| 22 | -0.174 | -0.071 | -0.103 | 0.008 | -0.182 | 0.054 | -0.109 | 0.163 | 0.016 | 0.039 |
| 23 | 0.001 | 0.092 | -0.090 | -0.146 | 0.147 | -0.135 | 0.155 | -0.290 | -0.044 | -0.092 |
| 24 | -0.031 | -0.088 | 0.057 | -0.114 | 0.083 | 0.111 | 0.008 | 0.103 | -0.057 | 0.168 |
| 25 | -0.089 | 0.009 | -0.098 | -0.050 | -0.039 | -0.108 | -0.041 | -0.066 | -0.005 | -0.103 |
| 26 | -0.076 | -0.027 | -0.049 | -0.019 | -0.057 | 0.139 | 0.062 | 0.077 | -0.002 | 0.140 |
| 27 | -0.033 | -0.099 | 0.066 | 0.030 | -0.063 | 0.012 | -0.056 | 0.068 | 0.018 | -0.006 |
| 28 | -0.162 | 0.036 | -0.198 | 0.006 | -0.168 | 0.354 | 0.034 | 0.320* | 0.020 | 0.334** |
| 29 | 0.035 | 0.168 | -0.133 | 0.029 | 0.006 | -0.006 | 0.260 | -0.266* | -0.109 | 0.103 |
| 30 | -0.059 | -0.169 | 0.111 | -0.089 | 0.031 | -0.303 | -0.173 | -0.131 | 0.079 | -0.382 |
| 31 | -0.171 | 0.014 | -0.186 | -0.051 | -0.120 | -0.149 | 0.047 | -0.196 | 0.042 | -0.191 |
| 32 | 0.003 | -0.037 | 0.039 | -0.081 | 0.084 | 0.001 | 0.012 | -0.011 | 0.009 | -0.008 |
| 33 | -0.021 | 0.071 | -0.092 | -0.122 | 0.101 | -0.045 | 0.188 | -0.233 | 0.024 | -0.069 |
| 34 | 0.123 | -0.123 | 0.246 | -0.084 | 0.207 | 0.432 | -0.221 | 0.653*** | 0.029 | 0.403** |
| 35 | 0.021 | -0.131 | 0.152 | -0.164 | 0.185 | 0.008 | -0.177 | 0.185 | -0.079 | 0.087 |
| 36 | -0.102 | 0.100 | -0.202* | -0.021 | -0.081 | -0.202 | -0.084 | -0.118 | -0.278 | 0.076 |

Notes: Abnormal returns are calculated based on the difference between realised excess returns and the fitted value using coefficients estimated individually for each firm during the control period. $DJSIE$ refers to firms which join the DJSI, $DJSIX$ being those who are de-listed. All firms include any share listed on the major US exchanges from the same industry as a joining firm, with large firms including only those with assets 80% of those of the smallest new entrant to/exiting firm from the DJSI. Evaluation processes are repeated annually such that reported figures represent the average effect across the period. In the returns case period represents the trading day for which the returns are reported. Diff reports the difference between the treated firms, listed or de-listed, and the untreated firms in the appropriate sample. Asterisks denote significance levels of a two-tailed t-test (*** - 1%, ** - 5% and * - 10%).

Table A3.5: Cumulative Abnormal Returns t-test Summaries: Listing

| From/To | 11 | 12 | 13 | 14 | 15 | ANN | 17 | 18 | 19 | 20 | EFF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.065 | -0.080 | -0.176 | -0.280 | -0.273 | 0.026 | 0.113 | 0.202 | 0.362 | 0.104 | 0.114 |
| 2 | 0.220 | 0.075 | -0.021 | -0.125 | -0.118 | 0.181 | 0.268 | 0.358 | 0.517 | 0.259 | 0.269 |
| 3 | 0.104 | -0.04 | -0.137 | -0.240 | -0.234 | 0.066 | 0.152 | 0.242 | 0.402 | 0.144 | 0.154 |
| 4 | 0.170 | 0.025 | -0.071 | -0.175 | -0.168 | 0.131 | 0.218 | 0.308 | 0.467 | 0.209 | 0.219 |
| 5 | 0.106 | -0.039 | -0.135 | -0.239 | -0.232 | 0.067 | 0.154 | 0.244 | 0.403 | 0.145 | 0.155 |
| 6 | 0.168 | 0.023 | -0.073 | -0.177 | -0.170 | 0.129 | 0.216 | 0.306 | 0.465 | 0.207 | 0.217 |
| 7 | 0.179 | 0.035 | -0.062 | -0.165 | -0.159 | 0.141 | 0.228 | 0.317 | 0.477 | 0.219 | 0.229 |
| 8 | 0.312 | 0.167 | 0.071 | -0.033 | -0.026 | 0.273 | 0.360 | 0.450 | 0.609* | 0.351 | 0.361 |
| 9 | 0.320* | 0.175 | 0.079 | -0.025 | -0.018 | 0.281 | 0.368 | 0.458 | 0.617* | 0.359 | 0.370 |
| 10 | 0.081 | -0.064 | -0.160 | -0.264 | -0.257 | 0.042 | 0.129 | 0.219 | 0.378 | 0.120 | 0.131 |
| 11 | -0.019 | -0.163 | -0.260 | -0.363 | -0.357 | -0.057 | 0.030 | 0.119 | 0.279 | 0.021 | 0.031 |
| 12 | | -0.145 | -0.241 | -0.345* | -0.338 | -0.038 | 0.048 | 0.138 | 0.297 | 0.039 | 0.050 |
| 13 | | | -0.096 | -0.200 | -0.193 | 0.106 | 0.193 | 0.283 | 0.442 | 0.184 | 0.194 |
| 14 | | | | -0.104 | -0.097 | 0.203 | 0.289 | 0.379* | 0.538* | 0.280 | 0.291 |
| 15 | | | | | 0.007 | 0.306* | 0.393** | 0.483** | 0.642*** | 0.384 | 0.394 |
| ANN | | | | | | 0.299*** | 0.386*** | 0.476*** | 0.635*** | 0.377 | 0.388 |
| 17 | | | | | | | 0.087 | 0.176 | 0.336* | 0.078 | 0.088 |
| 18 | | | | | | | | 0.090 | 0.249 | -0.009 | 0.002 |
| 19 | | | | | | | | | 0.159 | -0.099 | -0.088 |
| 20 | | | | | | | | | | -0.258* | -0.247* |
| EFF | | | | | | | | | | | 0.010 |

| From/To | EFF | 22 | 24 | 26 | 31 | 36 |
|---|---|---|---|---|---|---|
| 11 | 0.031 | -0.072 | -0.105 | -0.253 | -0.593 | -0.449 |
| 12 | 0.050 | -0.053 | -0.087 | -0.235 | -0.574 | -0.430 |
| 13 | 0.194 | 0.091 | 0.058 | -0.090 | -0.429 | -0.286 |
| 14 | 0.291 | 0.188 | 0.154 | 0.006 | -0.333 | -0.189 |
| 15 | 0.394 | 0.291 | 0.258 | 0.110 | -0.229 | -0.086 |
| ANN | 0.388 | 0.284 | 0.251 | 0.103 | -0.236 | -0.092 |
| 17 | 0.088 | -0.015 | -0.048 | -0.196 | -0.536 | -0.392 |
| 18 | 0.002 | -0.102 | -0.135 | -0.283 | -0.622 | -0.479 |
| 19 | -0.088 | -0.191 | -0.225 | -0.372 | -0.712 | -0.568 |
| 20 | -0.247* | -0.351* | -0.384 | -0.532 | -0.871* | -0.728 |
| EFF | 0.010 | -0.093 | -0.126 | -0.274 | -0.613 | -0.470 |
| 22 | | -0.103 | -0.136 | -0.284 | -0.624 | -0.480 |

Notes: Cumulative abnormal returns are calculated using the fitted values from the CAPM. Full Sample includes all firms that did not join the DJSI in any industry-year where one or more firms did join. Significance given for a two-sample t-test of equality between joining and non-joining firms, with * - 5%, ** - 1%, *** - 0.1%

Table A3.6: Cumulative Abnormal Returns t-test Summaries: Listing Base Sample

| From /To | 11 | 12 | 13 | 14 | 15 | ANN | 17 | 18 | 19 | 20 | EFF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.400 | 0.308 | 0.196 | 0.111 | 0.112 | 0.337 | 0.437 | 0.432 | 0.563 | 0.522 | 0.502 |
| 2 | 0.441 | 0.349 | 0.237 | 0.152 | 0.153 | 0.378 | 0.478 | 0.473 | 0.604 | 0.563 | 0.543 |
| 3 | 0.336 | 0.244 | 0.132 | 0.047 | 0.048 | 0.273 | 0.373 | 0.368 | 0.499 | 0.458 | 0.438 |
| 4 | 0.253 | 0.162 | 0.049 | -0.036 | -0.035 | 0.191 | 0.290 | 0.286 | 0.416 | 0.376 | 0.356 |
| 5 | 0.229 | 0.137 | 0.024 | -0.060 | -0.060 | 0.166 | 0.265 | 0.261 | 0.392 | 0.351 | 0.331 |
| 6 | 0.287 | 0.195 | 0.083 | -0.002 | -0.001 | 0.224 | 0.324 | 0.319 | 0.450 | 0.409 | 0.389 |
| 7 | 0.229 | 0.138 | 0.025 | -0.060 | -0.059 | 0.167 | 0.266 | 0.262 | 0.392 | 0.352 | 0.331 |
| 8 | 0.252 | 0.161 | 0.048 | -0.037 | -0.036 | 0.190 | 0.289 | 0.285 | 0.415 | 0.375 | 0.354 |
| 9 | 0.250 | 0.158 | 0.046 | -0.039 | -0.038 | 0.187 | 0.287 | 0.282 | 0.413 | 0.372 | 0.352 |
| 10 | 0.132 | 0.041 | -0.072 | -0.157 | -0.156 | 0.070 | 0.169 | 0.165 | 0.295 | 0.255 | 0.234 |
| 11 | 0.096 | 0.004 | -0.109 | -0.193 | -0.193 | 0.033 | 0.132 | 0.128 | 0.259 | 0.218 | 0.198 |
| 12 | | -0.092 | -0.205 | -0.289 | -0.289 | -0.063 | 0.036 | 0.032 | 0.163 | 0.122 | 0.102 |
| 13 | | | -0.113 | -0.197 | -0.197 | 0.029 | 0.128 | 0.124 | 0.255 | 0.214 | 0.194 |
| 14 | | | | -0.085 | -0.084 | 0.142 | 0.241 | 0.237 | 0.368 | 0.327 | 0.307 |
| 15 | | | | | 0.001 | 0.226 | 0.326* | 0.321* | 0.452* | 0.411 | 0.391 |
| ANN | | | | | | 0.226** | 0.325** | 0.321* | 0.452* | 0.411 | 0.391 |
| 17 | | | | | | | 0.099 | 0.095 | 0.226 | 0.185 | 0.165 |
| 18 | | | | | | | | -0.004 | 0.127 | 0.086 | 0.066 |
| 19 | | | | | | | | | 0.131 | 0.090 | 0.070 |
| 20 | | | | | | | | | | -0.041 | -0.061 |
| EFF | | | | | | | | | | | -0.02 |
| | EFF | 22 | 24 | 26 | 31 | 36 | | | | | |
| 11 | 0.198 | 0.016 | 0.246 | 0.150 | -0.164 | 0.331 | | | | | |
| 12 | 0.102 | -0.080 | 0.150 | 0.054 | -0.260 | 0.236 | | | | | |
| 13 | 0.194 | 0.012 | 0.242 | 0.146 | -0.168 | 0.327 | | | | | |
| 14 | 0.307 | 0.125 | 0.355 | 0.259 | -0.055 | 0.440 | | | | | |
| 15 | 0.391 | 0.210 | 0.440 | 0.344 | 0.030 | 0.525 | | | | | |
| ANN | 0.391 | 0.209 | 0.439 | 0.343 | 0.029 | 0.524 | | | | | |
| 17 | 0.165 | -0.017 | 0.213 | 0.117 | -0.197 | 0.298 | | | | | |
| 18 | 0.066 | -0.116 | 0.114 | 0.018 | -0.296 | 0.199 | | | | | |
| 19 | 0.070 | -0.112 | 0.118 | 0.022 | -0.292 | 0.203 | | | | | |
| 20 | -0.061 | -0.243 | -0.013 | -0.109 | -0.423 | 0.073 | | | | | |
| EFF | -0.020 | -0.202 | 0.028 | -0.068 | -0.382 | 0.113 | | | | | |
| 22 | | -0.182 | 0.048 | -0.048 | -0.362 | 0.133 | | | | | |

Notes: Cumulative abnormal returns are calculated using the fitted values from the CAPM. Full Sample includes all firms that did not join the DJSI in any industry-year where one or more firms did join. Base Sample restricts the full sample to include all joining firms and only those non-joining firms with an asset holding at least 80% of that of the lowest entrant in their industry-year. Significance given for a two-sample t-test of equality between joining and non-joining firms, with * - 5%, ** - 1%, *** - 0.1%

Table A3.7: Cumulative Abnormal Returns t-test Summaries: De-Listing

Panel (a): Full Sample ($N = 16747$):

| From/To | 11 | 12 | 13 | 14 | 15 | ANN | 17 | 18 | 19 | 20 | EFF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | -0.193 | -0.148 | -0.284 | -0.305 | -0.450 | -0.271 | -0.087 | 0.004 | -0.038 | -0.470 | -0.328 |
| 2 | 0.124 | 0.168 | 0.033 | 0.011 | -0.134 | 0.046 | 0.230 | 0.320 | 0.279 | -0.153 | -0.011 |
| 3 | 0.325 | 0.370 | 0.234 | 0.213 | 0.068 | 0.247 | 0.431 | 0.522 | 0.480 | 0.048 | 0.190 |
| 4 | 0.581 | 0.625 | 0.490 | 0.468 | 0.323 | 0.503 | 0.687 | 0.777 | 0.736 | 0.304 | 0.446 |
| 5 | 0.342 | 0.386 | 0.251 | 0.229 | 0.084 | 0.264 | 0.448 | 0.538 | 0.497 | 0.065 | 0.207 |
| 6 | 0.391 | 0.435 | 0.300 | 0.278 | 0.133 | 0.313 | 0.497 | 0.587 | 0.546 | 0.114 | 0.256 |
| 7 | 0.543* | 0.587* | 0.452 | 0.430 | 0.285 | 0.465 | 0.649 | 0.739* | 0.698* | 0.266 | 0.408 |
| 8 | 0.445* | 0.489 | 0.354 | 0.332 | 0.187 | 0.367 | 0.551 | 0.641 | 0.600 | 0.168 | 0.310 |
| 9 | 0.474** | 0.518* | 0.383 | 0.361 | 0.216 | 0.396 | 0.580 | 0.670 | 0.629 | 0.197 | 0.339 |
| 10 | 0.082 | 0.127 | -0.008 | -0.030 | -0.175 | 0.004 | 0.188 | 0.279 | 0.237 | -0.195 | -0.053 |
| 11 | -0.099 | -0.055 | -0.190 | -0.212 | -0.357 | -0.177 | 0.007 | 0.097 | 0.056 | -0.376 | -0.234 |
| 12 | | 0.044 | -0.091 | -0.113 | -0.258 | -0.078 | 0.106 | 0.196 | 0.155 | -0.277 | -0.135 |
| 13 | | | -0.135 | -0.157 | -0.302 | -0.122 | 0.062 | 0.152 | 0.111 | -0.321 | -0.179 |
| 14 | | | | -0.022 | -0.167 | 0.013 | 0.197 | 0.287 | 0.246 | -0.186 | -0.044 |
| 15 | | | | | -0.145 | 0.035 | 0.219 | 0.309 | 0.268 | -0.164 | -0.022 |
| ANN | | | | | | 0.180 | 0.364** | 0.454** | 0.413 | -0.019 | 0.122 |
| 17 | | | | | | | 0.184 | 0.274 | 0.233 | -0.199 | -0.057 |
| 18 | | | | | | | | 0.090 | 0.049 | -0.383 | -0.241 |
| 19 | | | | | | | | | -0.041 | -0.473** | -0.331 |
| 20 | | | | | | | | | | -0.432*** | -0.290 |
| EFF | | | | | | | | | | | 0.142 |

| From/To | EFF | 22 | 24 | 26 | 31 | 36 |
|---|---|---|---|---|---|---|
| 11 | -0.234 | -0.071 | -0.361 | -0.248 | -0.453 | 0.024 |
| 12 | -0.135 | 0.028 | -0.262 | -0.149 | -0.353 | 0.123 |
| 13 | -0.179 | -0.017 | -0.307 | -0.193 | -0.398 | 0.079 |
| 14 | -0.044 | 0.119 | -0.171 | -0.058 | -0.263 | 0.214 |
| 15 | -0.022 | 0.140 | -0.150 | -0.036 | -0.241 | 0.236 |
| ANN | 0.122 | 0.285 | -0.005 | 0.109 | -0.096 | 0.381 |
| 17 | -0.057 | 0.106 | -0.184 | -0.071 | -0.276 | 0.201 |
| 18 | -0.241 | -0.078 | -0.368 | -0.255 | -0.459 | 0.017 |
| 19 | -0.331 | -0.169 | -0.459 | -0.345 | -0.550 | -0.073 |
| 20 | -0.290 | -0.127 | -0.417 | -0.304 | -0.508 | -0.032 |
| EFF | 0.142 | 0.305 | 0.015 | 0.128 | -0.076 | 0.400 |
| 22 | | 0.163 | -0.127 | -0.014 | -0.218 | 0.258 |

Notes: Cumulative abnormal returns are calculated using the fitted values from the CAPM. Full Sample includes all firms that were not de-listed from the DJSI in any industry-year where one or more firms were de-listed. Significance given for a two-sample t-test of equality between joining and non-joining firms, with * - 5%, ** - 1%, *** - 0.1%

Table A3.8: Cumulative Abnormal Returns t-test Summaries: De-Listing Base Sample

| From/To | 11 | 12 | 13 | 14 | 15 | ANN | 17 | 18 | 19 | 20 | EFF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.538 | 0.690 | 0.774 | 0.835 | 0.853 | 0.991* | 1.000* | 0.974* | 0.990* | 0.932 | 0.951* |
| 2 | 0.677 | 0.830* | 0.913* | 0.975** | 0.993** | 1.130** | 1.140** | 1.113** | 1.130** | 1.071* | 1.090** |
| 3 | 0.823** | 0.975** | 1.059** | 1.120** | 1.138** | 1.276*** | 1.285** | 1.259** | 1.276** | 1.217** | 1.236** |
| 4 | 0.969*** | 1.121*** | 1.205*** | 1.266*** | 1.285*** | 1.422*** | 1.432*** | 1.405*** | 1.422*** | 1.363** | 1.382*** |
| 5 | 0.714** | 0.866** | 0.950** | 1.011** | 1.029** | 1.166*** | 1.176*** | 1.150** | 1.166** | 1.108** | 1.127** |
| 6 | 0.834** | 0.986*** | 1.070*** | 1.131*** | 1.150*** | 1.287*** | 1.297*** | 1.270*** | 1.287*** | 1.228*** | 1.247*** |
| 7 | 0.918*** | 1.070*** | 1.153*** | 1.215*** | 1.233*** | 1.370*** | 1.380*** | 1.354*** | 1.370*** | 1.312*** | 1.330*** |
| 8 | 0.575** | 0.728** | 0.811** | 0.873** | 0.891** | 1.028** | 1.038*** | 1.011** | 1.028** | 0.969** | 0.988** |
| 9 | 0.578** | 0.730** | 0.814** | 0.875** | 0.893** | 1.031*** | 1.040*** | 1.014** | 1.030** | 0.972** | 0.991** |
| 10 | 0.251 | 0.403* | 0.487* | 0.548* | 0.567* | 0.704** | 0.714** | 0.687* | 0.704* | 0.645 | 0.664 |
| 11 | 0.115 | 0.267 | 0.351 | 0.412 | 0.431 | 0.568* | 0.578* | 0.551 | 0.568 | 0.509 | 0.528 |
| 12 | | 0.152 | 0.236 | 0.297 | 0.316 | 0.453 | 0.463 | 0.436 | 0.453 | 0.394 | 0.413 |
| 13 | | | 0.084 | 0.145 | 0.163 | 0.301 | 0.310 | 0.284 | 0.300 | 0.242 | 0.261 |
| 14 | | | | 0.061 | 0.080 | 0.217 | 0.227 | 0.200 | 0.217 | 0.158 | 0.177 |
| 15 | | | | | 0.018 | 0.156 | 0.165 | 0.139 | 0.155 | 0.097 | 0.116 |
| 16 | | | | | | 0.137 | 0.147 | 0.121 | 0.137 | 0.079 | 0.097 |
| 17 | | | | | | | 0.010 | -0.017 | 0.000 | -0.059 | -0.040 |
| 18 | | | | | | | | -0.026 | -0.010 | -0.068 | -0.050 |
| 19 | | | | | | | | | 0.016 | -0.042 | -0.023 |
| 20 | | | | | | | | | | -0.058 | -0.040 |
| EFF | | | | | | | | | | | 0.019 |
| From/To | ANN | 22 | 24 | 26 | 31 | 36 | | | | | |
| 11 | 0.528 | 0.567 | 0.475 | 0.681 | 0.539 | 1.027 | | | | | |
| 12 | 0.413 | 0.452 | 0.360 | 0.566 | 0.424 | 0.912 | | | | | |
| 13 | 0.261 | 0.299 | 0.208 | 0.414 | 0.271 | 0.760 | | | | | |
| 14 | 0.177 | 0.216 | 0.124 | 0.330 | 0.188 | 0.676 | | | | | |
| 15 | 0.116 | 0.154 | 0.063 | 0.269 | 0.126 | 0.615 | | | | | |
| ANN | 0.097 | 0.136 | 0.044 | 0.251 | 0.108 | 0.597 | | | | | |
| 17 | -0.040 | -0.001 | -0.093 | 0.113 | -0.029 | 0.459 | | | | | |
| 18 | -0.050 | -0.011 | -0.103 | 0.104 | -0.039 | 0.450 | | | | | |
| 19 | -0.023 | 0.015 | -0.076 | 0.130 | -0.013 | 0.476 | | | | | |
| 20 | -0.040 | -0.001 | -0.093 | 0.113 | -0.029 | 0.459 | | | | | |
| EFF | 0.019 | 0.057 | -0.034 | 0.172 | 0.030 | 0.518 | | | | | |
| 22 | | 0.039 | -0.053 | 0.153 | 0.011 | 0.499 | | | | | |

Notes: Cumulative abnormal returns are calculated using the fitted values from the CAPM. Full Sample includes all firms that were not de-listed from the DJSI in any industry-year where one or more firms were de-listed. Base Sample restricts the full sample to include all listed firms and only those other firms with an asset holding at least 80% of that of the lowest entrant in their industry-year. Significance given for a two-sample t-test of equality between joining and non-joining firms, with * - 5%, ** - 1%, *** - 0.1%

the effective date, show significant negative CARs. Throughout the post effective date range we see negative CARs but few others are significant. When we focus only on the base sample, Table A3.6, the only notable significance that remains is the positive return surrounding the announcement date. Understandably the magnitude of these gains is smaller, but their continued existence merits further investigation.

Turning to de-listing effects, Table A3.7 may be sat neatly in contrast to Table A3.5 from the listing analysis. Immediate observations are the greater magnitudes of the CARs and the increased number of holding periods for which significance of the CARs is noted. Strong evidence of a pre-announcement effect is provided in those groups starting on days 7 to 9 of the treatment period and ending on days 9 to 12. This is far more pronounced than that seen in Table A3.5. That both effects are positive raises questions about the role of the pre-announcement effect; investors may be thinking that these firms would retain listing. Around the announcement date itself there are few significant effects but early gains quickly give way to negative CARs as the correction effect kicks in. Note here that the smaller magnitude of gains through the period before the effective date means the corrections are smaller than those observed in Table A3.5.

For the Base Sample the comparison between listing and de-listing is more stark. Picking up those shares that are to be de-listed offers higher CARs over large time ranges, provided the purchase of the shares takes place at least a week before the announcement date. Waiting until the announcement date offers little difference and hence any investor looking to take advantage would need to correctly identify those firms who were to de-list. From a trading perspective obtaining de-listed firms in the immediate aftermath of the announcement offers the highest probability of success; such shares offer a premium, albeit an insignificant one, in the base sample too.

### A3.2.5 OLS Regressions

To understand better the extent to which factors lie behind the observed CAR patterns we regress the CARs observed over five sub-periods from Table A3.3 on the listing dummy, size, profitability and leverage. We study $CAR_i[from, to]$ as the dependent variable, where this is either $CAR_i[-15, 1]$, $CAR_i[-15, 15]$, $CAR_i[-1, 1]$, $CAR_i[0]$ and $CAR_i[0, 10]$. Regression is performed following equation (3.23):

$$CAR_i[from, to] = \alpha + \beta_{DJSI} DJSIE_{iy} + \theta X_{iy} + \gamma_j + \psi_y + \epsilon_{iy} \tag{3.23}$$

Here $X_{iy}$ is the set of firm level covariates, $DJSIE_{iy}$ is a dummy equal to 1 if firm $i$ joins the DJSI in year $y$. $\beta$ is a vector of coefficients on the firm controls. $\gamma_j$ introduces fixed effects for industries where firm $i$ is in industry $j$. These fixed effects are incorporated to capture unobserved heterogeneity between industries, enabling the model to include any factors which act solely upon that sector. For the de-listing case the dummy for firm $i$ leaving the DJSI in year $y$ is $DJSIX_{iy}$. $\psi_y$ is the year fixed effect that is added to represent the variation in conditions over time, this includes those which would have been brought about during the GFC. Remaining error terms, $\epsilon_{iy}$, are assumed to have constant variance and an expected value of 0. To address questions about the best choice of covariates, or whether they should enter linearly, quadratically or otherwise, we follow Acemoglu et al. (2016) to allow each of the three controls to enter as linear, squared and cubic. Robustness checks have been performed using just the linear, and then the linear with quadratic effects.

Table A3.9 shows that across all five periods, and for both samples, the main consistency observed is that the DJSI joining dummy is not significant in any of the ten equations. Such a result is opposite to the univariate tests of the previous section, but is entirely in line with the ambiguity of conclusions on listing effects in the current literature. Firm size is used to split the sample and for the full sample log assets has significant coefficients on the linear, quadratic and cubic terms. By contrast in the base sample very few of these size coefficients are significant. Profitability is significant in the linear term, but not for the quadratic or cubic. Leverage in these equations is also significant in the full sample, this can be linked to the correlations observed in Table A3.3. When reducing to the base sample much of the significance of leverage disappears.

Table A3.10 indicates no significance to any of the de-listing dummies, this is consistent with the message on listing also. However, in the listing case there were significant effects arising from firm size; such are not found in the de-listing results. Consequently these tables offer little motivation for the movement to a base sample. Profitability coefficients become larger in magnitude in the base sample, whilst the significance of some leverage coefficients from the full sample disappear when only the larger firms have focus. Table A3.11 looks at an extended set of time ranges and reports only the coefficient on the DJSIX dummy. Occasional evidence of significance is seen. As in the listing analysis there is limited evidence of a DJSIX effect once firm characteristics are controlled for. Because the generalised synthetic control results look only at the full sample to maximise the possible candidates for the matched portfolio this lack of motivation for a reduced sample serves to aid the case for the Xu (2017) approach

Table A3.9: OLS Regressions for Cumulative Abnormal Returns and Firm Characteristics: Listing

| | Full Sample | | | | | Base Sample | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| From | 1 | 1 | 16 | 16 | 21 | 1 | 1 | 16 | 16 | 21 |
| To | 16 | 21 | 21 | 36 | 36 | 16 | 21 | 21 | 36 | 36 |
| *DJSIE* | 0.449 | 0.762 | 0.384 | 0.904 | 0.373 | 0.357 | 0.520 | 0.250 | 0.926 | 0.579 |
| | (0.606) | (0.694) | (0.369) | (0.730) | (0.640) | (0.460) | (0.531) | (0.273) | (0.558) | (0.497) |
| Size | 2.072** | 2.110* | −0.107 | 1.111 | 0.711 | −8.258 | −10.82 | −1.328 | −9.784 | −8.702 |
| | (0.720) | (0.825) | (0.439) | (0.869) | (0.762) | (5.565) | (6.420) | (3.302) | (6.747) | (6.009) |
| Size$^2$ | −0.242** | −0.269** | −0.009 | −0.178 | −0.110 | 0.741 | 0.988 | 0.117 | 0.786 | 0.692 |
| | (0.091) | (0.104) | (0.055) | (0.109) | (0.096) | (0.533) | (0.615) | (0.316) | (0.646) | (0.575) |
| Size$^3$ | 0.009* | 0.011* | 0.001 | 0.008 | 0.005 | −0.021 | −0.028 | −0.002 | −0.018 | −0.016 |
| | (0.004) | (0.004) | (0.002) | (0.004) | (0.004) | (0.017) | (0.019) | (0.010) | (0.020) | (0.018) |
| Profitability | −0.799*** | −1.538*** | −0.460*** | 0.547* | 1.039*** | −1.540* | −2.355** | −0.508 | 1.181 | 1.470* |
| | (0.221) | (0.253) | (0.135) | (0.267) | (0.234) | (0.641) | (0.739) | (0.380) | (0.777) | (0.692) |
| Profitability$^2$ | −0.025 | −0.056 | −0.018 | 0.001 | −0.011 | 0.223 | 1.374 | 1.046** | 1.624* | 0.642 |
| | (0.031) | (0.035) | (0.019) | (0.037) | (0.032) | (0.642) | (0.741) | (0.381) | (0.778) | (0.693) |
| Profitability$^3$ | 0.003 | 0.005 | −0.002 | −0.006 | −0.008* | −0.010 | −0.201 | −0.182* | −0.362* | −0.183 |
| | (0.003) | (0.004) | (0.002) | (0.004) | (0.003) | (0.127) | (0.147) | (0.075) | (0.154) | (0.137) |
| Leverage | −3.095 | −3.405 | −0.475 | 4.493 | 4.041* | 5.439 | 6.659 | 2.011 | 2.487 | −0.548 |
| | (1.926) | (2.206) | (1.173) | (2.323) | (2.036) | (4.448) | (5.132) | (2.639) | (5.393) | (4.803) |
| Leverage$^2$ | −1.317 | 0.242 | 1.790 | −16.20** | −14.98** | −22.08* | −25.54* | −5.290 | −10.32 | −3.274 |
| | (5.105) | (5.847) | (3.110) | (6.157) | (5.397) | (10.47) | (12.08) | (6.213) | (12.70) | (11.31) |
| Leverage$^3$ | 4.930 | 3.692 | −1.432 | 13.48** | 12.46** | 19.55** | 20.665* | 2.239 | 5.560 | 2.137 |
| | (3.679) | (4.215) | (2.241) | (4.437) | (3.890) | (7.137) | (8.234) | (4.235) | (8.654) | (7.707) |
| R$^2$ | 0.044 | 0.036 | 0.030 | 0.032 | 0.041 | 0.034 | 0.039 | 0.051 | 0.089 | 0.083 |
| Adj. R$^2$ | 0.042 | 0.034 | 0.028 | 0.030 | 0.039 | 0.022 | 0.028 | 0.040 | 0.078 | 0.072 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: Coefficients are reported for the full sample and base sample with just firms with a size at least 80% of the size of the smallest firm gaining listing (Large). Selected pairings of from and to dates are shown. Coefficients from regression $CAR_i[from, to] = \alpha + \beta_{DJSI} DJSIE_{iy} + \theta X_{iy} + \gamma_j + \psi_y + \epsilon_{iy}$ for cumulative abnormal returns between the from and to dates stated at the top of the column. $DJSIE_y$ is a dummy taking the value 1 if firm $i$ joins the DJSI in year $y$. $X_{iy}$ is a vector of common firm characteristics associated with stock returns, being size (log assets), profitability (return on equity) and leverage (ratio of debt to capital). All characteristics are included as linear, quadratic and cubic. $\gamma_j$ is an industry fixed effect where firm $i$ is in industry $j$ as defined by the North American Industry Classification System at the two-digit level. $\psi_y$ are year fixed effects. Figures in parentheses report robust standard errors. Significance denoted by * = 1%, ** = 5%, and ***=0.1%. $N$=22159

Table A3.10: OLS Regressions for Cumulative Abnormal Returns and Firm Characteristics De-Listing: Base

| | Full Sample | | | | | Base Sample | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| From | 1 | 1 | 16 | 16 | 21 | 1 | 1 | 16 | 16 | 21 |
| To | 16 | 21 | 21 | 36 | 36 | 16 | 21 | 21 | 36 | 36 |
| $DJSIX$ | 7.260 | 5.709 | 2.762 | 0.496 | -0.889 | 2.643 | 1.031 | -2.947 | -0.122 | 1.544 |
| | (5.240) | (4.661) | (8.982) | (5.270) | (6.223) | (3.788) | (3.324) | (6.170) | (3.856) | (4.588) |
| Size | 5.249 | 3.616 | -4.010 | -1.932 | -5.835 | 64.29 | 66.42 | 88.74 | -11.11 | -61.94 |
| | (5.360) | (4.768) | (9.188) | (5.391) | (6.365) | (51.07) | (44.81) | (83.17) | (51.98) | (61.84) |
| Size$^2$ | 0.691 | -0.622 | -0.012 | 0.064 | 0.635 | -5.890 | -6.048 | -7.787 | 1.137 | 5.688 |
| | (0.667) | (0.594) | (1.144) | (0.671) | (0.792) | (4.747) | (4.166) | (7.732) | (4.832) | (5.749) |
| Size$^3$ | 0.026 | 0.027 | 0.013 | 0.003 | -0.020 | 0.179 | 0.182 | 0.225 | -0.038 | -0.172 |
| | (0.027) | (0.024) | (0.046) | (0.027) | (0.032) | (0.145) | (0.128) | (0.237) | (0.148) | (0.176) |
| Profitability | -15.06*** | -12.94*** | -3.496 | 2.683** | 6.177*** | -15.61*** | -8.209** | 19.35*** | 21.41*** | 25.41*** |
| | (1.330) | (1.183) | (2.280) | (1.338) | (1.580) | (4.378) | (3.842) | (7.130) | (4.456) | (5.302) |
| Profitability$^2$ | 0.126 | 0.097 | -0.280 | -0.030 | 0.062 | 5.223 | 0.241 | -15.13* | -20.94*** | -27.56*** |
| | (0.362) | (0.322) | (0.620) | (0.364) | (0.430) | (5.090) | (4.467) | (8.290) | (5.181) | (6.164) |
| Profitability$^3$ | 0.033* | 0.030* | -0.003 | 0.005 | 0.004 | -0.542 | 0.235 | 2.400 | 3.354*** | 4.521*** |
| | (0.018) | (0.016) | (0.030) | (0.018) | (0.021) | (1.004) | (0.881) | (1.635) | (1.021) | (1.215) |
| Leverage | -33.45** | -18.96 | 25.89 | 29.22** | 35.90** | -5.904 | 6.141 | 23.65 | -12.64 | -24.61 |
| | (13.95) | (12.41) | (23.91) | (14.03) | (16.57) | (35.03) | (30.74) | (57.05) | (35.65) | (42.42) |
| Leverage$^2$ | 27.78 | 9.312 | 53.76 | -83.90** | -98.82** | -17.42 | -40.57 | -95.02 | -13.01 | 18.04 |
| | (36.71) | (32.65) | (62.92) | (36.92) | (43.59) | (79.41) | (69.69) | (129.3) | (80.83) | (96.17) |
| Leverage$^3$ | 7.497 | 12.28 | 31.80 | 62.71** | 72.45** | 24.63 | 37.37 | 76.44 | 20.12 | -2.318 |
| | (26.41) | (23.49) | (45.26) | (26.56) | (31.36) | (53.01) | (46.52) | (86.34) | (53.95) | (64.20) |
| $R^2$ | 0.010 | 0.007 | 0.014 | 0.006 | 0.008 | 0.015 | 0.013 | 0.036 | 0.012 | 0.015 |
| $Adj-R^2$ | 0.010 | 0.007 | 0.013 | 0.005 | 0.007 | 0.012 | 0.011 | 0.029 | 0.010 | 0.013 |

Notes: Coefficients are reported for the base sample (All), and for the reduced sample with just firms with a size at least 80% of the size of the smallest firm gaining listing (Large). Selected pairings of from and to dates are shown. Coefficients from regression $CAR_i[from, to] = \alpha + \beta_{DJSI} DJSIX_{iy} + \theta X_{iy} + \gamma_j + \psi_y + \epsilon_{iy}$ for cumulative abnormal returns between the from and to dates stated at the top of the column. $DJSIX_y$ is a dummy taking the value 1 if firm $i$ de-lists from the DJSI in year $y$. $X_{iy}$ is a vector of common firm characteristics associated with stock returns, being size (log assets), profitability (return on equity) and leverage (ratio of debt to capital). All characteristics are included as linear, quadratic and cubic. $\gamma_j$ is an industry fixed effect where firm $i$ is in industry $j$ as defined by the North American Industry Classification System at the two-digit level. $\psi_y$ are year fixed effects. Figures in parentheses report robust standard errors. Significance denoted by * = 1%, ** = 5%, and ***=0.1%. $N$=22159 adopted in this paper.

Table A3.11 reports a wider set of ranges for the CAR, providing coefficients on the DJSI joining dummy. These models maintain the full set of controls and fixed effects from Table A3.9, but the full details are not reported for brevity. There are now some significant coefficients at the 10% level, but these account for less than 5% of all the coefficients reported. As such this extended set does little to reverse the conclusions of a lack of DJSI joining abnormal return that was seen in Table A3.9.

Regressions presented here suggest that much of the difference assigned to a new DJSI listing by the two-sample tests may actually be a consequence of other characteristics. Attributing effects to the correct characteristic represents one of the many challenges of using a testing approach.

### A3.2.6 Summary

This appendix has detailed the construction of abnormal returns for market based models. We also evidence estimation of the listing effects through both two sample t-tests and a regression based approach. Both methods provide significant estimates for some holding periods. However, the main message is that listing is insignificant. In the main paper we contrast this insignificance with our gsynth results.

## A3.3 Model Fit Comparisons

Building on the precedent in Acemoglu et al. (2016, 2017) and Chamon et al. (2017), we employ the generalised framework of Xu (2017) to estimate said. This leap from the original Abadie and Gardeazabal (2003) and Abadie et al. (2010) approach is taken because there are too often more than one company obtaining listing on the DJSI from any given industry. The original synthetic control cannot deal efficiently with such. The main paper has already highlighted the presence of multiple treated firms within industry-year pairs. Numbers of treated firms are repeated within the fit comparisons of Table A3.12.

