International Journal of Operations and Production Management

The Impact of 3D Printing Implementation on Stock Returns: A Contingent Dynamic Capabilities Perspective

Journal:	*International Journal of Operations and Production Management*
Manuscript ID	IJOPM-01-2019-0075.R1
Manuscript Type:	Research Paper
Keywords:	3D printing, Additive manufacturing, Event study, Stock returns, Dynamic capabilities, Contingency theory

The Impact of 3D Printing Implementation on Stock Returns: A Contingent Dynamic Capabilities Perspective

Abstract

Purpose – The purpose of this paper is to theoretically hypothesize and empirically test the impact of 3D printing (3DP) implementation on stock returns. It further explores how the stock returns due to 3DP implementation vary across different industry environments.

Design/methodology/approach – This paper integrates the dynamic capabilities view with contingency theory to provide a contingent dynamic capabilities (CDC) perspective on 3DP implementation. It argues that implementing 3DP enables firms to enhance their manufacturing capabilities and gain a competitive advantage, but the extent to which the competitive advantage can be realized is contingent on the fit between 3DP-enhanced manufacturing capabilities and firms' operating environments. Those arguments are tested based on an event study of 232 announcements of 3DP implementation made by U.S. publicly listed firms between 2010 and 2017.

Findings – The event study results show that firms implementing 3DP gain higher stock returns compared with their non-implementation industry peers over two years after the implementation. Such stock returns due to 3DP implementation are more pronounced for firms operating in more munificent, more dynamic, and less competitive industry environments. Those findings are consistent with our CDC perspective.

Originality/value – This is the first research empirically examining the impact of 3DP implementation on stock returns. It provides important implications for managers to implement 3DP to enhance firms' manufacturing capabilities and for researchers to study 3DP implementation from the CDC perspective.

Keywords – 3D printing, Additive manufacturing, Event study, Stock returns, Dynamic capabilities, Contingency theory

1. Introduction

Investment in appropriate manufacturing technology has been a critical managerial decision, not only because it usually involves substantial resource commitments, but also due to its potential in creating competitive advantage (Grant *et al.*, 1991). In todays' rapidly-evolving business world, companies are making continuous efforts to identify innovative technologies that suit their market environments and support strategic goals (Grant *et al.*, 1991). 3D printing (3DP), also known as additive manufacturing, has caught noticeable attention from the business community in recent years (Ernst & Young, 2016; d'Aveni, 2015). Former U.S. President Obama highlighted the strategic importance of 3DP by saying that "3DP has the potential to revolutionize the way we make almost everything" (Gross, 2013). An Ernst & Young (2016) global survey shows that 36% of the firms have already implemented or are considering the implementation of 3DP. Originally adopted as a prototyping technology about thirty years ago, 3DP has evolved to be a direct manufacturing technology for the production of components, parts and even end-use products in different industries (Atzeni and Salmi, 2012; Ernst & Young, 2016). For example, GE aviation used 3DP to build the Advanced Turboprop, the components of which were reduced from 855 to only 12. The simplified design reduced the weight of the engine by 5%, ultimately saving 20% of fuel and achieving 10% more power than its competitors (Van Dusen, 2017). The transformation grows with a more astonishing speed in the U.S. hearing aid industry, which converted to 100% additive manufacturing in less than 500 days (d'Aveni, 2015).

Despite the great progress of 3DP within the past few years, little empirical evidence has been provided of its impact on firm performance. Most previous research of 3DP concentrates on its technological features and industrial applications (Lam *et al.*, 2002; Ventola, 2014; Williams *et al.*, 2010). Recently, the business implications of 3DP have received greater attention, though the majority of the studies only provide qualitative discussions of its benefits, limitations, and socio-economic impact (Huang *et al.*, 2012; Petrick and Simpson, 2013; Weller *et al.*, 2015; Ford and Despeisse, 2016; Shukla *et al.*, 2018; Eyers *et al.*, 2018). For example, prospective economic benefits of 3DP implementation discussed in the literature include improved resource efficiency, production flexibility, and enhanced mass-customization (Huang *et al.*, 2012; Shukla *et al.*, 2018). Moreover, sustainability benefits such as reduced waste during manufacturing, less energy consumption, and extended product life are also identified by researchers (Ford and Despeisse, 2016). In recent years, quantitative empirical investigations of 3DP implementation start to emerge. While some researchers have examined the antecedents of 3DP adoption using surveys (Schniederjans, 2017) or investigated the business models enabled by 3DP using computer modeling and simulation (Jia *et al.*, 2016), there is a lack of empirical research investigating the performance impact of 3DP implementation at the firm level.