The primary purpose of Table A3.12 is to report the fit statistics for the generalised synthetic control and to offer comparison with the CAPM generated fits. These are reported for the in-sample control period. MSPE values are reported at the two digit NAICS code level to indicate the quality of the fit through the training period. In the majority of cases these values are below 2, with high values appearing only where the number of controls is low. There are many occasions near the GFC where the synthetic

Table A3.11: Estimated Listing Effect from Cumulative Abnormal Returns OLS Regressions

| | From | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6 | 6 | 6 | 6 | 6 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | To | 15 | ANN | 17 | 18 | 19 | 20 | EFF | 22 | 26 | 11 | 15 | ANN | 17 | 20 |
| $DJSI^+$ | Full | 0.378 | 0.449 | 0.379 | 0.484 | 0.834 | 0.909 | 0.762 | 0.642 | 0.850 | 0.377 | 0.357 | 0.428 | 0.359 | 0.888 |
| | | (0.591) | (0.606) | (0.620) | (0.631) | (0.653) | (0.691) | (0.694) | (0.720) | (0.825) | (0.350) | (0.480) | (0.496) | (0.513) | (0.591) |
| | Base | 0.270 | 0.357 | 0.383 | 0.517 | 0.663 | 0.618 | 0.520 | 0.398 | 0.729 | 0.334 | 0.286 | 0.373 | 0.399 | 0.633 |
| | | (0.452) | (0.460) | (0.471) | (0.481) | (0.499) | (0.527) | (0.531) | (0.549) | (0.636) | (0.260) | (0.366) | (0.375) | (0.385) | (0.436) |
| $DJSI^-$ | Full | 6.888 | 7.260 | 6.328 | 6.425 | 6.516 | 6.398 | 5.709 | 5.704 | 3.978 | 15.80** | 12.09*** | 12.16* | 11.14* | 9.703* |
| | | (5.430) | (5.244) | (5.061) | (4.932) | (4.799) | (4.783) | (4.661) | (4.554) | (4.244) | (8.006) | (6.029) | (6.528) | (6.198) | (5.611) |
| | Base | 2.622 | 2.643 | 2.221 | 1.867 | 1.390 | 0.603 | 1.031 | 1.323 | 0.126 | 12.21** | 7.253 | 6.863 | 5.913 | 3.018 |
| | | (3.927) | (3.788) | (3.572) | (3.575) | (3.488) | (3.403) | (3.324) | (3.247) | (3.033) | (5.997) | (4.838) | (4.586) | (4.380) | (3.918) |
| | From | 6 | 6 | 11 | 11 | 11 | 11 | 11 | 11 | 15 | 15 | 15 | 15 | 15 | ANN |
| | To | EFF | 26 | 11 | 15 | ANN | 17 | EFF | 26 | 15 | ANN | 17 | 20 | EFF | 26 |
| $DJSI^+$ | Full | 0.741 | 0.829 | 0.108 | 0.088 | 0.159 | 0.090 | 0.472 | 0.560 | 0.087 | 0.158 | 0.088 | 0.618 | 0.471 | 0.559 |
| | | (0.596) | (0.728) | (0.145) | (0.351) | (0.371) | (0.389) | (0.496) | (0.632) | (0.155) | (0.206) | (0.244) | (0.379) | (0.395) | (0.544) |
| | Base | 0.536 | 0.745 | 0.089 | 0.041 | 0.129 | 0.155 | 0.291 | 0.501 | 0.113 | 0.201 | 0.227 | 0.461* | 0.363 | 0.573 |
| | | (0.444) | (0.546) | (0.114) | (0.284) | (0.294) | (0.305) | (0.381) | (0.489) | (0.119) | (0.151) | (0.178) | (0.275) | (0.290) | (0.417) |
| $DJSI^-$ | Full | 8.592 | 5.762 | 17.82 | 8.786 | 9.462 | 8.098 | 5.500 | 2.752 | -12.97 | -0.061 | -0.069 | 1.946 | 0.515 | -1.073 |
| | | (5.487) | (4.834) | (19.34) | (10.64) | (9.468) | (8.578) | (6.911) | (5.716) | (21.21) | (14.62) | (11.68) | (5.947) | (3.728) | (3.706) |
| | Base | 3.428 | 1.737 | 14.90 | 2.832 | 2.853 | 1.798 | -0.320 | -1.369 | -8.415 | -2.727 | -3.329 | -5.947 | -3.728 | -3.706 |
| | | (3.829) | (3.400) | (14.08) | (7.059) | (6.355) | (5.850) | (4.678) | (3.949) | (14.30) | (10.22) | (8.547) | (6.230) | (5.781) | (4.553) |
| | From | ANN | ANN | ANN | ANN | ANN | ANN | ANN | ANN | 17 | 17 | 18 | 19 | 20 | 20 |
| | To | ANN | 17 | 18 | 19 | 20 | EFF | 22 | 26 | 17 | EFF | EFF | EFF | EFF | 22 |
| $DJSI^+$ | Full | 0.071 | 0.002 | 0.107 | 0.457 | 0.531 | 0.384 | 0.264 | 0.472 | -0.069 | 0.313 | 0.382 | 0.277 | -0.073 | -0.192 |
| | | (0.140) | (0.196) | (0.246) | (0.292) | (0.349) | (0.369) | (0.399) | (0.530) | (0.133) | (0.334) | (0.307) | (0.265) | (0.218) | (0.261) |
| | Base | 0.088 | 0.114 | 0.248 | 0.393* | 0.348 | 0.250 | 0.129 | 0.460 | 0.026 | 0.162 | 0.136 | 0.002 | -0.143 | -0.265 |
| | | (0.100) | (0.142) | (0.182) | (0.213) | (0.256) | (0.273) | (0.300) | (0.409) | (0.098) | (0.248) | (0.223) | (0.193) | (0.154) | (0.190) |
| $DJSI^-$ | Full | 12.84 | 6.379 | 5.101 | 5.119 | 4.928 | 2.762 | 3.166 | 0.909 | -0.085 | 0.745 | 0.953 | 1.416 | -1.954 | -8.073 |
| | | (19.16) | (13.54) | (15.52) | (10.11) | (9.570) | (8.982) | (8.276) | (6.736) | (18.44) | (10.03) | (11.60) | (13.65) | (17.53) | (13.70) |
| | Base | 2.961 | -0.786 | -1.989 | -3.231 | 5.454 | -2.947 | -1.460 | -3.278 | -4.532 | -4.128 | -4.027 | -3.985 | -2.376 | 0.900 |
| | | (13.27) | (10.04) | (8.482) | (7.466) | (5.718) | (6.170) | (5.765) | (4.735) | (13.84) | (6.847) | (7.696) | (8.820) | (10.75) | (8.089) |
| | From | EFF | EFF | EFF | EFF | EFF | 22 | 22 | 22 | 26 | 26 | 31 | 31 | 36 | |
| | To | EFF | 22 | 26 | 31 | 36 | 22 | 26 | 36 | 26 | 36 | 31 | 36 | 36 | |
| $DJSI^+$ | Full | -0.147 | -0.267 | -0.059 | -0.158 | 0.373 | -0.120 | 0.088 | 0.520 | -0.060 | 0.372 | -0.144 | 0.387 | -0.010 | |
| | | (0.162) | (0.218) | (0.393) | (0.516) | (0.640) | (0.151) | (0.363) | (0.615) | (0.159) | (0.517) | (0.168) | (0.388) | (0.153) | |
| | Base | -0.098 | -0.219 | 0.112 | 0.135 | 0.579 | -0.121 | 0.210 | 0.676 | -0.067 | 0.400 | 0.004 | 0.447 | 0.048 | |
| | | (0.122) | (0.166) | (0.300) | (0.402) | (0.497) | (0.110) | (0.282) | (0.476) | (0.129) | (0.408) | (0.148) | (0.317) | (0.128) | |
| $DJSI^-$ | Full | 6.564 | -1.242 | -4.091 | -3.263 | -0.880 | 5.590 | -3.295 | -0.410 | 5.766 | 1.463 | -25.81 | -0.705 | -20.40 | |
| | | (23.44) | (15.91) | (9.329) | (7.684) | (6.223) | (20.71) | (10.08) | (6.434) | (21.57) | (7.729) | (22.41) | (9.605) | (21.39) | |
| | Base | 9.588 | 8.522 | -1.464 | 0.297 | 1.544 | 7.457 | -3.685 | 1.008 | -5.408 | 2.553 | -8.292 | 2.191 | -14.74 | |
| | | (14.53) | (10.40) | (6.568) | (5.491) | (4.588) | (13.59) | (7.240) | (4.783) | (16.05) | (5.816) | (16.16) | (7.492) | (16.64) | |

Notes: Coefficients on gaining DJSI listing are reported for the base sample (Full), and for the reduced sample with just firms with a size at least 80% of the size of the smallest firm gaining listing (Base). Coefficients for listing are from regression $CAR_i[from, to] = \alpha + \beta_{DJSI} DJSI^+_{iy} + \theta X_{iy} + \gamma_j + \psi_y + \epsilon_{iy}$ and are estimated for cumulative abnormal returns between the stated from and to dates, $CAR_i[from, to]$. $DJSI^+_{iy}$ is a dummy taking the value 1 if firm $i$ joins the DJSI in year $y$. $X_{iy}$ is a vector of common firm characteristics associated with stock returns, being size (log assets), profitability (return on equity) and leverage (ratio of debt to capital). All characteristics are included as linear, quadratic and cubic. $\gamma_j$ is an industry fixed effect where firm $i$ is in industry $j$ as defined by the North American Industry Classification System at the two-digit level. $\psi_y$ are year fixed effects. For de-listing regressions are repeated but with the de-listing dummy, $DJSI^-_i y$ replacing $DJSI^+_i y$. Figures in parentheses report robust standard errors. Significance denoted by * = 1%, ** = 5%, and ***=0.1%.

control model has an MSPE well below that associated with the CAPM, sometimes being less than half that of the original approach. Industry 21 in 2005 is a good example of this. In more recent years the number of times where the CAPM delivers a better fit is almost identical, though often the margin is very small. There remain times where the synthetic control error is less than half that of the CAPM model, including industry 21 in 2018 where the MSPE is just 0.827 compared to an MSPE of 1.839 for the CAPM. Overall there are 55 cases where the CAPM can be considered better fitting during the control period, compared to 82 for the generalised synthetic control approach. A t-test to compare the MSPE for the two models weighting all industry-years equally confirms a better fit from the generalised synthetic approach significant at the 5% level.

Model fit from the generalised synthetic control is again better than that from the corresponding CAPM, with the in sample MSPE comparison showing it to be the better fit in 31 cases compared to 24 for the CAPM. Table A3.13 provides the full comparison. This is a smaller differential than for the entering firms. As with entry where the generalised synthetic control does improve fit the margin of improvement is much larger, industry 51 in 2006 has two firms leaving the market and a MSPE of 4.355 from the CAPM but just 1.346 for the generalised synthetic control. Another parallel is seen in the more even performance of the two techniques in recent years.

Both Table A3.12 and A3.13 provide information on the number of cointegrating relationships which appear between the listed stocks and the unobserved factors. Few patterns can be seen in this value. Both Tables also contain a test for the cointegration of the error matrix. In all cases the value is 0. Therefore we may assume the model is correctly specified and continue to analyse the results.

Table A3.12: Fit Statistics by Industry: Listing

| Year | NAICS2 | V. | Co. | Tr | Ctrl | MSPE CAPM | Synth | Year | NAICS2 | V. | Co. | Tr | Ctrl | MSPE CAPM | Synth |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2005 | 21 | 0 | 3 | 1 | 129 | 3.344 | 1.358 | 2011 | 53 | 0 | 5 | 1 | 178 | 1.919 | 1.142 |
| 2005 | 22 | 0 | 5 | 6 | 99 | 1.488 | 0.631 | 2011 | 56 | 0 | 1 | 1 | 49 | 1.882 | 1.666 |
| 2005 | 23 | 0 | 3 | 1 | 31 | 2.703 | 2.639 | 2011 | 72 | 0 | 1 | 1 | 47 | 0.914 | 0.983 |
| 2005 | 31 | 0 | 1 | 3 | 105 | 0.783 | 0.839 | 2012 | 22 | 0 | 5 | 1 | 98 | 0.895 | 0.568 |
| 2005 | 32 | 0 | 5 | 8 | 318 | 1.041 | 1.003 | 2012 | 31 | 0 | 4 | 2 | 107 | 0.606 | 0.600 |
| 2005 | 33 | 0 | 2 | 9 | 661 | 1.602 | 1.540 | 2012 | 32 | 0 | 1 | 2 | 275 | 0.517 | 0.619 |
| 2005 | 44 | 0 | 1 | 4 | 89 | 1.628 | 1.607 | 2012 | 33 | 0 | 2 | 2 | 574 | 1.416 | 1.403 |
| 2005 | 45 | 0 | 2 | 1 | 53 | 1.149 | 1.032 | 2012 | 45 | 0 | 1 | 1 | 36 | 7.648 | 7.772 |
| 2005 | 48 | 0 | 5 | 1 | 89 | 0.915 | 0.825 | 2012 | 51 | 0 | 2 | 3 | 263 | 2.309 | 2.181 |
| 2005 | 51 | 0 | 1 | 4 | 285 | 0.866 | 0.960 | 2012 | 52 | 0 | 3 | 1 | 499 | 2.421 | 1.967 |
| 2005 | 52 | 0 | 2 | 7 | 535 | 0.707 | 0.716 | 2012 | 54 | 0 | 1 | 1 | 107 | 1.864 | 1.964 |
| 2005 | 54 | 0 | 4 | 2 | 112 | 1.744 | 1.751 | 2012 | 56 | 0 | 1 | 1 | 48 | 0.738 | 0.789 |
| 2005 | 56 | 0 | 3 | 1 | 57 | 0.862 | 0.897 | 2013 | 21 | 0 | 3 | 2 | 152 | 1.594 | 1.396 |
| 2005 | 72 | 0 | 5 | 1 | 62 | 1.180 | 1.093 | 2013 | 31 | 0 | 3 | 2 | 112 | 0.574 | 0.860 |
| 2006 | 21 | 0 | 5 | 2 | 140 | 4.530 | 1.608 | 2013 | 32 | 0 | 2 | 4 | 293 | 1.329 | 1.377 |
| 2006 | 22 | 0 | 5 | 4 | 104 | 0.786 | 0.936 | 2013 | 33 | 0 | 1 | 4 | 587 | 0.728 | 1.265 |
| 2006 | 31 | 0 | 4 | 1 | 109 | 0.402 | 0.416 | 2013 | 44 | 0 | 5 | 2 | 83 | 0.852 | 0.883 |
| 2006 | 32 | 0 | 3 | 3 | 327 | 2.244 | 1.721 | 2013 | 51 | 0 | 1 | 2 | 287 | 3.110 | 3.061 |
| 2006 | 33 | 0 | 1 | 1 | 683 | 1.767 | 1.826 | 2013 | 52 | 0 | 3 | 2 | 542 | 1.229 | 1.057 |
| 2006 | 42 | 0 | 5 | 1 | 82 | 0.852 | 0.896 | 2013 | 53 | 0 | 5 | 3 | 191 | 1.443 | 1.122 |
| 2006 | 51 | 0 | 1 | 1 | 301 | 4.355 | 4.331 | 2013 | 54 | 0 | 1 | 1 | 103 | 4.532 | 4.533 |
| 2006 | 52 | 0 | 3 | 3 | 540 | 0.872 | 0.841 | 2014 | 22 | 0 | 5 | 2 | 100 | 0.714 | 0.749 |
| 2007 | 21 | 0 | 3 | 1 | 162 | 1.623 | 0.936 | 2014 | 23 | 0 | 4 | 2 | 46 | 0.683 | 0.734 |
| 2007 | 22 | 0 | 1 | 1 | 106 | 1.143 | 1.111 | 2014 | 32 | 0 | 4 | 1 | 349 | 1.991 | 2.172 |
| 2007 | 33 | 0 | 4 | 2 | 694 | 3.035 | 2.754 | 2014 | 33 | 0 | 3 | 3 | 637 | 1.353 | 1.416 |
| 2007 | 45 | 0 | 4 | 1 | 49 | 2.592 | 2.509 | 2014 | 48 | 0 | 3 | 1 | 119 | 0.678 | 0.663 |
| 2007 | 51 | 0 | 4 | 1 | 318 | 2.442 | 2.465 | 2014 | 51 | 0 | 4 | 2 | 322 | 2.277 | 2.221 |
| 2007 | 52 | 0 | 4 | 3 | 517 | 1.047 | 1.042 | 2014 | 52 | 0 | 4 | 2 | 591 | 0.836 | 0.820 |
| 2007 | 54 | 0 | 1 | 1 | 114 | 1.681 | 1.719 | 2014 | 53 | 0 | 3 | 1 | 220 | 1.341 | 1.343 |
| 2007 | 62 | 0 | 3 | 1 | 52 | 3.394 | 3.211 | 2014 | 72 | 0 | 1 | 1 | 58 | 0.938 | 0.968 |
| 2008 | 31 | 0 | 5 | 1 | 104 | 1.820 | 1.835 | 2015 | 23 | 0 | 4 | 1 | 43 | 2.230 | 0.866 |
| 2008 | 32 | 0 | 4 | 1 | 282 | 3.700 | 3.610 | 2015 | 31 | 0 | 5 | 2 | 105 | 0.473 | 1.056 |
| 2008 | 33 | 0 | 4 | 2 | 573 | 5.592 | 3.728 | 2015 | 32 | 0 | 2 | 3 | 392 | 0.813 | 0.851 |
| 2008 | 45 | 0 | 2 | 1 | 34 | 5.020 | 2.519 | 2015 | 33 | 0 | 5 | 1 | 599 | 0.839 | 0.912 |
| 2008 | 51 | 0 | 1 | 1 | 256 | 4.680 | 4.631 | 2015 | 51 | 0 | 4 | 1 | 333 | 0.728 | 0.739 |
| 2008 | 52 | 0 | 3 | 2 | 440 | 4.913 | 3.562 | 2015 | 52 | 0 | 5 | 1 | 592 | 0.426 | 0.414 |
| 2008 | 53 | 0 | 2 | 2 | 156 | 3.518 | 2.810 | 2015 | 53 | 0 | 5 | 2 | 217 | 1.459 | 0.961 |
| 2008 | 56 | 0 | 2 | 1 | 51 | 1.604 | 1.598 | 2015 | 72 | 0 | 5 | 1 | 61 | 3.010 | 0.982 |
| 2009 | 21 | 0 | 1 | 1 | 119 | 10.00 | 5.781 | 2016 | 31 | 0 | 4 | 2 | 105 | 1.034 | 1.040 |
| 2009 | 31 | 0 | 5 | 1 | 88 | 2.317 | 2.103 | 2016 | 32 | 0 | 1 | 1 | 381 | 1.122 | 1.353 |
| 2009 | 32 | 0 | 3 | 4 | 221 | 4.630 | 4.636 | 2016 | 33 | 0 | 3 | 2 | 560 | 0.729 | 2.150 |
| 2009 | 33 | 0 | 5 | 2 | 430 | 3.386 | 3.409 | 2016 | 44 | 0 | 2 | 1 | 81 | 1.577 | 1.225 |
| 2009 | 42 | 0 | 1 | 2 | 60 | 4.482 | 4.687 | 2016 | 51 | 0 | 5 | 1 | 329 | 2.387 | 2.423 |
| 2009 | 44 | 0 | 4 | 1 | 60 | 4.626 | 4.573 | 2016 | 52 | 0 | 5 | 3 | 564 | 2.060 | 1.431 |
| 2009 | 45 | 0 | 5 | 1 | 26 | 9.064 | 5.498 | 2016 | 53 | 0 | 5 | 2 | 223 | 3.039 | 2.452 |
| 2009 | 48 | 0 | 4 | 1 | 84 | 3.057 | 2.609 | 2016 | 56 | 0 | 3 | 1 | 53 | 0.585 | 0.621 |
| 2009 | 51 | 0 | 5 | 1 | 204 | 2.138 | 2.161 | 2017 | 21 | 0 | 5 | 2 | 121 | 3.634 | 3.520 |
| 2009 | 52 | 0 | 5 | 3 | 353 | 9.198 | 7.351 | 2017 | 31 | 0 | 3 | 2 | 106 | 1.029 | 0.783 |
| 2009 | 54 | 0 | 1 | 1 | 87 | 4.522 | 4.543 | 2017 | 32 | 0 | 3 | 2 | 388 | 1.922 | 1.992 |
| 2010 | 21 | 0 | 2 | 3 | 141 | 4.235 | 1.947 | 2017 | 33 | 0 | 5 | 3 | 576 | 1.834 | 1.904 |
| 2010 | 32 | 0 | 1 | 4 | 274 | 1.314 | 1.333 | 2017 | 48 | 0 | 5 | 1 | 115 | 1.803 | 1.452 |
| 2010 | 33 | 0 | 5 | 3 | 572 | 1.365 | 1.262 | 2017 | 51 | 0 | 3 | 2 | 330 | 0.793 | 0.828 |
| 2010 | 51 | 0 | 5 | 1 | 248 | 0.593 | 0.664 | 2017 | 52 | 0 | 5 | 2 | 608 | 0.801 | 0.955 |
| 2010 | 54 | 0 | 5 | 2 | 111 | 2.241 | 2.227 | 2017 | 53 | 0 | 5 | 2 | 224 | 1.639 | 1.088 |
| 2010 | 56 | 0 | 1 | 1 | 46 | 2.192 | 2.343 | 2017 | 54 | 0 | 1 | 1 | 88 | 1.566 | 1.689 |
| 2011 | 32 | 0 | 4 | 1 | 273 | 0.954 | 1.003 | 2017 | 72 | 0 | 2 | 2 | 62 | 0.713 | 0.728 |
| 2011 | 33 | 0 | 3 | 4 | 577 | 1.463 | 1.477 | 2018 | 21 | 0 | 4 | 1 | 103 | 1.839 | 0.827 |
| 2011 | 44 | 0 | 1 | 1 | 80 | 3.391 | 3.390 | 2018 | 32 | 0 | 5 | 2 | 221 | 1.748 | 1.787 |
| 2011 | 45 | 0 | 5 | 1 | 33 | 1.628 | 1.382 | 2018 | 33 | 0 | 5 | 2 | 401 | 4.102 | 3.693 |
| 2011 | 48 | 0 | 4 | 2 | 88 | 3.359 | 2.664 | 2018 | 52 | 0 | 2 | 2 | 429 | 1.097 | 1.130 |
| 2011 | 52 | 0 | 4 | 3 | 462 | 1.284 | 0.969 | 2018 | 56 | 0 | 4 | 1 | 28 | 0.698 | 0.745 |

Notes: Models are fitted using the generalised synthetic control method of Xu (2017). NAICS2 reports the two-digit North American Industry Classification System (NAICS) code for the considered industry. MSPE is the Mean Squared Prediction Error when fitting the synthetic versions of the fitted shares to the training data. CAPM reports the MSPE for the CAPM based CARs from Section A3.2.3, whilst Synth reports the MSPE for the generalised synthetic control methodology. V. reports a test for the cointegration of the error matrix with 0 implying rejection. Co. gives the number of cointegrating relationships used in the construction of the unobserved parameter. Tr is the number of firms who joined the DJSI for that two digit NAICS code. Ctrl is the number of control firms used to construct the couterfactual model for entering firms. All firms with missing data are eliminated, including some new listings to the DJSI. All estimations performed using *gsynth* (Xu and Liu, 2018)

Table A3.13: Fit Statistics by Industry: De-Listing

| Year | NAICS2 | V. | Co. | Tr | Ctrl | MSPE CAPM | Synth | Year | NAICS2 | V. | Co. | Tr | Ctrl | MSPE CAPM | Synth |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2006 | 22 | 0 | 2 | 2 | 106 | 0.786 | 0.895 | 2013 | 33 | 0 | 4 | 3 | 588 | 0.728 | 0.895 |
| 2006 | 31 | 0 | 4 | 1 | 109 | 0.402 | 0.846 | 2013 | 44 | 0 | 4 | 1 | 84 | 0.852 | 1.923 |
| 2006 | 33 | 0 | 1 | 2 | 682 | 1.767 | 1.521 | 2013 | 52 | 0 | 3 | 3 | 541 | 1.229 | 3.065 |
| 2006 | 51 | 0 | 5 | 2 | 300 | 4.355 | 1.346 | 2014 | 32 | 0 | 5 | 1 | 349 | 1.991 | 0.679 |
| 2006 | 52 | 0 | 4 | 2 | 541 | 0.872 | 1.044 | 2014 | 51 | 0 | 2 | 1 | 323 | 2.277 | 0.719 |
| 2007 | 51 | 0 | 5 | 1 | 318 | 2.442 | 2.307 | 2014 | 72 | 0 | 1 | 1 | 58 | 0.938 | 0.417 |
| 2007 | 52 | 0 | 4 | 2 | 518 | 1.047 | 0.911 | 2015 | 23 | 0 | 3 | 1 | 43 | 2.230 | 1.137 |
| 2008 | 32 | 0 | 4 | 1 | 282 | 3.700 | 2.917 | 2015 | 31 | 0 | 4 | 1 | 106 | 0.473 | 0.398 |
| 2008 | 33 | 0 | 4 | 1 | 574 | 5.592 | 2.841 | 2015 | 33 | 0 | 5 | 4 | 596 | 0.839 | 0.987 |
| 2008 | 51 | 0 | 2 | 1 | 256 | 4.680 | 3.508 | 2015 | 52 | 0 | 3 | 1 | 592 | 0.426 | 0.927 |
| 2009 | 32 | 0 | 3 | 1 | 224 | 4.630 | 3.844 | 2015 | 53 | 0 | 2 | 1 | 218 | 1.459 | 1.226 |
| 2009 | 33 | 0 | 2 | 1 | 431 | 3.386 | 6.380 | 2016 | 31 | 0 | 4 | 1 | 106 | 1.034 | 0.465 |
| 2009 | 52 | 0 | 4 | 1 | 355 | 9.198 | 13.48 | 2016 | 32 | 0 | 2 | 1 | 381 | 1.122 | 1.250 |
| 2010 | 32 | 0 | 2 | 4 | 274 | 1.314 | 1.168 | 2016 | 33 | 0 | 4 | 2 | 560 | 0.729 | 1.128 |
| 2010 | 33 | 0 | 3 | 2 | 573 | 1.365 | 2.310 | 2016 | 52 | 0 | 5 | 1 | 566 | 2.060 | 0.520 |
| 2010 | 51 | 0 | 4 | 1 | 248 | 0.593 | 1.303 | 2016 | 56 | 0 | 4 | 1 | 53 | 0.585 | 1.370 |
| 2010 | 56 | 0 | 5 | 1 | 46 | 2.192 | 0.647 | 2017 | 21 | 0 | 4 | 3 | 120 | 3.634 | 1.236 |
| 2011 | 52 | 0 | 5 | 1 | 464 | 1.284 | 0.880 | 2017 | 31 | 0 | 4 | 2 | 106 | 1.029 | 1.647 |
| 2011 | 56 | 0 | 1 | 1 | 49 | 1.882 | 1.065 | 2017 | 32 | 0 | 1 | 1 | 389 | 1.922 | 0.502 |
| 2012 | 22 | 0 | 5 | 2 | 97 | 0.895 | 0.730 | 2017 | 33 | 0 | 1 | 1 | 578 | 1.834 | 1.942 |
| 2012 | 32 | 0 | 1 | 2 | 275 | 0.517 | 1.154 | 2017 | 51 | 0 | 1 | 1 | 331 | 0.793 | 0.761 |
| 2012 | 33 | 0 | 2 | 4 | 572 | 1.416 | 2.699 | 2017 | 52 | 0 | 4 | 1 | 609 | 0.801 | 0.538 |
| 2012 | 45 | 0 | 1 | 2 | 35 | 7.648 | 5.010 | 2017 | 53 | 0 | 5 | 1 | 225 | 1.639 | 2.989 |
| 2012 | 51 | 0 | 2 | 2 | 264 | 2.309 | 0.707 | 2017 | 72 | 0 | 5 | 1 | 63 | 0.713 | 1.679 |
| 2012 | 52 | 0 | 4 | 1 | 499 | 2.421 | 1.020 | 2018 | 31 | 0 | 5 | 2 | 57 | 2.133 | 1.103 |
| 2012 | 54 | 0 | 1 | 2 | 106 | 1.864 | 2.355 | 2018 | 32 | 0 | 4 | 2 | 221 | 1.748 | 1.795 |
| 2013 | 31 | 0 | 2 | 1 | 113 | 0.574 | 1.039 | 2018 | 52 | 0 | 4 | 2 | 429 | 1.097 | 0.610 |
| 2013 | 32 | 0 | 5 | 5 | 292 | 1.329 | 1.125 | | | | | | | | |

Notes: Models are fitted using the generalised synthetic control method of Xu (2017). NAICS2 reports the two-digit North American Industry Classification System (NAICS) code for the considered industry. MSPE is the Mean Squared Prediction Error when fitting the synthetic versions of the fitted shares to the training data. CAPM reports the MSPE for the CAPM based CARs from Section A3.2.3, whilst Synth reports the MSPE for the generalised synthetic control methodology. V. reports a test for the cointegration of the error matrix with 0 implying rejection. Co. gives the number of cointegrating relationships used in the construction of the unobserved parameter. Tr is the number of firms who exited the DJSI for that two digit NAICS code. Ctrl is the number of control firms used to construct the counterfactual model for de-listed firms. All firms with missing data are eliminated, including some de-listings from the DJSI. All estimations performed using *gsynth* (Xu and Liu, 2018)

# Chapter 4

## ESG Flavoured Alpha and Sustainably Responsible Investment Strategies on the S&P 500

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**Abstract**

Growth in ESG focused investment volumes suggests a wider utility from holding higher ESG performance stocks. A large theoretical literature is emerging in response. Evidence on the abnormal returns to ESG focused investment continues to suggest that there is little alpha justification for the observed patterns. Using a double-sort approach we demonstrate that traditional anomaly strategies may be enhanced by ESG to produce an ESG flavoured alpha. Whilst few of these ESG flavoured alphas are significantly different from the unconditional anomaly strategy, we show they do exist and are no lower than the unconditional counterpart. Investors may increase their ESG exposure without paying an alpha price. We demonstrate this for the highly liquid S&P 500 universe between 2005 and 2019 using a set of 24 anomalies. Our results are robust to choice of ESG measure, weighting and the asset pricing model used to generate the abnormal returns. Our strategies can therefore guide investors in making ESG informed choices.

Keywords: ESG, Abnormal Returns, Alpha, Investment Strategies, Large Stocks

## 4.1 Introduction

Investors are typically assumed to face a choice between selecting stocks based on their environmental, social and governance (ESG) performance, or choosing strategies that will maximise abnormal returns instead. However, by 2017 more than a quarter of all managed funds in the US were directed by ESG (USSIF 2018) and the figure had passed one third by 2019 (Bloomberg, 2021). Meanwhile, academic studies, including this paper, continue to evidence that taking a long position on ESG leaders and then a short position on those whose ESG performance is low (ESG laggards), consistently produces negative abnormal returns. This indicates that pure ESG alpha may not exist. Investment flows into ESG leaders may be motivated by a belief in the long-term benefits of ESG to firm performance. In this way investors give up short-term performance to gain long-term benefit (Renneboog et al., 2008). This paper presents a method for investors to ease the short-term performance loss when increasing the ESG loading of their portfolio.

Derwall et al. (2011) expresses the tension between “values based” and “return focused” investors, suggesting that the two aims are mutually exclusive. To avoid confusion with value in the book-to-market sense, we refer to “values based” investors as being “ESG driven”. Evidence from the literature supports the Derwall et al. (2011) position that ESG driven investments are mutually exclusive from those which generate the highest returns. Papers to suggest mutual exclusivity from contemporary data include Bruno et al. (2021) and Cerquetti et al. (2021). Attempts to identify an ESG factor by de Haan et al. (2012) and Becchetti et al. (2018) begin with the target of longing ESG leaders and shorting ESG laggards. In all cases these factor studies return to the conclusion of mutual exclusivity. New evidence from Cerquetti et al. (2021) adds to papers by Kim et al. (2014), Becchetti et al. (2015) and Albuquerque at al. (2019), which suggest ESG investments have lower risk. This literature motivates flows into ESG leaders' stocks on the risk-return trade off, investors being willing to give up return in exchange for the lower risk of ESG leaders. Investment in ESG brings negative alpha, but the continued growth of ESG funds may indicate that investors are happy with the risk premium they receive. In practice there are many reasons which cause investors to look beyond alpha, including consideration of long-term returns. For example recent legislation has caused many to look again at oil holdings within their portfolios because of the damage to long-run returns (Breitenstein et al. 2021). Here investors look to sustainability in the long term in place of firms that have long running negative relationships with the environment. Two problems face investors. Firstly, there is a growing call for investors to rebalance towards ESG. Secondly, the evidence on negative alpha remains strong, presenting a challenge for fund managers and investors when making the transition. This paper explores the possibility that the investor can reduce the negative alpha from the necessary move to ESG by rebalancing their portfolios in a way that does not harm returns too much.

To achieve an understanding of how investors may improve their returns while having an increased ESG exposure we consider strategies which combine traditional factor investing with ESG exposure. Factor investing is modelled through strategies which mirror those found in Fama and French (2015) and others. An example is the size factor of Fama and French (1993), which is based upon longing small stocks and shorting large stocks. To ensure a fair comparison between strategies, we consider only members of the S&P500. Focusing on the S&P 500 stocks ensures that we have liquid stocks, and that trading costs are considerably lower than had the full set of US listed stocks been used (Novy-Marx and Velikov, 2016). Two benchmark strategies are used. The first is the ESG benchmark which is long high ESG and short low ESG. Secondly, we have the unconditional strategy for the factor sort variable[1] which goes long on the theoretically highest returning stocks and short on the theoretically lowest. For Size this would mean long on small stocks and short on big. We then consider one-way enhancements sorting on ESG within the high sort portfolio, or sorting by the traditional factor variable within high ESG. Finally, we take two strategies using both the factor and ESG sorts. Firstly, there is the dual enhancement which longs high ESG high factor sort and low ESG low factor sort, whilst shorting high ESG low factor sort and low ESG high factor sort. Secondly we present a strategy that longs high ESG high factor sort and shorts low ESG low factor sort. This final strategy is designed to appeal to those ESG driven investors who only wish to long high ESG stocks. To ensure our assessed strategies are investable, we assume annual portfolio recomposition. Through the comparison of these strategies we ask whether combining ESG information with the traditional sorts can produce alpha.

Our approach involves a series of double sorts, employing two measures of ESG leadership and 24 common anomalies. ESG performance is measured through membership of the Dow Jones Sustainability Index North America (DJSI) and Refinitiv ESG Scores[2]. We begin with the 6 core anomalies discussed by Green et al. (2017) (henceforth GHZ). The core anomalies are size, book-to-market ratio, profitability and investment after Fama and French (2015), momentum after Jegadeesh (1990), Jegadeesh and Titman (1993) and Carhart (1997) and return on equity after Hou et al. (2015). We also study those 18 anomalies that GHZ identify as being able to explain the returns of non-microcaps[3] We say that an ESG flavoured alpha on one of these factor sorts

[1] In this paper we refer to existing factors such as size, book-to-market ratio, profitability etc. as being factor sorts to distinguish them from the ESG sorts.

[2] Refinitiv ESG replaced the well studied Thomson Reuters Asset 4 database, but incorporates all historic information from Asset 4.

[3] Non-microcaps excludes the smallest 20% of stocks in the CRSP-Compustat universe. The GHZ

exists where the alpha from one of our double sort strategies is significant. This can be beneficial for investors where the ESG flavoured alpha is not lower than that which would be realised from the anomaly benchmark.

Our results demonstrate that in every case, the ESG flavoured alpha is not significantly lower than the single-sort strategy benchmark. This applies for all 24 anomalies and both the DJSI membership and Refinitiv ESG scores. We find that ESG may enhance the traditional factor information for return volatility, earnings announcement return, the growth in sales less the growth in inventory, stock turnover and on the number of zero trading days. Our proposed strategy to long high ESG high factor sort and short low ESG low factor sort produces significant alpha against both the CAPM and the five factor model of Fama and French (2015) (FF5) under value weighting for both the Refinitiv ESG and DJSI membership high ESG definitions. After adjustment for trading costs, there are still no cases in which the ESG flavoured alpha falls below the single sort strategy benchmark[4]. An example of the significant alpha generated by longing high ESG high factor sort stocks and shorting low ESG low factor sort stocks, may be found in the factor sorts on return volatility. Sorts on return volatility and ESG score produce monthly alphas of 0.67% with a t-statistic of 2.99 under equal weighting and 2.80 under value weighting. DJSI membership produces an alpha of 0.56% with a t-statistic of 2.68 under equal weighting and a monthly alpha of 0.65% with a t-statistic of 3.01 under value weighting. After adjustment for trading costs, the respective alphas are 0.55, 0.54, 0.43 and 0.52. However, almost all of the significance for these return volatility-ESG score returns disappears when the FF5 model is used. Only the value weighted return using the ESG score produces a significant alpha against the FF5, the monthly alpha being 0.37% and having a t-statistic of 2.12. We thus confirm that being ESG driven and being alpha seeking need not be mutually exclusive. None of the

sample runs from January 1980 to December 2014. The 18 anomalies considered are the capital asset pricing model (CAPM) beta (Frazzini and Pedersen, 2014), asset growth (Cooper et al., 2008), the growth in inventory (Thomas and Zhang, 2002), the growth in book value of equity (Richardson et al., 2005), the growth of capital expenditure (Anderson and Garcia-Feijoo, 2006), the growth in long term net operating assets (Fairfield et al., 2003), the growth in sales minus the growth in inventory (Abarbanell and Bushee, 1998), the growth of shares outstanding (Pontiff and Woodgate, 2008), earning announcement returns (Kishore et al., 2008), the change in six month momentum (Gettleman and Marks, 2006), one month momentum (Jegadeesh and Titman, 1993), industry adjusted cashflow (Asness et al., 2000), return volatility (Ang et al., 2006), share turnover (Datar et al., 1998), turnover volatility (Chordia et al., 2001b), number of zero trading days (Liu, 2006), illiquidity (Amihud, 2002) and industry momentum (Moskowitz and Grinblatt, 1999).

[4]The trading cost adjustment applied follows Novy-Marx and Velikov (2016) and Chen and Velikov (2020) to deduct 1 basis point for each percentage point of turnover in one leg of the strategy. Trading costs are only deducted in months where the strategy actually trades. Full details are discussed in Section 4.5.3.

alphas for return volatility are significant after adjusting for trading costs against the FF5. However, there remains no alpha motivation for investors to switch away from the common anomaly strategy to incorporate ESG. If an investor is not ESG driven then we would not expect them to switch to our strategies that do consider ESG. However, an investor who is ESG driven can use our strategies to generate an alpha equivalent to the common anomaly strategy.

The remainder of the paper is organised as follows. Section 4.2 reviews the current state of the literature on integrating ESG into investment strategies. Data and the empirical approach are discussed in Section 4.3. Section 4.4 presents the raw portfolio returns for the DJSI and ESG score double-sorts. Alpha opportunities are evaluated in Section 4.5. Implications for ESG focused investment are then explored in Section 4.6 before Section 4.7 concludes.

## 4.2 Literature and Background

### 4.2.1 Background

Investors are increasingly asking for more than maximal financial returns to their investments. Derwall et al. (2011) identification of ESG driven investors is an early formalisation of this. Derwall et al. (2011) identifies ESG driven investors separately from returns focused investors. Immediately the utility function of the two types is different. Recent theoretical models by Pástor et al. (2020), Pedersen et al. (2020) and Ahmed et al. (2021) incorporate this by splitting investor utility into two parts. Firstly, the amount gained from the stock returns as in the classic literature. Secondly, they add the happiness which is gained from knowing that the firms invested in have positive ESG. Recognition of the importance of ESG has been a key development of understanding the behaviour of investors. However, despite the presence of ever higher numbers of ESG driven investors in the market, we still need to explain more about why there is the growth. We also need to think more about what that means for investment strategies.

An immediate strategy is to long stocks which have a high ESG score and short those with a low ESG score. However, such strategies typically do not produce alpha (Mollet and Ziegler, 2014; Becchetti et al., 2018; Kaiser, 2020). Early work by Kempf and Osthoff (2007) and Statman and Glushkov (2009) did locate alpha, but subsequent work has not found such. Rather Becchetti et al. (2018) argues that a strategy which longs low-ESG stocks and shorts high-ESG can yield abnormal returns. Many works therefore use the additional utlity from the sentiment of ESG investment to justify the growth of ESG despite the empirical evidence being indifferent (Pedersen et al., 2020). Hence, if the investor gains additional happiness from the ESG nature of the portfolio they will prefer these tilted strategies. A final approach is to restrict the potential investment universe to stocks with high ESG scores. Within the high ESG set traditional strategies can be calculated. Jin (2020) explores the cutoffs used and finds that alpha can be obtained from the restricted set of high ESG stocks. Observed flows into ESG focused funds are then a combination of investor utility and beliefs about the potential to apply traditional strategies after screening.

The Finance literature devotes considerable attention to finding investable strategies that are not priced by accepted factors. Many of these come from sorts on firm characteristics, with investors holding stocks at one end of the characteristic distribution and shorting those at the other. As an example, Fama and French (2020) documents how evidence on smaller stocks delivering higher returns in Banz (1981) and Fama and French (1992) informed the small-minus-big (SMB) factor that appears in Fama and French (1993). Where a strategy like this is not priced it is referred to as an anomaly. Subsequently a large number of firm characteristics have been identified as anomalies[5].

Often the identification of anomalies within the academic literature means that the mispricing ends (McLean and Pontiff, 2016). Continued mispricing is therefore hard to identify. The Sabranes-Oxley act of 2002 increased audit quality and financial reporting accuracy. By reducing information costs, the act is also regarded as having reduced the set of true anomalies (Brochet, 2010; Green et al., 2017). Further, decimalisation of the market in late 2000 to early 2001 had also eased trading (Bertone et al., 2015; Bessembinder, 2003). Additional evidence on the easing of trading reducing the potential for mispricing is provided in Chordia et al. (2001b) and French (2008). GHZ is one of many studies to document how very few anomalies are still mispriced since 2003, further examples being Chordia et al. (2014), Harvey et al. (2016) and Hou et al. (2020). ESG data is most readily available after 2003 and hence the potential for mispricing is reduced further by the improved trading environment.

[5]Hou et al. (2020) identify 452 anomalies for consideration. Following GHZ our focus is only on anomalies from single sorts. Consequently, we exclude many of the 452 that use interactions between variables to form anomalies.

### 4.2.2 Empirical Considerations

Within the literature there are many measures of ESG used. Approaches to analysing ESG include continuous ESG scores, like the Refinitiv ESG scores[6] used in this paper, and binary measures such as social index inclusion. MSCI, Standard and Poor's, and Bloomberg all produce indexes which name sustainability leaders. This paper uses the DJSI as a binary indicator. Binary measures make treatment effects easier to study. Abnormal returns to listing onto sustainability indexes are found by Robinson et al. (2011),Oberndorfer et al. (2013), Hawn et al. (2018) and Durand et al. (2019) amongst others. However, these effects are not persistent. Long-term differences in returns because of ESG leadership recognition are not suggested. There is also a literature which uses specific issues to examine potential ESG alpha. Edmans (2011) study of "America's 100 best companies to work for" list finds an alpha of around 3% per year. Li et al. (2019) finds a smaller alpha of 1.4% per year using global data. Continuous measures are advantageous for constructing sorted potrfolios, and are used for portfolio formation by Becchetti et al. (2018), Pedersen et al. (2020) and many others.

A challenge for investors comes from the differentials in the way that ESG perfromance is measured. Consequently when evaluating firms, it is seen that there are signficant disagreements between the measures, which may affect results (Dimson et al., 2020; Christensen et al., 2021). As an alternative to using a single measure, papers such as Kempf and Osthoff (2007) use a best in class approach to find the combination that produces the best returns. Following a best-in-class measure requires all of the data that is needed to construct the measure. Information costs increase for investors. Binary measures have the advantage of reducing information costs (Lewis and Carlos, 2019), but do discard much of the ranking information that is available in continuous measures. In using the DJSI and Refinitiv ESG scores we are thus using two of the most commonly studied measures from the literature to gain the benefits of both continuous and binary measures.

Data on ESG has a limited history compared to the firm characteristics used in other asset pricing studies. As a result work to explore ESG alpha will rely on the full available data. Because they work from different data sets it is intuitive that different conclusions can result. Bansal et al. (2021) is amongst the first papers to provide an explanation. Splitting on "good" and "bad" economic times, Bansal et al. (2021) show that there is ESG alpha in "good" times when the economy is performing well. This

[6] Refinitiv ESG replaced the Thomson Reuters Asset 4 scores that had been widely used in the literature. Historic scores from Refinitiv are thus the Asset 4 scores.

stands in contrast to the evidence of Lins et al. (2017) and others. Previously it had been argued that it was resilience to crises that made ESG portfolios outperform non-ESG portfolios (Lins et al., 2017). However, in the Covid-19 induced downturn of 2020 ESG has been less of a resilience factor (Albuquerque et al., 2020; Ding et al., 2021). Within the time period of this paper we have the global financial crisis, associated recovery, and a prolonged period of slow growth. Therefore there is a balance of “good” and “bad”.

### 4.2.3 ESG Investment Strategies

Focus on ESG creates further restrictions on the opportunities for alpha. By screening stocks on their ESG performance investors are reducing their scope for diversification. Giese et al. (2019) present a discussion of the opportunities to continue to diversify within the ESG universe, confirming that there are limitations that affect returns. Pedersen et al. (2020) demonstrates, through theory and practice, how that loss of diversification limits returns. Evidence in Renneboog et al. (2008) records little significiance to the diversification costs from ESG. This paper goes further by integrating traditional strategies as a means of enhancing ESG within the limited investment set. Nonetheless, any restriction on the investment set will theoretically be costly in the risk-return trade off.

Previous ESG alpha papers therefore ask whether other time-series factor models are able to price strategies that are formed from the ESG scores. In this paper we explore the potential mispricing of strategies that combine the anomalies identified in the Finance literature with ESG information. Our work is therefore positioned alongside works like Kaiser (2020) that add ESG tilts to traditional strategies. Kaiser (2020) finds that it is possible to generate alpha when weighting stocks in the traditional strategy portfolios according to their ESG score. Kaiser (2020) weights a firm’s performance on a composite value minus growth index equally with the industry adjusted ESG score to produce a single combined value for each firm. Investors are then assumed to hold the highest quantiles. A long-short strategy would also take a short position on the lowest quantiles. A long-short based on the combined score has similarity with strategy long high ESG high factor group short low ESG low factor group, strategy H in this paper[7]. Using the double sort also allows appraisal of the double enhancement strategy as we may isolate firms with high ESG but who score low on the factor sort, and firms who have low ESG but high factor sort. Further it is possible to use smart-beta

[7]We provide more discussion of the strategies and their definitions in the next section.

strategies which create weightings on variables other than value. Giese et al. (2016) note potential in using ESG weights, but Ielasi et al. (2020) analysis reveals ESG serves only to reduce the risk of the portfolio rather than enhancing existing strategies with returns. Alessandrini and Jondeau (2020) adds that screening out low ESG stocks need not adversely affect smart beta strategies. However, like other work on ESG screening Alessandrini and Jondeau (2020) also identifies a changed exposure to other sectoral risks as a consequence. Our work using sorted portfolios shows again how information within the factor variable, and the ESG sort, combine to explain any return differentials or alpha opportunities[8].

Within all explorations of trading strategies it is essential to consider the costs of actually trading. Novy-Marx and Velikov (2016) represents an important reminder of how implementing the suggested long-short strategies may quickly remove any abnormal returns. On this, DeMiguel et al. (2020) note costs may be reduced by diversifying on multiple characteristics, but that trading costs do eliminate many of the alphas identified in the literature. Of major importance is the liquidity of the stocks being traded. The S&P 500 stocks have lower bid-ask spreads than the small stocks that trouble most anomalies. Our strategies are therefore less costly to trade. We further mitigate the transaction costs using annual portfolio reconstitution.

In this paper we reduce our investment universe to the S&P 500. We do so for three reasons. Firstly, the liquidity of the stocks reduces trading costs (Novy-Marx and Velikov, 2016). High levels of analyst coverage means that investors are well informed about the stocks. Information costs are an important part of the ESG alpha search. Finally, ESG scores are only available for larger firms[9]. By focusing on a well understood universe we can abstract from issues of analyst coverage and the S&P 500 membership effects (Harris and Gurel, 1986; Shleifer, 1986). Chen and De Bondt (2004) demonstrates that investors can gain abnormal returns when trading in this well covered universe. Alphas are found for size, book-to-market and momentum. Cremers et al. (2012) also evidences alpha from within the S&P 500 set. Restricting the set should not prevent the identification of alpha.

Further thought must also be given to the way that common anomaly firm statistics influence ESG scores. Drempetic et al. (2019) present evidence that firm size is positively linked to ESG scores, larger firms are able to ensure higher scores in the

[8]Differences are also found in the focus on long only portfolios in Kaiser (2020) and the long-short that is used in this paper. This is a small difference since the scores given to each firm can also be used to construct a short portfolio at the lower quantiles (Kaiser, 2020).

[9]The universe for the Refinitiv ESG scores expands during our sample to include almost 1400. This is well below the full US CRSP-Compustat universe. Therefore the data is restricted in any case.

subsequent year. Garcia et al. (2020) show that in addition to size, low volatility and higher beta stocks are likely to have higher Refinitiv ESG scores. Although most accounting variables have strong persistence, the correlation between past accounting data and ESG scores does not trouble our portfolio analysis. We ensure there are no empty portfolios by limiting the maximum number of sorts to 9[10].

Investors must also consider risk when selecting their stocks. The risk-return trade-off would suggest that ESG portfolios that were delivering significantly lower returns would have significantly lower risk. Evidence on risk suggests that ESG portfolios do carry lower risk. Cerqueti et al. (2021) evidence the earlier findings of lower risk in Oikonomou et al. (2012). El Ghoul et al. (2011) attribute lower risk to a wider investor base. Hong and Kacperczyk (2009) also indicate that more responsible firms have wider investor bases. Derwall et al. (2011) describes the smaller investor base of low ESG stocks as meaning these “shunned stocks” must offer higher returns to attract investors. Hence what creates the low risk in high ESG stocks drives a gap in returns that favours low ESG stocks. Albuquerque et al. (2019) offer an alternative explanation for low risk from the product market. Firms with high ESG attract customer favour and therefore have lower price elasticity of demand (Albuquerque et al., 2019). In whichever way the low risk is created, reducing risk continues to be an argument for ESG investing. Given the low risk of the S&P 500 members we focus purely on returns in this paper.

### 4.2.4 Inference on Factor Sorts

There are many factor sorts within the asset pricing literature which may tie to the ESG performance of a firm. Within those shown to misprice non-microcaps in Green et al. (2017) used in this paper, there are also many that have links to stylised facts on ESG stocks. Both the CAPM beta and return volatility are common measures of risk in the literature (Fama and MacBeth, 1973; Frazzini and Pedersen, 2014; Ang et al., 2006). For each the recommended strategy is to long the low risk group and short the high risk. Frazzini and Pedersen (2014) result is surprising since it may be expected that high risk brings high return, but as Novy-Marx and Velikov (2021) shows, the longing of low beta stocks picks up many high theoretical return stocks. High ESG stocks would be expected to be found in the low risk group (Oikonomou et al., 2012; Pástor et al., 2020; Pedersen et al., 2020). It may be expected therefore that these risk sorts will be a potential source of ESG flavoured alpha.

[10]9 sorts arise in the case of Refinitiv ESG scores as the double sort is 3×3. For the DJSI we have just two ESG levels and so the total number of portfolios is just 6.

Lessons from the CSR-CFP literature in Chapter 2 inform us that profitability is linked to specific elements of ESG in a non linear way. However, for all firms there is a way to enhance profit and aggregate ESG performance[11]. Higher profits simply mean more funds to improve ESG. Rationale for profitability comes from consumer demand and the observations of Anderson Jr and Cunningham (1972), McWilliams and Siegel (2001) and Sen and Bhattacharya (2001), that firms with higher ESG enjoy greater consumer demand. Hence higher ESG firms will have growing sales and be able to sell their inventories. ESG therefore moves the same way as the growth in sales minus growth in inventory anomaly introduced in Abarbanell and Bushee (1998). Consumer demand is also stronger for small firms with high ESG, suggesting a further tilt towards small sized firms following Banz (1981) will be an effective combination of ESG and factor sort information (Green and Peloza, 2014; Gallardo-Vázquez et al., 2019). Here again our sorted portfolio strategies inform on the extent to which there are links through the consumer demand based sales and profitability channels. Whether through the demand or risk based channel, there is evidence in the existing literature to suggest that combining ESG information with factor sorts can enhance abnormal return performance. That is there are channels which motivate ESG flavoured alpha.

Our environment provides a strong test to the existence of mispricing based upon ESG performance. With the presence of disagreement in ratings, and the changing face of investor awareness, there remain reasons to believe inefficiency in the market may exist. This paper then asks whether investors obtain alpha from the decision to follow ESG strategies.

## 4.3 Data and Empirical Approach

This paper contributes an evaluation of investment strategies that integrate ESG with traditional factor investing. We do so using a double-sort approach and taking long-short positions based upon those sorts. Investors considering these strategies are assumed to rebalance their portfolios once each year. Rebalancing occurs each October using data up to and including September 30th. This is analogous to the use of 30th June in Fama and French (1992), but allows for the release of DJSI membership information in late September each year.

[11] Chapter 2 shows that low profit firms can improve long run profitability through investment in environmental performance, whilst mid-range firms for profitability can improve their profitability through the environment and by helping their employees. High profit firms are shown to have gains from employee focused CSR initiatives. In each case the focus on any one dimension translates to a higher ESG score and it is the aggregate ESG score used here.

### 4.3.1 ESG Measures

Two ESG measures are used, the Refinitiv ESG score and membership of the DJSI. Refinitiv ESG scores have been available for more than 20 years, beginning with the largest companies and then expanding to cover more than 1000 stocks since 2004. For our purposes we only require coverage of the S&P 500 stocks and this is present throughout the study period. Originally the Thomson Reuters Asset 4 scores, they have been widely used in the study of corporate financial performance and ESG. As a continuous measure of ESG performance it is possible to construct sorted portfolios. Continuous measures have a natural appeal for asset pricing studies. Refinitiv ESG scores are annual data, so may be treated like accounting data. In this paper we assume that the previous year's score is available to all investors in time for the September rebalancing. Elsewhere, the portfolio rebalancing in June also assumes that the previous year's ESG score is public information.

Our second measure of ESG leadership comes from membership of the DJSI. Specifically we define a firm as an ESG leader if they are listed on the North American regional index. Membership of the list comes after an assessment from independent researchers at Robecco SAM. Invites to submit for assessment are sent to the world's largest 5000 companies, including more than 1000 in the United States. Again this ensures that the invites go to all of the S&P 500 stocks. The DJSI we employ begins in 2005 with the first firms being announced in September 2005. Updates to the DJSI are announced annually in September, with the date changing slightly year on year. All changes are effective by the 1st of October and so for our monthly stock returns we treat October as the first month for the new membership list. On average, turnover of the DJSI is very low. After the October 2018 update we consider the returns until the end of September 2019. We do not consider the 2019 rebalancing to avoid the impacts of Covid-19 on the data in the subsequent year's holdings.

### 4.3.2 Factor Sort Variables

We consider sorts on 6 core characteristics following GHZ. Additionally, we consider a further 18 sorts based on those which GHZ identify as providing additional information in the pricing of returns of non-microcaps. All 24 of these factor characteristics have been considered as anomalies within the asset pricing literature. Table 4.2 gives a list of these sorting characteristics, together with details of their construction. GHZ additionally identify the number of consecutive quarters with earnings higher than the same quarter in the previous year. This does not have sufficient variation within the

S&P 500 to generate sorts. We therefore do not include this sort variable within the following analysis. There are also anomalies based upon the analyst coverage data. Given that we are using such a well covered universe we also do not consider analyst related factor sort variables.

The dataset is assembled using the code provided by GHZ[12] updated to run until December 31st 2020. We then subsequently subset for the period of interest to this paper to avoid any missing data at either end of our sample. The GHZ code winzorises all anomalies at the 1% level in order to minimise the effect of outliers. Firms with weakly negative assets are also removed. Although we may not expect S&P 500 firms to be amongst the outliers, this ensures that extreme values do not bias our sort results. Finally, we remove any observations with missing values for the core 6 sorts. Where there are missing values for any of the other anomalies we simply remove those firms with missing observations for that particular sort.

### 4.3.3 Investment Strategies

This paper aims to identify firstly whether information about ESG may enhance the performance of traditional strategies. Alternatively traditional strategies may enhance ESG investment. We therefore define a set of strategies that will be tested within the data. Table 4.1 details the eight strategies that are considered. Here, High ESG refers to either being in the top 30% of ESG scores, or being a member of the DJSI. Low ESG refers to the bottom 30% or non-DJSI members. High factor sort refers to either the top 30%, or bottom 30% of the distribution of the factor sorting variable, where high (low) factor group refers to those stocks that will offer a high (low) expected return according to the existing anomaly literature. In the case of size this means the high factor sort is small firms, the low factor sort is big firms. In the case of book-to-market the high factor sort is from the top 30% of the distribution and the low factor sort is from the bottom 30% of the book-to-market distribution. All cut-off points are based upon the full set of S&P 500 stocks for which data is available at the time of rebalancing.

Strategy A is the traditional factor strategy as it longs the portfolio that would be theoretically expected to bring the highest returns and shorts that which would be expected to bring the lowest. The small-minus-big (SMB) size factor of Fama and French (1993) is an example of strategy A. Strategy B is the strategy studied by the literature on ESG alpha. We refer to A and B as the unconditional strategies. Strategies C, D, E and F work within either a factor sort variable, or an ESG sort, to take a

[12]Code is made available on the site of Jeremiah Green at `https://sites.google.com/site/jeremiahrgreenacctg/home`. (Accessed 23rd July 2021).

Table 4.1: List of Strategies

| Letter | Notes | ESG Position |
|---|---|---|
| A | Long High factor group - Short Low factor group (no consideration of ESG) | Neutral |
| B | Long High ESG - Short Low ESG (no factor sort) | Tilt |
| C | Long High ESG High factor group - Short Low ESG High factor group (Strategy B in high factor group) | Tilt |
| D | Long High ESG High factor group - Short High ESG Low factor group (Strategy A in high ESG group) | Neutral |
| E | Long Low ESG High factor group - Short Low ESG Low factor group (Strategy A in low ESG group) | Neutral |
| F | Long High ESG Low factor group - Short Low ESG Low factor group (Strategy B in low factor group) | Tilt |
| G | Long Strategy D - Short Strategy E | Neutral |
| H | Long High ESG High factor group - Short Low ESG Low factor group | Tilt |

Notes: ESG is measured using both the Refinitv ESG score and membership of the Dow Jones Sustainability Index North America (DJSI). High ESG then refers to either having an ESG score in the top 30% or being a member of the DJSI. Low ESG refers to the bottom 30% or being a non-member of the DJSI. Factor group refers to the common anomalies used as a second sorting variable. High factor group then describes whichever of the top 30% or bottom 30% of the distribution is expected to bring the highest returns. Low factor group then describes the opposite end of the factor sort variable distribution to high factor sort. The final column indicates whether the strategy has an ESG tilt or is neutral on ESG. Tilt requires that the strategy take a long position on high ESG stocks and a short position on low ESG stocks. Strategies which both long and short stocks at the same ESG level are ESG neutral.

Table 4.2: Factor Sort Characteristics

| Characteristic | Paper | Description |
|---|---|---|
| Panel (a): Core Sorts | | |
| Size (market value of equity) | Banz (1981) | natural log of market capitalisation at end of month $t-1$ ($csho \times prcc\_f$) |
| Book-to-Market | Rosenberg et al. (1985) | Book-value of equity divided by current market value of equity ($ceq/me$) |
| Profitability | Fama and French (2015) | Revenue ($sale$) less cost of goods sold ($cogs$) less SG&A expense ($sga$) less interest expense ($int$) divided by the common shareholders equity ($ceq$) |
| Investment | Chen and Zhang (2010) | Annual change in gross property, plant and equipment ($ppegt$) plus the annual change in inventories ($invt$) all scaled by lagged total assets ($at$) |
| Return-on-Equity | Hou et al. (2015) | Earnings before extraordinary items ($ebo$) divided by lagged common shareholders equity ($ceq$) |
| 12-Month Momentum | (Jegadeesh, 1990) | 11 months cumulative return ending one month before current month end |
| Panel (b): Further Sorts | | |
| Capital Asset Pricing Model (CAPM) beta | Fama and MacBeth (1973) | Regression of excess weekly returns for previous 36 months. Requires at least 52 weekly returns |
| Asset Growth | Cooper et al. (2008) | Annual percentage change in total assets ($at$) |
| Growth in Inventory | Thomas and Zhang (2002) | Change in inventory ($invt$) scaled by average total assets ($at$) |
| Growth in Book Equity | Richardson et al. (2005) | Annual percentage change in book value of equity ($ceq$) |

*Continued on next page...*

Table 4.2: Factor Sort Characteristics

| Characteristic | Paper | Description |
|---|---|---|
| Growth in Capital Expenditure (capex) | Anderson and Garcia-Feijoo (2006) | Percentage change in capital expenditures (*capx*) from year $t-2$ to year $t$ |
| Growth in Long Term Net Operating Assets | Fairfield et al. (2003) | Sum of total accounts receivable (*rect*), inventory (*invt*), net value of property, plant and equipment (*ppent*), other current assets (*aco*), intangible assets (*intant*), (*ao*) less (*ap*), current liabilities (*lco*) and long term liablities (*lo*). We then subtract the lagged value of this expression. Depreciation (*dp*) is then subtracted. All of this is then scaled by the average of the total assets at time $t$ and $t-1$. |
| Growth in Sales - Growth in Inventory | Abarbanell and Bushee (1998) | Sales (*sale*) less lag of sales divided by lag of sales minus inventory (*inv*) less lag of inventory divided by lag of inventory. |
| Growth of Shares Outstanding | Pontiff and Woodgate (2008) | Percentage change in shares oustanding (*chso*) |
| Earnings Announcement Returns | Kishore et al. (2008) | Sum of daily returns in three days around earnings announcements. Earnings announcements from Compustat quarterly (*rdq*) |
| Change in 6-Month Momentum | Gettleman and Marks (2006) | Cumulative returns from months $t-6$ to $t-1$ less cumulative returns months $t-12$ to $t-7$ |
| 1-Month Momentum | Jegadeesh and Titman (1993) | 1-month cumulative return |
| Industry adjusted cashflow | Asness et al. (2000) | Operating cash flow divided by fiscal year-end market capitalisation. All values are then adjusted for industry |

*Continued on next page...*

Table 4.2: Factor Sort Characteristics

| Characteristic | Paper | Description |
|---|---|---|
| Return Volatility | Ang et al. (2006) | Standard deviation of daily returns from month $t-1$ |
| Share Turnover | Datar et al. (1998) | Average monthly trading volume for the most recent three months scaled by number of shares outstanding at time $t$ |
| Turnover Volatility | Chordia et al. (2001b) | Monthly standard deviation of daily share turnover |
| Zero Trading Days | Liu (2006) | Turnover weighted number of zero trading days for most recent month |
| Illiquidity | Amihud (2002) | Daily absolute return divided by trading volume, averaged over one month |
| Industry Momentum | Moskowitz and Grinblatt (1999) | Equal weighted average industry 12 month returns |

Notes: Core variables are those selected in Green et al. (2017) as being central to the determination of stock returns. These are the four tradable factors used in Fama and French (2015), the return on equity from Hou et al. (2015) q-factor model and momentum from Carhart (1997). Additional characteristics are those shown by Green et al. (2017) to determine returns on non-microcaps after controlling for the core 6. Paper provides the reference for the paper in which the characteristic is first associated with stock returns. Description features variable names from Compustat and CRSP in parentheses. All formulae follow Green et al. (2017).

long-short position based on the other. For example, strategy C works by applying strategy B (longing high ESG and shorting low ESG) within the high factor group. We may view strategies C and D as enhancing in one direction. Strategy E applies strategy B within the low ESG stocks. Since our focus is on high ESG, E does not provide useful information to the goal of this paper. Finally, strategy F is expected to bring lower returns because it acts at the opposite direction of the factor sort variable distribution to the one which theory suggests would bring the highest returns. Because E is tangential to the goal of the paper, and F is theoretically sub-optimal, neither E nor F are reported in the strategy comparisons that follow.

Strategy G is the test of whether both ESG information and the factor sort variable can further enhance returns when used together as bivariate independent sorts. Comparing G to C and D informs on whether two-way enhancement is superior to one-way enhancement. If strategy G returns more than A or B then we may conclude that there is enhancement versus the unconditional strategies. Finally, we consider strategy H which takes a long position on the high ESG stocks from the end of the factor sort distribution that is expected to bring the highest returns. The short position in strategy H is on low ESG and the end of the factor sort distribution that produces the lowest returns. The primary difference between G and H is that in H the only long position is on high ESG stocks. Strategy H therefore uses information from the factor sort variable to create a strategy which can be traded by investors who wish to only long ESG stocks.

A useful separation of the strategies may be made according to the ESG position taken. We define ESG tilt as applying to those strategies which have higher exposure to ESG. these are strategies B, C, F and H, all of which only long high ESG stocks. Strategies A, D, E and G are referred to as ESG neutral since they either ignore ESG (A), or take long and short positions within the same ESG level (D, E and G). The final column of Table 4.1 informs on the ESG position of the strategy.

All of our strategies assume an annual rebalancing. Because the DJSI members are updated in late September, and one ESG measure is DJSI membership, we rebalance at the end of September each year. In the standard literature rebalancing occurs at the end of June (Fama and French, 2020). Our rebalancing date is later and therefore we may assume that all accounting data from the previous calendar year is available to the investor. Stock market anomalies, such as size, are then based on closing values from the 30th of September rather than the 30th of June.

Strategies are compared on excess returns and on the alpha they are able to generate against common mispricing models. It follows that strategies which are unable to generate alpha against the capital asset pricing model (CAPM) will not generate alpha against more advanced models. Therefore a primary screening is to use the CAPM. Secondly, we consider alphas against the Fama and French (2015) five factor model (FF5). For strategy $X$ with excess return $R_{Xt}$ in month $t$, we have:

$$R_{Xt} = \alpha_X^{CAPM} + \beta_X^{CAPM} MKT_t + \epsilon_{Xt} \tag{4.1}$$

$$\begin{aligned} R_{Xt} =& \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t \\ &+ \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt} \end{aligned} \tag{4.2}$$

Superscripts for the two models are applied to distinguish the coefficients. In both cases $\epsilon_{Xt}$ is a mean 0 and constant variance error term. Models are estimated usng Newey et al. (1987) robust standard errors with lag 6. $MKT_t$, $SMB_t$, $HML_t$, $RMW_t$ and

$CMA_t$ are the Fama and French (2015) factors and are downloaded from the website of Ken French[13]. Excess returns are computed using the one-month treasury as also downloaded from the website of Ken French. Equations (4.1) and (4.2) are estimated for both measures of ESG, but we omit ESG subscripts for brevity.

## 4.4 Excess Returns

As a first step we examine the excess monthly returns on the investment strategies developed in Table 4.1. With 24 anomalies and 2 different ESG measures reporting of the full set of results consumes a large amount of space. In this section we report only the six core anomalies (size, book-to-market ratio, operating profit, investment, return on equity and 12-month momentum). Strategy returns are also calculated based on equally weighted and value weighted portfolios. Again for brevity we only report the value weighted results here. Results for other sorts under value weighting, and the full results for equal weighting, are available on request. In many contexts value weighting helps tilt the portfolio towards stocks that cost less to trade. Here we are using only highly liquid S&P 500 members and so it is still reasonable to use even weighting. We stick with convention to report the value weighted results.

Table 4.3 uses the Refinitiv ESG scores as the primary measure. Three levels of ESG are seen. ESG Low corresponds to the bottom 30% of ESG scores, ESG High is the top 30% of ESG scores and ESG mid runs from the 30th percentile to the 70th. Table 4.4 reports DJSI sorts and there are just two ESG levels. Non-DJSI is included first to maintain the ascending order of the ESG level seen for the Refinitiv ESG scores in Table 4.3.

Tables 4.3 and 4.4 have many significant excess returns amongst the individual portfolios. The top 30% of Refinitiv ESG scores produce an unconditional portfolio that also delivers significant positive returns. However, these are actually only slightly higher in value than those produced by the ESG low portfolio. There are also occasions when the Refinitiv ESG scores are used that Table 4.3 shows significance in the factor sort portfolios, but again the long-short is not significant. In Table 4.4 the pattern is similar though there is a significant long-short amongst the smallest 30% of firms. Longing the small and shorting the large firms within the DJSI members also produces a significant return of 60bps per month. A final significant long-short is identified on profitability, but here this is within the non-DJSI members and so not of interest to

[13]Data is available at: `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

Table 4.3: Value Weighted Excess Returns Crosstabulations - Refinitiv ESG Scores

| | Panel (a): Size | | | | | Panel (b): Book to Market | | | | | Panel (c): Profitability | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | All | LS | 1 | 2 | 3 | All | LS | 1 | 2 | 3 | All | LS |
| ESG Low | 0.69 | 0.65 | 0.72 | 0.68 | -0.03 | 0.71 | 0.84* | 0.46 | 0.68 | -0.25 | 0.42 | 0.78* | 0.81* | 0.68 | 0.39 |
| | (1.58) | (1.66) | (1.91) | (1.76) | (0.15) | (1.9) | (2.17) | (0.98) | (1.76) | (1.00) | (0.96) | (2.01) | (2.23) | (1.76) | (1.80) |
| ESG Mid | 0.84 | 0.67 | 0.72* | 0.71 | 0.12 | 0.76* | 0.74* | 0.57 | 0.71 | -0.19 | 0.69 | 0.66 | 0.82* | 0.71 | 0.13 |
| | (1.92) | (1.76) | (2.03) | (1.95) | (0.68) | (2.20) | (2.02) | (1.38) | (1.95) | (0.96) | (1.88) | (1.70) | (2.28) | (1.95) | (0.79) |
| ESG High | 0.60 | 0.79* | 0.71* | 0.72* | -0.11 | 0.81** | 0.67* | 0.66 | 0.72* | -0.15 | 0.50 | 0.77* | 0.77** | 0.72* | 0.27 |
| | (1.29) | (2.30) | (2.41) | (2.38) | (0.42) | (2.84) | (2.26) | (1.76) | (2.38) | (0.75) | (1.36) | (2.49) | (2.69) | (2.38) | (1.48) |
| All Stocks | 0.74 | 0.69 | 0.72* | 0.05 | 0.02 | 0.78* | 0.72* | 0.59 | 0.05 | -0.20 | 0.58 | 0.73* | 0.79* | 0.05 | 0.21 |
| | (1.71) | (1.89) | (2.29) | (1.71) | (0.12) | (2.54) | (2.19) | (1.47) | (1.71) | (1.10) | (1.56) | (2.13) | (2.60) | (1.71) | (1.62) |
| Long-Short | -0.09 | 0.14 | -0.02 | 0.04 | -0.07 | 0.20 | -0.16 | 0.10 | 0.04 | 0.10 | -0.04 | -0.02 | 0.08 | 0.04 | -0.12 |
| | (0.52) | (0.99) | (0.09) | (0.29) | (0.28) | (1.00) | (1.04) | (0.58) | (0.29) | (0.44) | (0.18) | (0.10) | (0.43) | (0.29) | (0.47) |
| | Panel (d): Investment | | | | | Panel (e): Return on Equity | | | | | Panel (f): 12-Month Momentum | | | | |
| | 1 | 2 | 3 | All | LS | 1 | 2 | 3 | All | | 1 | 2 | 3 | All | LS |
| ESG Low | 0.58 | 0.76* | 0.63 | 0.68 | -0.05 | 0.69 | 0.76* | 0.62 | 0.68 | -0.07 | 0.66 | 0.75* | 0.59 | 0.68 | -0.07 |
| | (1.42) | (2.00) | (1.55) | (1.76) | (0.24) | (1.51) | (2.05) | (1.59) | (1.76) | (0.36) | (1.49) | (2.04) | (1.42) | (1.76) | (0.30) |
| ESG Mid | 0.60 | 0.84* | 0.58 | 0.71 | 0.01 | 0.64 | 0.80* | 0.68 | 0.71 | 0.04 | 0.55 | 0.81* | 0.69 | 0.71 | 0.14 |
| | (1.48) | (2.35) | (1.63) | (1.95) | (0.10) | (1.58) | (2.32) | (1.80) | (1.95) | (0.27) | (1.37) | (2.29) | (1.76) | (1.95) | (0.55) |
| ESG High | 0.72 | 0.73* | 0.68* | 0.72* | 0.04 | 0.68 | 0.73* | 0.73* | 0.72* | 0.05 | 0.71* | 0.71* | 0.76* | 0.72* | 0.05 |
| | (1.95) | (2.48) | (2.27) | (2.38) | (0.23) | (1.92) | (2.20) | (2.46) | (2.38) | (0.19) | (2.02) | (2.39) | (2.44) | (2.38) | (0.21) |
| All Stocks | 0.67 | 0.78* | 0.62 | 0.05 | 0.05 | 0.66 | 0.76* | 0.69* | 0.05 | 0.03 | 0.66 | 0.75* | 0.72* | 0.05 | 0.06 |
| | (1.76) | (2.42) | (1.91) | (1.71) | (0.36) | (1.74) | (2.26) | (2.15) | (1.71) | (0.20) | (1.75) | (2.36) | (2.05) | (1.71) | (0.28) |
| Long-Short | 0.14 | -0.04 | 0.05 | 0.04 | 0.09 | 0.11 | -0.03 | -0.01 | 0.04 | 0.12 | 0.16 | -0.05 | 0.05 | 0.04 | 0.12 |
| | (0.97) | (0.22) | (0.26) | (0.29) | (0.45) | (0.58) | (0.20) | (0.05) | (0.29) | (0.52) | (0.83) | (0.34) | (0.22) | (0.29) | (0.60) |

Notes: Figures report the value-weighted excess returns. Values in parentheses are the Newey et al. (1987) adjusted t-statistics with lag 6. Table reports returns from double-sorts on the stated firm characteristic and the Refinitiv ESG score. In both cases the low portfolio, 1 or ESG low, represents values below the 30th percentile. The high portfolio, 3 or ESG High, represents those above the 70th percentile. All Stocks reports the values for the columns unconditional on ESG, whilst the All column reports the values for the rows unconditional on the sort variable. Long-Short takes a long position on ESG High and a short position on ESG Low. LS takes a long position on the theoretical high returning end of the characteristic sort, and a short position on the other end. At the intersection of the All Stocks row and All column is the overall S&P 500 average. At the intersection of the Long-Short row and LS column is strategy G. Significance * - 5%, ** - 1% and *** - 0.1%

Table 4.4: Value Weighted Excess Returns Crosstabulations - DJSI Membership

| | Panel (a): Size | | | | | Panel (b): Book to Market | | | | | Panel (c): Profitability | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | All | LS | 1 | 2 | 3 | All | | 1 | 2 | 3 | All | LS |
| Non | 0.70 | 0.68 | 0.75* | 0.72* | -0.05 | 0.81* | 0.74* | 0.58 | 0.72* | -0.22 | 0.57 | 0.73* | 0.86** | 0.72* | 0.29* |
| | (1.63) | (1.80) | (2.36) | (2.12) | (0.27) | (2.53) | (2.22) | (1.43) | (2.12) | (1.21) | (1.51) | (2.03) | (2.80) | (2.12) | (2.08) |
| DJSI | 1.24* | 0.75* | 0.65* | 0.68* | 0.60* | 0.72* | 0.68* | 0.64 | 0.68* | -0.08 | 0.63 | 0.75* | 0.66* | 0.68* | 0.02 |
| | (2.34) | (2.21) | (2.06) | (2.13) | (2.10) | (2.40) | (2.03) | (1.67) | (2.13) | (0.33) | (1.69) | (2.41) | (2.00) | (2.13) | (0.12) |
| All Stocks | 0.74 | 0.69 | 0.72* | 0.05 | 0.02 | 0.78* | 0.72* | 0.59 | 0.05 | -0.20 | 0.58 | 0.73* | 0.79* | 0.05 | 0.21 |
| | (1.71) | (1.89) | (2.29) | (1.71) | (0.12) | (2.54) | (2.19) | (1.47) | (1.71) | (1.10) | (1.56) | (2.13) | (2.60) | (1.71) | (1.62) |
| Long-Short | 0.54* | 0.07 | -0.10 | -0.05 | 0.65** | 0.06 | -0.06 | -0.09 | -0.05 | 0.15 | -0.20 | 0.02 | 0.06 | -0.05 | -0.26 |
| | (2.22) | (0.58) | (1.16) | (0.56) | (2.83) | (0.42) | (0.46) | (0.68) | (0.56) | (0.73) | (1.32) | (0.14) | (0.45) | (0.56) | (1.31) |
| | Panel (d): Investment | | | | | Panel (e): Return on Equity | | | | | Panel (f): 12-Month Momentum | | | | |
| | 1 | 2 | 3 | All | LS | 1 | 2 | 3 | All | | 1 | 2 | 3 | All | LS |
| Non | 0.67 | 0.79* | 0.65 | 0.72* | 0.01 | 0.67 | 0.77* | 0.70* | 0.72* | 0.03 | 0.65 | 0.80* | 0.70 | 0.72* | 0.05 |
| | (1.73) | (2.42) | (1.90) | (2.12) | (0.09) | (1.72) | (2.31) | (2.11) | (2.12) | (0.21) | (1.75) | (2.44) | (1.93) | (2.12) | (0.25) |
| DJSI | 0.63 | 0.74* | 0.45 | 0.68* | 0.18 | 0.60 | 0.72* | 0.64* | 0.68* | 0.04 | 0.67 | 0.66* | 0.71* | 0.68* | 0.04 |
| | (1.59) | (2.33) | (1.35) | (2.13) | (0.77) | (1.71) | (2.00) | (2.05) | (2.13) | (0.17) | (1.68) | (2.11) | (2.19) | (2.13) | (0.13) |
| All Stocks | 0.67 | 0.78* | 0.62 | 0.05 | 0.05 | 0.66 | 0.76* | 0.69* | 0.05 | 0.03 | 0.66 | 0.75* | 0.72* | 0.05 | 0.06 |
| | (1.76) | (2.42) | (1.91) | (1.71) | (0.36) | (1.74) | (2.26) | (2.15) | (1.71) | (0.20) | (1.75) | (2.36) | (2.05) | (1.71) | (0.28) |
| Long - Short | -0.04 | -0.05 | -0.21 | -0.05 | 0.17 | -0.06 | -0.05 | -0.08 | -0.05 | 0.02 | 0.01 | -0.14 | 0.02 | -0.05 | -0.02 |
| | (0.28) | (0.52) | (1.12) | (0.56) | (0.71) | (0.42) | (0.46) | (0.48) | (0.56) | (0.07) | (0.04) | (1.25) | (0.16) | (0.56) | (0.07) |

Notes: Figures report the value-weighted excess returns. Values in parentheses are the Newey et al. (1987) adjusted t-statistics with lag 6. Table reports returns from double-sorts on the stated firm characteristic and DJSI membership. For the traditional factor sort the low portfolio, 1, represents values below the 30th percentile. The high portfolio, 3, represents those above the 70th percentile. All Stocks reports the values for the columns unconditional on ESG, whilst the All column reports the values for the rows unconditional on the sort variable. Long-Short takes a long position on DJSI members and a short position on non DJSI members. LS takes a long position on the theoretical high returning end of the characteristic sort, and a short position on the other end. At the intersection of the All Stocks row and All column is the overall S&P 500 average. At the intersection of the Long-Short row and LS column is strategy G. Significance * - 5%, ** - 1% and *** - 0.1%

ESG investors. The unconditional return on the DJSI is lower than that for non-DJSI stocks.

The message amongst these core sorts is that only one ESG strategy can deliver significant excess returns. Given the number of options considered there is little here to argue that ESG enhances returns. However, there is also little in this consideration of core anomalies that suggests that investors considering ESG will harm their returns. Tables for the remaining sorts are available on request from the authors.

### 4.4.1 Returns Comparisons

To evaluate whether ESG information can enhance traditional investment strategies we perform a series of strategy return comparisions. Firstly, we compare the return on strategy C with B. Strategy C is based on an ESG sort within the high end of the factor sort, whilst B focuses only on ESG. If C offers the higher return then the additional information from the the traditional factor within the high sort is enhancing the ESG strategy. As a second comparison we may consider strategies D and A. D considers only stocks that have high ESG performance, whilst A is the traditional factor strategy. If D offers significantly higher returns than A then we may conclude that ESG is enhancing the traditional factor. Thirdly, we look at strategy G. If strategy G offers higher returns than A or B then this informs that the two-way enhancement is better than the unconditional strategy on the sort variable or ESG. If strategy G offers higher returns than C or D then we are seeing two-way enhancement offering a better return than one-way enhancement on the factor sort variable or ESG. Finally, we compare strategy H with A to ask whether an alternative strategy based on ESG and the factor sort can outperform the returns on the factor sort. In the case where any of these strategies' comparisons go in the opposite direction, we would conclude that the enhancement is actually counterproductive for the investor. Our primary focus is whether ESG tilt strategies (B, C, F and H) generate significant excess returns.

Table 4.5 presents counts of the number of significant returns on six strategies A, B, C, D, G and H. We then present the comparisons to check for return enhancement. We summarise using the t-statistic that the true value is 0 tested under Newey et al. (1987) robust standard errors of lag 6. In the commentary we refer to the factor sort variables, weightings and asset pricing models that are found to be significant. Table 4.6 provides a list of significant returns organised by ESG measure and porfolio construction weighting[14]. Immediately it may be seen that there are very few significant

[14] Full results are available on request from the authors.

Table 4.5: Strategy Returns Comparison Summary

| ESG | Wt | $t - stat$ | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Score | EW | $t \in [2,3)$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | $t \in (-2,2)$ | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 23 | 24 |
| | | $t \in (-3,-2]$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| | VW | $t \in [2,3)$ | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| | | $t \in (-2,2)$ | 24 | 24 | 24 | 24 | 23 | 24 | 23 | 24 | 23 | 24 | 23 | 24 | 24 |
| | | $t \in (-3,-2]$ | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| DJSI | EW | $t \in [2,3)$ | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| | | $t \in (-2,2)$ | 24 | 24 | 24 | 23 | 22 | 23 | 22 | 22 | 23 | 23 | 23 | 23 | 24 |
| | | $t \in (-3,-2]$ | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |
| | VW | $t \in [2,3)$ | 0 | 0 | 1 | 1 | 3 | 0 | 1 | 1 | 0 | 3 | 1 | 0 | 1 |
| | | $t \in (-2,2)$ | 24 | 24 | 23 | 23 | 21 | 24 | 23 | 22 | 24 | 21 | 23 | 23 | 23 |
| | | $t \in (-3,-2]$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 |

Notes: Table reports number of traditional factor sorts for which the t-statistic in a test of excess strategy returns being non-zero lies in the stated range. ESG informs whether we are using the Refintiv ESG Score (Score), or membership of the Dow Jones Sustainability Index North America (DJSI) to define ESG leadership. Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. High ESG is defined as the top 30% of Refinitiv ESG scores or members of the DJSI. Low ESG is defined as the bottom 30% of Refinitiv ESG scores or non-DJSI members. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

differences. Amongst those strategies with ESG tilt, there are are just two significant returns. For those ESG neutral strategies there are seven significant positive returns and one significant negative return. Both of the ESG tilts generate significant positive excess returns.

Refinitiv ESG scores produce no significant raw returns amongst the six strategies presented when equal weighting is used. There is just one significant return when value weighting is applied. We see a significant return to the double enhanced strategy G for return volatility. In the comparisons of strategies there is a single signficant difference for the equal weighting. Here the one-way enhancement of ESG by the industry momentum, strategy D, outperforms relative to the two-way enhancement from strategy G. When applying value weighting the strategy comparisons inform that strategy G outperforms the one-way ESG enhanced return volatility strategy. We also see our proposed strategy H obtain significant raw returns for the change in sales less the change in inventory. Finally, strategy G produces lower returns than the unconditional factor return, suggesting ESG has not helped to enhance change in sales less change in inventory.

When we use DJSI as the ESG measure there are more significant results under both equal weighting and value weighting. Strategy C provides significant positive returns under value weighting for the size sort. Strategy D produces significant positive returns under value weighting with size as the secondary sort, and under equal weighting when the sort variable is the percentage change in sales less the percentage change in inventory. The dual enhancement in strategy G produces positive returns under equal weighting with size as the sort variable. We also see strategy H generate significant positive returns under equal weighting with the change in sales minus the change in inventory as the factor sort.

From the pure strategy returns, it is apparent that benefits from considering ESG appear within size and the growth of sales minus the growth of inventory. Rationale for size may be found in the expectation that large firms practise CSR (Green and Peloza, 2014; Gallardo-Vázquez et al., 2019). Evidence from the study of firm size as a moderator to the CSR-CFP link shows that smaller firms are more efficient at incorporating CSR acitivities into their business operation. Smaller firms are therefore able to do well in their profitability whilst at the same time doing good with their CSR. Consequently, the cashflow of smaller firms is less impacted by CSR performance improvement. Such efficiency makes smaller firms better value for their investors over and above the understood size effect. Sales minus inventory can also be understood from the perspective of consumers. Demand for firms with higher CSR is greater (An-

Table 4.6: Significant Excess Returns

| Strategy | Position | Anomaly | ESG | Weight | Return | t-stat |
|---|---|---|---|---|---|---|
| Panel (a) ESG Score Equal Weighting | | | | | | |
| G-D | | Industry Momentum | Score | EW | -0.45* | 2.21 |
| Panel (b) ESG Score Value Weighting | | | | | | |
| G | Neutral | Return Volatility | Score | VW | 0.29* | 2.08 |
| C-B | | Industry Momentum | Score | VW | -0.29* | 2.06 |
| G-A | | Growth in Sales - Growth in Inventory | Score | VW | -0.27* | 2.47 |
| G-C | | Return Volatility | Score | VW | 0.40* | 2.05 |
| Panel (c) DJSI Membership Equal Weighting | | | | | | |
| D | Neutral | Growth in Sales - Growth in Inventory | DJSI | EW | 0.30* | 2.01 |
| G | Neutral | Return Volatility | DJSI | EW | -0.59* | 2.60 |
| G | Neutral | Size | DJSI | EW | 0.69* | 2.09 |
| H | Tilt | Growth in Sales - Growth in Inventory | DJSI | EW | 0.32* | 2.02 |
| C-B | | Illiquidity | DJSI | EW | -0.14* | 2.07 |
| C-B | | Growth in Sales - Growth in Inventory | DJSI | EW | 0.30* | 2.28 |
| D-A | | Size | DJSI | EW | 0.63* | 1.98 |
| D-A | | Turnover Volatility | DJSI | EW | -0.51** | 2.61 |
| G-A | | Turnover Volatility | DJSI | EW | -0.54* | 2.05 |
| G-B | | Turnover Volatility | DJSI | EW | -0.61* | 2.37 |
| G-C | | Turnover Volatility | DJSI | EW | -0.51* | 2.32 |
| G-D | | Growth of Shares Outstanding | DJSI | EW | -0.23* | 1.98 |
| Panel (d) DJSI Membership Value Weighting | | | | | | |
| C | Tilt | Size | DJSI | VW | 0.54* | 2.22 |
| D | Neutral | Size | DJSI | VW | 0.60* | 2.10 |
| G | Neutral | Size | DJSI | VW | 0.65** | 2.83 |
| G | Neutral | Return Volatility | DJSI | VW | 0.43* | 2.48 |
| G | Neutral | Zero Trading Days | DJSI | VW | 0.50* | 2.24 |
| C-B | | Growth in Sales - Growth in Inventory | DJSI | VW | 0.31* | 2.30 |
| D-A | | Size | DJSI | VW | 0.58** | 2.67 |
| D-A | | Turnover Volatility | DJSI | VW | -0.40* | 2.11 |
| G-B | | Gowth of Inventory | DJSI | VW | 0.26* | 2.04 |
| G-B | | Return Volatility | DJSI | VW | 0.47** | 2.72 |
| G-B | | Zero Trading Days | DJSI | VW | 0.55* | 2.31 |
| G-C | | Return Volatility | DJSI | VW | 0.52** | 2.78 |
| G-D | | Growth in Sales - Growth in Inventory | DJSI | VW | -0.30* | 2.01 |
| H-A | | Size | DJSI | VW | 0.47* | 1.97 |

Notes: Position reports whether the strategy has an ESG tilt or is neutral to ESG. Tilts arise where the strategy longs higher ESG stocks than it shorts, whilst neutral strategies long and short stocks at the same ESG level. Position only applies to pure strategies and not to comparisons. ESG reports the measure used to identify ESG leaders and laggards, this may be either the ESG Score or membership of the Dow Jones Sustainability Index North America (DJSI). Return refers to the monthly excess return in %. t-stat is the Newey et al. (1987) adjusted t-statistic for a test that the true average excess return is not equal to zero.

derson Jr and Cunningham, 1972; McWilliams and Siegel, 2001; Sen and Bhattacharya, 2001). The increase in sales will therefore link to CSR. Meanwhile, inventory builds when the firm orders too many products and demand does not materialise (Abarbanell and Bushee, 1998). Again the link with CSR can reduce the extent to which demand falls in future. Both sales and inventory elements of the Abarbanell and Bushee (1998) anomaly can benefit from further input from ESG. Nonetheless the overall result on the strategy excess returns remains one of insignificance.