Our study fills this important gap in the literature by providing an empirical investigation of the impact of 3DP implementation on stock returns, which are regarded as a proxy for overall firm value and more likely to capture the full performance impact due to 3DP implementation (Joshi and Hanssens, 2010; Sorescu *et al.*, 2017). Specifically, we conducted an event study based on 232 announcements of 3DP implementation made by U.S. publicly listed firms between 2010 and 2017. Our event study results suggest that firms implementing 3DP gain higher stock returns compared with their non-implementation industry peers over two years after the implementation. This finding is consistent with our dynamic capabilities view (Barreto, 2010; Schilke *et al.*, 2018) which argues that 3DP implementation enables firms to enhance their manufacturing capabilities and gain a competitive advantage, resulting in positive stock returns.

However, it is less likely that firms operating in different environments will gain the same benefits from their 3DP implementation. For example, while implementing 3DP may enable firms operating in dynamic environments with changing customer preferences and fluctuating market demands to gain a competitive advantage due to its ability to enhance firms' manufacturing capabilities to satisfy the requirements emerging from such environments (Jansen *et al.*, 2006), firms operating in less munificent environments without sufficient resources and support available may encounter difficulty in implementing 3DP to enhance their manufacturing capabilities, thus preventing them from reaping the benefits of 3DP innovation (Park and Mezias, 2005). Therefore, our research further considers how the stock returns due to 3DP implementation vary across firms operating in different environments. In particular, we deploy contingency theory (Reinking, 2012; Sousa and Voss, 2008) to hypothesize how external contingent factors in terms of industry munificence, dynamism, and competition affect the extent to which firms benefit from 3DP implementation. Consistent with the contingency perspective, our cross-sectional regression analysis shows that the stock returns due to 3DP implementation are more pronounced for firms operating in more munificent, more dynamic, and less competitive industry environments. These findings highlight the importance of the fit between 3DP-enhanced manufacturing capabilities and firms' operating environments.

Our study makes several important contributions. First, this is one of the first research efforts that empirically examine the impact of 3DP implementation on firm performance in terms of stock returns. The positive stock returns documented in our research provide empirical support for firms to implement 3DP. Moreover, our research further shows the moderating role of operating environments in the 3DP implementation-stock returns relationship, urging firms to take account of their operating environments in order to reap more benefits from 3DP implementation. On the other hand, we integrate the dynamic capabilities view with contingency theory to offer a more comprehensive and complementary explanation of the 3DP implementation-stock returns relationship. Our theoretical perspective helps explain not only how 3DP implementation enables firms to gain a competitive advantage through enhancing manufacturing capabilities but also how the competitive advantage can be realized depends on the fit between 3DP-enhanced manufacturing capabilities and firms' operating environments. This perspective can serve as a useful theoretical foundation for future 3DP research. It also extends the research on manufacturing capabilities beyond the structure-conduct-performance framework (Terjesen *et al.*, 2011) as we view environmental conditions as a moderator, rather than a driver, in the manufacturing capabilities-firm performance relationship.

2. Hypotheses development

2.1 Literature review

The extant research about 3DP has primarily focused on its technological advancements and industrial applications (Lam *et al.*, 2002; Ventola, 2014; Williams *et al.*, 2010). Although the manufacturing process of 3DP may use different printer technologies or printing materials, the basic steps remain the same: (1) A computerized 3D model of the object to be manufactured is developed in a computer-aided design (CAD) file. (2) The printer follows the instructions of the CAD file to build a foundation of the object by moving the printhead along the *x*-*y* plane. (3) The printhead then moves along the *z*-axis to add materials layer by layer. The additive manufacturing process differs from conventional manufacturing techniques which subtract materials from a larger piece (Ventola, 2014). 3DP has been adopted by manufacturers as a complementary technology for rapid prototyping since 1980s (Huang *et al.*, 2012). About thirty years into its development, 3DP has revealed great potential as a direct manufacturing technique in various contexts including repairing existing products, manufacturing tools and machine parts, and manufacturing end-use components and products (Atzeni and Salmi, 2012; Thomas-Seale *et al.*, 2018).

Studies seeking to understand the implications of 3DP implementation have started to emerge in recent years (Dong *et al.*, 2017; Ford and Despeisse, 2016; Holmström *et al.*, 2016;

Huang *et al.*, 2012; Petrick and Simpson, 2013; Weller *et al.*, 2015; Shukla *et al.*, 2018; Eyers *et al.*, 2018; Jia *et al.*, 2016). On the one hand, these studies provided preliminary discussions about the advantages of 3DP such as accelerating product development, offering customized products, and increasing production flexibility. For instance, Huang *et al.* (2012) claimed that 3DP by nature eliminates the need for tooling, molding, warehousing, transportation, and packaging. The simplified supply chain leads to improved material efficiency, resource efficiency, part flexibility, and production flexibility, thus enabling on-demand manufacturing. Shukla *et al.* (2018) discussed the impact of 3DP implementation on mass-customization and proposed that 3DP facilitates four key practices in mass-customization including agility, customer involvement, postponement (i.e. “print-to-order”), and modularization. Dong *et al.* (2017) conducted one of the few analytical studies about the optimal manufacturing strategy under traditional flexible technology and 3DP. They proved that, compared with traditional flexible technology, 3DP excels in enhancing product diversity by allowing firms to choose a large product assortment with little profit loss.