Comparing the returns of strategies allows us to comment further on the opportunities for enhancement using ESG information. The difference between Strategies C and B informs whether traditional factors enhance the DJSI ESG investment strategy. Growth in sales less the growth in inventory produces a significant difference for both equal weighting and value weighting. Here we do see the traditional factor enhancing the DJSI ESG strategy. When strategy D offers a higher return than strategy A ESG enhances the traditional factor. This happens under both equal and value weighting when the secondary sort is size. Small firms benefit more in consumer perception when enhancing ESG, providing theoretical support to this result. Hence there is some evidence of ESG enhancing traditional strategies, and no evidence that there is a negative return to following the ESG enhanced strategy.

Double enhancement is understood through the returns of strategy G. We see no cases where double enhancement outperforms the pure anomaly, that is strategy G does not offer signficantly higher returns than strategy A. There are two cases where the double enhancement actually reduces returns relative to strategy A. The pure sort on ESG, strategy B, did not produce any significant returns and hence it is unsurprising that G may outperform B. We see this outperformance in return volatility, zero trading days and the growth of inventory. In each case the outperformance occurs for DJSI membership under value investing. In the former two cases, volatility and zero trading days, strategy G alone had offered significant positive returns. Compared to the factor sort enhancement of the ESG, strategy C, there is a significant returns differential on return volatility. There are no significant returns differences between G and the ESG enhancement of the traditional sort, strategy D.

This paper also proposes a final strategy, H, which asks whether using the information in the double sort, on the factor variable and ESG, can generate significant returns. Strategy H produces a significant excess return of 32bps when growth in sales minus growth in inventory is the factor sort, membership of the DJSI is the ESG measure and equal weighting is applied. Under all other combinations of weight, ESG measures and factor sort there is no significance. In the comparison with the factor sort strategy A, we see that there is one occasion when H offers a significantly higher excess return. With size as the anomaly and DJSI membership as the ESG measure there is an enhancement from strategy H over strategy A of 47bps. Neither result meets the t-statistic of 3 suggested as a threshold by Harvey et al. (2016) and each of the two results represents just one of the 96 possible factor, weight, ESG combinations.

Of the few significant results most come from the DJSI. The most relevant anomalies are the well-studied size anomaly after Banz (1981), the change in sales less the change in inventory of Abarbanell and Bushee (1998) and the return volatility anomaly discussed in Ang et al. (2006). Links between size and ESG are understood through the expectations of consumers and investors for high levels of ESG from larger firms. Change in sales minus change in inventory is also understood through consumer demand since higher demand means more sales and a reduction in inventory[15]. Within the seven return comparisons, return volatility has also emerged as a sort where there are significant return differentials. The traditional anomaly holds low volatility stocks and shorts high, being counterintuitive to the standard risk-return relationship (Ang et al., 2006). ESG stocks are regarded as being lower volatility (Oikonomou et al., 2012; Cerqueti et al., 2021). Albuquerque et al. (2019) offers an explanation for the low risk of ESG stocks from the product market, tying again to the demand of consumers and consumer perceptions of CSR. Because high CSR firms can do well in the future they become lower risk, without necessarily offering lower return. Evidence here supports this notion of low risk and comparable returns, but is not strong enough to conclude that this is the channel through which the effect occurs.

Across all of the comparisons the dominant result is insignificance. No significant returns to strategy B confirm that there is no return to the pure ESG strategy, in line with the contemporary evidence of Pedersen et al. (2020). Significant returns to strategy H show ESG can enhance traditional strategies, particularly the DJSI measure. Although, there are just two significant raw returns for ESG tilt strategies, both are positive. Further, we see enhancement from ESG to the size sort for both equal and value weighting. Although these results suggest potential returns motivation for ESG investment, it must be noted that observing so few significant results amongst a large set of tests may simply be chance. Harvey and Liu (2021) recommend applying a threshold

[15] Abarbanell and Bushee (1998) motivates the change in sales minus change in inventory factor by noting that any firm which has inventory must have been expecting future sales. Hence if a firm is increasing inventory but losing sales then the change in sales minus change in inventory is negative. Such a firm is performing badly and so returns are low. Decomposing the exact combination of reduction in inventory and increase in sales is possible using the compustat data, but this will not inform on the ESG impact. Therefore we simply recognise the theoretical impact of firm CSR performance on the overall change in sales minus change in inventory value.

to the t-statistic of 3. Under the high threshold there are no significant returns. Our message on returns is that the incorporation of ESG into investment strategies does not cause harm, but cannot be stated to bring significant gains either.

## 4.5 Alphas

Significance of the excess returns is only the first step to understanding whether ESG can enhance investment strategies. Adopting the new strategies proposed in this paper may also change the risk profile of the investments. Therefore a more useful comparison is between the abnormal returns generated from following the respective strategies. We initially generate alphas using the CAPM and FF5 models of equations (4.1) and (4.2). We regress the returns from the 6 strategies, A, B, C, D, G and H on the CAPM and FF5 models. We also regress the comparisons C-B, D-A, G-A, G-B, G-C, G-D and H-A on the CAPM and FF5 models to see if ESG can enhance traditional factor sorts. Full strategy alphas under value weighting are provided for the core sorts. We then discuss a summary table of the number of significant alphas for each ESG-strategy-weighting-model combination across the 24 factor sorts.

### 4.5.1 6 Core Anomalies

We begin with the 6 core anomalies identified in GHZ. Table 4.7 presents results for the Refinitiv ESG scores. Results for the DJSI are in Table 4.8. For brevity only the value weighted results are reported here; full results are available in the supplementary material.

Taking first the ESG score sorts in Table 4.7, we see that there are significant alphas on profitability. Amongst these significant alphas, the abnormal returns to strategy G survive against the FF5. The profitability anomaly is one of the factors in the FF5 and so it is unsurprising that many of the results have lower significance when the FF5 is used. Strategy H is of interest as it allows the longing of only high ESG stocks. We see a significant CAPM alpha from both the pure strategy H and the comparison with strategy A. The t-statistics associated with the CAPM alpha to strategies G and H exceed the 3 threshold suggested by Harvey et al. (2016). However, when using the FF5 the t-statistic of strategy G drops to 2.84 and H to 1.93. G is therefore significant at the 1% level but H is marginally insignificant at the 5% level. As with the returns, the main message is one of insignificance.

When using the DJSI as the ESG indicator the results have far less emphasis on

Table 4.7: Strategy Alphas - ESG Score - Value Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Size | CAPM | -0.14 | 0.16 | -0.06 | -0.29 | -0.02 | -0.19 | -0.23 | -0.15 | 0.13 | -0.18 | 0.05 | 0.27 | -0.05 |
| | | (0.94) | (1.39) | (0.36) | (1.25) | (0.17) | (0.80) | (1.15) | (0.96) | (0.70) | (1.07) | (0.24) | (1.15) | (0.23) |
| | FF5 | -0.06 | 0.09 | -0.11 | -0.22 | -0.10 | -0.17 | -0.19 | -0.16 | -0.03 | -0.18 | 0.01 | 0.13 | -0.11 |
| | | (0.51) | (0.70) | (0.57) | (1.03) | (0.77) | (0.81) | (0.91) | (1.00) | (0.18) | (0.95) | (0.05) | (0.54) | (0.56) |
| Book-to-Market | CAPM | -0.28 | 0.16 | 0.24 | -0.29 | 0.04 | -0.05 | 0.08 | -0.01 | 0.33 | -0.12 | -0.20 | 0.34 | 0.23 |
| | | (1.72) | (1.39) | (1.47) | (1.63) | (0.39) | (0.25) | (0.86) | (0.11) | (1.84) | (0.63) | (0.91) | (1.68) | (1.46) |
| | FF5 | -0.07 | 0.09 | 0.11 | -0.08 | 0.08 | 0.02 | 0.02 | -0.02 | 0.15 | 0.00 | -0.02 | 0.17 | 0.09 |
| | | (0.62) | (0.70) | (0.65) | (0.57) | (0.65) | (0.13) | (0.21) | (0.21) | (1.13) | (0.01) | (0.10) | (0.95) | (0.55) |
| Investment | CAPM | -0.01 | 0.16 | 0.23 | -0.04 | -0.01 | 0.08 | 0.06 | -0.03 | 0.00 | -0.17 | -0.24 | 0.03 | -0.07 |
| | | (0.10) | (1.39) | (1.53) | (0.24) | (0.11) | (0.44) | (0.56) | (0.35) | (0.03) | (1.29) | (1.68) | (0.20) | (0.66) |
| | FF5 | 0.18 | 0.09 | 0.15 | 0.18 | 0.01 | 0.08 | 0.07 | 0.00 | -0.17 | -0.07 | -0.14 | -0.16 | -0.07 |
| | | (1.34) | (0.70) | (1.13) | (1.09) | (0.12) | (0.44) | (0.58) | (0.04) | (1.15) | (0.51) | (1.08) | (1.12) | (0.66) |
| Profitability | CAPM | 0.28* | 0.16 | 0.20 | 0.37* | 0.31*** | 0.57** | 0.03 | 0.09 | 0.03 | 0.15 | 0.12 | -0.06 | 0.28* |
| | | (2.21) | (1.39) | (1.18) | (2.03) | (3.48) | (3.12) | (0.21) | (0.81) | (0.24) | (1.18) | (0.60) | (0.34) | (2.05) |
| | FF5 | 0.11 | 0.09 | 0.09 | 0.23 | 0.23** | 0.32 | 0.00 | 0.12 | 0.12 | 0.14 | 0.14 | 0.00 | 0.21 |
| | | (0.98) | (0.70) | (0.55) | (1.38) | (2.84) | (1.93) | (0.01) | (1.33) | (0.78) | (1.08) | (0.75) | (0.01) | (1.42) |
| Return-on-Equity | CAPM | 0.07 | 0.16 | 0.14 | 0.09 | -0.04 | 0.23 | -0.02 | 0.02 | -0.11 | -0.20 | -0.18 | -0.13 | 0.16 |
| | | (0.41) | (1.39) | (0.72) | (0.29) | (0.37) | (0.95) | (0.10) | (0.12) | (0.72) | (1.32) | (0.67) | (0.52) | (1.15) |
| | FF5 | -0.14 | 0.09 | -0.09 | -0.04 | -0.03 | -0.12 | -0.17 | 0.10 | 0.11 | -0.11 | 0.06 | 0.01 | 0.02 |
| | | (1.12) | (0.70) | (0.46) | (0.16) | (0.25) | (0.60) | (0.97) | (0.86) | (0.90) | (0.65) | (0.24) | (0.05) | (0.11) |
| 12-Month Momentum | CAPM | 0.13 | 0.16 | 0.16 | 0.13 | 0.16 | 0.29 | 0.00 | 0.00 | 0.03 | 0.00 | 0.00 | 0.03 | 0.17 |
| | | (0.62) | (1.39) | (0.86) | (0.59) | (1.52) | (1.18) | (0.01) | (0.02) | (0.12) | (0.02) | (0.02) | (0.11) | (0.87) |
| | FF5 | -0.08 | 0.09 | 0.12 | -0.11 | 0.18 | 0.01 | 0.03 | -0.02 | 0.26 | 0.09 | 0.06 | 0.28 | 0.10 |
| | | (0.45) | (0.70) | (0.57) | (0.51) | (1.37) | (0.05) | (0.24) | (0.26) | (1.05) | (0.51) | (0.21) | (1.11) | (0.45) |

Notes: Table reports estimated alphas for the 6 core sorts with the ESG score under value weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} + \beta_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. Size is the market value of equity following Fama and French (1992). Investment and profitability are as defined in Fama and French (2015). Return on equity follows Hou et al. (2015) and 12-month momentum uses returns from time $t-12$ to $t-2$ following Jegadeesh (1990). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the top 30% of Refinitiv ESG scores. Low ESG is defined as the bottom 30% of Refinitiv ESG scores. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table 4.8: Strategy Alphas - DJSI - Value Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Size | CAPM | -0.14 | 0.01 | 0.56* | 0.43 | 0.01 | 0.36 | 0.55* | 0.58* | 0.15 | 0.00 | -0.55 | -0.42 | 0.50 |
| | | (0.94) | (0.12) | (2.06) | (1.74) | (0.06) | (1.30) | (2.23) | (2.42) | (0.63) | (0.01) | (1.81) | (1.43) | (1.85) |
| | FF5 | -0.06 | -0.05 | 0.51 | 0.49 | -0.04 | 0.38 | 0.56* | 0.55* | 0.03 | 0.01 | -0.55 | -0.52 | 0.45 |
| | | (0.51) | (0.60) | (1.93) | (1.83) | (0.15) | (1.31) | (2.25) | (2.37) | (0.11) | (0.04) | (1.61) | (1.51) | (1.70) |
| Book-to-Market | CAPM | -0.28 | 0.01 | -0.01 | -0.17 | 0.02 | -0.18 | -0.02 | 0.11 | 0.31 | 0.02 | 0.03 | 0.20 | 0.10 |
| | | (1.72) | (0.12) | (0.07) | (0.73) | (0.17) | (0.92) | (0.18) | (0.71) | (1.72) | (0.08) | (0.14) | (1.02) | (0.97) |
| | FF5 | -0.07 | -0.05 | -0.04 | -0.04 | 0.06 | -0.09 | 0.00 | 0.02 | 0.12 | 0.10 | 0.10 | 0.10 | -0.02 |
| | | (0.62) | (0.60) | (0.30) | (0.18) | (0.38) | (0.41) | (0.04) | (0.13) | (0.94) | (0.58) | (0.42) | (0.52) | (0.14) |
| Investment | CAPM | -0.01 | 0.01 | -0.03 | 0.08 | 0.21 | -0.06 | -0.04 | 0.09 | 0.22 | 0.20 | 0.24 | 0.13 | -0.04 |
| | | (0.10) | (0.12) | (0.21) | (0.31) | (1.29) | (0.32) | (0.34) | (0.44) | (1.38) | (1.12) | (1.32) | (0.83) | (0.37) |
| | FF5 | 0.18 | -0.05 | -0.14 | 0.22 | 0.29 | 0.05 | -0.09 | 0.04 | 0.11 | 0.33 | 0.43* | 0.07 | -0.13 |
| | | (1.34) | (0.60) | (1.04) | (0.90) | (1.88) | (0.33) | (0.82) | (0.15) | (0.57) | (1.83) | (2.32) | (0.42) | (1.23) |
| Profitability | CAPM | 0.28* | 0.01 | 0.10 | 0.09 | 0.23 | 0.19 | 0.09 | -0.20 | -0.05 | 0.22 | 0.13 | 0.14 | -0.10 |
| | | (2.21) | (0.12) | (0.70) | (0.39) | (1.94) | (1.10) | (0.63) | (1.26) | (0.39) | (1.73) | (0.59) | (0.75) | (0.83) |
| | FF5 | 0.11 | -0.05 | 0.13 | -0.10 | 0.10 | 0.03 | 0.18 | -0.21 | -0.01 | 0.15 | -0.03 | 0.20 | -0.08 |
| | | (0.98) | (0.60) | (0.81) | (0.43) | (0.80) | (0.22) | (1.19) | (1.26) | (0.06) | (1.05) | (0.13) | (0.96) | (0.61) |
| Return-on-Equity | CAPM | 0.07 | 0.01 | 0.01 | 0.08 | 0.02 | 0.09 | 0.00 | 0.01 | -0.05 | 0.01 | 0.00 | -0.06 | 0.02 |
| | | (0.41) | (0.12) | (0.09) | (0.25) | (0.12) | (0.38) | (0.02) | (0.04) | (0.36) | (0.06) | (0.02) | (0.25) | (0.19) |
| | FF5 | -0.14 | -0.05 | -0.08 | -0.09 | 0.01 | -0.17 | -0.03 | 0.05 | 0.15 | 0.05 | 0.09 | 0.09 | -0.03 |
| | | (1.12) | (0.60) | (0.50) | (0.36) | (0.06) | (0.86) | (0.21) | (0.33) | (0.95) | (0.40) | (0.36) | (0.44) | (0.25) |
| 12-Month Momentum | CAPM | 0.13 | 0.01 | 0.05 | 0.16 | 0.16 | 0.20 | 0.04 | 0.03 | 0.03 | 0.15 | 0.11 | 0.00 | 0.07 |
| | | (0.62) | (0.12) | (0.32) | (0.61) | (1.12) | (0.90) | (0.29) | (0.16) | (0.10) | (1.00) | (0.54) | (0.01) | (0.59) |
| | FF5 | -0.08 | -0.05 | -0.04 | -0.02 | 0.22 | -0.06 | 0.01 | 0.06 | 0.30 | 0.26 | 0.25 | 0.24 | 0.02 |
| | | (0.45) | (0.60) | (0.26) | (0.11) | (1.33) | (0.31) | (0.06) | (0.32) | (1.14) | (1.57) | (1.11) | (0.91) | (0.15) |

Notes: Table reports estimated alphas for the 6 core sorts with the DJSI under value weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} + \beta_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. Size is the market value of equity following Fama and French (1992). Investment and profitability are as defined in Fama and French (2015). Return on equity follows Hou et al. (2015) and 12-month momentum uses returns from time $t-12$ to $t-2$ following Jegadeesh (1990). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the members of the DJSI. Low ESG is defined as non-DJSI members. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

profitability. First, significant alphas are seen for size, including on the comparison between C and B and then between D and A. Through these alphas we see that enhancing the ESG sort with size information generates significant abnormal returns. Further enhancing the traditional sort on size with membership of the DJSI also yields significant abnormal returns. Although the t-statistics are well below Harvey et al. (2016) suggested threshold of 3, the alpha remains significant against the FF5. Strategy C offers signficant returns against the CAPM but is marginally insignificant against the FF5. In the comparison of C and B, as with D versus A, it is the poor performance of the pure strategy that opens the way for enhancement. Strategy A offers an insignificant negative alpha against both the CAPM and the FF5. Meanwhile longing DJSI and shorting non-DJSI, strategy B, has negative alpha against the FF5. There are also significant alphas in the value weighted DJSI case for the pure anomaly strategy on profitability and the G-C comparison on investment. We note again that the overriding result is insignificance.

Within the core sorts, size and profit are the two anomalies which offer abnormal returns in combination with ESG. Rationale here comes from the belief that successful firms should improve their ESG; those successful firms who do not have high ESG being duly punished. Within the strategy returns we saw higher returns to those strategies which long small firms with high ESG and short large firms with poor ESG. These results also appear in the alpha when DJSI is used as the ESG measure. Profit has similiarities to size as a driver of differences in the expectations on ESG from investors and consumers. Chapter 2 showed that CSR activity towards employees and product improvements could bring significant profit gains. Evidence on profitability double sorts here is suggestive that the most profitable firms have realised their optimal ESG strategies. Double enhancement with ESG is able to generate alpha because of the differentiation within high, and low, profit firms on their expected ESG performance. It is however reminded that most alphas are insignificant and that none have higher t-statistics than 3.

### 4.5.2 Further Factor Sorts

For brevity the full strategy comparison tables are presented in the supplementary material. Table 4.9 presents the count of significant alphas together with the extent of the significance. Following GHZ and Harvey et al. (2016) we also provide counts for t-statistics larger than three. These counts apply to all 24 factor sorts.

The first immediate message from Tables 4.9 and 4.10 is that most alphas are not

Table 4.9: Strategy Alpha Comparison Summary - Equal Weighting

| ESG | Model | $t - stat$ | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Score | CAPM | $t \in [2,3)$ | 2 | 0 | 3 | 1 | 1 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 |
| | | $t \in (2,2)$ | 22 | 24 | 21 | 23 | 23 | 17 | 24 | 24 | 22 | 22 | 22 | 21 | 21 |
| | | $t \in (-3,-2]$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 2 | 2 | 2 | 0 |
| | | $t \leq -3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| Score | FF5 | $t \geq 3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | $t \in [2,3)$ | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| | | $t \in (2,2)$ | 24 | 24 | 24 | 24 | 23 | 23 | 24 | 24 | 21 | 22 | 24 | 21 | 23 |
| | | $t \in (-3,-2]$ | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 3 | 2 | 0 | 3 | 0 |
| DJSI | CAPM | $t \geq 3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | $t \in [2,3)$ | 2 | 0 | 3 | 2 | 1 | 5 | 2 | 1 | 0 | 0 | 2 | 0 | 2 |
| | | $t \in (2,2)$ | 22 | 24 | 21 | 22 | 22 | 19 | 20 | 22 | 17 | 21 | 20 | 19 | 22 |
| | | $t \in (-3,-2]$ | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 1 | 6 | 3 | 2 | 5 | 0 |
| DJSI | FF5 | $t \geq 3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | $t \in [2,3)$ | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| | | $t \in (2,2)$ | 24 | 24 | 24 | 23 | 24 | 23 | 23 | 23 | 22 | 24 | 24 | 24 | 24 |
| | | $t \in (-3,-2]$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 |

Notes: Table reports number of traditional factor sorts for which the t-statistic in a test of alphas being non-zero lies in the stated range. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} + \beta_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. ESG informs whether we are using the Refintiv ESG Score (Score), or membership of the Dow Jones Sustainability Index North America (DJSI) to define ESG leadership. Strategy A longs the theoretically high returning factor sort portfolio (sort high) and shorts the theoretically low returning factor sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs factor sort high and shorts factor sort low. Strategy D considers only factor sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high factor sort and low ESG-low factor sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high factor sort and short on low ESG-low factor sort. High ESG is defined as the top 30% of Refinitiv ESG scores or members of the DJSI. Low ESG is defined as the bottom 30% of Refinitiv ESG scores or non-DJSI members. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table 4.10: Strategy Alpha Comparison Summary - Value Weighting

| ESG | Model | $t - stat$ | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Score | CAPM | $t \geq 3$ | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | $t \in [2, 3)$ | 5 | 0 | 2 | 1 | 1 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| | | $t \in (2, 2)$ | 18 | 24 | 22 | 22 | 22 | 20 | 24 | 24 | 20 | 24 | 23 | 23 | 22 |
| | | $t \in (-3, -2]$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 1 | 1 | 0 |
| Score | FF5 | $t \geq 3$ | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | $t \in [2, 3)$ | 4 | 0 | 0 | 0 | 1 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | $t \in (2, 2)$ | 20 | 24 | 24 | 23 | 22 | 22 | 24 | 24 | 22 | 24 | 24 | 24 | 24 |
| | | $t \in (-3, -2]$ | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| | | $t \leq -3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| DJSI | CAPM | $t \geq 3$ | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | $t \in [2, 3)$ | 5 | 0 | 1 | 1 | 2 | 5 | 1 | 1 | 0 | 2 | 2 | 0 | 0 |
| | | $t \in (2, 2)$ | 18 | 24 | 23 | 23 | 22 | 18 | 21 | 22 | 24 | 22 | 22 | 22 | 24 |
| | | $t \in (-3, -2]$ | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 1 | 0 | 0 | 0 | 2 | 0 |
| DJSI | FF5 | $t \geq 3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | $t \in [2, 3)$ | 4 | 0 | 0 | 1 | 0 | 2 | 2 | 1 | 0 | 0 | 2 | 0 | 0 |
| | | $t \in (2, 2)$ | 20 | 24 | 24 | 23 | 24 | 22 | 21 | 23 | 24 | 24 | 22 | 23 | 24 |
| | | $t \in (-3, -2]$ | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |

Notes: Table reports number of traditional factor sorts for which the t-statistic in a test of alphas being non-zero lies in the stated range. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. ESG informs whether we are using the Refintiv ESG Score (Score), or membership of the Dow Jones Sustainability Index North America (DJSI) to define ESG leadership. Strategy A longs the theoretically high returning factor sort portfolio (sort high) and shorts the theoretically low returning factor sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs factor sort high and shorts factor sort low. Strategy D considers only factor sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high factor sort and low ESG-low factor sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high factor sort and short on low ESG-low factor sort. High ESG is defined as the top 30% of Refinitiv ESG scores or members of the DJSI.High ESG is defined as the top 30% of Refinitiv ESG scores or members of the DJSI. Low ESG is defined as the bottom 30% of Refinitiv ESG scores or non-DJSI members. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

significant. Secondly, there are no cases in which strategy B, the unconditional ESG strategy, produces significant alpha. All other strategies produce alpha under at least one weighting-factor model combination. Unconditional strategies only produce alpha in the CAPM when equal weighting is applied. When we apply value weighting we see more alpha, both from the CAPM and FF5 models. Again all of these alphas are positive, working in the theoretical direction of the factor sort unconditional strategy. Table 4.11 lists all of the significant alphas that appear for both the ESG score and DJSI membership. A column is also included to show where the strategies A to H have ESG tilts. We subsequently refer back to this table in the commentary.

In Table 4.11, under value weighting we see alpha against both models for growth in the book value of equity, return volatility, turnover volatility and zero trading days. As strategy A is unconditional on ESG these results appear in both of the ESG measures. Additionally, CAPM alphas are seen under value weighting for profitability, beta, growth in sales less growth in inventory and share turnover. Under equal weighting there is an alpha for return volatility in the CAPM. Amongst these alphas only the CAPM alpha for return volatility has a t-statistic which beats the suggested 3 threshold of Harvey et al. (2016). Nonetheless, these results indicate that it is possible to gain alpha within our restricted universe.

Strategy C works within the high level of the traditional sort and takes a long position on high ESG and short position on low ESG. In both equal weighting and value weighting we do see some significant alphas from the CAPM. CAPM alphas are found for 9 ESG weighting factor combinations including stock turnover under equal and value weighting with Refinitiv ESG scores, and operating profit under equal weighting with both ESG measures. There are no significant alphas for the FF5. The interpretation of a positive alpha would be that the traditional factor was enhancing the ESG unconditional strategy. Consequently we may conclude that there is insufficient power within the 24 anomalies to enable a long-short position based upon ESG. This applies to both Refinitiv ESG scores and the DJSI. Strategy D works within the high ESG stocks to take a long-short position based upon the traditional sort. Return volatility has significant alpha against both the CAPM and FF5 when Refinitiv ESG scores are used and value weightings are applied. Both of these alphas have t-statistics above 3. Return volatility also generates a CAPM alpha under equal weighting using Refinitiv ESG scores, and value weighting when DJSI membership is the ESG measure. Growth in sales minus growth in inventory has a significant alpha against both CAPM and FF5 when using DJSI membership and equal weighting. The FF5 alphas also survives under value weighting. A further two strategy D CAPM alphas are also found,

Table 4.11: Significant Alphas

| Strategy | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| Panel (a) Factor Sorts Equal Weighting: | | | | | | | |
| A | Neutral | CAPM Beta | | EW | CAPM | 0.60* | 2.18 |
| A | Neutral | Return Volatility | | EW | CAPM | 0.52** | 2.78 |
| Panel (b) Factor Sorts Value Weighting: | | | | | | | |
| A | Neutral | CAPM Beta | | VW | CAPM | 0.60* | 1.97 |
| A | Neutral | Operating Profit | | VW | CAPM | 0.28* | 2.21 |
| A | Neutral | Return Volatility | | VW | CAPM | 0.66*** | 3.41 |
| A | Neutral | Return Volatility | | VW | FF5 | 0.39** | 2.97 |
| A | Neutral | Growth in Sales - Growth in Inventory | | VW | FF5 | 0.23* | 2.07 |
| A | Neutral | Stock Turnover | | VW | CAPM | 0.45* | 2.12 |
| A | Neutral | Turnover Volatility | | VW | CAPM | 0.39** | 2.85 |
| A | Neutral | Turnover Volatility | | VW | FF5 | 0.28* | 2.46 |
| A | Neutral | Zero Trading Days | | VW | CAPM | 0.49* | 2.35 |
| A | Neutral | Zero Trading Days | | VW | FF5 | 0.34* | 2.07 |
| Panel (c) ESG Score Equal Weighting: | | | | | | | |
| C | Tilt | Book-to-Market Ratio | Score | EW | CAPM | 0.30* | 2.33 |
| C | Tilt | Stock Turnover | Score | EW | CAPM | 0.28* | 2.39 |
| C | Tilt | Operating Profit | Score | EW | CAPM | 0.38* | 2.30 |
| D | Neutral | Return Volatility | Score | EW | CAPM | 0.60* | 2.58 |
| G | Neutral | Industry Adjusted Cash-flow | Score | EW | FF5 | -0.40* | 2.04 |
| G | Neutral | Earnings Announcement Returns | Score | EW | CAPM | 0.46* | 2.17 |
| H | Tilt | CAPM Beta | Score | EW | CAPM | 0.70* | 2.59 |
| H | Tilt | Operating Profit | Score | EW | CAPM | 0.44** | 2.62 |
| H | Tilt | Return Volatility | Score | EW | CAPM | 0.67** | 2.99 |
| H | Tilt | Growth in Sales - Growth in Inventory | Score | EW | CAPM | 0.33* | 2.20 |
| H | Tilt | Growth in Sales - Growth in Inventory | Score | EW | FF5 | 0.36* | 2.25 |
| H | Tilt | Stock Turnover | Score | EW | CAPM | 0.58* | 2.37 |
| H | Tilt | Turnover Volatility | Score | EW | CAPM | 0.51* | 2.46 |
| H | Tilt | Zero Trading Days | Score | EW | CAPM | 0.62* | 2.40 |
| G-A | | Industry Adjusted Cash-flow | Score | EW | FF5 | -0.54* | 2.36 |

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Table 4.11: Significant Alphas

| Strategy | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| G-A | | Earnings Announcement Returns | Score | EW | CAPM | -0.48* | 2.08 |
| G-A | | Earnings Announcement Returns | Score | EW | FF5 | -0.53* | 2.12 |
| G-A | | Industry Momentum | Score | EW | FF5 | -0.47* | 1.99 |
| G-A | | Return Volatility | Score | EW | CAPM | -0.53* | 2.10 |
| G-B | | Industry Adjusted Cash-flow | Score | EW | FF5 | -0.48* | 2.02 |
| G-B | | Earnings Announcement Returns | Score | EW | CAPM | -0.62** | 2.73 |
| G-B | | Earnings Announcement Returns | Score | EW | FF5 | -0.55* | 1.99 |
| G-B | | Operating Profit | Score | EW | CAPM | -0.45* | 2.11 |
| G-C | | Earnings Announcement Returns | Score | EW | CAPM | -0.39* | 2.51 |
| G-C | | Operating Profit | Score | EW | CAPM | -0.67* | 1.98 |
| G-D | | Industry Adjusted Cash-flow | Score | EW | FF5 | -0.31* | 2.04 |
| G-D | | Industry Momentum | Score | EW | FF5 | -0.47* | 2.59 |
| G-D | | Operating Profit | Score | EW | CAPM | -0.35 | 1.97 |
| G-D | | Return Volatility | Score | EW | CAPM | -0.61** | 3.00 |
| G-D | | Return Volatility | Score | EW | FF5 | -0.39* | 2.08 |
| G-D | | Turnover Volatility | Score | EW | CAPM | -0.37* | 2.08 |
| H-A | | Operating Profit | Score | EW | CAPM | 0.30* | 2.24 |
| H-A | | Growth in Sales - Growth in Inventory | Score | EW | CAPM | 0.30* | 2.23 |
| H-A | | Growth in Sales - Growth in Inventory | Score | EW | FF5 | 0.27* | 2.00 |
| H-A | | Industry Momentum | Score | EW | CAPM | 0.31* | 2.12 |
| Panel (d) ESG Score Value Weighting: | | | | | | | |
| C | Tilt | Growth of Inventory | Score | VW | CAPM | 0.29* | 2.39 |
| C | Tilt | Stock Turnover | Score | VW | CAPM | 0.33* | 2.18 |
| D | Neutral | Operating Profit | score | VW | CAPM | 0.37* | 2.03 |
| D | Neutral | Return Volatility | Score | VW | CAPM | 0.86*** | 3.36 |
| D | Neutral | Return Volatility | Score | VW | FF5 | 0.58** | 3.05 |
| G | Neutral | Operating Profit | Score | VW | CAPM | 0.31*** | 3.48 |
| G | Neutral | Operating Profit | Score | VW | FF5 | 0.23** | 2.84 |
| G | Neutral | Return Volatility | Score | VW | CAPM | 0.27* | 2.01 |

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Table 4.11: Significant Alphas

| Strategy | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| G | Neutral | Growth in Sales - Growth in Inventory | Score | VW | FF5 | -0.20* | 2.05 |
| H | Tilt | Operating Profit | Score | VW | CAPM | 0.57** | 3.12 |
| H | Tilt | Return Volatility | Score | VW | CAPM | 0.67** | 2.80 |
| H | Tilt | Return Volatility | Score | VW | FF5 | 0.37* | 2.12 |
| H | Tilt | Growth in Sales - Growth in Inventory | Score | VW | CAPM | 0.39* | 2.21 |
| H | Tilt | Growth in Sales - Growth in Inventory | Score | VW | FF5 | 0.36* | 2.04 |
| H | Tilt | Zero Trading Days | Score | VW | CAPM | 0.51* | 1.99 |
| G-A | | CAPM Beta | Score | VW | CAPM | -0.62* | 2.19 |
| G-A | | Growth of Long-Term Net Operating Assets | Score | VW | FF5 | -0.27* | 2.29 |
| G-A | | Return Volatility | Score | VW | CAPM | -0.39* | 2.09 |
| G-A | | Growth in Sales - Growth in Inventory | Score | VW | CAPM | -0.23* | 2.09 |
| G-A | | Growth in Sales - Growth in Inventory | Score | VW | FF5 | -0.43*** | 3.90 |
| G-A | | Turnover Volatility | Score | VW | CAPM | -0.43** | 2.64 |
| G-C | | Growth of Inventory | Score | VW | CAPM | -0.32* | 2.24 |
| G-D | | Return Volatility | Score | VW | CAPM | -0.60* | 2.58 |
| H-A | | Industry Momentum | Score | VW | CAPM | 0.28* | 1.99 |
| H-A | | Operating Profit | Score | VW | CAPM | 0.28* | 2.05 |
| Panel (e) DJSI Membership Equal Weighting: | | | | | | | |
| C | Tilt | Asset Growth | DJSI | EW | CAPM | 0.31* | 2.40 |
| C | Tilt | Operating Profit | DJSI | EW | CAPM | 0.26* | 2.02 |
| C | Tilt | Growth in Sales - Growth in Inventory | DJSI | EW | CAPM | 0.40* | 2.28 |
| D | Neutral | Asset Growth | DJSI | EW | CAPM | 0.35* | 2.19 |
| D | Neutral | Growth in Sales - Growth in Inventory | DJSI | EW | CAPM | 0.30* | 1.97 |
| D | Neutral | Growth in Sales - Growth in Inventory | DJSI | EW | FF5 | 0.42* | 2.36 |
| G | Neutral | Size | DJSI | EW | CAPM | 0.57* | 2.09 |
| G | Neutral | Turnover Volatility | DJSI | EW | CAPM | -0.52* | 2.29 |
| H | Tilt | Asset Growth | DJSI | EW | CAPM | 0.36** | 2.83 |
| H | Tilt | CAPM Beta | DJSI | EW | CAPM | 0.67* | 2.34 |
| H | Tilt | Return Volatility | DJSI | EW | CAPM | 0.56** | 2.68 |

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Table 4.11: Significant Alphas

| Strategy | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| H | Tilt | Growth in Sales - Growth in Inventory | DJSI | EW | CAPM | 0.37* | 2.39 |
| H | Tilt | Growth in Sales - Growth in Inventory | DJSI | EW | FF5 | 0.35* | 2.13 |
| H | Tilt | Turnover Volatility | DJSI | EW | CAPM | 0.37* | 2.07 |
| C-B | | Asset Growth | DJSI | EW | CAPM | 0.20* | 2.08 |
| C-B | | Growth of Shares Outstanding | DJSI | EW | CAPM | -0.18* | 2.05 |
| C-B | | Illiquidity | DJSI | EW | CAPM | -0.17* | 2.36 |
| C-B | | Growth in Sales - Growth in Inventory | DJSI | EW | CAPM | 0.28* | 2.20 |
| C-B | | Growth in Sales -Growth in Inventory | DJSI | EW | FF5 | 0.29* | 2.11 |
| D-A | | Size | DJSI | EW | CAPM | 0.51* | 1.98 |
| D-A | | Growth in Sales - Growth in Inventory | DJSI | EW | FF5 | 0.33* | 2.00 |
| D-A | | Turnover Volatility | DJSI | EW | CAPM | -0.46* | 2.36 |
| G-A | | CAPM Beta | DJSI | EW | CAPM | -0.67* | 2.17 |
| G-A | | Growth of Shares Outstanding | DJSI | EW | CAPM | -0.52* | 2.33 |
| G-A | | Operating Profit | DJSI | EW | CAPM | -0.47* | 2.07 |
| G-A | | Return Volatility | DJSI | EW | CAPM | -0.78* | 2.56 |
| G-A | | Stock Turnover | DJSI | EW | CAPM | -0.70** | 2.73 |
| G-A | | Stock Turnover | DJSI | EW | FF5 | -0.82*** | 3.57 |
| G-A | | Turnover Volatility | DJSI | EW | CAPM | -0.50* | 2.19 |
| G-A | | Zero Trading Days | DJSI | EW | CAPM | -0.68** | 2.85 |
| G-A | | Zero Trading Days | DJSI | EW | FF5 | -0.47* | 2.18 |
| G-B | | Operating Profit | DJSI | EW | CAPM | -0.45* | 2.33 |
| G-B | | Growth of Shares Outstanding | DJSI | EW | CAPM | -0.45* | 2.08 |
| G-B | | Turnover Volatility | DJSI | EW | CAPM | -0.63* | 2.45 |
| G-C | | Return Volatility | DJSI | EW | CAPM | 0.39* | 2.48 |
| G-C | | Zero Trading Days | DJSI | EW | CAPM | 0.42* | 2.20 |
| G-C | | Operating Profit | DJSI | EW | CAPM | -0.59* | 2.04 |
| G-C | | Turnover Volatility | DJSI | EW | CAPM | -0.53* | 2.43 |
| G-D | | CAPM Beta | DJSI | EW | CAPM | -0.61* | 2.24 |
| G-D | | Stock Turnover | DJSI | EW | CAPM | -0.40* | 2.07 |
| G-D | | Turnover Volatility | DJSI | EW | CAPM | -0.36* | 2.42 |
| G-D | | Zero Trading Days | DJSI | EW | CAPM | -0.39* | 2.10 |

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Table 4.11: Significant Alphas

| Strategy | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| G-D | | Return Volatility | DJSI | EW | CAPM | -0.56** | 2.89 |
| H-A | | Asset Growth | DJSI | EW | CAPM | 0.26* | 2.22 |
| H-A | | Growth in Sales - Growth in Inventory | DJSI | EW | CAPM | 0.34* | 2.22 |
| Panel (f) DJSI Membership Value Weighting: | | | | | | | |
| C | Tilt | Size | DJSI | VW | CAPM | 0.56* | 2.06 |
| D | Neutral | Return Volatility | DJSI | VW | CAPM | 0.68** | 2.62 |
| D | Neutral | Growth in Sales - Growth in Inventory | DJSI | VW | FF5 | 0.50* | 2.55 |
| G | Neutral | Return Volatility | DJSI | VW | CAPM | 0.39* | 2.48 |
| G | Neutral | Zero Trading Days | DJSI | VW | CAPM | 0.42* | 2.20 |
| H | Tilt | Asset Growth | DJSI | VW | CAPM | 0.33* | 2.31 |
| H | Tilt | Return Volatility | DJSI | VW | CAPM | 0.65** | 3.01 |
| H | Tilt | Growth in Sales - Growth in Inventory | DJSI | VW | CAPM | 0.34* | 2.11 |
| H | Tilt | Growth in Sales - Growth in Inventory | DJSI | VW | FF5 | 0.38* | 2.30 |
| H | Tilt | Stock Turnover | DJSI | VW | CAPM | 0.47* | 2.18 |
| H | Tilt | Turnover Volatility | DJSI | VW | CAPM | 0.45** | 2.95 |
| H | Tilt | Turnover Volatility | DJSI | VW | FF5 | 0.27* | 2.12 |
| H | Tilt | Zero Trading Days | DJSI | VW | CAPM | 0.48* | 2.31 |
| C-B | | Illiquidity | DJSI | VW | CAPM | -0.09** | 2.76 |
| C-B | | Illiquidity | DJSI | VW | FF5 | -0.08* | 2.18 |
| C-B | | Industry Momentum | DJSI | VW | CAPM | -0.26* | 2.07 |
| C-B | | Size | DJSI | VW | CAPM | 0.55* | 2.23 |
| C-B | | Size | DJSI | VW | FF5 | 0.56* | 2.25 |
| C-B | | Growth in Sales - Growth in Inventory | DJSI | VW | FF5 | 0.31* | 2.10 |
| D-A | | Industry Momentum | DJSI | VW | CAPM | -0.30* | 2.14 |
| D-A | | Size | DJSI | VW | CAPM | 0.58* | 2.42 |
| D-A | | Size | DJSI | VW | FF5 | 0.55* | 2.37 |
| G-B | | Return Volatility | DJSI | VW | CAPM | 0.38* | 2.40 |
| G-B | | Zero Trading Days | DJSI | VW | CAPM | 0.41* | 2.00 |
| G-C | | Growth of Shares Outstanding | DJSI | VW | CAPM | 0.28* | 2.17 |
| G-C | | Investment | DJSI | VW | FF5 | 0.43* | 2.32 |
| G-C | | Return Volatility | DJSI | VW | CAPM | 0.43* | 2.52 |
| G-C | | Return Volatility | DJSI | VW | FF5 | 0.38* | 1.96 |

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Table 4.11: Significant Alphas

| Strategy | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| G-D | | Asset Growth | DJSI | VW | CAPM | -0.35* | 2.19 |
| G-D | | Growth in Sales - Growth in Inventory | DJSI | VW | CAPM | -0.30* | 1.97 |
| G-D | | Growth in Sales - Growth in Inventory | DJSI | VW | FF5 | -0.42* | 2.36 |

Notes: Table provides a list of all strategy, sort variable, ESG measure, weighting and asset pricing model combinations that produce significant alpha from the approximately 2200 possible combinations. Strategies are as defined in the main paper. A to G are pure strategies, whilst two letters denotes a comparison between the respective pure strategies. Position reports whether the strategy has an ESG tilt, that is the strategy longs higher ESG stocks than it shorts, or whether the strategy is neutral on ESG. We do not have any strategies which long lower ESG than they short. ESG reports the measure of ESG used in the portfolio construction and is either Score for the Refinitiv ESG Score, or DJSI for the firm being a member of the Dow Jones Sustainability Index North America. Weightings for portfolio calculations are either equal (EW) or value (VW). Two asset pricing models are used, being the capital asset pricing model (CAPM) and the Fama and French (2015) five factor model (FF5). Alpha reports the abnormal return estimate from the model, with significance determined by a test that the true alpha coefficient is 0. Tests are estimated with Newey et al. (1987) adjusted standard errors at lag 6. Significance denoted by $* - 5\%$, $** -1\%$ and $*** - 0.1\%$

for operating profit with ESG scores and value weighting, and asset growth with DJSI membership and equal weighting.

Return volatility, as discussed in Ang et al. (2006), takes a long position on stocks with low volatility. The volatility anomaly is considered a puzzle given higher returns are typically associated with high volatility. Significance of alpha in strategy A confirms that Ang et al. (2006) result persists in our smaller and more contemporary universe. Alphas on strategy D inform that investors may generate abnormal returns by longing low volatility and high ESG stocks. Further, it is possible to improve on the pure volatility strategy A. Given ESG stocks have lower volatility on average, we may expect that the combination of sorts would aid identification of a very low volatility group.

Strategy G uses both way enhancement. It has already been seen that there is a significant positive alpha for the profitability anomaly of Fama and French (2015). Under value weighting strategy G generates both CAPM and FF5 alpha from operating profit when Refinitiv scores are used as the ESG sort. Return volatility sees alpha for G against the CAPM with both DJSI and Refinitiv ESG scores. However, in both cases this alpha disappears when the FF5 is used. There is a positive alpha under equal weighting for earnings announcement returns on the Refinitiv ESG scores. For DJSI membership we see equal weighted CAPM alphas for size under equal weighting and the number of zero trading days under value weighting. Again these disappear for the FF5. Finally, we note that there are cases where alpha is negative. There is a negative alpha identified for the change in sales less change in inventory for the CAPM and equal weighting when Refinitiv ESG scores are the ESG measure. Turnover volatility is also seen to produce a negative alpha for equal weighting with DJSI membership as the ESG sort. Results for the double enhancement are focused on profit and the ESG score as the alpha signal. Double enhancment does little in comparison to the single enhancement strategies C and D.

This paper introduces a sixth possible strategy, a hybrid which seeks to use information on the factor sort and the ESG. Strategy H takes a long position on high ESG-high factor sort stocks and shorts those low ESG-low factor sort stocks. There are several factor sort characteristics for which the CAPM alpha is significant under equal weighting for both ESG measures, including the CAPM beta and turnover volatility. For the growth in sales less the growth in inventory we see significant alpha under both equal and value weighting, with both DJSI and Refinitiv ESG scores, and for both CAPM and FF5. For return volatility there is significant CAPM alpha under equal weighting for both ESG measures. We also see significant alpha for return volatility against the FF5 when value weighting is applied. Amongst the significant alphas for strategy H, the position on return volatility with value weighting and DJSI ESG comes with a t-statistic greater than 3. Therefore, under the higher threshold proposed by Harvey et al. (2016), there is a significant alpha.

Alphas for strategy H are again themed around consumer demand and volatility, the universal significance of the change in sales minus the change in inventory stands out clearly. Volatilty is captured in both beta and return volatility here. The betting against beta strategy discussed in Frazzini and Pedersen (2014) also goes in the counter-intuitive direction of holding low risk firms. Again the ESG stocks being low risk means that there is potential to enhance the traditional sort effect by bringing in ESG information. High asset growth produces low returns, including amongst the subset of large stocks (Cooper et al., 2008). Investment in improved ESG yields low asset growth, which is consistent again with ESG information enhancing the factor sort. To formally conclude on the link, more investigation is needed about the nature of the asset growth in relation to ESG projects.

Considering the significance in the context of the ESG tilt versus ESG neutral comparison, we note 37 cases in which the ESG tilt strategies generate significant positive alpha. This represents around 5% of the 768 model-weight-ESG-factor combination tested. There are 12 significant abnormal returns to the pure factor sort strategy, strategy A. All abnormal returns to strategy A are positive. There are 192 model-weight-factor combinations for strategy A. Finally, there are 19 significant alphas seen on ESG neutral strategies over and above those seen on strategy A. Of these 4 are negative. Again there are a total of 768 model-weight-ESG-factor combinations for ESG neutral strategies. Whilst we see more significant positive alphas from the ESG tilts, it is still only a small proportion of the total tests performed. We note too that there is little in the pure strategies that exceeds the t-statistic threshold of 3. Only when comparing with other strategies can we fully evaluate our single strategy results.

Two comparisons are made to ask whether introducing information in one direction can enhance the unconditional strategies. Taking a long position on strategy C and short on B allows us to test whether the traditional factor enhances the ESG strategy. The only significant results appear with DJSI membership as the ESG sort. We see that there are positive significant alphas for this strategy on asset growth, change in sales minus change in inventory, and size. These anomalies are already seen to have links with ESG information, ESG giving better returns for small, low profit firms. Negative alphas are reported for industry momentum, changes in the number of shares outstanding and illiquidity. Of these factor sorts that produce negative alphas, illiquidity is the only one to appear in more than one of the model-weight-ESG measure combinations. Rationale can be found in the discussion of Datar et al. (1998) and the longer term perspective of ESG investors. Low turnover stocks have been understood to be held by long term investors and to offer higher returns (Datar et al., 1998). ESG investors are understood to take a long term perspective, creating a link between ESG and liquidity[16]. The enhancement from strategy H on illiquidity is consistent with the alignment of long-term perspectives and ESG. A lack of alpha in the C-B comparison indicates the link does not work the other way in our reduced universe.

Taking a long position on strategy D and short on A tests whether ESG can enhance traditional strategies. Table 4.11 shows few significant alphas under either weighting or model. Size is identified under value weighting and DJSI as the ESG measure, as reported previously. Amongst the other sorts, the growth in sales less the growth in inventory produces a significant alpha for the CAPM when using the DJSI as the ESG measure. However, there are again cases where the alpha on D-A goes in the opposite direction of enhancement and suggests that ESG information makes the traditional factor strategy worse. This applies for turnover volatility when using the DJSI and

[16]This point is established in the well cited working papers of Fulton et al. (2012) and Starks et al. (2017).

applies only to equal weighting and the CAPM. There is also a negative significant alpha with industry momentum as the sort, value weighting and DJSI membership. Both of these negative effects disappear for the FF5 and when the Refinitiv ESG scores are used to capture ESG. Again enhancement is ocurring on size and on the demand focused growth in sales minus growth in inventory. ESG performance is linked to industry, with membership of the DJSI, or high Refinitiv ESG scores, identifying industry leaders. It is rational that the strength of a firms ESG may help it to move against industry momentum. However, on this evidence is limited. That only one alpha is significant suggests that the negative impact of enhancing ESG strategies with the use of industry momentum is yet to be established as a concern for ESG investing.

Strategy G represents the use of both sorts for enhancement. We see most significance in the G-A and G-B columns of Table 4.9. Where alphas are significant in the G-A comparison only for the number of zero trading days, with DJSI membership as the ESG measure and value weighting, are the alphas positive. In all other cases, where significant, the G-A comparison produces negative alphas. Return volatility has significant negative CAPM alphas with Refinitiv ESG scores and both equal and value weighting. There is also a negative CAPM alpha from return volatility with DJSI membership and equal weighting. Earnings announcement returns produce a negative alpha from both CAPM and FF5 models with Refinitiv ESG scores and equal weighting. Similarly a negative alpha from growth in sales minus growth in inventory using Refinitiv ESG scores and value weighting is robust to both CAPM and FF5. Finally, model robustness is also seen for stock turnover with DJSI membership as the ESG indicator and equal weighting. There are then a further 8 combinations of weighting, ESG and model alphas. G-B produces very little enhancement; only CAPM alphas for return volatility and zero trading days with value weighting, DJSI membership are significant and positive. There are 7 significant negative alphas, all of which appear under equal weighting. Of these earnings announcement returns have a significant negative alpha against both CAPM and FF5 under equal weighting with Refinitiv ESG scores as the ESG sort. Using a double enhancement therefore offers little compared to the unconditional strategies.

G-C compares the full two-way enhancement with an ESG strategy within the top performing traditional sort. Again, very little significance is noted. There is no case in which either both ESG measures, or both weightings, or both asset pricing models agree on an alpha. Return volatility offers significant alphas with DJSI membership as the ESG leadership indicator against the CAPM for both equal and value weighting, as well as against the FF5 with value weighting. There are a further 3 positive and 5 negative significant alphas in the G-C comparison. Amongst these 8 only operating profit appears more than once, generating significant negative CAPM alphas under equal weighting irrespective of whether Refinitiv ESG scores or DJSI membership is used as the ESG measure. Compared to the traditional strategy within the high ESG stocks, strategy D, strategy G also offers little improvement. All of the identified significant alphas are negative. Amongst the sorts, return volatility is associated with negative CAPM alpha for Refinitiv ESG scores under both weightings and for DJSI membership with equal weighting. The CAPM alpha from return volatility with Refinitiv ESG scores and equal weighting has a t-statistic above 3 in absolute value. A t-statistic above 3 also applies when using the FF5 as the asset pricing model. Growth in sales minus growth in inventory produces alpha against both CAPM and FF5 when considering DJSI membership and applying value weighting but not in any other model ESG weighting combination. There are then a further 9 negative significant alphas identified in Table 4.11. Identification of negative alphas when comparing G with the unconditional, or one-way enhanced, strategies can be understood theoretically. Double enhancement within the already restricted universe of S&P 500 stocks is difficult given the small portfolios involved and the lack of significance seen in most ESG informed strategies.

This paper also introduces a final strategy H, which is designed to allow investors to long high ESG stocks, short low ESG stocks, and use the information from the traditional factor sort. The natural comparison to test the performance of H is against the unconditional traditional sort A. Significant CAPM alphas are found from the Refinitiv ESG scores on industry momentum and profitability under both equal and value weighting. These alphas are not significant for the FF5 though. Growth in sales minus growth in inventory, which has been shown to be associated with significant alpha already, also produces a singificant alpha in the H-A case for the CAPM under even weighting with both Refinitiv ESG scores and membership of the DJSI. Growth in sales minus growth in inventory also produces a significant alpha against the FF5 under equal weighting with the Refinitiv ESG score to add robustness. Finally, we note that asset growth produces a significant CAPM alpha under equal weighting with the DJSI as the ESG measure. In these results there are suggestions ESG information can work with traditional factor sorts to produce alpha. However, there is again the caution that the t-statistics seldom exceed 3.

Our overall evidence points to the existence of strategies that may bring alpha for those who wish to only long sustainable stocks. However, the evidence remains very limited and most of the alphas identified do not survive the higher t-statistic threshold of Harvey et al. (2016). With so many tests performed it is necessary to find more evidence to confirm that the results we do have are not the result of statistical chance. There are theoretical rationales behind size, profit, volatility, liquidity and growth in sales minus growth in inventory, but the results on these anomalies are certainly not robust to different weightings, ESG measures and asset pricing models. On the likelihood that ESG reduces the alpha of the portfolios the evidence is more clear. A balance of significant alphas on D-A prevents any conclusion that the ESG enhanced strategy performs worse than the unconditional strategy.

### 4.5.3 Trading Strategies

A major consideration with any proposed means of generating alpha is the robustness to trading costs. An investor considering our ESG flavoured strategy would wish to know if they can generate abnormal returns after the deduction of trading costs. Restricting focus to the S&P 500 universe means that such costs should be low even with a large turnover of the portfolios. ESG scores are relatively stable over time, especially membership of the DJSI. Therefore there is little reason to assume significant additional turnover of the portfolios compared to the traditional strategies. In order to evaluate the impact of trading costs we first identify the turnover associated with each of the strategies detailed in Table 4.1. Amongst our set of 24 anomalies some produce high turnover; the average two-leg total turnover is 94%. For the double enhancement strategy H the average two-leg turnover is 113% [17]. These turnover statistics only apply for October, with turnover in all other months being 0% by assumption.

Taking the rule of thumb from Chen and Velikov (2020), and following Novy-Marx and Velikov (2016), we apply a 1bps transaction fee for each percentage point of turnover within a strategy. The maximum trading cost for a two legged strategy which replaces all of its holdings in both legs is 200bps. In reality trading costs will be lower than the estimates because of the highly liquid nature of the S&P 500 stocks relative to the universe upon which the 1bps per percentage turnover is based. Trading costs are applied in any month where the strategy trades, hence only in October of each year[18]. For each portfolio we compute turnover and the trading cost adjusted excess returns. These trading cost adjusted returns are then regressed on the market factor and the FF5 factors to identify trading cost adjusted alphas.

[17] Full details of the turnovers of strategies A, B and H are available in the supplementary material. Other strategies are available on request from the authors.

[18] Although we include strategies, such as momentum, which Novy-Marx and Velikov (2016) consider as monthly rebalancing strategies, we design our strategies with annual recomposition.

Table 4.12: Selected Trading Cost Adjusted Alphas

| Strat. | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| Panel (a) Factor Sorts Equal Weighting: | | | | | | | |
| A | Neutral | Book-to-Market Ratio | | EW | CAPM | -0.33* | -2.24 |
| A | Neutral | Return-on-Equity | | EW | FF5 | -0.32** | -2.82 |
| A | Neutral | Return Volatility | | EW | CAPM | 0.4* | 2.09 |
| A | Neutral | Zero Trading Days | | EW | CAPM | -0.49* | -2.47 |
| Panel (b) Factor Sorts Value Weighting: | | | | | | | |
| A | Neutral | Book-to-Market Ratio | | VW | CAPM | -0.41* | -2.43 |
| A | Neutral | Illiquidity | | VW | CAPM | -0.25* | -2.13 |
| A | Neutral | Return-on-Equity | | VW | FF5 | -0.26* | -2.01 |
| A | Neutral | Return Volatility | | VW | CAPM | 0.53** | 2.74 |
| A | Neutral | Return Volatility | | VW | FF5 | 0.27* | 2.02 |
| A | Neutral | Zero Trading Days | | VW | CAPM | -0.62** | -2.92 |
| A | Neutral | Zero Trading Days | | VW | FF5 | -0.46** | -2.8 |
| Panel (c) ESG Score Equal Weighting: | | | | | | | |
| H | Tilt | CAPM Beta | Score | EW | CAPM | 0.58* | 2.13 |
| H | Tilt | Return Volatility | Score | EW | CAPM | 0.55* | 2.41 |
| H-A | | Operating Profit | Score | EW | CAPM | 0.29* | 2.22 |
| H-A | | Growth in Sales minus Growth in Inventory | Score | EW | CAPM | 0.3* | 2.20 |
| H-A | | Growth in Sales minus Growth in Inventory | Score | EW | FF5 | 0.27* | 2.00 |
| Panel (d) ESG Score Equal Weighting: | | | | | | | |
| H | Tilt | Operating Profit | Score | VW | CAPM | 0.43* | 2.41 |
| H | Tilt | Return Volatility | Score | VW | CAPM | 0.54* | 2.25 |
| H | Tilt | Industry Momentum | Score | VW | FF5 | -0.47* | -2.34 |
| H-A | | Operating Profit | Score | VW | CAPM | 0.28* | 2.01 |
| Panel (e) DJSI Membership Equal Weighting: | | | | | | | |
| H | Tilt | Realised Volatility | DJSI | EW | CAPM | 0.43* | 2.06 |
| H-A | | Asset Growth | DJSI | EW | CAPM | 0.25* | 2.18 |
| H-A | | Growth in Sales minus Growth in Inventory | DJSI | EW | CAPM | 0.34* | 2.19 |
| Panel (f) DJSI Membership Value Weighting: | | | | | | | |
| H | Tilt | Return Voltaility | DJSI | VW | CAPM | 0.52* | 2.40 |
| H | Tilt | Turnover Volatility | DJSI | VW | CAPM | 0.32* | 2.07 |

Notes: Table provides a list of all sort variable, ESG measure, weighting and asset pricing model combinations that produce significant trading cost adjusted alpha for the factor sort strategies, ESG strategies, the double enhancement strategy H, and the comparison between strategy H and strategy A. Strategies are as defined in the main paper. Trading costs are computed as 1bps for each 1% of turnover in each leg of the strategy and are applied only in October when the reconstitution takes place. H-A is the comparison between strategy H and A after the deduction of trading costs from both strategies' returns. Position reports whether the strategy has an ESG tilt, that is the strategy longs higher ESG stocks than it shorts, or whether the strategy is neutral on ESG. We do not have any strategies which long lower ESG than they short. ESG reports the measure of ESG used in the portfolio construction and is either Score for the Refinitiv ESG Score, or DJSI for the firm being a member of the Dow Jones Sustainability Index North America. Weightings for portfolio calculations are either equal (EW) or value (VW). Two asset pricing models are used, being the capital asset pricing model (CAPM) and the Fama and French (2015) five factor model (FF5). Alpha reports the abnormal return estimate from the model after deduction of trading costs. Significance determined by a test that the true alpha coefficient is 0. Tests are estimated with Newey et al. (1987) adjusted standard errors at lag 6. Significance denoted by $* - 5\%$, $** - 1\%$ and $*** - 0.1\%$

Table 4.12 reports the trading cost adjusted alphas for strategies A, B, H and the comparison between H and A[19]. Relative to the unadjusted alphas there are fewer instances of significant alpha on the double enhancement ESG strategy after accounting for trading costs. There are still no cases in which the single sort ESG strategy, B, produces a significant alpha, either negative or positive. In all but one case the alpha generated from strategy H is positive. Table 4.12 reveals that the industry momentum sort produces a negative trading cost adjusted alpha of -0.37% against the FF5. Amongst those strategy H which produce significant positive alpha, return volatility is the most common factor sort. Return volatility produces a trading cost adjusted CAPM alpha with both equal and value weights and when both Refinitiv ESG scores and DJSI membership are the ESG leadership indicator. For all of the factor sorts that produce significant positive alpha, the uniting theme is risk; return volatility, CAPM beta and turnover volatility being associated with the risk of investing in the underlying asset. When comparing strategy H with strategy A, we see significant alpha for operating profit when Refinitiv ESG scores are used under both equal and value weighting. Under equal weighting the growth in sales minus growth in inventory factor sort produces alpha for the CAPM and FF5 when the ESG sort is based upon the Refinitiv ESG scores. When we use DJSI membership as the ESG proxy and equal weighting, asset growth produces a significant positive trading cost adjusted alpha.

Dominance of risk based factors is understandable since ESG leadership has been associated with lower volatility (Oikonomou et al., 2012; Cerqueti et al., 2021). However, the number of cases where the trading cost adjusted alpha is significant is low. None of the strategy-ESG-weight-factor combinations in Table 4.12 have a t-statistic above 3, and the number of strategies with alpha amongst the total number of combinations is low. Of the 218 possible ESG-weight-factor-asset pricing model combinations we find 25 significant trading cost adjust alphas, a little over 10% of the tested strategies. Our results demonstrate that even after the adjustment for trading costs it is still possible to obtain an ESG flavoured alpha.

## 4.6 Discussion

Absence of a significant alpha in the unconditional ESG strategy is consistent with the wealth of papers that fail to identify alpha from strategies formed solely on ESG. Approximately 5% of the ESG tilt strategies generate significant positive alpha, compared to a much lower percentage of the ESG neutral strategies. That there are no

[19]A full table of trading cost adjusted alphas is available in the supplementary material.

negative significant returns is already indicative of ESG stock performance improving. This paper focuses on using further information from the stocks to construct tradable strategies that can generate an ESG flavoured alpha. Our empirical work sought to study the ability of investors to generate returns whilst having ESG exposure. Benchmarks to our work therefore include the unconditional strategy on traditional sorts as well as the long-short ESG strategies.

Restricting the potential investment universe by focusing on ESG comes at the cost of diversification. However, the costs to this loss of diversification are small (Renneboog et al., 2008). Performance of conditional strategies within our results shows that there are few occasions when the unconditional strategy performs better. Comparison with returns on portfolios that include non-S&P stocks would be expected to show lower returns for the restricted strategy. Within our data all stocks have ESG information and so applying the ESG filter does not exclude stocks from analysis.

Return volatility is consistently a sort which generates alpha. We note that the return volatility is the only factor sort to produce significant alpha after adjustment for trading costs. It is understood from past works that investment in ESG allows the reduction of risk (Oikonomou et al., 2012; Cerqueti et al., 2021, and others). Consequentially the ESG stocks will be found at the lower end of the risk sort. Ang et al. (2006) anomaly suggests longing the low risk stocks and shorting the high in order to obtain alpha. Having more low risk stocks in the portfolio because of the ESG score is therefore of expected benefit. However, although we see strategy H perform well for return volatility the comparison with the unconditional return volatility sort does not produce a significant alpha. Pedersen et al. (2020) argue reduced risk as a motivation to long high ESG stocks, but this may also result in alpha given the evidence of this paper. Pedersen et al. (2020) and others are all built upon the assumption of ESG driven investors being willing to obtain a worse risk-return tradeoff to long ESG leaders.

Amongst the abnormal returns we identify many may be traced back to consumer demand in the product market. Consumers have been understood to value CSR when making purchasing decisions since Anderson Jr and Cunningham (1972), with more contemporary evidence in McWilliams and Siegel (2001) and Sen and Bhattacharya (2001). Evidence in the CSR literature states that consumers have expectations that larger, or more profitable, firms will practise the most CSR (Green and Peloza, 2014; Gallardo-Vázquez et al., 2019). Therefore we may expect that large firms with poor CSR, or profitable firms with poor CSR will be expected to yield lower returns in the future. Hence the information about ESG will inform on which profitable firms to avoid, and which large firms will not bring returns because consumers punish their insufficient ESG efforts. Consumer demand drives future profitability and hence the expected value of holding a stock. Higher future profits drive up the value of a stock and hence create returns. Consumer demand can also create sales in the short term, helping firms to reduce their inventories. Abarbanell and Bushee (1998) argue increasing sales and falling inventories are signs of a successful firm, whilst increasing inventories mean that the firm is not making the sales that it had expected. ESG offers a potential explanation for why the firm is not reaching expected sales.

The universe of stocks used for this paper is highly liquid and well covered by analysts. With the additional reforms to the market that made trading easier in the early part of the 21st century, opportunities for alpha are expected to be limited (Chordia et al., 2001a; French, 2008; Green et al., 2017). Despite the easier trading conditions we identify some pockets of alpha which can be explored by investors. On liquidity, we note that ESG investors may long stocks in the least liquid parts of the universe to gain abnormal CAPM returns. These results are not robust to more advanced asset pricing models so are only indicative of a possible interaction between ESG and liquidity. There remain comparatively few compared to the number of tests performed.

Our traditional sort characteristics are inspired by GHZ evidence on the mispricing of non-microcaps. We also consider the core sorts that inspire the Fama and French (2015) five factor model, the Hou et al. (2015) q-factor model and the Carhart (1997) four factor model. Both Fama and French (2015) and Carhart (1997) nest the original three factor model of Fama and French (1993). Collectively these are some of the most studied anomalies in the literature (Green et al., 2017). Beyond this set the choice of factors may be considered a data-mining exercise. For this reason we use the GHZ evidence rather than select factors we believe may be of interest to ESG. Extending into further factors would be unlikely to produce any significant alpha. Should characteristics not be mispriced in the wider dataset then they are unlikely to be so in our restricted universe.

Firm characteristics do have influence on future ESG scores (Drempetic et al., 2019; Garcia et al., 2020). Size, volatility and the stock beta were all suggested by Garcia et al. (2020) to be significant in the explanation of Refinitiv ESG scores. We have seen already that volatility is an area where ESG information can enhance the traditional strategy. Size and beta have also been shown to produce significant alphas when combined with ESG. Unlike volatility, size and beta do not have significant alphas to the unconditional sort strategy. Therefore, the links picked up in the sorted portfolios also suggest correlation between sorts and ESG scores. Further exploration of the links within our dataset may be fruitful.

Our dataset spans the global financial crisis and associated recovery, but only covers 14 years in total. Bansal et al. (2021) evidences the higher levels of performance from ESG stocks in good economic times. It may therefore be expected that some of our results would change depending on the sub-period being covered. Lins et al. (2017) have shown that ESG stocks were more resilient in the global financial crisis. Despite the falls in stock values through the crisis years, in the comparison between our ESG flavoured strategies and unconditional sorts we may expect favour for the ESG flavour. An exploration of the dynamics of our results is also dependent on the way that the sort variables change over the economic cycle. At this stage making maximal use of the full dataset, rather than subsetting, would appear optimal.

Focus in this paper remains on the identification of an ESG flavoured alpha. There is no alpha motivation for investors who do not have ESG in their utility function to switch to our ESG strategies. Equally there is no alpha motivation for those who would like to have ESG exposure to switch their investments away from that ESG exposure. We thus show that being ESG driven and returns driven need not be mutually exclusive.

## 4.7 Conclusion

ESG focused investment is rising rapidly, with increasing volumes of investors appearing to account for ESG in their stock selection. Evidence on abnormal returns does not support such a strong ESG focus. Instead theoretical modelling considers that it is a utility from investing in companies that have strong ESG performance that explains choices. Evidence presented in this paper demonstrates that investors may increase their ESG exposure without compromising their ability to generate abnormal returns. We achieve this by introducing an ESG flavoured alpha from ESG-tilted strategies that enhance traditional anomalies with ESG information. These ESG flavoured alphas are tested against those from traditional strategies and it is shown that in almost every case the difference is insignificant. That there are no significant negative alphas means investors need not lose out on abnormal returns when increasing their ESG exposure. Our results are robust to choice of ESG measure, asset pricing model and weighting.

Within the set of 24 factor sorts considered there are cases in which ESG enhancement can generate abnormal returns which are greater than the unconditional anomaly strategy. We show this particularly occurs for factor sorts on return volatility and characteristics related to liquidity. However, neither the number of factor sorts showing significance, or the strength of the significance, provide sufficient volume of evidence to conclude that ESG enhances traditional sorting. Nonetheless this paper still makes an important contribution in highlighting these potential opportunities. Our focus on the highly liquid S&P 500 stocks is designed to reduce the extent of mispricing. Liquidity of the market, and high levels of analyst coverage, make trading conditions easier. Operating entirely within the S&P 500 means investors may follow the strategies we outline to pursue the ESG flavoured alpha with low trading costs.

There are limitations to our study which future work may seek to address. Firstly, the limited time period over which the ESG information is available means that evidence on the effectiveness of the investment strategies is hard to test. Secondly, we only consider 24 of the factors which exist within the factor zoo. Extensions to this work may consider a fuller set of anomalies for the traditional sorts. Whilst we focused on those identified by GHZ as carrying significance in explaining non-microcaps, it may be fruitful to ask if any other firm characteristics can be enhanced with ESG information. Focusing on just two ESG measures means that our results only directly apply to the most commonly used measures of ESG leadership. Verifying the results against alternative ESG measures has potential, although some measures do not have the same extensive history as the DJSI and Refinitiv. We considered alpha against the set of well cited factor models but there is potential that further factor models may price the few significant alphas that were identified. As data availability increases it becomes possible to consider sub-periods and capture the dynamics of the relationship. Economic cycles are long, and the history of ESG data short, but already there is a research conversation around cyclicality to which our work can add a further dimension. When evaluating trading costs we applied a simple rule of thumb of 1bps per % traded in either leg. Using higher frequency data, and trading data to form accurate tansaction cost estimates in the same way as Novy-Marx and Velikov (2016), would overcome the limitation. As we focus upon the highly liquid S&P 500 only, the trading costs are likely to be much smaller. Our estimates serve as a lower bound on trading returns, but it would be valuable to work with more accurate trading costs data. Extension in all of these directions represents an active research agenda. Notwithstanding these considerations, our evidence represents a comprehensive demonstration that ESG need not cause investors to suffer lower returns.

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# Appendices

## A4.1 Alpha Comparisons

### A4.1.1 Core Sorts

This appendix considers the 6 core shorts identified by Green et al. (2017). As in the main paper we refer to Green et al. (2017) as GHZ. The core sorts are size (Banz, 1981), book-to-market ratio (Rosenberg et al., 1985), profitability (Fama and French, 2015), investment (Chen and Zhang, 2010), return-on-equity (Hou et al., 2015) and 12-month momentum (Jegadeesh, 1990). These factor sorts are identified by GHZ as being core as they are in the most widely adopted asset pricing models of Fama and French (1993), Carhart (1997), Fama and French (1993) and Hou et al. (2015). We discuss more of the link between these factor sorts and ESG in the main paper.

To understand the robustness of our inference, we first consider the Refinitiv ESG score as the ESG sort variable. Alphas are reported for equal weighted returns in Table A4.1. Tables for value weighting appear in the main paper. The majority of the significance comes from book-to-market and the operating profit measure of profitability favoured by Fama and French (2015).

The message of limited significance is in clear evidence Table A4.2. Looking at the full set of strategy-model-factor sort combinations for DJSI membership as the ESG measure when equal weighting is applied helps us to see the qualitative robustness of the results from value weighting in the main paper. Here there is more significance to the size factor sort than the book-to-market, and the positive signficant alpha from strategy H-A has disappeared from the profitability sort compared to Table A4.1. Whilst these specifics may be of interest to investors forming portfolios, caution must again be added that the t-statistics are not above the 3 threshold recommended by Harvey et al. (2016).

Table A4.1: Strategy Alphas - ESG Score - Equal Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Size | CAPM | -0.09 | 0.16 | -0.09 | -0.27 | -0.13 | -0.23 | -0.25 | -0.18 | -0.04 | -0.29 | -0.04 | 0.14 | -0.14 |
| | | (0.54) | (1.57) | (0.45) | (1.15) | (0.5) | (0.99) | (1.4) | (1.06) | (0.13) | (1.05) | (0.26) | (0.67) | (0.69) |
| | FF5 | 0.03 | 0.08 | -0.08 | -0.13 | -0.10 | -0.10 | -0.16 | -0.15 | -0.13 | -0.18 | -0.02 | 0.02 | -0.13 |
| | | (0.19) | (0.78) | (0.39) | (0.54) | (0.35) | (0.44) | (0.82) | (0.86) | (0.41) | (0.60) | (0.13) | (0.12) | (0.71) |
| Book-to-Market | CAPM | -0.20 | 0.16 | 0.30* | -0.34 | -0.14 | -0.04 | 0.50* | 0.50* | 0.13 | 0.50* | 0.13 | 0.16 | -0.20 |
| | | (1.40) | (1.57) | (2.33) | (1.68) | (0.49) | (0.23) | (2.41) | (2.41) | (1.21) | (2.41) | (1.21) | (0.98) | (1.26) |
| | FF5 | 0.02 | 0.08 | 0.22 | -0.17 | -0.18 | 0.05 | 0.20 | 0.20 | 0.14 | 0.20 | 0.14 | 0.03 | -0.03 |
| | | (0.27) | (0.78) | (1.55) | (0.95) | (0.63) | (0.31) | (1.22) | (1.22) | (1.15) | (1.22) | (1.15) | (0.19) | (0.24) |
| Investment | CAPM | -0.05 | 0.16 | 0.23 | -0.03 | 0.05 | 0.15 | 0.07 | 0.02 | 0.10 | -0.11 | -0.18 | 0.08 | -0.01 |
| | | (0.41) | (1.57) | (1.58) | (0.20) | (0.28) | (1.00) | (0.72) | (0.23) | (0.44) | (0.56) | (1.18) | (0.42) | (0.08) |
| | FF5 | 0.18 | 0.08 | 0.09 | 0.16 | -0.04 | 0.29 | 0.01 | -0.02 | -0.22 | -0.12 | -0.13 | -0.21 | 0.22 |
| | | (1.47) | (0.78) | (0.75) | (1.12) | (0.22) | (1.53) | (0.11) | (0.16) | (0.84) | (0.51) | (0.76) | (0.96) | (1.36) |
| Profitability | CAPM | 0.140 | 0.160 | 0.38* | 0.06 | -0.29 | 0.44** | 0.22 | -0.08 | -0.43 | -0.45* | -0.67* | -0.35 | 0.30* |
| | | (1.24) | (1.57) | (2.30) | (0.34) | (1.41) | (2.62) | (1.57) | (0.69) | (1.76) | (2.11) | (1.98) | (1.97) | (2.24) |
| | FF5 | -0.02 | 0.08 | 0.14 | 0.00 | -0.11 | 0.14 | 0.06 | 0.02 | -0.09 | -0.19 | -0.25 | -0.12 | 0.17 |
| | | (0.22) | (0.78) | (0.90) | (0.01) | (0.52) | (1.03) | (0.43) | (0.21) | (0.40) | (0.92) | (0.75) | (0.68) | (1.28) |
| Return-on-Equity | CAPM | 0.04 | 0.16 | 0.17 | 0.13 | 0.08 | 0.29 | 0.00 | 0.09 | 0.04 | -0.09 | -0.09 | -0.05 | 0.25 |
| | | (0.30) | (1.57) | (0.94) | (0.52) | (0.33) | (1.37) | (0.03) | (0.57) | (0.16) | (0.34) | (0.24) | (0.28) | (1.94) |
| | FF5 | -0.20 | 0.08 | -0.05 | -0.01 | 0.22 | -0.06 | -0.13 | 0.19 | 0.42 | 0.14 | 0.27 | 0.23 | 0.14 |
| | | (1.83) | (0.78) | (0.27) | (0.05) | (0.90) | (0.34) | (0.83) | (1.19) | (1.56) | (0.55) | (0.67) | (1.22) | (1.06) |
| 12-Month Momentum | CAPM | 0.01 | 0.16 | 0.22 | -0.03 | 0.05 | 0.19 | 0.06 | -0.04 | 0.05 | -0.11 | -0.17 | 0.08 | 0.03 |
| | | (0.03) | (1.57) | (1.40) | (0.11) | (0.27) | (0.69) | (0.52) | (0.37) | (0.16) | (0.51) | (0.53) | (0.32) | (0.15) |
| | FF5 | -0.23 | 0.08 | 0.20 | -0.28 | -0.05 | -0.09 | 0.12 | -0.06 | 0.18 | -0.13 | -0.25 | 0.23 | -0.17 |
| | | (1.00) | (0.78) | (1.16) | (1.11) | (0.26) | (0.32) | (0.97) | (0.50) | (0.60) | (0.59) | (0.74) | (0.94) | (0.73) |

Notes: Table reports estimated alphas for the 6 core sorts with the ESG score under equal weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. Size is the market value of equity following Fama and French (1992). Investment and profitability are as defined in Fama and French (2015). Return on equity follows Hou et al. (2015) and 12-month momentum uses returns from time $t-12$ to $t-2$ following Jegadeesh (1990). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the top 30% of Refinitiv ESG scores. Low ESG is defined as the bottom 30% of Refinitiv ESG scores. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.2: Strategy Alphas - DJSI- Equal Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Size | CAPM | -0.09 | 0.11 | 0.49 | 0.42 | 0.57* | 0.34 | 0.37 | 0.51* | 0.66 | 0.45 | 0.08 | 0.15 | 0.23 |
| | | (0.54) | (1.42) | (1.69) | (1.43) | (2.09) | (1.10) | (1.51) | (1.98) | (1.94) | (1.81) | (0.83) | (0.83) | (0.77) |
| | FF5 | 0.03 | 0.03 | 0.46 | 0.52 | 0.55 | 0.44 | 0.43 | 0.49 | 0.52 | 0.51 | 0.09 | 0.02 | 0.41 |
| | | (0.19) | (0.42) | (1.53) | (1.51) | (1.92) | (1.19) | (1.53) | (1.83) | (1.82) | (1.83) | (0.95) | (0.14) | (1.13) |
| Book-to-Market | CAPM | -0.20 | 0.11 | 0.15 | -0.20 | 0.00 | -0.04 | 0.04 | 0.01 | 0.21 | -0.11 | -0.15 | 0.20 | -0.16 |
| | | (1.40) | (1.42) | (1.24) | (1.02) | (0.01) | (0.30) | (0.34) | (0.04) | (0.69) | (0.50) | (0.47) | (1.24) | (1.05) |
| | FF5 | 0.02 | 0.03 | 0.13 | -0.10 | -0.15 | 0.03 | 0.10 | -0.12 | -0.18 | -0.19 | -0.28 | -0.05 | 0.00 |
| | | (0.27) | (0.42) | (0.92) | (0.52) | (0.64) | (0.20) | (0.78) | (0.61) | (0.65) | (0.75) | (0.79) | (0.57) | (0.03) |
| Investment | CAPM | -0.05 | 0.11 | 0.10 | -0.13 | -0.09 | 0.06 | -0.01 | -0.08 | -0.04 | -0.20 | -0.19 | 0.04 | -0.06 |
| | | (0.41) | (1.42) | (0.61) | (0.83) | (0.46) | (0.37) | (0.12) | (0.52) | (0.15) | (1.03) | (1.44) | (0.31) | (0.44) |
| | FF5 | 0.18 | 0.03 | -0.10 | -0.07 | -0.29 | 0.12 | -0.13 | -0.25 | -0.47 | -0.32 | -0.20 | -0.22 | 0.09 |
| | | (1.47) | (0.42) | (0.63) | (0.42) | (1.37) | (0.77) | (1.05) | (1.43) | (1.64) | (1.48) | (1.42) | (1.55) | (0.70) |
| Profitability | CAPM | 0.14 | 0.11 | 0.26* | -0.14 | -0.33 | 0.12 | 0.14 | -0.28 | -0.47* | -0.45* | -0.59* | -0.19 | 0.00 |
| | | (1.24) | (1.42) | (2.02) | (0.75) | (1.73) | (0.80) | (1.24) | (1.76) | (2.07) | (2.33) | (2.04) | (1.63) | (0.02) |
| | FF5 | -0.02 | 0.03 | 0.13 | -0.20 | -0.22 | -0.07 | 0.10 | -0.18 | -0.20 | -0.25 | -0.35 | -0.02 | -0.11 |
| | | (0.22) | (0.42) | (0.86) | (0.96) | (0.98) | (0.61) | (0.74) | (0.97) | (0.80) | (1.11) | (1.01) | (0.16) | (0.99) |
| Return-on-Equity | CAPM | 0.04 | 0.11 | 0.13 | 0.06 | 0.02 | 0.19 | 0.01 | 0.02 | -0.02 | -0.09 | -0.10 | -0.04 | 0.07 |
| | | (0.30) | (1.42) | (0.89) | (0.25) | (0.10) | (0.91) | (0.10) | (0.12) | (0.07) | (0.42) | (0.31) | (0.29) | (0.47) |
| | FF5 | -0.20 | 0.03 | -0.05 | -0.09 | 0.12 | -0.15 | -0.08 | 0.11 | 0.31 | 0.08 | 0.17 | 0.21 | -0.18 |
| | | (1.83) | (0.42) | (0.33) | (0.44) | (0.52) | (0.89) | (0.58) | (0.57) | (1.26) | (0.37) | (0.47) | (1.79) | (1.40) |
| 12-Month Momentum | CAPM | 0.01 | 0.11 | 0.14 | 0.00 | 0.00 | 0.14 | 0.02 | 0.00 | -0.01 | -0.11 | -0.14 | 0.00 | 0.03 |
| | | (0.03) | (1.42) | (0.78) | (0.01) | (0.00) | (0.56) | (0.17) | (0.02) | (0.02) | (0.44) | (0.36) | (0.01) | (0.11) |
| | FF5 | -0.23 | 0.03 | 0.01 | -0.24 | -0.01 | -0.23 | -0.02 | -0.01 | 0.22 | -0.04 | -0.02 | 0.23 | -0.26 |
| | | (1.00) | (0.42) | (0.09) | (0.91) | (0.03) | (0.99) | (0.14) | (0.06) | (0.64) | (0.15) | (0.06) | (0.99) | (1.13) |

Notes: Table reports estimated alphas for the 6 core sorts with the DJSI under equal weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. Size is the market value of equity following Fama and French (1992). Investment and profitability are as defined in Fama and French (2015). Return on equity follows Hou et al. (2015) and 12-month momentum uses returns from time $t-12$ to $t-2$ following Jegadeesh (1990). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the members of the DJSI. Low ESG is defined as non-DJSI members. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

### A4.1.2 Further Sorts

We now present the alpha comparisons from the remaining 18 sorts under both equal weighting and value weighting. A full discussion of the significant results is presented within the main paper and we include these tables here as a means of demonstrating the broad lack of significance across the wider set of strategy-model-factor sort-weighting combinations. We show that this applies when both high Refinitiv ESG scores and DJSI membership are used as the means of identifying ESG leaders.

We begin with the Refinitiv ESG score sorts in Tables A4.3 to A4.8. As identified in the main paper, much of the significance is concentrated on return volatility, growth in sales minus growth in inventory, and the measures of liquidity in Tables A4.7 and A4.8. Links from these factor sorts to ESG are drawn in the main paper. The connections are drawn through the importance of the consumer demand for ESG channel (Anderson Jr and Cunningham, 1972; McWilliams and Siegel, 2001; Sen and Bhattacharya, 2001), the observed lower risk of ESG leaders (Oikonomou et al., 2012; Pedersen et al., 2020), and the longer term horizons of ESG investors (Datar et al., 1998). By visualising the alphas in full these messages are reinforced.

Turning to the DJSI as the ESG measure in Tables A4.9 to A4.14, we see very similar results emerging. Whilst the list of significant alphas in the main paper appears long, setting those alphas in tables of the full set of combinations tested reveals that there is still strong limitation on pronouncing that there is an ESG flavoured alpha for investors. As with the Refinitiv ESG scores, seeing all of the DJSI results does reinforce the message that there is no significant alpha gain from reducing ESG exposure.

## A4.2 Trading Costs

In the main paper we give brief consideration to the application of turnover based trading costs to our proposed strategies. In this appendix we report the annual turnovers for each of our strategies and provide a full list of trading cost adjusted alphas. As in the main paper we restrict focus to those strategies which long high ESG firms and only consider alphas from the CAPM and FF5 models.