On the other hand, previous studies also indicated that 3DP has not been accepted as a standard production technology due to limitations including technological constraints, investment costs, and business challenges (Attaran, 2017; Shukla *et al.*, 2018; Thomas-Seale *et al.*, 2018; Weller *et al.*, 2015). First, compared with conventional subtractive manufacturing, 3DP lacks economy of scale. Different from conventional injection molding, the production throughput speed of the additive manufacturing process is rather low, so 3DP is mostly adopted and advantageous in multi-variant and low-volume production (Petrick and Simpson, 2013). Second, the limitations of printing materials, colors, and surface finishes could impede broader applications of 3DP (Petrick and Simpson, 2013; Weller *et al.*, 2015). For example, at current stage, additive manufacturing still cannot compete with the subtractive manufacturing in terms of precision (Shukla *et al.*, 2018). As a result, significant efforts are required for the polishing and finishing surfaces afterwards. Third, the purchasing costs for 3D printers are unneglectable, not to mention additional costs including supporting machinery, printing materials, and highly skilled personnel (Huang *et al.*, 2012; Shukla *et al.*, 2018). Last but not least, “soft barriers” such as the lack of technological know-how (Thomas-Seale *et al.*, 2018), CAD software complexity (Shukla *et al.*, 2018), and unestablished global quality and test standards (Weller *et al.*, 2015) may also hinder the implementation of 3DP.

Taken together, although previous research has adopted various research methods such as case studies and analytical modeling to explore the opportunities and challenges of 3DP implementation (Dong *et al.*, 2017; Eyers *et al.*, 2018; Shukla *et al.*, 2018), the question remains whether, and to what extent, 3DP implementation affects firm performance. Our study complements the literature by theoretically hypothesizing and empirically testing the impact of 3DP implementation on firm performance in terms of stock returns.

2.2 A contingent dynamic capabilities perspective on 3DP implementation

We integrate the dynamic capabilities view with contingency theory to provide a contingent dynamic capabilities (CDC) perspective on the 3DP implementation-stock returns relationship, for several reasons. First, different from the static resource-based view of the firm that is focused on a firm’s existing resource base, the dynamic capabilities view stresses a firm’s capacity to “purposefully create, extend, or modify its resource base” (Helfat *et al.*, 2007, p. 1). This conceptualization enables us to adopt the dynamic capabilities view to theorize how firms implement 3DP to renew their resource base and enhance manufacturing capabilities. Moreover, the dynamic capabilities literature has commonly linked firms’ dynamic capabilities to competitive advantage (Barreto, 2010; Schilke *et al.*, 2018), consistent with our research objective which is to investigate the impact of 3DP implementation on firm performance in general and stock returns in particular. However, although the dynamic capabilities view is concerned with the "rapidly changing environments" (Teece *et al.*, 1997, p. 516) or dynamic environments, it pays less attention to other dimensions of the environments such as environmental munificence. We thus adopt contingency theory to further explore how the impact of 3DP implementation is contingent on different dimensions of firms' operating environments. Contingency theory suits our research well as it focuses on the fit between firms' internal endogenous processes or practices (e.g., 3DP implementation) and external exogenous contexts (e.g., operating environments) (Chavez *et al.*, 2013; Wong *et al.*, 2011). Also, consistent with the dynamic capabilities view, firm performance is a typical dependent variable investigated in the contingency literature (Sousa and Voss, 2008). Therefore, a combination of the dynamic capabilities view and contingency theory provides a complementary and comprehensive perspective on not only the direct relationship between 3DP implementation and stock returns but also the indirect moderating role of firms' operating environments. In what follows, we first deploy the dynamic capabilities view to theorize how 3DP implementation enables firms to broaden their operational scopes without cost penalties, thus enhancing manufacturing capabilities and gaining a competitive advantage. We also explain how the competitive advantage can be quantified as stock returns. We then adopt contingency theory to explore the fit between 3DP-enhanced manufacturing capabilities and industry environments in terms of industry munificence, dynamism, and competition, thus moderating the 3DP implementation-stock returns relationship. Our research model is shown in Figure 1.

(Insert Figure 1 about here)

Previous studies have identified operational scope as a multi-dimensional concept, comprised of product/service scope, geographic scope, and process scope (Clark and Huckman, 2011; Hitt *et al.*, 1997; Kovach *et al.*, 2015). Product/service scope is the breadth of the product/service portfolio offered by a firm (Clark and Huckman, 2011). Geographic scope is the breath of expansion into different geographic locations or markets (Hitt *et al.*, 1997).