### A4.2.1 Strategy Turnover

In the absence of bid ask spread data, we assume that each percentage point of turnover incurs a 1 basis point transaction cost in any month in which that turnover takes place. In so doing we follow Chen and Velikov (2020) and the timing assumptions

Table A4.3: Strategy Alphas - ESG Score - Equal Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| CAPM Beta | CAPM | 0.60* | 0.16 | 0.14 | 0.63 | 0.07 | 0.70* | -0.02 | 0.03 | -0.53 | -0.10 | -0.08 | -0.56 | 0.11 |
| | | (2.18) | (1.57) | (0.90) | (1.83) | (0.34) | (2.59) | (0.16) | (0.25) | (1.88) | (0.41) | (0.39) | (1.93) | (0.79) |
| | FF5 | 0.33 | 0.08 | 0.08 | 0.34 | 0.05 | 0.37 | 0.00 | 0.01 | -0.28 | -0.03 | -0.03 | -0.29 | 0.04 |
| | | (1.51) | (0.78) | (0.46) | (1.20) | (0.26) | (1.59) | (0.00) | (0.10) | (1.02) | (0.12) | (0.15) | (1.07) | (0.29) |
| Asset Growth | CAPM | 0.11 | 0.16 | 0.10 | 0.20 | 0.05 | 0.25 | -0.06 | 0.09 | -0.06 | -0.11 | -0.05 | -0.15 | 0.14 |
| | | (0.97) | (1.57) | (0.79) | (1.31) | (0.27) | (1.60) | (0.63) | (0.73) | (0.22) | (0.50) | (0.32) | (0.78) | (1.51) |
| | FF5 | 0.07 | 0.08 | -0.07 | 0.11 | -0.11 | 0.16 | -0.14 | 0.04 | -0.18 | -0.19 | -0.04 | -0.22 | 0.08 |
| | | (0.91) | (0.78) | (0.55) | (1.08) | (0.55) | (1.03) | (1.35) | (0.35) | (0.72) | (0.78) | (0.26) | (1.24) | (0.77) |
| Growth in Inventory | CAPM | 0.05 | 0.16 | 0.24 | 0.13 | 0.09 | 0.28 | 0.08 | 0.08 | 0.04 | -0.07 | -0.15 | -0.04 | 0.23 |
| | | (0.45) | (1.57) | (1.90) | (0.72) | (0.42) | (1.45) | (0.63) | (0.53) | (0.16) | (0.25) | (0.87) | (0.21) | (1.57) |
| | FF5 | 0.10 | 0.08 | 0.04 | 0.08 | -0.11 | 0.23 | -0.04 | -0.03 | -0.21 | -0.19 | -0.15 | -0.19 | 0.12 |
| | | (0.93) | (0.78) | (0.35) | (0.42) | (0.43) | (1.08) | (0.28) | (0.16) | (0.70) | (0.59) | (0.73) | (0.93) | (0.86) |
| Growth in Book Equity | CAPM | 0.18 | 0.16 | 0.13 | 0.27 | 0.11 | 0.30* | -0.03 | 0.09 | -0.08 | -0.05 | -0.03 | -0.17 | 0.11 |
| | | (1.56) | (1.57) | (0.97) | (1.57) | (0.51) | (1.98) | (0.19) | (0.70) | (0.30) | (0.20) | (0.16) | (0.83) | (1.08) |
| | FF5 | 0.16 | 0.08 | -0.02 | 0.21 | 0.03 | 0.16 | -0.1 | 0.04 | -0.14 | -0.05 | 0.05 | -0.18 | 0.00 |
| | | (1.28) | (0.78) | (0.17) | (1.27) | (0.14) | (1.02) | (0.78) | (0.36) | (0.54) | (0.21) | (0.29) | (0.90) | (0.02) |
| Growth in Capex | CAPM | 0.00 | 0.02 | -0.02 | -0.15 | -0.18 | 0.02 | -0.04 | -0.14 | -0.18 | -0.20 | -0.16 | -0.04 | 0.02 |
| | | (0.02) | (0.16) | (0.13) | (0.84) | (0.98) | (0.11) | (0.33) | (1.43) | (0.90) | (0.88) | (1.19) | (0.23) | (0.21) |
| | FF5 | 0.04 | 0.06 | 0.06 | -0.04 | 0.10 | -0.04 | 0.04 | -0.08 | 0.07 | 0.05 | 0.04 | 0.15 | -0.08 |
| | | (0.33) | (0.39) | (0.38) | (0.24) | (0.95) | (0.25) | (0.36) | (0.87) | (0.41) | (0.28) | (0.27) | (0.84) | (0.64) |
| Growth in LTNOA | CAPM | 0.06 | 0.16 | 0.19 | 0.15 | 0.26 | 0.08 | 0.03 | 0.08 | 0.20 | 0.10 | 0.07 | 0.11 | 0.02 |
| | | (0.62) | (1.57) | (1.35) | (0.90) | (1.26) | (0.48) | (0.29) | (0.71) | (0.83) | (0.45) | (0.45) | (0.59) | (0.14) |
| | FF5 | 0.17 | 0.08 | 0.13 | 0.26 | 0.22 | 0.17 | 0.05 | 0.10 | 0.06 | 0.14 | 0.09 | -0.04 | 0.01 |
| | | (1.59) | (0.78) | (0.93) | (1.64) | (0.99) | (0.84) | (0.44) | (0.79) | (0.20) | (0.58) | (0.53) | (0.20) | (0.05) |

Notes: Table reports estimated alphas for the 6 stated sorts with the ESG score under equal weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. The capital asset pricing model beta follows Fama and MacBeth (1973), asset growth follows Cooper et al. (2008), growth in inventory follows Thomas and Zhang (2002), growth in book equity is after Richardson et al. (2005) and growth in capital expenditure (capex) is after Anderson and Garcia-Feijoo (2006). Growth in long term net operating assets (LTNOA Growth) is after Fairfield et al. (2003). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the top 30% of Refinitiv ESG scores. Low ESG is defined as the bottom 30% of Refinitiv ESG scores. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.4: Strategy Alphas - ESG Score - Value Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| CAPM Beta | CAPM | 0.60* | 0.16 | 0.15 | 0.61 | -0.01 | 0.56 | -0.01 | 0.01 | -0.62* | -0.18 | -0.17 | -0.63 | -0.04 |
| | | (1.97) | (1.39) | (0.85) | (1.59) | (0.10) | (1.84) | (0.05) | (0.10) | (2.19) | (0.99) | (0.75) | (1.83) | (0.27) |
| | FF5 | 0.32 | 0.09 | 0.07 | 0.31 | -0.03 | 0.24 | -0.01 | 0.00 | -0.35 | -0.11 | -0.10 | -0.34 | -0.08 |
| | | (1.31) | (0.70) | (0.36) | (1.04) | (0.21) | (0.94) | (0.07) | (0.04) | (1.42) | (0.65) | (0.42) | (1.20) | (0.46) |
| Asset Growth | CAPM | 0.16 | 0.16 | 0.08 | 0.23 | 0.03 | 0.28 | -0.08 | 0.07 | -0.13 | -0.13 | -0.05 | -0.20 | 0.12 |
| | | (1.16) | (1.39) | (0.55) | (1.18) | (0.26) | (1.30) | (0.62) | (0.66) | (1.04) | (0.91) | (0.42) | (1.31) | (0.98) |
| | FF5 | 0.08 | 0.09 | -0.05 | 0.16 | 0.04 | 0.16 | -0.13 | 0.07 | -0.04 | -0.04 | 0.09 | -0.11 | 0.08 |
| | | (0.98) | (0.70) | (0.34) | (1.12) | (0.36) | (0.85) | (1.07) | (0.77) | (0.52) | (0.31) | (0.64) | (1.08) | (0.56) |
| Growth in Inventory | CAPM | 0.07 | 0.16 | 0.29* | 0.11 | -0.02 | 0.23 | 0.13 | 0.04 | -0.09 | -0.19 | -0.32* | -0.13 | 0.16 |
| | | (0.57) | (1.39) | (2.39) | (0.68) | (0.27) | (1.05) | (1.18) | (0.38) | (0.64) | (1.46) | (2.24) | (0.72) | (1.04) |
| | FF5 | 0.08 | 0.09 | 0.13 | 0.12 | 0.05 | 0.15 | 0.05 | 0.04 | -0.03 | -0.04 | -0.08 | -0.08 | 0.07 |
| | | (0.73) | (0.70) | (1.05) | (0.83) | (0.45) | (0.69) | (0.38) | (0.39) | (0.24) | (0.32) | (0.60) | (0.42) | (0.41) |
| Growth in Book Equity | CAPM | 0.28* | 0.16 | 0.25 | 0.35 | 0.08 | 0.35 | 0.09 | 0.07 | -0.20 | -0.08 | -0.17 | -0.27 | 0.07 |
| | | (2.07) | (1.39) | (1.60) | (1.89) | (0.67) | (1.48) | (0.58) | (0.71) | (1.35) | (0.57) | (1.01) | (1.57) | (0.41) |
| | FF5 | 0.21* | 0.09 | 0.13 | 0.31 | 0.10 | 0.16 | 0.05 | 0.10 | -0.11 | 0.01 | -0.03 | -0.21 | -0.05 |
| | | (2.00) | (0.70) | (0.83) | (1.83) | (0.83) | (0.81) | (0.33) | (0.98) | (0.83) | (0.09) | (0.19) | (1.27) | (0.32) |
| Growth in Capex | CAPM | -0.02 | 0.16 | 0.06 | -0.17 | -0.19 | 0.09 | 0.06 | -0.02 | -0.01 | -0.14 | -0.20 | 0.01 | 0.19 |
| | | (0.16) | (1.57) | (0.49) | (0.95) | (1.05) | (0.53) | (0.64) | (0.11) | (0.03) | (0.81) | (1.40) | (0.09) | (1.43) |
| | FF5 | 0.06 | 0.08 | -0.07 | -0.11 | -0.26 | 0.09 | -0.01 | -0.16 | -0.26 | -0.23 | -0.21 | -0.10 | 0.05 |
| | | (0.60) | (0.78) | (0.57) | (0.68) | (1.42) | (0.51) | (0.13) | (1.00) | (1.12) | (1.20) | (1.51) | (0.88) | (0.40) |
| Growth in LTNOA | CAPM | 0.07 | 0.16 | 0.11 | 0.06 | -0.09 | 0.03 | -0.05 | -0.01 | -0.16 | -0.25 | -0.20 | -0.15 | -0.04 |
| | | (0.50) | (1.24) | (0.63) | (0.28) | (0.74) | (0.14) | (0.27) | (0.10) | (1.34) | (1.47) | (1.45) | (0.90) | (0.23) |
| | FF5 | 0.15 | 0.09 | 0.04 | 0.15 | -0.11 | 0.10 | -0.04 | 0.00 | -0.27* | -0.20 | -0.16 | -0.26 | -0.05 |
| | | (1.23) | (0.64) | (0.23) | (0.72) | (0.90) | (0.39) | (0.20) | (0.03) | (2.29) | (1.06) | (1.06) | (1.64) | (0.29) |

Notes: Table reports estimated alphas for the 6 stated sorts with the ESG score under value weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. The capital asset pricing model beta follows Fama and MacBeth (1973), asset growth follows Cooper et al. (2008), growth in inventory follows Thomas and Zhang (2002), growth in book equity is after Richardson et al. (2005) and growth in capital expenditure (capex) is after Anderson and Garcia-Feijoo (2006). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the top 30% of Refinitiv ESG scores. Low ESG is defined as the bottom 30% of Refinitiv ESG scores. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.5: Strategy Alphas - ESG Score - Equal Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Growth in Sales - Inventory | CAPM | 0.03 | 0.16 | 0.30 | 0.11 | 0.08 | 0.33* | 0.14 | 0.08 | 0.06 | -0.08 | -0.22 | -0.02 | 0.17 |
| | | (0.32) | (1.57) | (1.90) | (0.80) | (0.44) | (2.20) | (1.07) | (0.62) | (0.25) | (0.37) | (1.45) | (0.14) | (1.02) |
| | FF5 | 0.08 | 0.08 | 0.28 | 0.28 | 0.20 | 0.36* | 0.20 | 0.19 | 0.12 | 0.12 | -0.08 | -0.08 | 0.28 |
| | | (1.00) | (0.78) | (1.49) | (1.86) | (0.94) | (2.25) | (1.22) | (1.47) | (0.51) | (0.56) | (0.56) | (0.48) | (1.63) |
| Growth Shares Outstanding | CAPM | 0.18 | 0.16 | 0.06 | 0.21 | 0.00 | 0.27 | -0.10 | 0.02 | -0.19 | -0.17 | -0.06 | -0.21 | 0.11 |
| | | (1.40) | (1.57) | (0.39) | (0.98) | (0.02) | (1.42) | (1.09) | (0.19) | (0.88) | (0.75) | (0.36) | (1.15) | (0.68) |
| | FF5 | 0.16 | 0.08 | -0.06 | 0.24 | 0.02 | 0.16 | -0.14 | 0.08 | -0.14 | -0.06 | 0.08 | -0.21 | 0.08 |
| | | (1.44) | (0.78) | (0.37) | (1.39) | (0.11) | (0.95) | (1.07) | (0.66) | (0.57) | (0.23) | (0.47) | (1.08) | (0.54) |
| Earnings Ann. Returns | CAPM | -0.02 | 0.16 | -0.07 | 0.21 | 0.46* | 0.14 | -0.23 | 0.23 | 0.48* | 0.30 | 0.53 | 0.25 | 0.16 |
| | | (0.23) | (1.57) | (0.40) | (1.35) | (2.17) | (0.76) | (1.72) | (1.81) | (2.08) | (1.23) | (1.46) | (1.57) | (1.15) |
| | FF5 | -0.05 | 0.08 | -0.17 | 0.21 | 0.47 | 0.04 | -0.25 | 0.27 | 0.53* | 0.39 | 0.64 | 0.26 | 0.10 |
| | | (0.63) | (0.78) | (0.90) | (1.04) | (1.89) | (0.21) | (1.60) | (1.57) | (2.12) | (1.48) | (1.58) | (1.73) | (0.65) |
| Change in 6-Month Mom. | CAPM | 0.10 | 0.16 | 0.05 | 0.17 | 0.13 | 0.23 | -0.11 | 0.08 | 0.03 | -0.03 | 0.07 | -0.05 | 0.13 |
| | | (0.58) | (1.57) | (0.36) | (0.83) | (0.69) | (0.94) | (0.88) | (0.81) | (0.13) | (0.16) | (0.24) | (0.22) | (1.05) |
| | FF5 | -0.02 | 0.08 | -0.03 | 0.07 | 0.09 | 0.04 | -0.11 | 0.09 | 0.11 | 0.01 | 0.13 | 0.02 | 0.06 |
| | | (0.10) | (0.78) | (0.21) | (0.26) | (0.43) | (0.14) | (0.84) | (0.76) | (0.46) | (0.06) | (0.36) | (0.11) | (0.46) |
| 1-Month Momentum | CAPM | -0.09 | 0.16 | 0.03 | 0.02 | 0.27 | 0.05 | -0.13 | 0.10 | 0.36 | 0.11 | 0.24 | 0.26 | 0.14 |
| | | (0.33) | (1.57) | (0.26) | (0.05) | (1.24) | (0.18) | (1.14) | (0.90) | (1.24) | (0.51) | (0.77) | (0.97) | (1.18) |
| | FF5 | -0.26 | 0.08 | -0.04 | -0.15 | 0.28 | -0.19 | -0.12 | 0.11 | 0.55 | 0.20 | 0.32 | 0.44 | 0.07 |
| | | (0.98) | (0.78) | (0.27) | (0.49) | (1.13) | (0.70) | (0.96) | (0.86) | (1.73) | (0.87) | (0.94) | (1.56) | (0.53) |
| Cashflow (Ind Adj.) | CAPM | 0.12 | 0.16 | 0.27 | -0.07 | -0.29 | 0.20 | 0.11 | -0.19 | -0.41 | -0.45 | -0.55 | -0.22 | 0.07 |
| | | (1.05) | (1.57) | (1.62) | (0.44) | (1.33) | (0.99) | (0.94) | (1.52) | (1.48) | (1.75) | (1.57) | (1.12) | (0.57) |
| | FF5 | 0.14 | 0.08 | 0.25 | -0.09 | -0.40* | 0.15 | 0.17 | -0.23 | -0.54* | -0.48* | -0.65 | -0.31* | 0.02 |
| | | (1.29) | (0.78) | (1.50) | (0.57) | (2.04) | (0.86) | (1.48) | (1.81) | (2.36) | (2.02) | (1.95) | (2.04) | (0.13) |

Notes: Table reports estimated alphas for the 6 stated sorts with the ESG score under equal weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. Growth in sales less growth in inventory (Growth in Sales - Inventory) follows Abarbanell and Bushee (1998), growth of shares outstanding (Growth Shares Outstanding) is after Pontiff and Woodgate (2008), earnings announcement returns (Earnings Ann. Returns) follow Kishore et al. (2008), change in 6-month momentum (Change in 6-Month Mom.) follows Gettleman and Marks (2006), 1-month momentum is the short-term reversal effect of Jegadeesh and Titman (1993) and industry adjusted cashflow is as developed by Asness et al. (2000). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the top 30% of Refinitiv ESG scores. Low ESG is defined as the bottom 30% of Refinitiv ESG scores. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.6: Strategy Alphas - ESG Score - Value Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Growth in Sales-Inventory | CAPM | 0.15 | 0.19 | 0.20 | 0.02 | -0.09 | 0.39* | 0.04 | -0.12 | -0.23* | -0.28 | -0.28 | -0.11 | 0.20 |
| | | (1.43) | (1.22) | (0.96) | (0.14) | (0.88) | (2.21) | (0.19) | (1.11) | (2.09) | (1.34) | (1.21) | (0.80) | (1.20) |
| | FF5 | 0.23* | 0.13 | 0.06 | 0.08 | -0.20* | 0.36* | -0.02 | -0.15 | -0.43*** | -0.33 | -0.26 | -0.28 | 0.24 |
| | | (2.07) | (0.80) | (0.30) | (0.51) | (2.05) | (2.04) | (0.08) | (1.33) | (3.90) | (1.54) | (1.01) | (1.86) | (1.54) |
| Growth Shares Outstanding | CAPM | 0.25 | 0.16 | 0.02 | 0.25 | 0.04 | 0.27 | -0.14 | 0.00 | -0.21 | -0.12 | 0.02 | -0.21 | 0.11 |
| | | (1.70) | (1.39) | (0.15) | (1.17) | (0.46) | (1.16) | (1.27) | (0.03) | (1.32) | (0.92) | (0.11) | (0.98) | (0.62) |
| | FF5 | 0.19 | 0.09 | -0.02 | 0.23 | -0.01 | 0.12 | -0.10 | 0.04 | -0.20 | -0.10 | 0.01 | -0.24 | 0.03 |
| | | (1.54) | (0.70) | (0.13) | (1.20) | (0.11) | (0.64) | (0.89) | (0.41) | (1.54) | (0.68) | (0.06) | (1.39) | (0.23) |
| Earnings Ann. Returns | CAPM | -0.03 | 0.16 | -0.02 | 0.18 | -0.03 | 0.16 | -0.18 | 0.21 | 0.00 | -0.19 | -0.01 | -0.21 | 0.19 |
| | | (0.24) | (1.39) | (0.09) | (1.05) | (0.26) | (0.80) | (1.20) | (1.95) | (0.02) | (1.23) | (0.05) | (1.35) | (1.20) |
| | FF5 | -0.05 | 0.09 | -0.12 | 0.20 | -0.01 | 0.08 | -0.20 | 0.25 | 0.03 | -0.10 | 0.11 | -0.21 | 0.13 |
| | | (0.40) | (0.70) | (0.62) | (0.93) | (0.10) | (0.35) | (1.19) | (1.93) | (0.25) | (0.56) | (0.44) | (1.04) | (0.73 |
| Change in 6-Month Mom | CAPM | 0.11 | 0.16 | -0.12 | 0.21 | 0.04 | 0.09 | -0.28 | 0.10 | -0.07 | -0.13 | 0.15 | -0.17 | -0.02 |
| | | (0.63) | (1.39) | (0.59) | (0.88) | (0.32) | (0.39) | (1.48) | (1.07) | (0.42) | (0.76) | (0.56) | (0.83) | (0.12) |
| | FF5 | 0.02 | 0.09 | -0.18 | 0.13 | 0.06 | -0.05 | -0.26 | 0.10 | 0.03 | -0.03 | 0.24 | -0.07 | -0.08 |
| | | (0.11) | (0.70) | (0.84) | (0.44) | (0.43) | (0.19) | (1.20) | (0.89) | (0.14) | (0.17) | (0.81) | (0.26) | (0.50) |
| 1-Month Momentum | CAPM | 0.11 | 0.16 | -0.02 | 0.13 | 0.11 | 0.11 | -0.18 | 0.02 | 0.00 | -0.05 | 0.13 | -0.02 | 0.00 |
| | | (0.41) | (1.39) | (0.11) | (0.38) | (1.08) | (0.38) | (1.12) | (0.16) | (0.02) | (0.31) | (0.54) | (0.05) | (0.01) |
| | FF5 | -0.07 | 0.09 | -0.09 | -0.05 | 0.10 | -0.14 | -0.17 | 0.02 | 0.17 | 0.02 | 0.19 | 0.15 | -0.07 |
| | | (0.27) | (0.70) | (0.46) | (0.15) | (0.97) | (0.50) | (0.96) | (0.16) | (0.64) | (0.12) | (0.81) | (0.49) | (0.45) |
| Cashflow (Ind Adj.) | CAPM | -0.06 | 0.16 | 0.32 | -0.13 | -0.06 | 0.19 | 0.16 | -0.07 | 0.00 | -0.22 | -0.38 | 0.07 | 0.25 |
| | | (0.43) | (1.39) | (1.71) | (0.80) | (0.77) | (0.82) | (1.33) | (0.88) | (0.03) | (1.67) | (1.85) | (0.44) | (1.50) |
| | FF5 | -0.02 | 0.09 | 0.30 | -0.12 | -0.03 | 0.18 | 0.22 | -0.09 | 0.00 | -0.11 | -0.33 | 0.09 | 0.21 |
| | | (0.20) | (0.70) | (1.46) | (0.75) | (0.37) | (0.82) | (1.63) | (1.15) | (0.02) | (0.82) | (1.51) | (0.57) | (1.19) |

Notes: Table reports estimated alphas for the 6 stated sorts with the ESG score under value weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. Growth in sales less growth in inventory (Growth in Sales - Inventory) follows Abarbanell and Bushee (1998), growth of shares outstanding (Growth Shares Outstanding) is after Pontiff and Woodgate (2008), earnings announcement returns (Earnings Ann. Returns) follow Kishore et al. (2008), change in 6-month momentum (Change in 6-Month Mom.) follows Gettleman and Marks (2006), 1-month momentum is the short-term reversal effect of Jegadeesh and Titman (1993) and industry adjusted cashflow is as developed by Asness et al. (2000). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the top 30% of Refinitiv ESG scores. Low ESG is defined as the bottom 30% of Refinitiv ESG scores. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.7: Strategy Alphas - ESG Score - Equal Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Return Volatility | CAPM | 0.52** | 0.16 | 0.06 | 0.60* | -0.01 | 0.67** | -0.10 | 0.08 | -0.53* | -0.17 | -0.08 | -0.61** | 0.15 |
| | | (2.78) | (1.57) | (0.45) | (2.58) | (0.06) | (2.99) | (0.77) | (0.66) | (2.10) | (0.67) | (0.43) | (3.00) | (1.19) |
| | FF5 | 0.24 | 0.08 | -0.03 | 0.35 | -0.04 | 0.35 | -0.11 | 0.11 | -0.28 | -0.12 | 0.00 | -0.39* | 0.11 |
| | | (1.55) | (0.78) | (0.24) | (1.83) | (0.20) | (1.83) | (0.90) | (1.03) | (1.22) | (0.49) | (0.03) | (2.08) | (0.78) |
| Share Turnover | CAPM | 0.37 | 0.16 | 0.28* | 0.37 | 0.07 | 0.58* | 0.12 | 0.00 | -0.30 | -0.10 | -0.21 | -0.31 | 0.42* |
| | | (1.82) | (1.57) | (2.39) | (1.43) | (0.31) | (2.37) | (1.21) | (0.02) | (1.18) | (0.36) | (1.04) | (1.46) | (2.29) |
| | FF5 | 0.19 | 0.08 | 0.21 | 0.34 | 0.17 | 0.37 | 0.13 | 0.15 | -0.02 | 0.09 | -0.03 | -0.16 | 0.29 |
| | | (1.02) | (0.78) | (1.60) | (1.44) | (0.84) | (1.69) | (1.31) | (1.14) | (0.07) | (0.36) | (0.15) | (0.85) | (1.72) |
| Turnover Volatility | FF5 | 0.31 | 0.16 | 0.14 | 0.28 | -0.09 | 0.51* | -0.02 | -0.02 | -0.39 | -0.25 | -0.23 | -0.37* | 0.35* |
| | | (1.95) | (1.57) | (1.43) | (1.28) | (0.45) | (2.46) | (0.23) | (0.18) | (1.72) | (1.01) | (1.23) | (2.08) | (2.46) |
| | FF5 | 0.14 | 0.08 | 0.06 | 0.20 | -0.02 | 0.29 | -0.02 | 0.07 | -0.16 | -0.10 | -0.08 | -0.23 | 0.21 |
| | | (0.82) | (0.78) | (0.58) | (0.93) | (0.13) | (1.50) | (0.23) | (0.52) | (0.72) | (0.43) | (0.44) | (1.26) | (1.48) |
| Zero Trading Days | CAPM | 0.37 | 0.16 | 0.28 | 0.34 | -0.05 | 0.62* | 0.12 | -0.03 | -0.42 | -0.21 | -0.34 | -0.40 | 0.46* |
| | | (1.86) | (1.57) | (1.24) | (1.34) | (0.24) | (2.40) | (0.74) | (0.20) | (1.59) | (0.76) | (0.77) | (1.83) | (2.44) |
| | FF5 | 0.18 | 0.08 | 0.13 | 0.27 | -0.01 | 0.39 | 0.05 | 0.08 | -0.20 | -0.09 | -0.14 | -0.28 | 0.31 |
| | | (0.98) | (0.78) | (0.54) | (1.13) | (0.06) | (1.68) | (0.28) | (0.63) | (0.71) | (0.32) | (0.32) | (1.31) | (1.78) |
| Illiquidity | CAPM | 0.04 | 0.16 | 0.09 | 0.12 | 0.04 | 0.17 | -0.07 | 0.08 | 0.00 | -0.12 | -0.05 | -0.08 | 0.01 |
| | | (0.29) | (1.57) | (0.43) | (0.57) | (0.14) | (1.07) | (0.43) | (0.46) | (0.01) | (0.47) | (0.25) | (0.38) | (0.08) |
| | FF5 | -0.13 | 0.08 | 0.00 | -0.09 | -0.09 | -0.01 | -0.08 | 0.04 | 0.04 | -0.16 | -0.08 | 0.01 | -0.09 |
| | | (1.04) | (0.78) | (0.01) | (0.42) | (0.28) | (0.06) | (0.41) | (0.23) | (0.14) | (0.56) | (0.42) | (0.02) | (1.02) |
| Industry Momentum | CAPM | 0.06 | 0.16 | 0.02 | 0.07 | -0.27 | 0.36 | -0.14 | 0.02 | -0.33 | -0.43 | -0.29 | -0.34 | 0.20 |
| | | (0.33) | (1.57) | (0.12) | (0.41) | (1.37) | (1.87) | (1.11) | (0.13) | (1.16) | (1.91) | (1.86) | (1.60) | (1.09) |
| | FF5 | 0.19 | 0.08 | -0.07 | 0.19 | -0.28 | 0.40 | -0.15 | -0.01 | -0.47* | -0.36 | -0.21 | -0.47* | 0.32 |
| | | (1.15) | (0.78) | (0.45) | (0.93) | (1.41) | (1.96) | (1.12) | (0.06) | (1.99) | (1.50) | (1.31) | (2.59) | (1.78) |

Notes: Table reports estimated alphas for the 6 stated sorts with the ESG score under equal weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance.Return volatility is calculated as in Ang et al. (2006), the share turnover follows Datar et al. (1998), turnover volatility is after Chordia et al. (2001a), zero trading days is based on Liu (2006), illiquidity is after Amihud (2002) and finally industry momentum is after Moskowitz and Grinblatt (1999). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the top 30% of Refinitiv ESG scores. Low ESG is defined as the bottom 30% of Refinitiv ESG scores. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.8: Strategy Alphas - ESG Score - Value Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Return Volatility | CAPM | 0.66*** | 0.16 | 0.02 | 0.86*** | 0.27* | 0.67** | -0.14 | 0.21 | -0.39* | 0.11 | 0.25 | -0.60* | 0.01 |
| | | (3.41) | (1.39) | (0.13) | (3.36) | (2.01) | (2.80) | (0.99) | (1.85) | (2.09) | (0.62) | (1.50) | (2.58) | (0.09) |
| | FF5 | 0.39** | 0.09 | -0.11 | 0.58** | 0.23 | 0.37* | -0.19 | 0.19 | -0.16 | 0.15 | 0.34 | -0.35 | -0.02 |
| | | (2.97) | (0.70) | (0.67) | (3.05) | (1.80) | (2.12) | (1.27) | (1.80) | (0.97) | (0.85) | (1.95) | (1.83) | (0.15) |
| Share Turnover | CAPM | 0.45* | 0.16 | 0.33* | 0.52 | 0.15 | 0.45 | 0.17 | 0.07 | -0.30 | -0.01 | -0.18 | -0.37 | 0.29 |
| | | (2.12) | (1.39) | (2.18) | (1.77) | (1.03) | (1.73) | (1.23) | (0.51) | (1.46) | (0.05) | (0.86) | (1.43) | (1.49) |
| | FF5 | 0.31 | 0.09 | 0.23 | 0.48 | 0.14 | 0.26 | 0.15 | 0.17 | -0.17 | 0.06 | -0.09 | -0.34 | 0.17 |
| | | (1.82) | (0.70) | (1.44) | (1.88) | (0.93) | (1.15) | (1.09) | (1.12) | (0.86) | (0.29) | (0.42) | (1.44) | (1.08) |
| Turnover Volatility | CAPM | 0.39** | 0.16 | 0.13 | 0.25 | -0.04 | 0.43 | -0.03 | -0.14 | -0.43** | -0.20 | -0.16 | -0.28 | 0.27 |
| | | (2.85) | (1.39) | (1.04) | (1.25) | (0.33) | (1.95) | (0.30) | (1.08) | (2.64) | (1.23) | (1.01) | (1.28) | (1.69) |
| | FF5 | 0.28* | 0.09 | 0.00 | 0.22 | 0.01 | 0.21 | -0.07 | -0.07 | -0.27 | -0.07 | 0.01 | -0.20 | 0.12 |
| | | (2.46) | (0.70) | (0.04) | (1.12) | (0.11) | (1.19) | (0.63) | (0.46) | (1.53) | (0.44) | (0.06) | (0.93) | (1.01) |
| Zero Trade Days | CAPM | 0.49* | 0.16 | -0.08 | 0.59 | 0.25 | 0.51* | -0.24 | 0.10 | -0.25 | 0.08 | 0.32 | -0.34 | 0.35 |
| | | (2.35) | (1.39) | (0.26) | (1.94) | (1.57) | (1.99) | (0.96) | (0.65) | (1.18) | (0.42) | (0.82) | (1.34) | (1.92) |
| | FF5 | 0.34* | 0.09 | -0.20 | 0.51 | 0.24 | 0.31 | -0.27 | 0.16 | -0.10 | 0.15 | 0.43 | -0.27 | 0.22 |
| | | (2.07) | (0.70) | (0.64) | (1.87) | (1.46) | (1.35) | (1.08) | (0.98) | (0.51) | (0.77) | (1.07) | (1.13) | (1.44) |
| Illiquidity | CAPM | 0.13 | 0.16 | 0.08 | 0.09 | -0.03 | 0.25 | -0.08 | -0.04 | -0.16 | -0.19 | -0.11 | -0.12 | 0.08 |
| | | (1.12) | (1.39) | (0.40) | (0.57) | (0.22) | (1.61) | (0.49) | (0.35) | (0.83) | (1.13) | (0.48) | (0.57) | (0.87) |
| | FF5 | 0.00 | 0.09 | -0.02 | 0.01 | 0.10 | 0.11 | -0.10 | 0.01 | 0.10 | 0.01 | 0.11 | 0.09 | 0.03 |
| | | (0.01) | (0.70) | (0.08) | (0.05) | (0.62) | (0.74) | (0.50) | (0.05) | (0.47) | (0.07) | (0.49) | (0.42) | (0.29) |
| Industy Momentum | CAPM | -0.09 | 0.16 | -0.19 | 0.02 | 0.09 | -0.17 | -0.35 | 0.11 | 0.18 | -0.07 | 0.28 | 0.07 | -0.09 |
| | | (0.52) | (1.39) | (0.92) | (0.10) | (0.77) | (0.89) | (1.86) | (1.23) | (1.02) | (0.42) | (1.00) | (0.41) | (0.52) |
| | FF5 | -0.19 | 0.09 | -0.27 | -0.07 | 0.12 | -0.34 | -0.35 | 0.12 | 0.31 | 0.03 | 0.39 | 0.19 | -0.15 |
| | | (1.08) | (0.70) | (1.24) | (0.31) | (0.92) | (1.73) | (1.72) | (1.26) | (1.74) | (0.17) | (1.31) | (0.93) | (0.88) |

Notes: Table reports estimated alphas for the 6 stated sorts with the ESG score under value weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. Return volatility is calculated as in Ang et al. (2006), the share turnover follows Datar et al. (1998), turnover volatility is after Chordia et al. (2001a), zero trading days is based on Liu (2006), illiquidity is after Amihud (2002) and finally industry momentum is after Moskowitz and Grinblatt (1999). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the top 30% of Refinitiv ESG scores. Low ESG is defined as the bottom 30% of Refinitiv ESG scores. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.9: Strategy Alphas - DJSI - Equal Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| CAPM Beta | CAPM | 0.60* | 0.11 | 0.06 | 0.54 | -0.07 | 0.67* | -0.06 | -0.06 | -0.67* | -0.19 | -0.13 | -0.61* | 0.07 |
| | | (2.18) | (1.42) | (0.59) | (1.52) | (0.35) | (2.34) | (0.64) | (0.35) | (2.17) | (0.79) | (0.68) | (2.24) | (0.86) |
| | FF5 | 0.33 | 0.03 | -0.01 | 0.21 | -0.16 | 0.35 | -0.04 | -0.12 | -0.49 | -0.19 | -0.14 | -0.36 | 0.02 |
| | | (1.51) | (0.42) | (0.14) | (0.67) | (0.81) | (1.55) | (0.49) | (0.75) | (1.87) | (0.82) | (0.76) | (1.67) | (0.23) |
| Asset Growth | CAPM | 0.11 | 0.11 | 0.31* | 0.35* | 0.30 | 0.36** | 0.20* | 0.24 | 0.19 | 0.18 | -0.02 | -0.05 | 0.26* |
| | | (0.97) | (1.42) | (2.40) | (2.19) | (1.75) | (2.83) | (2.08) | (1.69) | (0.84) | (1.01) | (0.11) | (0.41) | (2.22) |
| | FF5 | 0.07 | 0.03 | 0.13 | 0.12 | 0.07 | 0.18 | 0.10 | 0.05 | 0.00 | 0.04 | -0.06 | -0.05 | 0.11 |
| | | (0.91) | (0.42) | (0.99) | (0.81) | (0.41) | (1.28) | (1.01) | (0.34) | (0.01) | (0.22) | (0.37) | (0.57) | (0.94) |
| Growth in Inventory | CAPM | 0.05 | 0.11 | 0.08 | -0.16 | -0.25 | 0.16 | -0.04 | -0.21 | -0.30 | -0.36 | -0.32 | -0.09 | 0.11 |
| | | (0.45) | (1.42) | (0.50) | (0.60) | (0.92) | (1.05) | (0.24) | (0.95) | (1.07) | (1.18) | (1.76) | (0.73) | (0.98) |
| | FF5 | 0.10 | 0.03 | -0.09 | -0.27 | -0.45 | 0.09 | -0.12 | -0.37 | -0.55 | -0.48 | -0.36 | -0.18 | -0.01 |
| | | (0.93) | (0.42) | (0.56) | (1.05) | (1.58) | (0.55) | (0.74) | (1.59) | (1.82) | (1.54) | (1.96) | (1.50) | (0.09) |
| Growth in Book Equity | CAPM | 0.18 | 0.11 | 0.15 | 0.35 | 0.21 | 0.29** | 0.03 | 0.17 | 0.03 | 0.10 | 0.07 | -0.14 | 0.17 |
| | | (1.56) | (1.42) | (1.16) | (1.86) | (1.03) | (2.73) | (0.38) | (0.96) | (0.11) | (0.44) | (0.34) | (1.05) | (1.71) |
| | FF5 | 0.16 | 0.03 | -0.03 | 0.14 | -0.02 | 0.13 | -0.06 | -0.03 | -0.19 | -0.05 | 0.01 | -0.16 | 0.10 |
| | | (1.28) | (0.42) | (0.26) | (0.71) | (0.10) | (1.09) | (0.74) | (0.16) | (0.64) | (0.22) | (0.04) | (1.09) | (0.85) |
| Growth in LTNOA | CAPM | 0.06 | 0.11 | 0.03 | 0.10 | 0.04 | 0.08 | -0.09 | 0.04 | -0.02 | -0.07 | 0.02 | -0.06 | 0.02 |
| | | (0.62) | (1.42) | (0.18) | (0.55) | (0.23) | (0.54) | (0.80) | (0.23) | (0.09) | (0.34) | (0.13) | (0.50) | (0.15) |
| | FF5 | 0.17 | 0.03 | -0.09 | 0.10 | -0.08 | 0.09 | -0.12 | -0.07 | -0.25 | -0.12 | 0.00 | -0.18 | -0.07 |
| | | (1.59) | (0.42) | (0.65) | (0.50) | (0.45) | (0.57) | (1.03) | (0.44) | (1.25) | (0.58) | (0.02) | (1.75) | (0.62) |
| Growth in Capex | CAPM | -0.02 | 0.11 | 0.18 | -0.04 | -0.02 | 0.17 | 0.06 | -0.02 | -0.01 | -0.14 | -0.20 | 0.01 | 0.19 |
| | | (0.16) | (1.42) | (1.22) | (0.22) | (0.14) | (1.26) | (0.64) | (0.11) | (0.03) | (0.81) | (1.40) | (0.09) | (1.43) |
| | FF5 | 0.06 | 0.03 | 0.02 | -0.10 | -0.20 | 0.11 | -0.01 | -0.16 | -0.26 | -0.23 | -0.21 | -0.10 | 0.05 |
| | | (0.60) | (0.42) | (0.11) | (0.57) | (1.03) | (0.79) | (0.13) | (1.00) | (1.12) | (1.20) | (1.51) | (0.88) | (0.40) |

Notes: Table reports estimated alphas for the 6 stated sorts with the DJSI under equal weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. The capital asset pricing model beta follows Fama and MacBeth (1973), asset growth follows Cooper et al. (2008), growth in inventory follows Thomas and Zhang (2002), growth in book equity is after Richardson et al. (2005) and growth in capital expenditure (capex) is after Anderson and Garcia-Feijoo (2006). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the members of the DJSI. Low ESG is defined as non-DJSI members. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.10: Strategy Alphas - DJSI- Value Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| CAPM Beta | CAPM | 0.60* | 0.01 | -0.06 | 0.62 | 0.08 | 0.55 | -0.07 | 0.02 | -0.52 | 0.07 | 0.15 | -0.54 | -0.05 |
| | | (1.97) | (0.12) | (0.60) | (1.54) | (0.43) | (1.74) | (0.85) | (0.09) | (1.79) | (0.37) | (0.73) | (1.52) | (0.57) |
| | FF5 | 0.32 | -0.05 | -0.12 | 0.23 | 0.02 | 0.26 | -0.07 | -0.09 | -0.30 | 0.07 | 0.14 | -0.21 | -0.06 |
| | | (1.31) | (0.60) | (1.13) | (0.71) | (0.12) | (0.98) | (0.81) | (0.53) | (1.09) | (0.33) | (0.71) | (0.67) | (0.64) |
| Asset Growth | CAPM | 0.16 | 0.01 | 0.22 | 0.31 | -0.04 | 0.33* | 0.21 | 0.15 | -0.20 | -0.05 | -0.26 | -0.35* | 0.17 |
| | | (1.16) | (0.12) | (1.82) | (1.58) | (0.35) | (2.31) | (1.92) | (1.08) | (1.62) | (0.33) | (1.49) | (2.19) | (1.62) |
| | FF5 | 0.08 | -0.05 | 0.10 | 0.11 | -0.02 | 0.17 | 0.14 | 0.02 | -0.10 | 0.03 | -0.11 | -0.12 | 0.09 |
| | | (0.98) | (0.60) | (0.84) | (0.73) | (0.12) | (1.41) | (1.32) | (0.19) | (0.86) | (0.20) | (0.64) | (0.81) | (0.85) |
| Growth in Inventory | CAPM | 0.07 | 0.01 | 0.09 | -0.01 | 0.15 | 0.18 | 0.08 | -0.08 | 0.08 | 0.14 | 0.06 | 0.16 | 0.11 |
| | | (0.57) | (0.12) | (0.58) | (0.04) | (1.44) | (1.02) | (0.45) | (0.39) | (0.50) | (1.26) | (0.34) | (0.60) | (1.09) |
| | FF5 | 0.08 | -0.05 | -0.01 | -0.10 | 0.17 | 0.14 | 0.03 | -0.18 | 0.09 | 0.22 | 0.19 | 0.27 | 0.06 |
| | | (0.73) | (0.60) | (0.09) | (0.41) | (1.66) | (0.79) | (0.18) | (0.85) | (0.57) | (1.79) | (0.97) | (1.05) | (0.57) |
| Growth in Book Equity | CAPM | 0.28* | 0.01 | 0.16 | 0.43* | 0.07 | 0.37* | 0.04 | 0.15 | -0.21 | 0.06 | -0.08 | -0.35 | 0.36** |
| | | (2.07) | (0.12) | (1.46) | (2.25) | (0.51) | (2.59) | (0.51) | (1.05) | (1.25) | (0.39) | (0.54) | (1.86) | (2.90) |
| | FF5 | 0.21* | -0.05 | 0.04 | 0.28 | 0.14 | 0.21 | 0.01 | 0.07 | -0.06 | 0.19 | 0.10 | -0.14 | 0.25* |
| | | (2.00) | (0.60) | (0.40) | (1.58) | (0.94) | (1.68) | (0.11) | (0.51) | (0.43) | (1.10) | (0.61) | (0.71) | (2.49) |
| Growth in LTNOA | CAPM | 0.07 | 0.01 | -0.09 | -0.10 | -0.20 | 0.05 | -0.10 | -0.17 | -0.27 | -0.21 | -0.11 | -0.10 | -0.03 |
| | | (0.50) | (0.09) | (0.77) | (0.62) | (1.29) | (0.25) | (1.04) | (1.52) | (1.57) | (1.17) | (0.59) | (0.55) | (0.25) |
| | FF5 | 0.15 | -0.05 | -0.15 | -0.05 | -0.14 | 0.08 | -0.10 | -0.20 | -0.30 | -0.10 | 0.00 | -0.10 | -0.07 |
| | | (1.23) | (0.55) | (1.23) | (0.30) | (0.89) | (0.44) | (1.08) | (1.95) | (1.59) | (0.56) | (0.02) | (0.50) | (0.66) |
| Growth in Capex | CAPM | 0.04 | 0.01 | 0.00 | 0.03 | 0.06 | 0.04 | -0.01 | -0.01 | 0.02 | 0.05 | 0.06 | 0.04 | 0.00 |
| | | (0.32) | (0.17) | (0.02) | (0.17) | (0.55) | (0.27) | (0.10) | (0.08) | (0.15) | (0.30) | (0.39) | (0.22) | (0.03) |
| | FF5 | 0.12 | -0.04 | -0.04 | 0.08 | 0.18 | 0.10 | 0.01 | -0.04 | 0.06 | 0.22 | 0.22 | 0.10 | -0.02 |
| | | (1.07) | (0.54) | (0.29) | (0.50) | (1.43) | (0.75) | (0.06) | (0.30) | (0.38) | (1.37) | (1.19) | (0.57) | (0.23) |

Notes: Table reports estimated alphas for the 6 stated sorts with the DJSI under value weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. The capital asset pricing model beta follows Fama and MacBeth (1973), asset growth follows Cooper et al. (2008), growth in inventory follows Thomas and Zhang (2002), growth in book equity is after Richardson et al. (2005) and growth in capital expenditure (capex) is after Anderson and Garcia-Feijoo (2006). Growth in long term net operating assets (LTNOA Growth) is after Fairfield et al. (2003). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the members of the DJSI. Low ESG is defined as non-DJSI members. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.11: Strategy Alphas - DJSI - Equal Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Growth in Sales - Inventory | CAPM | 0.03 | 0.11 | 0.40* | 0.30 | 0.32 | 0.37* | 0.28* | 0.27 | 0.29 | 0.21 | -0.07 | 0.03 | 0.34* |
| | | (0.32) | (1.42) | (2.28) | (1.97) | (1.77) | (2.39) | (2.20) | (1.82) | (1.33) | (1.20) | (0.53) | (0.26) | (2.22) |
| | FF5 | 0.08 | 0.03 | 0.32 | 0.42* | 0.40 | 0.35* | 0.29* | 0.33* | 0.31 | 0.37 | 0.07 | -0.02 | 0.26 |
| | | (1.00) | (0.42) | (1.95) | (2.36) | (1.93) | (2.13) | (2.11) | (2.00) | (1.36) | (1.81) | (0.53) | (0.21) | (1.84) |
| Growth Shares Outstanding | CAPM | 0.18 | 0.11 | -0.07 | -0.10 | -0.34 | 0.17 | -0.18* | -0.29 | -0.52* | -0.45* | -0.27 | -0.23 | -0.02 |
| | | (1.40) | (1.42) | (0.62) | (0.45) | (1.63) | (1.02) | (2.05) | (1.64) | (2.33) | (2.08) | (1.78) | (1.79) | (0.22) |
| | FF5 | 0.16 | 0.03 | -0.13 | -0.08 | -0.28 | 0.07 | -0.16 | -0.24 | -0.44 | -0.31 | -0.15 | -0.20 | -0.09 |
| | | (1.44) | (0.42) | (1.21) | (0.38) | (1.37) | (0.49) | (1.74) | (1.38) | (1.90) | (1.42) | (0.99) | (1.76) | (1.02) |
| Earnings Ann. Returns | CAPM | 0.02 | 0.11 | 0.05 | -0.11 | -0.15 | 0.09 | -0.07 | -0.12 | -0.16 | -0.26 | -0.19 | -0.04 | 0.07 |
| | | (0.23) | (1.42) | (0.35) | (0.53) | (0.71) | (0.54) | (0.63) | (0.72) | (0.78) | (1.15) | (1.10) | (0.47) | (0.56) |
| | FF5 | 0.05 | 0.03 | -0.08 | -0.16 | -0.25 | 0.01 | -0.11 | -0.21 | -0.30 | -0.28 | -0.17 | -0.09 | -0.05 |
| | | (0.63) | (0.42) | (0.61) | (0.73) | (1.14) | (0.05) | (1.05) | (1.16) | (1.36) | (1.24) | (1.03) | (1.03) | (0.40) |
| Change in 6-Month Mom. | CAPM | 0.10 | 0.11 | 0.11 | 0.16 | 0.08 | 0.28 | 0.00 | 0.07 | -0.02 | -0.04 | -0.04 | -0.09 | 0.18 |
| | | (0.58) | (1.42) | (0.93) | (0.65) | (0.33) | (1.24) | (0.01) | (0.33) | (0.06) | (0.16) | (0.11) | (0.51) | (1.23) |
| | FF5 | -0.02 | 0.03 | -0.04 | 0.16 | 0.21 | 0.12 | -0.07 | 0.18 | 0.23 | 0.18 | 0.25 | 0.05 | 0.14 |
| | | (0.10) | (0.42) | (0.29) | (0.53) | (0.93) | (0.44) | (0.59) | (0.93) | (0.81) | (0.83) | (0.78) | (0.26) | (0.97) |
| 1-Month Momentum | CAPM | -0.09 | 0.11 | 0.04 | -0.09 | 0.00 | -0.05 | -0.07 | 0.00 | 0.09 | -0.11 | -0.04 | 0.09 | 0.04 |
| | | (0.33) | (1.42) | (0.28) | (0.29) | (0.01) | (0.19) | (0.64) | (0.01) | (0.26) | (0.45) | (0.11) | (0.35) | (0.30) |
| | FF5 | -0.26 | 0.03 | -0.02 | -0.24 | 0.03 | -0.26 | -0.05 | 0.02 | 0.29 | 0.00 | 0.05 | 0.27 | 0.01 |
| | | (0.98) | (0.42) | (0.12) | (0.75) | (0.13) | (0.93) | (0.40) | (0.12) | (0.85) | (0.01) | (0.14) | (1.02) | (0.04) |
| Cashflow (Ind Adj) | CAPM | 0.12 | 0.11 | 0.18 | -0.01 | -0.17 | 0.17 | 0.07 | -0.14 | -0.30 | -0.29 | -0.35 | -0.16 | 0.04 |
| | | (1.05) | (1.42) | (1.13) | (0.07) | (0.97) | (0.89) | (0.55) | (0.92) | (1.40) | (1.46) | (1.15) | (1.30) | (0.31) |
| | FF5 | 0.14 | 0.03 | 0.09 | 0.04 | -0.13 | 0.12 | 0.05 | -0.10 | -0.26 | -0.16 | -0.21 | -0.16 | -0.01 |
| | | (1.29) | (0.42) | (0.65) | (0.20) | (0.72) | (0.71) | (0.53) | (0.67) | (1.29) | (0.88) | (0.79) | (1.49) | (0.10) |

Notes: Table reports estimated alphas for the 6 stated sorts with the DJSI under equal weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. Growth in sales less growth in inventory (Growth in Sales - Inventory) follows Abarbanell and Bushee (1998), growth of shares outstanding (Growth Shares Outstanding) is after Pontiff and Woodgate (2008), earnings announcement returns (Earnings Ann. Returns) follow Kishore et al. (2008), change in 6-month momentum (Change in 6-Month Mom.) follows Gettleman and Marks (2006), 1-month momentum is the short-term reversal effect of Jegadeesh and Titman (1993) and industry adjusted cashflow is as developed by Asness et al. (2000). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the members of the DJSI. Low ESG is defined as non-DJSI members. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.12: Strategy Alphas - DJSI - Value Weighting

| Sort | Model | Strategies A | B | C | D | G | H | Comparisons C-B | D-A | G-A | G-B | G-C | G-D | H-A |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Growth in Sales-Inventory | CAPM | 0.15 | -0.01 | 0.23 | 0.35 | 0.05 | 0.34* | 0.25 | 0.20 | -0.10 | 0.06 | -0.19 | -0.30 | 0.19 |
| | | (1.43) | (0.12) | (1.37) | (1.89) | (0.37) | (2.11) | (1.79) | (1.27) | (0.70) | (0.34) | (0.95) | (1.97) | (1.38) |
| | FF5 | 0.23* | -0.09 | 0.21 | 0.50* | 0.08 | 0.38* | 0.31* | 0.27 | -0.15 | 0.17 | -0.14 | -0.42* | 0.15 |
| | | (2.07) | (0.98) | (1.21) | (2.55) | (0.55) | (2.30) | (2.10) | (1.64) | (0.95) | (0.97) | (0.69) | (2.36) | (1.06) |
| Growth shares outstanding | CAPM | 0.25 | 0.01 | -0.07 | 0.11 | 0.21 | 0.21 | -0.08 | -0.15 | -0.04 | 0.20 | 0.28* | 0.10 | -0.04 |
| | | (1.70) | (0.12) | (0.52) | (0.48) | (1.79) | (1.06) | (0.78) | (0.87) | (0.23) | (1.81) | (2.17) | (0.45) | (0.39) |
| | FF5 | 0.19 | -0.05 | -0.09 | 0.04 | 0.12 | 0.12 | -0.05 | -0.15 | -0.07 | 0.16 | 0.21 | 0.08 | -0.06 |
| | | (1.54) | (0.60) | (0.82) | (0.21) | (1.25) | (0.72) | (0.53) | (0.97) | (0.48) | (1.55) | (1.75) | (0.38) | (0.66) |
| Earnings Ann. Returns | CAPM | 0.03 | 0.01 | -0.09 | -0.13 | -0.03 | -0.03 | -0.10 | -0.16 | -0.05 | -0.04 | 0.07 | 0.11 | -0.06 |
| | | (0.24) | (0.12) | (0.55) | (0.54) | (0.19) | (0.17) | (0.67) | (0.85) | (0.36) | (0.22) | (0.39) | (0.53) | (0.40) |
| | FF5 | 0.05 | -0.05 | -0.16 | -0.11 | 0.04 | -0.07 | -0.11 | -0.16 | 0.00 | 0.09 | 0.21 | 0.16 | -0.12 |
| | | (0.40) | (0.60) | (0.93) | (0.48) | (0.29) | (0.40) | (0.76) | (0.93) | (0.02) | (0.52) | (1.11) | (0.73) | (0.86) |
| Change in 6-Month Mom. | CAPM | 0.11 | 0.01 | -0.02 | 0.21 | 0.05 | 0.19 | -0.03 | 0.10 | -0.06 | 0.04 | 0.07 | -0.16 | 0.08 |
| | | (0.63) | (0.12) | (0.11) | (0.84) | (0.42) | (0.86) | (0.19) | (0.57) | (0.30) | (0.25) | (0.28) | (0.65) | (0.68) |
| | FF5 | 0.02 | -0.05 | -0.07 | 0.16 | 0.00 | 0.08 | -0.03 | 0.13 | -0.03 | 0.04 | 0.07 | -0.16 | 0.06 |
| | | (0.11) | (0.60) | (0.45) | (0.51) | (0.01) | (0.31) | (0.19) | (0.78) | (0.11) | (0.26) | (0.28) | (0.53) | (0.49) |
| 1-Month Momentum | CAPM | 0.11 | 0.01 | -0.02 | 0.01 | 0.10 | -0.01 | -0.03 | -0.10 | -0.01 | 0.09 | 0.12 | 0.09 | -0.12 |
| | | (0.41) | (0.12) | (0.16) | (0.03) | (0.96) | (0.04) | (0.28) | (0.62) | (0.04) | (0.65) | (0.65) | (0.29) | (1.00) |
| | FF5 | -0.07 | -0.05 | -0.07 | -0.09 | 0.15 | -0.16 | -0.03 | -0.02 | 0.22 | 0.20 | 0.23 | 0.24 | -0.09 |
| | | (0.27) | (0.60) | (0.55) | (0.27) | (1.57) | (0.56) | (0.23) | (0.11) | (0.86) | (1.62) | (1.42) | (0.75) | (0.77) |
| Cashflow (Ind Adj.) | CAPM | -0.06 | 0.01 | 0.02 | -0.05 | -0.03 | -0.02 | 0.01 | 0.01 | 0.02 | -0.04 | -0.05 | 0.01 | 0.03 |
| | | (0.43) | (0.12) | (0.16) | (0.24) | (0.26) | (0.12) | (0.11) | (0.07) | (0.15) | (0.33) | (0.31) | (0.07) | (0.26) |
| | FF5 | -0.02 | -0.05 | -0.05 | 0.03 | 0.00 | -0.01 | 0.00 | 0.06 | 0.02 | 0.04 | 0.04 | -0.04 | 0.01 |
| | | (0.20) | (0.60) | (0.39) | (0.19) | (0.03) | (0.07) | (0.00) | (0.47) | (0.12) | (0.31) | (0.24) | (0.20) | (0.09) |

Notes: Table reports estimated alphas for the 6 stated sorts with the DJSI under value weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. Growth in sales less growth in inventory (Growth in Sales - Inventory) follows Abarbanell and Bushee (1998), growth of shares outstanding (Growth Shares Outstanding) is after Pontiff and Woodgate (2008), earnings announcement returns (Earnings Ann. Returns) follow Kishore et al. (2008), change in 6-month momentum (Change in 6-Month Mom.) follows Gettleman and Marks (2006), 1-month momentum is the short-term reversal effect of Jegadeesh and Titman (1993) and industry adjusted cashflow is as developed by Asness et al. (2000). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the members of the DJSI. Low ESG is defined as non-DJSI members. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.13: Strategy Alphas - DJSI - Equal Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Return Volatility | CAPM | 0.52** | 0.11 | 0.00 | 0.30 | -0.26 | 0.56** | -0.11 | -0.22 | -0.78* | -0.38 | -0.26 | -0.56** | 0.04 |
| | | (2.78) | (1.42) | (0.00) | (1.11) | (1.12) | (2.68) | (1.01) | (1.13) | (2.56) | (1.39) | (1.33) | (2.89) | (0.45) |
| | FF5 | 0.24 | 0.03 | -0.11 | 0.07 | -0.21 | 0.18 | -0.14 | -0.17 | -0.45 | -0.24 | -0.10 | -0.28 | -0.06 |
| | | (1.55) | (0.42) | (0.98) | (0.27) | (0.92) | (0.99) | (1.27) | (0.88) | (1.73) | (0.96) | (0.58) | (1.80) | (0.77) |
| Share Turnover | CAPM | 0.37 | 0.11 | 0.02 | 0.07 | -0.33 | 0.42 | -0.09 | -0.30 | -0.70** | -0.44 | -0.35 | -0.40* | 0.05 |
| | | (1.82) | (1.42) | (0.25) | (0.22) | (1.40) | (1.87) | (1.42) | (1.46) | (2.73) | (1.63) | (1.54) | (2.07) | (0.73) |
| | FF5 | 0.19 | 0.03 | -0.07 | -0.02 | -0.25 | 0.15 | -0.10 | -0.21 | -0.44 | -0.28 | -0.17 | -0.23 | -0.04 |
| | | (1.02) | (0.42) | (0.91) | (0.07) | (1.03) | (0.81) | (1.55) | (1.03) | (1.90) | (1.02) | (0.77) | (1.28) | (0.60) |
| Turnover Volatility | CAPM | 0.31 | 0.11 | 0.01 | -0.16 | -0.52* | 0.37* | -0.10 | -0.46* | -0.82*** | -0.63* | -0.53* | -0.36* | 0.06 |
| | | (1.95) | (1.42) | (0.13) | (0.55) | (2.29) | (2.07) | (1.60) | (2.36) | (3.57) | (2.45) | (2.43) | (2.42) | (0.92) |
| | FF5 | 0.14 | 0.03 | -0.06 | -0.18 | -0.37 | 0.12 | -0.10 | -0.32 | -0.50* | -0.40 | -0.30 | -0.18 | -0.02 |
| | | (0.82) | (0.42) | (0.83) | (0.60) | (1.57) | (0.70) | (1.31) | (1.57) | (2.19) | (1.48) | (1.30) | (1.17) | (0.26) |
| Zero Trading Days | CAPM | 0.37 | 0.11 | 0.35 | 0.08 | -0.32 | 0.42 | 0.23 | -0.29 | -0.68** | -0.43 | -0.66 | -0.39* | 0.06 |
| | | (1.86) | (1.42) | (1.62) | (0.25) | (1.52) | (1.95) | (1.33) | (1.60) | (2.85) | (1.72) | (1.60) | (2.10) | (0.80) |
| | FF5 | 0.18 | 0.03 | 0.22 | -0.06 | -0.29 | 0.16 | 0.19 | -0.25 | -0.47* | -0.32 | -0.51 | -0.22 | -0.03 |
| | | (0.98) | (0.42) | (1.01) | (0.21) | (1.37) | (0.83) | (1.03) | (1.37) | (2.18) | (1.28) | (1.20) | (1.25) | (0.44) |
| Illiquidity | CAPM | 0.04 | 0.11 | -0.05 | -0.16 | -0.24 | 0.03 | -0.17* | -0.19 | -0.27 | -0.35 | -0.18 | -0.08 | -0.01 |
| | | (0.29) | (1.42) | (0.55) | (0.53) | (0.88) | (0.15) | (2.36) | (0.76) | (0.92) | (1.12) | (0.62) | (0.59) | (0.17) |
| | FF5 | -0.13 | 0.03 | -0.09 | -0.27 | -0.18 | -0.18 | -0.12 | -0.14 | -0.05 | -0.21 | -0.09 | 0.09 | -0.05 |
| | | (1.04) | (0.42) | (0.98) | (0.79) | (0.64) | (1.16) | (1.94) | (0.51) | (0.20) | (0.69) | (0.30) | (0.72) | (0.68) |
| Industry Momentum | CAPM | 0.06 | 0.11 | -0.14 | -0.20 | -0.30 | -0.03 | -0.25 | -0.26 | -0.36 | -0.42 | -0.17 | -0.11 | -0.09 |
| | | (0.33) | (1.42) | (0.69) | (0.88) | (1.25) | (0.14) | (1.62) | (1.25) | (1.09) | (1.90) | (1.48) | (0.58) | (0.52) |
| | FF5 | 0.19 | 0.03 | -0.26 | -0.10 | -0.35 | -0.01 | -0.29 | -0.30 | -0.54 | -0.38 | -0.09 | -0.24 | -0.21 |
| | | (1.15) | (0.42) | (1.25) | (0.42) | (1.29) | (0.05) | (1.63) | (1.31) | (1.58) | (1.46) | (0.76) | (1.36) | (1.20) |

Notes: Table reports estimated alphas for the 6 stated sorts with the DJSI under equal weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. Return volatility is calculated as in Ang et al. (2006), the share turnover follows Datar et al. (1998), turnover volatility is after Chordia et al. (2001a), zero trading days is based on Liu (2006), illiquidity is after Amihud (2002) and finally industry momentum is after Moskowitz and Grinblatt (1999). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the members of the DJSI. Low ESG is defined as non-DJSI members. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.14: Strategy Alphas - DJSI- Value Weighting

| | | Strategies | | | | | | Comparisons | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sort | Model | A | B | C | D | G | H | C-B | D-A | G-A | G-B | G-C | G-D | H-A |
| Return Volatility | CAPM | 0.66*** | 0.01 | -0.05 | 0.68** | 0.39* | 0.65** | -0.05 | 0.02 | -0.27 | 0.38* | 0.43* | -0.30 | -0.01 |
| | | (3.41) | (0.12) | (0.41) | (2.62) | (2.48) | (3.01) | (0.60) | (0.14) | (1.28) | (2.40) | (2.52) | (1.11) | (0.08) |
| | FF5 | 0.39** | -0.05 | -0.15 | 0.30 | 0.23 | 0.32 | -0.11 | -0.09 | -0.16 | 0.28 | 0.38 | -0.07 | -0.07 |
| | | (2.97) | (0.60) | (1.38) | (1.55) | (1.34) | (1.90) | (1.25) | (0.55) | (0.72) | (1.55) | (1.96) | (0.27) | (0.85) |
| Share Turnover | CAPM | 0.45* | 0.01 | 0.03 | 0.37 | 0.30 | 0.47* | 0.02 | -0.08 | -0.15 | 0.29 | 0.27 | -0.07 | 0.02 |
| | | (2.12) | (0.12) | (0.36) | (1.02) | (1.46) | (2.18) | (0.33) | (0.35) | (0.61) | (1.33) | (1.33) | (0.22) | (0.31) |
| | FF5 | 0.31 | -0.05 | -0.06 | 0.25 | 0.27 | 0.26 | -0.02 | -0.07 | -0.04 | 0.32 | 0.33 | 0.02 | -0.06 |
| | | (1.82) | (0.60) | (0.76) | (0.76) | (1.09) | (1.58) | (0.29) | (0.28) | (0.14) | (1.17) | (1.32) | (0.07) | (0.80) |
| Turnover Volatility | CAPM | 0.39** | 0.01 | 0.00 | 0.05 | 0.21 | 0.45** | -0.01 | -0.34 | -0.18 | 0.20 | 0.21 | 0.16 | 0.07 |
| | | (2.85) | (0.12) | (0.00) | (0.20) | (1.38) | (2.95) | (0.14) | (1.65) | (0.88) | (1.20) | (1.30) | (0.55) | (0.92) |
| | FF5 | 0.28* | -0.05 | -0.09 | 0.02 | 0.20 | 0.27* | -0.04 | -0.26 | -0.08 | 0.25 | 0.29 | 0.18 | -0.01 |
| | | (2.46) | (0.60) | (0.92) | (0.09) | (1.08) | (2.12) | (0.55) | (1.23) | (0.32) | (1.24) | (1.56) | (0.60) | (0.19) |
| Zero Trading Days | CAPM | 0.49* | 0.01 | -0.01 | 0.49 | 0.42* | 0.48* | -0.02 | 0.00 | -0.08 | 0.41* | 0.43 | -0.08 | -0.01 |
| | | (2.35) | (0.12) | (0.05) | (1.54) | (2.20) | (2.31) | (0.10) | (0.02) | (0.31) | (2.00) | (1.29) | (0.25) | (0.10) |
| | FF5 | 0.34* | -0.05 | -0.04 | 0.30 | 0.37 | 0.27 | 0.01 | -0.04 | 0.02 | 0.41 | 0.40 | 0.06 | -0.08 |
| | | (2.07) | (0.60) | (0.15) | (1.02) | (1.54) | (1.72) | (0.05) | (0.21) | (0.08) | (1.61) | (1.04) | (0.21) | (0.96) |
| Illiquidity | CAPM | 0.13 | 0.01 | -0.08 | -0.05 | 0.11 | 0.10 | -0.09** | -0.18 | -0.02 | 0.10 | 0.19 | 0.16 | -0.03 |
| | | (1.12) | (0.12) | (0.87) | (0.23) | (0.57) | (0.65) | (2.76) | (0.90) | (0.10) | (0.50) | (0.93) | (0.53) | (0.42) |
| | FF5 | 0.00 | -0.05 | -0.12 | -0.12 | 0.14 | -0.07 | -0.08* | -0.13 | 0.14 | 0.19 | 0.27 | 0.27 | -0.07 |
| | | (0.01) | (0.60) | (1.30) | (0.54) | (0.60) | (0.53) | (2.18) | (0.62) | (0.55) | (0.79) | (1.08) | (0.79) | (0.95) |
| Industry Momentum | CAPM | 0.09 | 0.01 | -0.25 | -0.21 | -0.01 | -0.06 | -0.26* | -0.30* | -0.10 | -0.02 | 0.24 | 0.20 | -0.15 |
| | | (0.52) | (0.12) | (1.62) | (1.08) | (0.06) | (0.30) | (2.07) | (2.14) | (0.46) | (0.10) | (0.98) | (0.88) | (1.23) |
| | FF5 | 0.19 | -0.05 | -0.31 | -0.09 | 0.01 | -0.02 | -0.26 | -0.28 | -0.18 | 0.06 | 0.32 | 0.10 | -0.21 |
| | | (1.08) | (0.60) | (1.94) | (0.43) | (0.06) | (0.12) | (1.85) | (1.89) | (0.75) | (0.26) | (1.22) | (0.42) | (1.77) |

Notes: Table reports estimated alphas for the 6 stated sorts with the DJSI under value weighting. For strategy X, CAPM reports $\alpha_X^{CAPM}$ from the model $R_{Xt} = \alpha_X^{CAPM} MKT_t + \epsilon_{Xt}$, and FF5 reports $\alpha_x^{FF5}$ from the regression $R_{Xt} = \alpha_X^{FF5} + \beta_{X1}^{FF5} MKT_t + \beta_{X2}^{FF5} SMB_t + \beta_{X3}^{FF5} HML_t + \beta_{X4}^{FF5} RMW_t + \beta_{X5}^{FF5} CMA_t + \epsilon_{Xt}$. In these regressions $R_{Xt}$ is the excess return of strategy $X$ at time $t$ and $\epsilon_{Xt}$ is a random error term with mean 0 and constant variance. Return volatility is calculated as in Ang et al. (2006), the share turnover follows Datar et al. (1998), turnover volatility is after Chordia et al. (2001a), zero trading days is based on Liu (2006), illiquidity is after Amihud (2002) and finally industry momentum is after Moskowitz and Grinblatt (1999). Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the members of the DJSI. Low ESG is defined as non-DJSI members. For brevity $t \leq -3$ is only reported in the case when there is actually a strategy producing a t-statistic in this range. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

of Novy-Marx and Velikov (2016). Unlike Novy-Marx and Velikov (2016), who split factors according to their intended trading freqency, our strategies assume a single reconstitution of portfolios and therefore only trade anually. Consequently, trading costs in our strategies are only applied once each year. Tables A4.15 and A4.16 report the average trading cost for each strategy with each of the 24 factor sort variables.

Tables A4.15 and A4.16 reveal that the factor sorts may be split into two groups. First are those where the traditional factor sort, strategy A, has an annual trading cost around 50bps. In the first group are the CAPM beta, size, illiqudity, profitability and the book-to-market ratio. Second are those factors for which the trading costs are above 100bps. Examples of high turnover anomalies include growth in sales minus growth in inventory, 1-month momentum, 12-month momentum, change in 6-month momentum and the earnings announcement returns. Of these high trading cost factors, the growth in sales minus growth in inventory has been found to offer a potential ESG flavoured alpha. Therefore our trading costs suggest a reduction in the set of ESG flavoured alphas available. Comparing Table A4.15 and A4.16 confirms that the ESG scores have a higher turnover than the DJSI index membership. In the former case we see strategy B with a trading cost of 50bps, compared to just 25bps for the DJSI[20].

### A4.2.2 Alpha Comparison

Using the information on strategy turnover we may then construct the trading cost adjusted returns. As noted all of the turnover in Tables A4.15 and A4.16 occurs in October. Therefore the appropriate turnover for each strategy-year is deducted from the October return. We then recalculate the alphas based on the adjusted returns. Note that we do not consider the costs of trading the individual factors and continue to apply the values from the website of Ken French. As in the main paper, we now report only the results for combinations of strategy, factor sort, weighting and asset pricing model for which there are significant alphas.

Table A4.17 confirms that there are a lot more negative significant alphas when we account for the trading costs. This is to be expected. Further, the comparisons involving strategy G produce more negative significant alphas owing to the additional costs of trading the four legs of G. Panels (a) and (b) demonstrate that there are many cases in which the traditional factor sort strategy A produces a negative alpha. The number of zero trading days has a negative alpha against both the CAPM and FF5 models under value weighting. Return volatility, by contrast, has a positive significant

[20]Small variations are noted because for non-core sorts we drop any stocks which do not have the required characteristics information.

Table A4.15: Strategy Portfolio Trading Costs - ESG Scores

| Factor | Equal Weighting | | | | | | Value Weighting | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | A | B | C | D | G | H | A | B | C | D | G | H |
| Asset Growth | 1.2 | 0.49 | 1.32 | 1.35 | 2.66 | 1.24 | 1.13 | 0.42 | 1.34 | 1.28 | 2.57 | 1.15 |
| CAPM Beta | 0.44 | 0.49 | 0.81 | 0.67 | 1.58 | 0.69 | 0.39 | 0.42 | 0.72 | 0.61 | 1.48 | 0.64 |
| Book-to-Market Ratio | 0.44 | 0.49 | 0.75 | 0.68 | 1.45 | 0.76 | 0.38 | 0.44 | 0.75 | 0.57 | 1.35 | 0.7 |
| Growth in Shares Outstanding | 1.02 | 0.5 | 1.14 | 1.17 | 2.33 | 1.16 | 0.98 | 0.42 | 1.04 | 1.04 | 2.13 | 1.04 |
| Growth in Book Value of Equity | 1.21 | 0.49 | 1.35 | 1.29 | 2.67 | 1.43 | 1.14 | 0.44 | 1.27 | 1.2 | 2.55 | 1.38 |
| Industry Adjusted Cashflow | 1.07 | 0.5 | 1.13 | 1.18 | 2.41 | 1.17 | 1.02 | 0.42 | 1.08 | 1.12 | 2.29 | 1.05 |
| Growth in Inventory | 1.18 | 0.49 | 1.43 | 1.35 | 2.66 | 1.29 | 1.16 | 0.42 | 1.44 | 1.29 | 2.61 | 1.26 |
| Change in 6-Month Momentum | 1.41 | 0.49 | 1.48 | 1.51 | 3.07 | 1.5 | 1.39 | 0.42 | 1.46 | 1.49 | 3 | 1.42 |
| Earnings Announcement Returns | 1.38 | 0.49 | 1.45 | 1.46 | 2.93 | 1.44 | 1.4 | 0.42 | 1.45 | 1.45 | 2.94 | 1.47 |
| Growth in Capital Expenditure | 1.08 | 0.49 | 1.19 | 1.17 | 2.47 | 1.23 | 1.02 | 0.42 | 1.16 | 1.12 | 2.37 | 1.17 |
| Growth in Long Term Net Operating Assets | 1.18 | 0.5 | 1.35 | 1.33 | 2.63 | 1.29 | 1.15 | 0.42 | 1.36 | 1.31 | 2.56 | 1.24 |
| Illiquidity | 0.52 | 0.49 | 0.89 | 0.71 | 1.66 | 1.04 | 0.48 | 0.42 | 1.01 | 0.71 | 1.62 | 1.01 |
| Industry Momentum | 1.34 | 0.49 | 1.55 | 1.39 | 2.94 | 1.44 | 1.31 | 0.42 | 1.56 | 1.36 | 2.97 | 1.5 |
| Investment | 1 | 0.5 | 1.27 | 1.14 | 2.37 | 1.16 | 0.94 | 0.42 | 1.24 | 1.02 | 2.25 | 1.09 |
| 1-Month Momentum | 1.47 | 0.5 | 1.55 | 1.59 | 3.14 | 1.58 | 1.47 | 0.42 | 1.58 | 1.57 | 3.13 | 1.62 |
| 12-Month Momentum | 1.4 | 0.49 | 1.54 | 1.54 | 3.06 | 1.53 | 1.42 | 0.44 | 1.48 | 1.55 | 3.1 | 1.59 |
| Size | 0.34 | 0.49 | 0.74 | 0.59 | 1.33 | 0.8 | 0.33 | 0.42 | 0.82 | 0.58 | 1.32 | 0.8 |
| Profitability | 0.41 | 0.49 | 0.7 | 0.66 | 1.49 | 0.71 | 0.36 | 0.44 | 0.64 | 0.6 | 1.46 | 0.72 |
| Return-on-Equity | 0.68 | 0.49 | 0.85 | 0.89 | 1.85 | 0.84 | 0.66 | 0.44 | 0.76 | 0.8 | 1.75 | 0.79 |
| Return Volatility | 0.98 | 0.5 | 1.21 | 1.11 | 2.36 | 1.07 | 0.96 | 0.42 | 1.11 | 1.08 | 2.38 | 1.04 |
| Growth in Sales minus Growth in Inventory | 1.49 | 0.5 | 1.54 | 1.55 | 3.1 | 1.58 | 1.46 | 0.42 | 1.53 | 1.51 | 3.1 | 1.58 |
| Stock turnover | 0.61 | 0.5 | 0.86 | 0.78 | 1.75 | 0.73 | 0.55 | 0.42 | 0.72 | 0.72 | 1.65 | 0.68 |
| Turnover volatility | 0.9 | 0.5 | 1.06 | 0.99 | 2.18 | 0.92 | 0.87 | 0.42 | 0.93 | 0.99 | 2.17 | 0.88 |
| Zero Trading Days | 0.68 | 0.5 | 0.91 | 0.81 | 1.83 | 1.09 | 0.61 | 0.42 | 0.96 | 0.76 | 1.73 | 1.02 |

Notes: Table reports total trading costs in percentage points based upon 1bps per % turnover in each leg of the strategy. Maximum turnover is 2 with the exception of strategy G. Factor sorts are detailed in the main paper. Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High (Low) ESG is defined as firms in the top (bottom) 30% of Refinitiv ESG scores. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.16: Strategy Portfolio Trading Costs - DJSI Membership

| Factor | Equal Weighting | | | | | | Value Weighting | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | A | B | C | D | G | H | A | B | C | D | G | H |
| Asset Growth | 1.2 | 0.26 | 1.19 | 1.3 | 2.51 | 1.19 | 1.13 | 0.22 | 1.16 | 1.2 | 2.37 | 1.11 |
| CAPM Beta | 0.44 | 0.26 | 0.51 | 0.53 | 1.07 | 0.52 | 0.39 | 0.22 | 0.49 | 0.53 | 1.02 | 0.56 |
| Book-to-Market Ratio | 0.44 | 0.25 | 0.55 | 0.56 | 1.07 | 0.56 | 0.38 | 0.23 | 0.58 | 0.56 | 1.03 | 0.56 |
| Growth in Shares Outstanding | 1.02 | 0.26 | 1.06 | 1.12 | 2.17 | 1.07 | 0.98 | 0.23 | 1.01 | 1.08 | 2.13 | 1.07 |
| Growth in Book Value of Equity | 1.21 | 0.25 | 1.23 | 1.21 | 2.47 | 1.31 | 1.14 | 0.23 | 1.09 | 1.13 | 2.35 | 1.21 |
| Industry Adjusted Cashflow | 1.07 | 0.26 | 1.03 | 1.18 | 2.28 | 1.14 | 1.02 | 0.23 | 0.99 | 1.12 | 2.2 | 1.09 |
| Growth in Inventory | 1.18 | 0.26 | 1.35 | 1.26 | 2.47 | 1.19 | 1.16 | 0.22 | 1.36 | 1.21 | 2.41 | 1.15 |
| Change in 6-Month Momentum | 1.41 | 0.26 | 1.36 | 1.39 | 2.84 | 1.35 | 1.39 | 0.22 | 1.37 | 1.43 | 2.87 | 1.36 |
| Earnings Announcement Returns | 1.38 | 0.26 | 1.4 | 1.44 | 2.82 | 1.41 | 1.4 | 0.22 | 1.42 | 1.51 | 2.89 | 1.44 |
| Growth in Capital Expenditure | 1.08 | 0.26 | 1.07 | 1.15 | 2.26 | 1.12 | 1.02 | 0.23 | 1.08 | 1.09 | 2.15 | 1.11 |
| Growth in Long Term Net Operating Assets | 1.18 | 0.26 | 1.26 | 1.32 | 2.52 | 1.25 | 1.15 | 0.23 | 1.28 | 1.32 | 2.49 | 1.25 |
| Illiquidity | 0.52 | 0.26 | 0.84 | 0.74 | 1.34 | 0.79 | 0.48 | 0.22 | 0.94 | 0.73 | 1.29 | 0.74 |
| Industry Momentum | 1.34 | 0.26 | 1.42 | 1.4 | 2.77 | 1.36 | 1.31 | 0.22 | 1.44 | 1.41 | 2.74 | 1.37 |
| Investment | 1 | 0.26 | 1.16 | 1.04 | 2.1 | 1.02 | 0.94 | 0.23 | 1.14 | 0.94 | 2 | 0.95 |
| 1-Month Momentum | 1.47 | 0.26 | 1.48 | 1.46 | 2.97 | 1.48 | 1.47 | 0.23 | 1.56 | 1.54 | 3.03 | 1.49 |
| 12-Month Momentum | 1.4 | 0.25 | 1.48 | 1.5 | 2.93 | 1.45 | 1.42 | 0.23 | 1.44 | 1.51 | 2.98 | 1.49 |
| Size | 0.34 | 0.26 | 0.61 | 0.56 | 0.97 | 0.53 | 0.33 | 0.22 | 0.69 | 0.57 | 0.97 | 0.54 |
| Profitability | 0.41 | 0.25 | 0.53 | 0.5 | 0.99 | 0.54 | 0.36 | 0.23 | 0.46 | 0.51 | 0.96 | 0.48 |
| Return-on-Equity | 0.68 | 0.25 | 0.7 | 0.75 | 1.5 | 0.72 | 0.66 | 0.23 | 0.64 | 0.78 | 1.53 | 0.72 |
| Return Volatility | 0.98 | 0.26 | 1 | 1.01 | 2.06 | 0.95 | 0.96 | 0.23 | 0.88 | 0.96 | 2.05 | 0.98 |
| Growth in Sales minus Growth in Inventory | 1.49 | 0.26 | 1.49 | 1.43 | 2.95 | 1.47 | 1.46 | 0.23 | 1.51 | 1.41 | 2.93 | 1.47 |
| Stock turnover | 0.61 | 0.26 | 0.66 | 0.73 | 1.43 | 0.65 | 0.55 | 0.23 | 0.53 | 0.69 | 1.35 | 0.6 |
| Turnover volatility | 0.9 | 0.26 | 0.88 | 0.98 | 1.94 | 0.91 | 0.87 | 0.23 | 0.69 | 0.96 | 1.93 | 0.87 |
| Zero Trading Days | 0.68 | 0.26 | 0.79 | 0.75 | 1.52 | 0.81 | 0.61 | 0.23 | 0.83 | 0.68 | 1.41 | 0.73 |

Notes: Table reports total trading costs in percentage points based upon 1bps per % turnover in each leg of the strategy. Maximum turnover is 2 with the exception of strategy G. Factor sorts are detailed in the main paper. Strategy A longs the theoretically high returning sort portfolio (sort high) and shorts the theoretically low returning sort portfolio (sort low). Strategy B longs the highest ESG and shorts the lowest ESG. Strategy C considers only high ESG and then longs sort high and shorts sort low. Strategy D considers only sort high and then longs high ESG and shorts low ESG. Strategy G takes a long position on the high ESG-high sort and low ESG-low sort portfolios. Strategy G then takes a short position on the high ESG-low sort and low ESG-high sort portfolios. Strategy H is long on high ESG-high sort and short on low ESG-low sort. High ESG is defined as the members of the DJSI. Low ESG is defined as non-DJSI members. Data is monthly from October 2005 to September 2019. Portfolios are reconstituted anually on 1st October immediately after the annual DJSI membership is announced.