Process scope is the level of flexibility to cope with the change in output (Anand and Ward, 2009). A consensus has been reached concerning the trade-off between operational scope and efficiency in existing research (Clark and Huckman, 2011). It has been well acknowledged that diversification is not free, and expanding operational scope almost inevitably increases operational complexity and inflates costs (Hitt *et al.*, 1997; Ramdas, 2009).

3DP potentially challenges this conventional wisdom as it implies increased operational scope without cost penalties, thus renewing firms' resource base and enhancing their manufacturing capabilities (Petrick and Simpson, 2013; Schniederjans, 2017; Weller *et al.*, 2015). Specifically, first, 3DP expands product scope through cost-effective and time-efficient product innovation, customization and intricacy (Shukla *et al.*, 2018; Weller *et al.*, 2015). Traditionally, offering a diverse product portfolio incurs additional operational costs such as tooling and variety-related inventory holding costs (Kovach *et al.*, 2015). However, as there are no tooling requirements nor minimum batch size pressure in the one-step additive manufacturing process, diversified product design can be achieved without additional tooling costs or inventory holding of a large variety of products (Weller *et al.*, 2015). Moreover, 3DP enhances new product development by removing the restrictions of innovation. 3DP can be used to manufacture any sophisticated parts that can be imaged without the need to compromise on the functionality for the ease of manufacturing (Attaran, 2017). Beyond manufacturing settings, 3DP has also been adopted to provide services of producing 3D-printed items for customers, mostly in healthcare, retailing, logistics and transportation industries (Ernst & Young, 2016). For example, Henry Schein, a worldwide dental supplier, provided 3D-printed mouth guards for their customers using intra-oral scanners (Bloomberg, 2017). UPS, aside from package delivery service, has expanded its service scope to provide 3DP services in UPS stores since 2013 (Carey, 2016).

Second, 3DP expands the geographic locations where firms produce and sell products through decentralized manufacturing (Attaran, 2017). With a 3D printer, customers are allowed to download digital models from websites, and then additively manufacture the parts in need by themselves at almost any locations. Manufacturing at the point of use is expected to reduce the requirement of extensive physical inventory and large-volume logistics and transportations. For instance, Ford launched an online 3DP store to provide 3DP services that allow customers to "print" the scale automotive models with the digital models downloaded from their website (McCue, 2015).

Third, 3DP achieves broad process scope with increased production flexibility. Process scope is associated with both mix flexibility and volume flexibility (Kovach *et al.*, 2015). 3DP increases mix flexibility in the manufacturing process as any changes of design are allowed by simply modifying the 3D model stored in the CAD file. Moreover, 3DP enables direct manufacturing without the need for tools or molds, so the design changes can be easily transferred into production (Ernst & Young, 2016). In addition, 3DP substantially reduces manufacturing steps by removing the processes of casting, molding, machining, and assembly, thus reducing manufacturing costs. The negligible changeover costs and simplified manufacturing steps contribute to the increased flexibility of adjusting production according to varying designs, sequences, or volumes (Weller *et al.*, 2015).

The above discussion suggests that 3DP implementation helps firms broaden their operational scopes (i.e., product/service scope, geographic scope, and process scope) and mitigate operational complexities and costs, thus enhancing manufacturing capabilities. The dynamic capabilities literature has commonly agreed that improved firm capabilities enable the focal firm to gain an advantage over its competitors (Barreto, 2010; Schilke *et al.*, 2018). Empirically, the operations management literature has well documented the positive relationship between enhancing manufacturing capabilities and various dimensions of firm performance such as sales growth, cost reduction, and profitability improvement (White, 1996;

Terjesen *et al.,* 2011; Corbett and Claridge, 2002). We thus expect 3DP implementation to foster a competitive advantage for firms through enhancing their manufacturing capabilities. While prior dynamic capabilities research has used different performance measures such as profitability, growth, and survival to indicate a firm's competitive advantage (Schilke *et al.*, 2018; Shamsie *et al.*, 2009), we quantify it in terms of abnormal stock returns in this research. This is because abnormal stock returns, as measured based on the event study method discussed in Section 3, are the difference in stock returns between firms implementing 3DP and their industry peers without 3DP implementation, which is more in line with the concept of competitive advantage discussed in the literature. Moreover, such "abnormal" stock returns are consistent with the "above average returns" or "abnormal rents" emphasized in prior research on dynamic capabilities (Jiang *et al.*, 2015; Oliver and Holzinger, 2008). Therefore, we hypothesize that:

H1: Firms' 3DP implementation has a positive impact on their stock returns.

2.3 The contingent role of industry environments

Contingency theory submits that there is no one best way of organizing or one-size-fits-all strategy (Chavez *et al.*, 2013; Zhang *et al.*, 2012). Instead, the contingency literature has commonly agreed that firms do not operate in a vacuum and better firm performance is a consequence of the proper alignment of firms' internal characteristics with external contextual factors (Sousa and Voss, 2008; Wong *et al.*, 2011). Put into our research context, it is possible that the extent to which the competitive advantage due to 3DP implementation can be realized depends on the alignment of the 3DP-enhanced manufacturing capabilities with firms' operating environments. For example, if firms' operating environments do not provide sufficient resources and support for firms to implement 3DP, it may be difficult for the firms to reap the benefits of 3DP innovation. Similarly, if firms' operating environments do not present the need for more advanced manufacturing capabilities, the manufacturing capabilities enhanced by 3DP implementation may not help firms to gain a competitive advantage.

In fact, although the positive relationship between manufacturing capabilities and competitive advantage has been well documented in the literature, some prior studies have shown non-significant or even negative relationships under certain circumstances. For instance, a meta-analysis conducted by White (1996) suggested that the manufacturing capabilities-business performance relationships as documented in the literature range from positive to non-significant, while Corbett and Claridge (2002) showed that such relationships could be negative in some industries. Kim and Arnold (1993) also questioned whether manufacturing capabilities matter in all industries or they matter more in some specific industries. Informed by the findings of those prior studies and through the lens of contingency theory, we consider how industry environments moderate the impact of 3DP implementation on stock returns. In particular, we focus on three industry characteristics, namely munificence, dynamism, and competition (Jansen *et al.*, 2006; Park and Mezias, 2005) in this research because they represent different levels of environmental support and environmental requirement for 3DP implementation, as discussed below.

Industry munificence refers to the level of resources available to support the sustained growth of the firms in the industry (Dess and Beard, 1984; Park and Mezias, 2005). It is primarily determined by the rate of sales growth in the industry (Dess and Beard, 1984). In an industry with high level of munificence, firms are more likely to accumulate slack resources such as venture capital, government funds, labor markets, and suppliers (Dess and Beard, 1984; Park and Mezias, 2005). Dess and Beard (1984) indicated that these slack resources not only function as buffer during times of scarcity, but also facilitate organizational innovation. Firms implementing 3DP in munificent industries are more likely to gain benefits because the effectiveness of 3DP depends on the availability of several critical resources such as qualified experts, software vendors, and investment capitals (Huang *et al.*, 2012; Shukla *et al.*, 2018; Thomas-Seale *et al.*, 2018). On the contrary, firms in the industry with low level of munificence could encounter several obstacles preventing them from accessing the resources for development. These obstacles may include tax burdens, fragile infrastructure, inaccessible technology support from educational institutions, and lack of qualified labor (Chen *et al.*, 2014). In general, 3DP implementation is more likely to be effective when firms are operating in more munificent industries (Chen *et al.*, 2014; Terjesen *et al.*, 2011). Thus we hypothesize that:

H2: The impact of 3DP implementation on stock returns will be higher for firms operating in more munificent industries.

Industry dynamism refers to the instability of the environment (Dess and Beard, 1984; Jansen *et al.*, 2006). Dess and Beard (1984) further emphasized that dynamism should be restricted to the changes which are unpredictable. Dynamic industries are characterized by changeable customer preferences, unpredictable technology development, fluctuated market demand, and inconstant government regulations (Anand and Ward, 2009; Stoel and Muhanna, 2009). Anand and Ward (2009) indicated that in order to cope with a large number of unpredictable scenarios, firms are required to broaden process scope by maintaining diverse capabilities and building up excess capacity, which inevitably leads to higher costs. As a result, manufacturing capabilities play a significant role in gaining competitive advantage in dynamic industries. Firms investing in 3DP are allowed to move between different product designs and production volumes with less incurring time and cost penalties, and thus are likely to gain greater advantages. Similar to Stoel and Muhanna's (2009) argument about externally-oriented IT, we believe that the effectiveness of 3DP is more pronounced in dynamic environments in that it enables firms to better sense the market through customization and timely respond to the fluctuations in customer and supplier demand. Overall, we expect the 3DP-enhanced manufacturing capabilities to enable firms to better meet the requirements induced in more dynamic industries and gain a competitive advantage. Therefore, we hypothesize that:

H3: The impact of 3DP implementation on stock returns will be higher for firms operating in more dynamic industries.