Table A4.17: Significant Alphas with Trading Cost Adjustment

| Strategy | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| Panel (a) Factor Sorts Equal Weighting: | | | | | | | |
| A | Neutral | Book-to-Market Ratio | | EW | CAPM | -0.33* | -2.24 |
| A | Neutral | Return-on-Equity | | EW | FF5 | -0.32** | -2.82 |
| A | Neutral | Return Volatility | | EW | CAPM | 0.4* | 2.09 |
| A | Neutral | Zero Trading Days | | EW | CAPM | -0.49* | -2.47 |
| Panel (b) Factor Sorts Value Weighting: | | | | | | | |
| A | Neutral | Book-to-Market Ratio | | VW | CAPM | -0.41* | -2.43 |
| A | Neutral | Illiquidity | | VW | CAPM | -0.25* | -2.13 |
| A | Neutral | Return-on-Equity | | VW | FF5 | -0.26* | -2.01 |
| A | Neutral | Return Volatility | | VW | CAPM | 0.53** | 2.74 |
| A | Neutral | Return Volatility | | VW | FF5 | 0.27* | 2.02 |
| A | Neutral | Zero Trading Days | | VW | CAPM | -0.62** | -2.92 |
| A | Neutral | Zero Trading Days | | VW | FF5 | -0.46** | -2.8 |
| Panel (c) ESG Score Equal Weighting: | | | | | | | |
| D | Neutral | Book-to-Market Ratio | Score | EW | CAPM | -0.47* | -2.32 |
| D | Neutral | Return Volatility | Score | EW | CAPM | 0.47* | 1.98 |
| G | Neutral | Profitability | Score | EW | CAPM | -0.53* | -2.59 |
| G | Neutral | Growth in Captial Expenditure | Score | EW | CAPM | -0.44* | -2.23 |
| G | Neutral | Growth in Captial Expenditure | Score | EW | FF5 | -0.49* | -2.56 |
| G | Neutral | 1-Month Momentum | Score | EW | CAPM | -0.52* | -2.22 |
| G | Neutral | Industry Adjusted Cashflow | Score | EW | CAPM | -0.53* | -2.38 |
| G | Neutral | Industry Adjusted Cashflow | Score | EW | FF5 | -0.63** | -2.97 |
| H | Tilt | CAPM Beta | Score | EW | CAPM | 0.58* | 2.13 |
| H | Tilt | Return Volatility | Score | EW | CAPM | 0.55* | 2.41 |
| C-B | | Earnings Announcement Returns | Score | EW | CAPM | -0.33* | -2.35 |
| G-A | | Profitability | Score | EW | CAPM | -0.55* | -2.24 |
| G-A | | CAPM Beta | Score | EW | CAPM | -0.65* | -2.33 |
| G-A | | Return Volatility | Score | EW | CAPM | -0.65* | -2.57 |
| G-A | | Turnover Volatility | Score | EW | CAPM | -0.51* | -2.21 |
| G-A | | Earnings Announcement Returns | Score | EW | FF5 | 0.53* | 2.12 |
| G-A | | Industry Adjusted Cashflow | Score | EW | FF5 | -0.54* | -2.36 |
| G-A | | Industry Momentum | Score | EW | FF5 | 0.47* | 1.99 |
| G-B | | Profitability | Score | EW | CAPM | -0.66** | -3.05 |

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Table A4.17: Significant Alphas with Trading Cost Adjustment

| Strategy | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| G-B | | Growth in Captial Expenditure | Score | EW | CAPM | -0.56* | -2.43 |
| G-B | | 1-Month Momentum | Score | EW | CAPM | -0.64* | -2.34 |
| G-B | | Industry Adjusted Cashflow | Score | EW | CAPM | -0.66* | -2.49 |
| G-B | | Industry Adjusted Cashflow | Score | EW | FF5 | -0.48* | -2.02 |
| G-C | | Profitability | Score | EW | CAPM | -0.78* | -2.32 |
| G-C | | Growth in Captial Expenditure | Score | EW | CAPM | -0.37** | -2.67 |
| G-C | | Growth in Sales minus Growth in Inventory | Score | EW | CAPM | -0.33* | -2.16 |
| G-C | | 1-Month Momentum | Score | EW | CAPM | -0.42* | -2.16 |
| G-C | | Zero Trading Days | Score | EW | CAPM | -0.34** | -2.64 |
| G-D | | Profitability | Score | EW | CAPM | -0.46* | -2.58 |
| G-D | | CAPM Beta | Score | EW | CAPM | -0.67* | -2.33 |
| G-D | | Return Volatility | Score | EW | CAPM | -0.72*** | -3.56 |
| G-D | | Return Volatility | Score | EW | FF5 | -0.39* | -2.08 |
| G-D | | Stock Turnover | Score | EW | CAPM | -0.42* | -1.98 |
| G-D | | Turnover Volatility | Score | EW | CAPM | -0.48** | -2.69 |
| G-D | | Industry Adjusted Cashflow | Score | EW | FF5 | -0.31* | -2.04 |
| G-D | | Industry Momentum | Score | EW | FF5 | 0.47* | 2.59 |
| H-A | | Profitability | Score | EW | CAPM | 0.29* | 2.22 |
| H-A | | Growth in Sales minus Growth in Inventory | Score | EW | CAPM | 0.3* | 2.20 |
| H-A | | Growth in Sales minus Growth in Inventory | Score | EW | FF5 | 0.27* | 2.00 |
| Panel (d) ESG Score Value Weighting: | | | | | | | |
| D | Neutral | Book-to-Market Ratio | Score | VW | CAPM | -0.43* | -2.34 |
| D | Neutral | Return Volatility | Score | VW | CAPM | 0.73** | 2.83 |
| D | Neutral | Return Volatility | Score | VW | FF5 | 0.45* | 2.41 |
| D | Neutral | Zero Trading Days | Score | VW | CAPM | -0.72* | -2.37 |
| D | Neutral | Zero Trading Days | Score | VW | FF5 | -0.63* | -2.34 |
| G | Neutral | Industry Adjusted Cashflow | Score | VW | CAPM | -0.66** | -2.82 |
| G | Neutral | Industry Adjusted Cashflow | Score | VW | FF5 | -0.69** | -2.96 |
| G | Neutral | Zero Trading Days | Score | VW | CAPM | -0.67* | -2.24 |
| G | Neutral | Zero Trading Days | Score | VW | FF5 | -0.65* | -2.06 |
| H | Tilt | Profitability | Score | VW | CAPM | 0.43* | 2.41 |
| H | Tilt | Return Volatility | Score | VW | CAPM | 0.54* | 2.25 |
| H | Tilt | Industry Momentum | Score | VW | FF5 | -0.47* | -2.34 |

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Table A4.17: Significant Alphas with Trading Cost Adjustment

| Strategy | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| C-B | | Change in 6-Month Momentum | Score | VW | CAPM | -0.37* | -2.19 |
| C-B | | Industry Momentum | Score | VW | CAPM | -0.45* | -2.44 |
| G-A | | Return Volatility | Score | VW | CAPM | -0.57* | -2.27 |
| G-A | | Turnover Volatility | Score | VW | CAPM | -0.57* | -2.29 |
| G-A | | Return-on-Equity | Score | VW | FF5 | 0.4* | 2.18 |
| G-A | | Earnings Announcement Returns | Score | VW | FF5 | 0.61** | 2.89 |
| G-A | | Industry Momentum | Score | VW | FF5 | 0.73** | 2.69 |
| G-B | | Profitability | Score | VW | CAPM | -0.48* | -2.01 |
| G-B | | Industry Adjusted Cashflow | Score | VW | CAPM | -0.79** | -2.91 |
| G-B | | Industry Adjusted Cashflow | Score | VW | FF5 | -0.54* | -2.01 |
| G-B | | Zero Trading Days | Score | VW | CAPM | -0.8** | -2.7 |
| G-C | | Growth in Sales minus Growth in Inventory | Score | VW | CAPM | -0.49* | -2.29 |
| G-C | | Industry Adjusted Cashflow | Score | VW | CAPM | -0.85* | -2.26 |
| G-C | | Zero Trading Days | Score | VW | CAPM | -0.47** | -3.18 |
| G-D | | Profitability | Score | VW | CAPM | -0.59** | -2.91 |
| G-D | | Return Volatility | Score | VW | CAPM | -0.77*** | -3.64 |
| G-D | | Return Volatility | Score | VW | FF5 | -0.48** | -2.63 |
| G-D | | Turnover Volatility | Score | VW | CAPM | -0.42* | -2.24 |
| G-D | | Earnings Announcement Returns | Score | VW | FF5 | 0.37* | 2.44 |
| G-D | | Industry Momentum | Score | VW | FF5 | 0.61** | 2.76 |
| H-A | | Profitability | Score | VW | CAPM | 0.28* | 2.01 |
| Panel (e) DJSI Equal Weighting: | | | | | | | |
| C | Tilt | Return Volatility | DJSI | EW | FF5 | -0.23* | -2.21 |
| C | Tilt | Stock Turnover | DJSI | EW | FF5 | -0.2* | -2.26 |
| C | Tilt | Turnover Volatility | DJSI | EW | FF5 | -0.19* | -2.22 |
| C | Tilt | Illiquidity | DJSI | EW | FF5 | -0.22* | -2.24 |
| G | Neutral | Profitability | DJSI | EW | CAPM | -0.58** | -2.82 |
| G | Neutral | Industry Adjusted Cashflow | DJSI | EW | CAPM | -0.41* | -2.29 |
| G | Neutral | Return Volatility | DJSI | EW | CAPM | -0.5* | -2.22 |
| G | Neutral | Stock Turnover | DJSI | EW | CAPM | -0.57* | -2.39 |
| G | Neutral | Turnover Volatility | DJSI | EW | CAPM | -0.76** | -3.28 |
| G | Neutral | Turnover Volatility | DJSI | EW | FF5 | -0.6* | -2.5 |
| G | Neutral | Investment | DJSI | EW | FF5 | -0.52* | -2.45 |
| G | Neutral | CAPM Beta | DJSI | EW | FF5 | -0.38* | -1.97 |
| G | Neutral | Growth in Inventory | DJSI | EW | FF5 | -0.68* | -2.41 |

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Table A4.17: Significant Alphas with Trading Cost Adjustment

| Strategy | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| G | Neutral | Growth in Captial Expenditure | DJSI | EW | FF5 | -0.43* | -2.29 |
| H | Tilt | Return Volatility | DJSI | EW | CAPM | 0.43* | 2.06 |
| C-B | | Change in Shares Outstanding | DJSI | EW | CAPM | -0.16* | -2.09 |
| C-B | | Stock Turnover | DJSI | EW | CAPM | -0.19** | -2.68 |
| C-B | | Stock Turnover | DJSI | EW | FF5 | -0.19** | -2.63 |
| C-B | | Turnover Volatility | DJSI | EW | CAPM | -0.2** | -2.79 |
| C-B | | Turnover Volatility | DJSI | EW | FF5 | -0.18* | -2.28 |
| C-B | | Illiquidity | DJSI | EW | CAPM | -0.26*** | -3.72 |
| C-B | | Illiquidity | DJSI | EW | FF5 | -0.21** | -3.15 |
| C-B | | Industry Momentum | DJSI | EW | CAPM | -0.35* | -2.14 |
| C-B | | Industry Momentum | DJSI | EW | FF5 | -0.38* | -2.04 |
| C-B | | Return Volatility | DJSI | EW | FF5 | -0.22* | -2.17 |
| D-A | | Turnover Volatility | DJSI | EW | CAPM | -0.47* | -2.4 |
| G-A | | Profitability | DJSI | EW | CAPM | -0.59* | -2.54 |
| G-A | | CAPM Beta | DJSI | EW | CAPM | -0.79* | -2.58 |
| G-A | | CAPM Beta | DJSI | EW | FF5 | -0.60* | -2.32 |
| G-A | | Industry Adjusted Cashflow | DJSI | EW | CAPM | -0.42* | -1.99 |
| G-A | | Stock Turnover | DJSI | EW | CAPM | -0.82** | -3.19 |
| G-A | | Stock Turnover | DJSI | EW | FF5 | -0.55* | -2.39 |
| G-A | | Turnover Volatility | DJSI | EW | CAPM | -0.94*** | -4.05 |
| G-A | | Turnover Volatility | DJSI | EW | FF5 | -0.61** | -2.64 |
| G-A | | Zero Trading Days | DJSI | EW | CAPM | 0.56* | 2.33 |
| G-A | | Investment | DJSI | EW | FF5 | -0.58* | -2.02 |
| G-A | | Growth in Inventory | DJSI | EW | FF5 | -0.66* | -2.19 |
| G-A | | Return Volatility | DJSI | EW | FF5 | -0.56* | -2.19 |
| G-B | | Profitability | DJSI | EW | CAPM | -0.66** | -3.29 |
| G-B | | Investment | DJSI | EW | CAPM | -0.41* | -2.06 |
| G-B | | Investment | DJSI | EW | FF5 | -0.52* | -2.35 |
| G-B | | Growth in Captial Expenditure | DJSI | EW | CAPM | -0.35* | -2.05 |
| G-B | | Growth in Captial Expenditure | DJSI | EW | FF5 | -0.42* | -2.27 |
| G-B | | Industry Adjusted Cashflow | DJSI | EW | CAPM | -0.49* | -2.51 |
| G-B | | Return Volatility | DJSI | EW | CAPM | -0.58* | -2.23 |
| G-B | | Stock Turnover | DJSI | EW | CAPM | -0.65* | -2.37 |
| G-B | | Turnover Volatility | DJSI | EW | CAPM | -0.84** | -3.19 |
| G-B | | Turnover Volatility | DJSI | EW | FF5 | -0.59* | -2.15 |

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Table A4.17: Significant Alphas with Trading Cost Adjustment

| Strategy | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| G-B | | Growth in Inventory | DJSI | EW | FF5 | -0.67* | -2.17 |
| G-C | | Profitability | DJSI | EW | CAPM | -0.71* | -2.41 |
| G-C | | Investment | DJSI | EW | CAPM | -0.3* | -2.31 |
| G-C | | Investment | DJSI | EW | FF5 | -0.3* | -2.17 |
| G-C | | Growth in Inventory | DJSI | EW | CAPM | -0.43* | -2.38 |
| G-C | | Growth in Inventory | DJSI | EW | FF5 | -0.46* | -2.55 |
| G-C | | Growth in Captial Expenditure | DJSI | EW | CAPM | -0.32* | -2.28 |
| G-C | | Stock Turnover | DJSI | EW | CAPM | -0.46* | -2.03 |
| G-C | | Turnover Volatility | DJSI | EW | CAPM | -0.64** | -2.94 |
| G-C | | Growth in Capital Expenditure | DJSI | EW | FF5 | -0.32* | -2.34 |
| G-D | | Profitability | DJSI | EW | CAPM | -0.3* | -2.49 |
| G-D | | CAPM Beta | DJSI | EW | CAPM | -0.72** | -2.66 |
| G-D | | CAPM Beta | DJSI | EW | FF5 | -0.46* | -2.17 |
| G-D | | Change in Shares Outstanding | DJSI | EW | CAPM | -0.24* | -1.97 |
| G-D | | Industry Adjusted Cashflow | DJSI | EW | CAPM | -0.27* | -2.24 |
| G-D | | Industry Adjusted Cashflow | DJSI | EW | FF5 | -0.27* | -2.38 |
| G-D | | Return Volatility | djsi | EW | CAPM | -0.67*** | -3.5 |
| G-D | | Return Volatility | djsi | EW | FF5 | -0.38* | -2.44 |
| G-D | | Stock Turnover | DJSI | EW | CAPM | -0.51** | -2.64 |
| G-D | | Turnover Volatility | DJSI | EW | CAPM | -0.47** | -3.12 |
| G-D | | Investment | DJSI | EW | FF5 | -0.32* | -2.22 |
| G-D | | Growth in Inventory | DJSI | EW | FF5 | -0.28* | -2.32 |
| G-D | | Growth of Long Term Net Operating Assets | DJSI | EW | FF5 | -0.28* | -2.59 |
| H-A | | Asset Growth | DJSI | EW | CAPM | 0.25* | 2.18 |
| H-A | | Growth in Sales minus Growth in Inventory | DJSI | EW | CAPM | 0.34* | 2.19 |
| Panel (f) DJSI Value Weighting: | | | | | | | |
| C | Tilt | Illiquidity | DJSI | VW | CAPM | -0.21* | -2.13 |
| C | Tilt | Illiquidity | DJSI | VW | FF5 | -0.25* | -2.46 |
| C | Tilt | Industry Momentum | DJSI | VW | CAPM | -0.37* | -2.38 |
| C | Tilt | Industry Momentum | DJSI | VW | FF5 | -0.43** | -2.65 |
| C | Tilt | CAPM Beta | DJSI | VW | FF5 | -0.24* | -2.15 |
| C | Tilt | Growth in Long Term Net Operating Assets | DJSI | VW | FF5 | -0.27* | -2.26 |
| C | Tilt | Return Volatility | DJSI | VW | FF5 | -0.27* | -2.46 |

*Continued on next page...*

Table A4.17: Significant Alphas with Trading Cost Adjustment

| Strategy | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| C | Tilt | Stock Turnover | DJSI | VW | FF5 | -0.19* | -2 |
| C | Tilt | Turnover Volatility | DJSI | VW | FF5 | -0.21* | -2.03 |
| D | Neutral | Return Volatility | DJSI | VW | CAPM | 0.55* | 2.11 |
| G | Neutral | Profitability | DJSI | VW | CAPM | -0.52* | -2.29 |
| G | Neutral | Profitability | DJSI | VW | FF5 | -0.52* | -2.17 |
| G | Neutral | Growth in Long Term Net Operating Assets | DJSI | VW | CAPM | -0.48** | -3.04 |
| G | Neutral | Growth in Long Term Net Operating Assets | DJSI | VW | FF5 | -0.51*** | -3.67 |
| G | Neutral | Turnover Volatility | DJSI | VW | CAPM | -0.65* | -2.39 |
| G | Neutral | Turnover Volatility | DJSI | VW | FF5 | -0.57* | -2.05 |
| H | Tilt | Return Volatility | DJSI | VW | CAPM | 0.52* | 2.4 |
| H | Tilt | Turnover Volatility | DJIS | VW | CAPM | 0.32* | 2.07 |
| C-B | | Growth in Long Term Net Operating Assets | DJSI | VW | CAPM | -0.19* | -2.11 |
| C-B | | Growth in Long Term Net Operating Assets | DJSI | VW | FF5 | -0.19* | -2.09 |
| C-B | | Illiquidity | DJSI | VW | CAPM | -0.19*** | -4.5 |
| C-B | | Illiquidity | DJSI | VW | FF5 | -0.17*** | -3.63 |
| C-B | | Industry Momentum | DJSI | VW | CAPM | -0.35** | -2.74 |
| C-B | | Industry Momentum | DJSI | VW | FF5 | -0.35* | -2.42 |
| C-B | | Return Volatility | DJSI | VW | FF5 | -0.19* | -2.27 |
| D-A | | Size | DJSI | VW | CAPM | 0.57* | 2.37 |
| D-A | | Industry Momentum | DJSI | VW | CAPM | 0.29* | 2.1 |
| D-A | | Size | DJSI | VW | FF5 | 0.55* | 2.33 |
| D-A | | Growth in Long Term Net Operating Assets | DJSI | VW | FF5 | -0.21* | -2.04 |
| G-A | | Size | DJSI | VW | CAPM | 0.66* | 2.00 |
| G-A | | Size | DJSI | VW | FF5 | 0.57* | 2.03 |
| G-A | | Profitability | DJSI | VW | CAPM | -0.67** | -3.01 |
| G-A | | Profitability | DJSI | VW | FF5 | -0.51* | -2.27 |
| G-A | | CAPM Beta | DJSI | VW | CAPM | -0.72* | -2.26 |
| G-A | | CAPM Beta | DJSI | VW | FF5 | -0.57* | -1.97 |
| G-A | | Return Volatility | DJSI | VW | CAPM | -0.8** | -2.71 |
| G-A | | Return Volatility | DJSI | VW | FF5 | -0.67** | -2.61 |
| G-A | | Stock Turnover | DJSI | VW | CAPM | -0.64* | -2.24 |
| G-A | | Turnover Volatility | DJSI | VW | CAPM | -0.92** | -3.27 |
| G-A | | Turnover Volatility | DJSI | VW | FF5 | -0.73** | -2.63 |

*Continued on next page...*

Table A4.17: Significant Alphas with Trading Cost Adjustment

| Strategy | Position | Anomaly | ESG | Weight | Model | Alpha | t-stat |
|---|---|---|---|---|---|---|---|
| G-A | | Growth in Long Term Net Operating Assets | DJSI | VW | FF5 | -0.54** | -2.9 |
| G-B | | Profitability | DJSI | VW | CAPM | -0.5* | -2.3 |
| G-B | | Growth in Long Term Net Operating Assets | DJSI | VW | CAPM | -0.46* | -2.5 |
| G-B | | Growth in Long Term Net Operating Assets | DJSI | VW | FF5 | -0.43** | -2.63 |
| G-B | | Turnover Volatility | DJSI | VW | CAPM | -0.63* | -2.2 |
| G-C | | Turnover Volatility | DJSI | VW | CAPM | -0.53* | -2.23 |
| G-D | | Profitability | DJSI | VW | CAPM | -0.47*** | -3.62 |
| G-D | | Profitability | DJSI | VW | FF5 | -0.3* | -2.5 |
| G-D | | CAPM Beta | DJSI | VW | CAPM | -0.73* | -2.49 |
| G-D | | CAPM Beta | DJSI | VW | FF5 | -0.48* | -2.03 |
| G-D | | Return Volatility | DJSI | VW | CAPM | -0.81*** | -4 |
| G-D | | Return Volatility | DJSI | VW | FF5 | -0.58*** | -3.89 |
| G-D | | Stock Turnover | DJSI | VW | CAPM | -0.56** | -2.85 |
| G-D | | Stock Turnover | DJSI | VW | FF5 | -0.43** | -2.62 |
| G-D | | Turnover Volatility | DJSI | VW | CAPM | -0.57*** | -3.97 |
| G-D | | Turnover Volatility | DJSI | VW | FF5 | -0.46*** | -3.69 |
| G-D | | Growth in Long Term Net Operating Assets | DJSI | VW | FF5 | -0.33* | -2.57 |
| G-D | | Growth in Sales minus Growth in Inventory | DJSI | VW | FF5 | -0.27* | -2 |

Notes: Table provides a list of all strategy, sort variable, ESG measure, weighting and asset pricing model combinations that produce significant alpha from the approximately 2200 possible combinations. All returns are calculated after the deduction of trading costs of 1bps per % turnover on each leg of the strategy in each month following the rule of thumb in Chen and Velikov (2020). Strategies are as defined in the main paper. A to G are pure strategies, whilst two letters denotes a comparison between the respective pure strategies. Position reports whether the strategy has an ESG tilt, that is the strategy longs higher ESG stocks than it shorts, or whether the strategy is neutral on ESG. We do not have any strategies which long lower ESG than they short. ESG reports the measure of ESG used in the portfolio construction and is either Score for the Refinitiv ESG Score, or DJSI for the firm being a member of the Dow Jones Sustainability Index North America. Weightings for portfolio calculations are either equal (EW) or value (VW). Two asset pricing models are used, being the capital asset pricing model (CAPM) and the Fama and French (2015) five factor model (FF5). Alpha reports the abnormal return estimate from the model, with significance determined by a test that the true alpha coefficient is 0. Tests are estimated with Newey et al. (1987) adjusted standard errors at lag 6. Significance denoted by $* - 5\%$, $** - 1\%$ and $*** - 0.1\%$

alpha against both CAPM and FF5 under value weighting, demonstrating that not all of the traditional factors lose significance when trading costs are introduced.

Since our focus is on strategies which long only high ESG stocks, the poor performance of G is of less concern. The double enhancement strategy, H, produces positive alphas and, where the H-A comparison is significant, is able to deliver higher trading cost adjusted returns than the factor sort benchmark strategy A. Looking at the associated t-statistics reveals that none of these results meet the stricter criteria of Harvey et al. (2016) that the t-statistic should exceed 3. When comparing the single enhancement of strategy D with A there are also occasions where the consideration of only high ESG stocks delivers higher alpha than strategy A. Examples include size for the DJSI under value weighting, the comparison with strategy A revealing additional alpha against the CAPM is 0.57 and against the FF5 is 0.55.

In summary the number of siginificant positive alphas is reduced greatly by the consideration of trading costs. However, there remain cases where having a strategy tilted towards ESG can still produce a significant positive ESG flavoured alpha.

# Chapter 5

# Conclusions

## 5.1 Conclusion

This thesis explores the links between firms' corporate social responsibility (CSR) performance and stock returns. The thesis further recognises the importance of corporate financial performance (CFP) as a key moderator. Chapter 2 asks how the impact of CSR on CFP varies across the CFP distribution. An improved counterfactual to Dow Jones Sustainability Index North America (DJSI) index listings is targeted in Chapter 3. The aim of Chapter 3 is then to evaluate the effect of CSR recognition on stock returns. Finally, Chapter 4 asks whether it is possible to increase exposure to stocks with high Environment Social Governance (ESG) ratings without paying an alpha cost. Each chapter fuses innovative empirical approaches with established knowledge from the finance literature to give new insight on the role CSR is playing in financial markets.

Links between CSR and CFP are understood through the stakeholder dimensions of Freeman (1984) and Freeman et al. (2010). Typically the result is an insignificant coefficient on each CSR dimension in the regressions for CFP (Gillan et al., 2021). Motivation for heterogeneity in the effect of CSR can be found in the arguments of Green and Peloza (2014) and Gallardo-Vázquez et al. (2019) on consumer demand being dependent on the relative CFP of the firm. There is also evidence in Orlitzky (2001) and subsequent work that size matters. Chapter 2 uses unconditional quantile regression (UQR) to show that relative CFP is important. Different stakeholder dimensions are shown to be significant at different quantiles. To make comparison with the existing literature, coefficients from a linear model of the type commonly used in the literature are also reported. These linear model coefficients are insignificant in the way that they are in the existing literature. It is shown that this is because the ordinary least squares (OLS) model averages across conflicting significant coefficients in the UQR. A good example is provided when we consider environment as a stakeholder dimension and return on assets as the measurement of CFP. Low profit firms have a negative coefficient on the environment, but those near the median have significant positive coefficients. The best CFP performing firms also have a negative coefficient. Here we may see that improving environmental performance can raise CFP for some firms, but that low profit firms will suffer even poorer financial performance if they increase environmental strengths. Chapter 2 also shows that effects of CSR on CFP have increased since the global financial crisis. By considering the results of Chapter 2, business decision makers may better select between potential investment projects, policymakers may understand the incentives needed to promote CSR performance, and academics may learn more about the true links between CSR and CFP.

Identification of the listing effects to social indexes like the DJSI allows a deeper understanding of the way recognition as a CSR leader impacts on stock returns. Chapter 3 uses the generalised synthetic control (gsynth) method of Xu (2017), inspired by the benefits of the standard synthetic control method of Abadie and Gardeazabal (2003) and Abadie et al. (2010). Acemoglu et al. (2016) argues that synthetic controls offer improvement relative to the widely used event study techniques because the synthetic control removes the parallel trend assumption. The advantage of gsynth is that it allows more than one unit to be treated simultaneously by preserving cointegrating relationships between the treated units. That is, if there is more than one firm listed to the DJSI in the same year from the same industry then the counterfactual from gsynth is robust. Further value is provided by the robustness of synthetic controls to shocks that only affect relevant peer stocks, in this case firms in the same industry. From the new counterfactual, it is shown that abnormal returns to listing are stronger than previously identified, that these effects have intensified since the global financial crisis, and that the returns are much larger when the listing firm comes from outside the S&P 500. It is also shown that the abnormal return effects are more persistent than previously estimated for both listing and de-listing. Evidence is provided that DJSI listing effects are becoming analogous to those for the S&P 500. The conclusion from Chapter 3 is thus that recognition as a CSR leader does bring abnormal returns and that those returns are increasingly persistent.

A trade off between the goals of increased ESG exposure and abnormal returns has long been identified in the literature. This prompts Derwall et al. (2011) to conclude that investors must be either “values based” or “profit seeking”. The distinction is also made in the contemporary theoretical work of Pástor et al. (2020). Chapter 4 demonstrates that the two goals need not be mutually exclusive. That is we show that there is no significant alpha cost to increasing ESG exposure. To achieve this insight, we propose ESG flavoured strategies in which ESG information is included alongside traditional factors in the selection of stocks. Across the 24 firm characteristics identified by Green et al. (2017) to have been mispriced for non-microcaps, we show that there are no cases in which an ESG enhanced strategy produces lower abnormal returns than the traditional factor. To ensure an investable and well-researched universe, we consider only members of the S&P 500. Resulting strategies may therefore be implemented with limited transaction costs. Although the results offer no incentive for investors who do not care about ESG to follow ESG enhancement, the results do offer economic rationale for the increase in assets under management in sustainable funds.

## 5.2 Contributions and Implications

The prominence of sustainability within the finance landscape is beyond doubt. Globally, assets under management in sustainable funds have gone above one third of the total assets under management in all funds[1], whilst firms make sustainability reports a critical element of their communication with investors and stakeholders (Goloshchapova et al., 2019; Du and Yu, 2020). The academic literature on sustainability, as captured through CSR and ESG, is expanding rapidly (Gillan et al., 2021). This thesis contains three papers which each make a contribution to the understanding of the economic relevance of CSR. In turn the thesis contributes valuable new insight to the academic community, investors, business decision makers and policymakers.

### 5.2.1 Academic Contributions

Each chapter of the thesis targets contribution to the debate on the role of CSR in financial markets. The work addresses failures to account for heterogeneities in the CSR-CFP-stock returns nexus. In all cases the new insights are made possible by the application of new empirical techniques that better reflect the theoretical underpinnings of the links being modelled. Whether that is recognising the importance of relative CSR in Chapter 2, overcoming the parallel trend assumption in Chapter 3, or giving strategies an ESG flavour in Chapter 4, the approach adopted allows the results to give deeper understanding.

Since Anderson Jr and Cunningham (1972) recognition of the value of CSR to CFP the academic community has been theorising about, and empirically modelling,

[1] See the Bloomberg discussion article from March 2021 at https://www.bloomberg.com/professional/blog/esg-assets-may-hit-53-trillion-by-2025-a-third-of-global-aum/.

the relationship. The stakeholder dimensions of Freeman (1984) and Freeman et al. (2010) have been the main measure of CSR (Mattingly, 2017). Chapter 2 contributes against the inconclusive results in the existing literature (Perrault and Quinn, 2016; Gillan et al., 2021) to show that the relative CFP of the firm matters. In many cases, insignificance of the OLS estimates comes from there being significant positive CFP coefficients at some parts of the CFP distribtuion and significant negative coefficients at others. Uncovering these effects is important to practice and also allows the verification of theoretical results. For example, Wagner et al. (2002) argues that the marginal returns to CSR are diminishing and this inspires Meier et al. (2019) and Sun et al. (2019) to posit the "inverted-U" shaped relationship. Chapter 2 shows the "inverted-U" is present but that it only applies to external dimensions like environment and community. This split between internal and external adds further weight to the position of Mattingly and Berman (2006) that environment and community respond differently to the internal dimensions of product, employees and diversity. Past attempts to bring quantile regression to the discussion showed mixed results. Kang and Liu (2014) found there were no differences in coefficients across quantiles for a single aggregate CSR measure, but Shawtari et al. (2016) found that there are differences for when the CSR measure is corporate governance. As the first to apply quantile regression in any form to the stakeholder dimensions, Chapter 2 contributes further evidence of variation across the distribution. Support is provided for a further development of theory which recognises asymmetry between the stakeholder dimensions that is argued for by Perrault and Quinn (2016).

Within the attempts to understand the effects of listing to social indexes, like the DJSI, there have been mixed results. Heterogeneity is seen in the time period over which abnormal returns to listing are captured and the means through which those abnormal returns are measured. Uniformity is found in the use of the capital asset pricing model (CAPM) to identify the abnormal returns for an individual stock. Existing studies follow guidance in MacKinlay (1997) to construct abnormal returns as the difference between observed returns and those which would be predicted using a pricing model such as the CAPM that was fitted to the returns of the same stock during a pre-treatment period. Listing effects are identified by either two-sample tests on the abnormal returns of listed and non-listed firms, or by a regression where a dummy indicates a listing firm (Acemoglu et al., 2016; Hawn et al., 2018; Durand et al., 2019). Chapter 3 argues the CAPM is not approrpriate since it assumes that the trend of the stock post listing is parallel to the pre-listing[2]. Previous work to overcome the

[2] To understand the parallel trend, consider that the CAPM model regresses the excess return of

parallel trend in stock return event studies has used GARCH family models, such as the BEKK-GARCH (Yin et al., 2018), to model the volatility of the treated firm and market in a bivariate setting. However, using such models creates complexity and is not employed within the existing DJSI listing effects literature. There is still a reliance on the control period modelling and a lack of robustness to shocks to peers. By dropping the parallel trend assumption, synthetic control methods have clear advantages in finance (Acemoglu et al., 2016). To overcome the parallel trend problem, the synthetic control creates a set of stocks whose weighted average return during the control period matches closely to the return performance of the listing stock. The assumption is then that the listing stock would have continued to behave in the same way as that weighted portfolio if it had not been listed. The counterfactual portfolio is unique to the listing stock and does not need to continue on a parallel path relative to the market during the listing period. Unlike the synthetic control method of Abadie and Gardeazabal (2003) and Abadie et al. (2010), the gsynth method allows for multiple listings in the same industry. Identifying the listing effect as the difference in returns between the listing stock and the synthetic portfolio of industry peers means Chapter 3 contributes a better representation of the counterfactual case that the listed stock was not listed.

When comparing event study methodologies it is essential to remember that it is not possible to ever know the true counterfactual. Advances, like using the gsynth approach, simply aim to obtain a better estimate of the counterfactual. Because the gsynth counterfactual comes from a control group of stocks that are very similar to the listing stock in observed behaviour, any unobserved risk that affects the control group and the listing stock is accounted for. The weights of the counterfactual portfolio further ensure that the relative strengths of the unobserved risks are also accounted for. This is distinct from the asset pricing model approaches, which assume no change in risk exposure as the coefficients are unchanged from the control period. Allowing changes in risk as a result of the listing is a key advantage of synthetic control approaches like gsynth. The demonstration of significant cumulative abnormal returns ahead of the formal listing announcements, and the persistence of the abnormal returns post global financial crisis, show a significance in our results that was not found in Hawn et al.

a stock on the excess return on the market. The coefficient on the market is beta and is interpreted as capturing the risk of the share relative to the market. By using a control period estimate for beta during the treatment period, it is assumed that beta does not change because of the event. This is referred to as a parallel trend since it is being assumed that the returns continue to follow the same trend relative to the market. It is problematic in event studies because it assumes that the risk of the stock does not change because of the event. This parallel trend issue generalises to more advanced asset pricing models and is a concern of the construction of the abnormal return from control period coefficients rather than the choice of asset pricing model.

(2018) and Durand et al. (2019). A further contribution is made through the evidencing that the average listing effects observed are driven by the non-S&P 500 index members. Because of the lower analyst coverage of these firms the DJSI announcement can be thought of as providing information about the firm to the market. By advancing the methodology, Chapter 3 furthers the literature on listing effects for social indexes.

Derwall et al. (2011) argues that investors can be either motivated by ESG, or by profit, but not both because ESG and profit are mutually exclusive. Motivation for Chapter 4 comes from the need to test whether the mutual exclusivity of ESG exposure and obtaining abnormal returns continues. The demonstration that ESG exposure can be increased without an alpha cost through the use of ESG flavoured strategies shows that the two motivations need not be mutually exclusive. The tendency to model stock returns and ESG using sorts solely on ESG has not produced alpha for the long high ESG and short low ESG strategy. Becchetti et al. (2018) and Pedersen et al. (2020) find the opposite, that there is an alpha when longing low ESG and shorting high ESG. Chapter 4 gives a new way to think about investment strategies in which ESG sorts are used to enhance traditional factor sorts.

It is shown that sorts on risk, growth in sales minus growth in inventory, and stock turnover have potential to generate significant positive ESG flavoured alpha. ESG stocks are understood as being lower risk (Oikonomou et al., 2012), benefitting from consumer preference in the product market (Anderson Jr and Cunningham, 1972; McWilliams and Siegel, 2001; Sen and Bhattacharya, 2001), and being better suited to longer term investors. Therefore the result that these characteristics can be interacted with ESG sorts to produce effective ESG flavoured alpha aligns the findings of Chapter 4 with a wider CSR literature. The contributions of the chapter are thus to show that ESG investment need not be suboptimal from an alpha perspective. At a time when investors are seeking to expand their ESG exposure our results are particularly timely.

### 5.2.2 Implications for Investors

Through the theoretic framework of the thesis, each chapter informs investors on the links between CSR and stock returns. The headline implication of the work is that incorporation of CSR information into investment strategies need not impose any cost on abnormal returns. Chapter 2 demonstrates how CSR can affect short-term and long-term CFP. Investors will intuitively look to hold those firms with the best future prospects and therefore learn from the messages of Chapter 2. To make best use of our results, the investor must evaluate the relative position of the firm on the profitability distribution and then consider whether the CSR activities the firm is undertaking are consistent with higher future profits. Chapter 3 shows that it is possible to make significant abnormal returns by longing stocks that will be listed to the DJSI. By identifying likely listings ahead of the announcement an investor may then obtain the listing returns, especially where the firm joining the DJSI is from outside the S&P 500. Results in Chapter 3 show that deletions from the DJSI that are not members of the S&P 500 have significant negative abnormal returns. Investors must pay attention for likely deletions from the DJSI that are outside the S&P 500 to avoid realising the strong negative returns on delisting. Finally, Chapter 4 speaks directly to the investment implications of ESG, comparing the returns on portfolios on factor sorts with those that make use of ESG information. It is seen that raising the exposure to ESG need not restrict the ability to make abnormal returns. Hence, whether understanding the furture profitability, the opportunities for quick gains around listing events, or designing portfolios in light of ESG information, the results in this thesis provide direction to investor choice.

### 5.2.3 Implications for Business Decision Makers

Managers' direct goals align with the financial performance of the firm. Therefore when determining engagement with CSR, managers will appraise the likely impact on CFP. Chapter 2 demonstrates that the relative CFP of the firm is important in determining the extent to which investment in CSR improvement can yield CFP benefits. For example, investment in improving the strengths of the firm in employee relations can be highly profitable for the best performing firms, but brings little benefit to those at the lower end of the CFP distribution. Examples of such employee relations actions are provided by Amazon and Walmart who have both increased the wages of warehouse staff. As Amazon and Walmart are high profit businesses, it may be that they are recongnising the profit relevance of increasing employee dimension strengths that Chapter 2 demonstrates empirically. Absent of a government incentive to raise environmental strengths, the highest CFP firms may understand from our results that it is actually better to reduce their strengths. Environmental performance is shown beneficial only to those firms whose CFP is around the median. Poorer performing firms may gain from investment in the external dimensions, but only on longer term CFP measures like Tobin's q. Managers may thus appraise competing projects using our results and are advised to consider their relative CFP when conducting those appraisals. Both Chapters 3 and 4 demonstrate that there are motivations for investors to hold high ESG stocks. Managers may then understand that improving CSR strength can increase the market value of the firm. Across the three papers of this thesis, the benefits of engaging with CSR, and specifically which dimensions of CSR, are signposted to business decision makers.

### 5.2.4 Implications for Policymakers

Policymakers face well understood incentives to improve the CSR performance of the firms within the economy. Whether that is to meet environmental targets, or to improve the wellbeing of employees and the wider community, the government gains from firms enhancing their CSR strengths and reducing their CSR concerns. Chapter 2 offers direct suggestions for policy from the coefficients of the regressions. Policymakers benefit from being able to see how the intended stakeholder dimension will affect the CFP of firms in different parts of the CFP distribution. Should the target be improved environmental performance, then the overall conclusion is that there is no significant effect of CFP; all firms should be subsidised to improve their environmental performance. However, the results in Chapter 2 show that in fact those performing around the median have significant benefit to improving their environmental performance and do not require incentives. Low profit firms do require subsidies to overcome negative coefficients of environmental strengths on CFP. The best performers also face negative coefficients, but have the profitability necessary to pay for the improvements without subsidy. Policymakers may therefore offer subsidies only to poorer performers. Negative coefficients in our model suggests that the best performing firms get greater profits from not having environmental strengths. Imposing a penalty on firms with the highest CFP that do not improve environmental performance will reduce the profit associated with not having environmental strengths. Lower differences in profit mean that it is more likely firms will comply with the policymakers aim of getting improved environmental performance from all firms. Lessons like this offer clear savings to the government as the revenues from the penalties on the highest CFP firms may be used to fund the subsidies to the low CFP firms. Chapter 2 also shows that only the low CFP firms need incentives for better treatment of employees, and that all firms require incentives to engage more with their local communities. The benefits from longing firms who are to be listed to the DJSI in Chapter 3 mean that investment funds move towards ESG. Promotion of ESG in this way is the goal of the policymaker and so there is little to trouble policymakers in the results. Likewise, the results of Chapter 4 show that funds can follow ESG and so again the government has little need to intervene to reach the high ESG goal.

## 5.3 Directions for Further Research

The contributions of this thesis are designed to open new conversations about the economic relevance of CSR. There are therefore many directions in which the work may be extended that can leverage the insight offered in this thesis.

### 5.3.1 Timing of CSR Investment Recognition

Chapter 2 informs of the importance of the relative CFP of a firm in determining the impact of CSR on CFP. This work is based upon the role that relative CFP plays in consumer perception of firms (Green and Peloza, 2014; Gallardo-Vázquez et al., 2019). However, within this there is an implicit need for consumers to see the CSR activity before it can filter into their demand decisions. Hence, there is a lag to the CSR activity becoming part of the profit of the firm. Meanwhile, there is also a lag between the CSR activity becoming part of the independent CSR assessment data. In Chapter 2 the MSCI KLD dataset is used and this is only updated annually. Therefore, Chapter 2 assumes that the time taken for CSR activity to appear in sales and profit data is similar to the time taken for that CSR activity to appear in the ratings data. This question needs more evaluation. Some projects, such as the construction of a new energy efficient production facility are likely to be obvious to stakeholders long before their impact is felt in ratings. Meanwhile, other dimensions, such as improved wellbeing support schemes for employees, may not become apparent to investors until the ratings agency reports them. It will be fruitful to dig deeper into this question and explore the extent to which different stakeholder dimensions need different treatment within the model timing. These timing questions then impact on the ability of investors to forecast likely listings to the DJSI.

### 5.3.2 Enhancing Understanding of Listing Effects

The gsynth method that is introduced into the study of listing effects in Chapter 3 enables a closer identification of the counterfactual of how a stock which lists to the DJSI would have behaved in the absence of listing. A strength of gsynth is that it makes the estimated abnormal returns robust to any shock which affects the listing firm and a relevant subset of peers. The choice of peers raises questions for further research. In this thesis, the relevant peer group is seen as the other firms in the industry of the listing firm. However, we may use ESG scores to construct a set of peers with similar ESG and hence isolate the investor recognition effect of listing to the DJSI. The gsynth method also allows control variables to contribute to the creation of the counterfactual. Creating counterfactuals using control variables requires data at a higher frequency than the annual accounting information used in Chapter 3, but such data could be identified and used in future work. All of the advantages of gsynth may also be brought to the study of listing effects on other indexes, or to wider finance event studies. Acemoglu et al. (2016) and Acemoglu et al. (2017) discuss the benefits of the simple synthetic control method for financial applications. The gsynth method provides all of these benefits plus the ability to cope with more than one treated unit simultaneously.

### 5.3.3 Time Variance of ESG Flavoured Alphas

Bansal et al. (2021) identifies that socially responsible investments perform best when the economy is performing well. As the time period for which ESG data is available expands, it is possible to understand more about the way in which the performance of our ESG flavoured strategies changes over time. Within the sample for Chapter 4, there is the global financial crisis and associated recovery. Theoretically there is then a balance between good and bad economic times. The Covid-19 period has brought a rapid fall and regrowth in the stock market, but also raises many questions about the likely performance of the economy in the coming decade. Understanding more of the time variance of the ESG flavoured alphas will contribute to the guidance of investors in the developing economic climate. Because of the growth of the assets under management in ESG funds, and the expansion of investor awareness, there is also a need to incorporate the time variance of these demand aspects within the evaluation. Clarity on the long-term validity of our conclusion that ESG exposure may be increased without alpha cost is therefore an ongoing area for research.

### 5.3.4 Financial Data Science and ESG Investment

Machine Learning offers much to the identification of non-linear relationships within datasets like those used in this thesis. Each chapter may be usefully extended by considering the application of supervised learning to the data. Such applications risk overfitting the data. Machine Learning models also face the critique of being black box models that do not make clear to investors, business decision makers, or policymakers why they should act based upon the recommendations. Therefore the most practical aspects of data science that can contribute to the enhancement of research in this thesis lie in the identification of firm level ESG performance. Raghupathi et al. (2020) and Sokolov et al. (2021) both explore means through which firms can be assessed for ESG from more regularly updated information, like news reports. Text mining measures offer near live information on ESG in a way that the annually released independent assessments used in this thesis do not. Investors may use the gathered information from higher frequency sources in decision making. For example, an investor may look at the news report data to identify likely DJSI listings to exploit the gains identified in Chapter 3. However, employing such measures in the studies of this thesis opens up discussions of timing of investor recognition. A major new timing question comes from the fact that the profit data from the firm will remain at much lower frequency than the news announcement ESG measures. Taking maximum benefit from higher frequency data, whilst simultaneously recognising the practical timing concerns, will require important further research to perfect.

From an investor perspective, there are also questions about the construction of ESG flavoured portfolios. There is already a growing literature that applies Machine Learning to stock selection. For example Sokolov et al. (2021) take the higher frequency ESG data they gather to select stocks based upon their ESG performance. The techniques used there may inform the ESG enhanced portfolios of Chapter 4. Bryzgalova et al. (2020) shows how random forest regressions can segment the set of stocks based on the factor variables that are used in Chapter 4. This principle may be extended to include the ESG dimension, as well as exploring whether ESG information can enhance the portfolios created by the random forest. Such splitting of stocks is open to the black box critique, but by looking at the selected stocks we may understand more about the interaction of ESG with the established factor variables.

## 5.4 Limitations of the Study

As with any empirical study there are natural limitations imposed on the inference by the availability of data. Chapter 2 is restricted to 2005 to 2015 inclusive. The creation of the DJSI in 2005 means that Chapters 3 and 4 are also limited for the start of the sample, whilst the need to avoid the impact of Covid-19 means that the upper ends of the datasets are constrained to 2019. ESG scores are only available for the largest firms and so although there can be more than 1000 firms each year the number is still well below the 3000 plus firms that there are in the standard CRSP-Compustat linked sample[3].

Interpretation of the results in Chapter 2 requires consideration of relative financial performance. Although it is reasonable to expect that a manager knows whether their firm is performing near the top, in the middle, or near the bottom of the performance range, it must be understood that they do not know the exact quantile at which they operate. Care must be taken in using any result which is only significant for a very small range of the CFP quantiles. In Chapter 3 it is assumed that no information about listings is available until the official announcement of new members. Large abnormal returns to listing on other days pre-listing may suggest a time when information leaked. No such periods are identified within the data. Chapter 4 has been constructed based on factor sorts that have been shown to be mispriced in Green et al. (2017), but the set of factors may be different if based upon the most up to date data. It is still necessary for investors to excercise judgement before using their own funds to seek the ESG flavoured alpha. These caveats aside the contributions of this thesis remain strong.

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[3]See Bali et al. (2016) for a discussion of the CRSP-Compustat sample and the evolution of firm numbers over time.

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