Industry competition refers to intensity of competition in an industry, often reflected in the number of competitors and the concentration of market shares (Jansen *et al.*, 2006; Melville *et al.*, 2004). Low level of concentration represents a competitive market with market shares almost evenly distributed among a large number of competitors, while high level of concentration depicts a monopoly or oligopoly industry with a small number of competitors dominating the market (Azadegan *et al.*, 2013). While industry munificence and industry dynamism indicate the levels of environmental support and environmental requirement, respectively, for 3DP implementation, industry competition implies a more complicated situation. First, similar to industry dynamism, industry competition can represent the level of environmental requirement for 3DP implementation. For example, in highly competitive industries, firms are motivated to break out the price war by differentiating themselves from their competitors who are providing homogeneous products or services (Chen *et al.*, 2014). In particular, through product innovation, new market exploration, and enhanced tailoring of products or services, firms are able to gain an advantage over their competitors (Jansen *et al.*, 2006). The implementation of 3DP can help firms achieve such differentiations and satisfy the requirements arising from the competitive markets. Specifically, 3DP facilitates product innovation by eliminating the iteration costs and manufacturing limitations in the product design process (Weller *et al.*, 2015). 3DP also allows customization without cost penalties, consequently increasing customers' perceived values and willingness to pay (Shukla *et al.*, 2018). Therefore, it is possible that 3DP implementation will be more valuable for firms in industries with high level of competition. As a result, industry competition is expected to have a positive moderating effect on the 3DP implementation-stock returns relationship such that the impact of 3DP implementation on stock returns will be higher for firms operating in more competitive industries.

However, industry competition can also be related to the level of environmental support for 3DP implementation. This is because in highly competitive industries with a large number of competitors, resources are relatively scarce as firms compete not only for customers and market shares but also for inputs into the production processes such as qualified labors and investment capitals (Prajogo and Oke, 2016). Moreover, due to low entry barriers and intensive competition in such industries, the adoption of new innovation such as 3DP will be aggressively matched by competitors, reducing the adopters' first-mover advantage and the power to generate abnormal rents from the innovation adoption (Jansen *et al.*, 2006; Melville *et al.*, 2004). As a result, competitive industries exhibit a low level of environmental support for firms to implement 3DP. By contrast, in monopoly or oligopoly industries with a small number of competitors, resources are readily available to a few dominant players to support their 3DP implementation. Due to low competition, they have strong power to charge a price premium for the products and services offered by them. Weller *et al.* also suggested that "in a monopoly, the adoption of AM [Additive manufacturing] allows a firm to increase profits by capturing consumer surplus when flexibly producing customized products" (2015, p. 43). Therefore, from the environmental support perspective, industry competition will have a negative, rather than positive, moderating effect on the 3DP implementation-stock returns relationship such that the impact of 3DP implementation on stock returns will be higher for firms operating in less competitive industries.

The above discussion suggests two opposite moderating roles for industry competition. In fact, past empirical studies have also documented mixed results regarding the role of competition (Prajogo and Oke, 2016; Wilden *et al.*, 2013). For example, Wilden *et al.* (2013) found that the performance impact of dynamic capabilities improves in competitive environments, whereas Prajogo and Oke (2016) showed that competitive environments weaken the relationship between service innovation advantage and business performance. Informed by the findings of those past studies and based on the above discussion, we propose two competing hypotheses for the role of industry competition:

H4a: The impact of 3DP implementation on stock returns will be higher for firms operating in more competitive industries.

H4b: The impact of 3DP implementation on stock returns will be higher for firms operating in less competitive industries.

3. Methods

3.1 Sample

We attempt to identify the population of U.S. publicly listed firms that announced the implementation of 3DP. Consistent with prior studies (Ding *et al.*, 2018; Sorescu *et al.*, 2017), we conducted a comprehensive search in the Factiva news database with 3DP related keywords to collect firm announcements of 3DP implementation across all industries between 2010 and 2017. The keywords used in this study are (NASDAQ or NYSE or AMEX) and (3D print* or three-dimensional print* or additive manufactur* or rapid manufactur* or rapid prototyp*). We reviewed all the announcements collected from Factiva to ascertain that they meet the following criteria. (1) The announcement should be related to applying 3DP technology to the firm's business practices such as product design and development, rapid prototyping, specialized manufacturing, service providing and other related activities. Announcements only informationally associated with 3DP without applications were excluded. For example, the announcement about Staples becoming the first U.S. retailer to sell 3D printers was eliminated.

(2) For the same type of 3DP implemented by a firm, only the earliest announcement was included (Ding *et al.*, 2018). However, announcements made by the same firm reporting different types of 3DP implementation were included. For example, the announcement about Ford using 3DP to produce prototype parts and the announcement about Ford launching an online 3DP store to provide scale model printing services for customers were both included. (3) Announcements made by private firms or firms not listed on NYSE, AMEX, or NASDAQ were excluded. The process resulted in 242 announcements made by 132 firms. For further matching process, we excluded 7 firms without data in Compustat and 3 firms with negative book to market ratios. The final sample consists of 232 announcements made by 122 firms. Some examples of the announcements are shown below.

- Under Armour’s 3D-printed shoes bring computer designer to heel.
- Ford begins large-scale 3D printing trial.
- Amazon offers 3D printing to customize earrings, bobble head toys.
- UPS store makes 3D printing accessible to start-ups and small business owners.

A key challenge of relying on announcements for this kind of research is the issue of “decoupling”, meaning that firms may not actually implement 3DP after they make the announcements. To verify the consistency of words and deeds, we further searched in Google to check whether firms implemented the announced 3DP based on information from various sources. For each of the 232 announcements, our search included the type of 3DP mentioned in the announcement and the name of the announcing firm. We were able to identify 207 announcements with information related to the implementation of the 3DP announced, representing about 89% of the 232 announcements used in our research. As most announcements have been verified, we believe the decoupling issue is not a major concern in our research.

(Insert Table 1 about here)

Table 1 presents the distributions of the announcements across years and industries and the descriptive characteristics of the announcing firms. It shows that the majority (81%) of the announcements were made in the recent four years from 2014 to 2017, indicating soaring adoption rates. Most of the announcements (66%) are from manufacturing industries, while the remaining are from service industries or others[1]. The average market value of the announcing firms is 72160.8 million U.S. dollars, suggesting that the announcements are mostly from large-scale firms.

3.2 Long-term event study method

We employ the long-term event study method to quantify the performance impact of 3DP implementation in terms of stock returns (Kothari and Warner, 2007). We choose to focus on stock returns rather than accounting-based operating performance indicators such as sales growth and cost reduction (De Jong *et al.*, 2014; Orzes *et al.*, 2017) for several reasons. First, the implementation of 3DP varies greatly across industries such as healthcare, automotive manufacturing, fashion, consumer products, and aerospace, so it is difficult to determine appropriate operating performance measures that fit in all the contexts of different types of implementation. Moreover, operating performance indicators such as sales and costs focus on a firm's tangible value, which may fail to account for the impact of 3DP implementation on the firm's intangible value. Stock returns, on the other hand, represent a firm's overall value, taking both tangible and intangible components into account (Joshi and Hanssens, 2010;

[1] To verify whether our sample is representative in terms of industry distribution, we included the keyword "service" and "manufacturing", and searched the announcements of 3DP implementation made by both publicly listed and private firms in Factiva between 2010 and 2017. About 68% of the announcements were found when the keyword "manufacturing" was included, corresponding with our sample distribution.

Sorescu *et al.*, 2017) and thus more likely to capture the overall performance impact due to 3DP implementation. In addition, accounting-based performance indicators are lagging measures, representing a firm's performance over a specific period (e.g., a fiscal year). This suggests that it may take a relatively long time period for the impact of a firm's strategy to be reflected in the accounting-based performance measures, especially when technology implementation is involved. For example, Hendricks *et al.* (2007) examined the impact of the implementation of enterprise systems on accounting-based performance measures over a five-year period. Such an approach is not feasible for our research as 63% of the 3DP implementation were announced in 2015 to 2017, suggesting that our sample size will drop drastically if a five-year investigation period is applied. On the other hand, stock returns are a forward-looking measure (Sorescu *et al.*, 2017), which indicates investors' expectation of a firm's future performance and better suits our research context.

We prefer quantifying the impact of 3DP implementation in terms of long-term rather than short-term stock returns (Ding *et al.*, 2018) as stock markets may fail to reveal the true intrinsic value of 3DP implementation within a short time period. Specifically, immediately after the announcements are made, investors possibly over-react to the 3DP implementation due to over-optimism and limited knowledge. In an investigation of e-commerce, Ferguson *et al.* (2010) argued that stock market may overprice the added value of technologies which are regarded as innovative, exciting, and glamorous. Similarly, we believe that there could also be an upward bias in investors' valuation of 3DP, which is perceived as a groundbreaking technology to disrupt conventional manufacturing. As Hendricks and Singhal (2001) indicated in a study of TQM, the market may wait for more information to incrementally acquire knowledge about new innovation and judge its effectiveness. Therefore, we adopt the long-term event study method to examine the stock returns due to the implementation of 3DP which is a pioneering technology with relatively little knowledge of its value.

For the long-term event study, we calculate the abnormal stock returns as the buy-and-hold return (BHR) of the sample firms less the BHR of an appropriate benchmark (Barber and Lyon, 1997; Lyon *et al.*, 1999). The buy-and-hold abnormal return (BHAR) is

$$\text{BHAR} = \prod_{t=1}^{T}(1 + R_{it}) - \prod_{t=1}^{T}(1 + R_{bt}),$$

where R_{it} is the monthly stock return of the sample firm i in month t, R_{bt} is the monthly stock return of the control firm paired with sample firm i in month t, and T is the length of the event window. Monthly stock returns were retrieved from the Center for Research in Security Prices (CRSP) database. In developing the benchmark, we follow the standard procedures proposed in previous research (Barber and Lyon, 1997; Hendricks and Singhal, 2001) and match each sample firm to a control firm based on different combinations of three widely-accepted characteristics, namely industry, size, and market-to-book (MTB) ratio. The control firm approach has advantages in eliminating new listing bias, rebalancing bias, and the skewness problem compared with the portfolio approach (Barber and Lyon, 1997). As the maturity level and magnitude of sustainability benefits of 3DP vary across industries (Thomas-Seale *et al.*, 2018), we emphasize industry as an important matching criteria to control for industry heterogeneity (Hendricks and Singhal, 2001). We use all the NYSE, NASDAQ, and AMEX listed firms without 3DP implementation announcements as the benchmark pool[2]. Industry is indicated by the firm's primary SIC code, size is measured as the market value of equity, and MTB ratio is calculated as market value of equity divided by book value of equity. All the accounting data are in the most recent fiscal year prior to the announcement year and were

[2] We further verified whether the matched control firms have implemented 3DP. Specifically, we searched a combination of 3DP related keywords and the names of the matched control firms in Factiva between 2010 and 2017. We could not identify any control firm that had implemented 3DP in this time period, confirming the appropriateness of the control firms used in our research.

retrieved from the Compustat database. To enable us to check the sensitivity of our results, we take three different matching approaches to identify the control firm for each firm-year observation: (1) For the industry-size match, we first match a sample firm to control firms with the same four-digit SIC code, then the control firm closest in size is identified. If the control firm is not found, we match the sample firm to control firms with the same three-digit SIC code. The control firm must have at least same two-digit SIC code as the sample firm and is closest in size. (2) For industry-MTB match, we follow similar procedures as in the industry-size match, but the control firm closest in MTB ratio is identified. (3) For industry-size-MTB match, we follow similar procedures as in the industry-size match, but the control firm closest in the absolute percentage difference between size and MTB ratio is identified. As a robustness test, we adopt propensity score matching (PSM) as an alternative matching approach to control for other factors besides industry, size, and MTB ratio, as discussed in Section 4.

We set the calendar month when the announcement was made public as the event month 0. The month before and after the event month are denoted as month -1 and 1, respectively. In reality, it usually takes several months for firms to finish the implementation of 3DP, suggesting that the effectiveness of 3DP implementation may not manifest until a few months after the announcement month. However, as there is little guidance in the literature regarding the appropriate time period for 3DP implementation, we determine the length of implementation period based on the evidence provided in our sample announcements. For example, Mattel Inc. announced on April 20, 2016 that they start a collaboration with Autodesk Inc. to power the Mattel toy line with cutting-edge 3D printing technology. Ten months later, Mattel introduced their 3D printing eco-system named ThingMaker to enable consumers to design, create, and print their own toys (Business Wire, 2015). Based on the information in the announcements and previous long-term event studies (Hendricks and Singhal, 2001), we set month (1, 12) as the time period required for implementation. A long post-implementation investigation period may capture the effect of 3DP implementations more extensively but also reduce our sample size substantially as most of our announcements were released between 2014 and 2017. To strike a balance, we set the post-implementation period as month (13, 24). We measure the effect of 3DP implementation over both implementation and post-implementation periods, i.e., month (1, 12) and month (1, 24), to fully capture the market reactions. Month (-24, -1) is set as the pre-implementation period. We conduct *t*-test, Wilcoxon-signed rank (WSR) test, and sign test to determine the significance of the BHARs over different periods but mainly focus on the non-parametric test results due to their better ability to account for possible extreme values of BHARs. Moreover, as the multiple event windows used in our research might increase the possibility of false positive results, we follow Orzes *et al.* (2017) and adopt the approach proposed by Benjamini and Hochberg (1995) to control the false discovery rate (FDR) and address the multiple testing concern.

3.3 Cross-sectional regression

(Insert Table 2 about here)

We construct a cross-sectional regression model as shown below to investigate the moderating role of environmental factors including industry munificence, dynamism, and competition. Table 2 presents the measures, data sources, and references of the variables in the regression analysis.

$$BHAR_i = \beta_0 + \beta_1 Firm\ size_i + \beta_2 MTB\ ratio_i + \beta_3 R\&D\ intensity_i + \beta_4\ Prior\ performance_i + \beta_5 Capital\ structure_i + \beta_6 Momentum_i + \beta_7\ Velocity_i + \beta_8 Manufacturing_i + Year\ dummies + \beta_9 Munificence_i + \beta_{10}\ Dynamism_i + \beta_{11} Competition_i + \varepsilon_i$$

The dependent variable is the BHAR calculated for each sample firm over a specific event window. As to the independent variables, we control for several firm-specific, industry-specific and market-specific factors that have been commonly identified to potentially affect firms' stock returns (Ding *et al.*, 2018; Lam, 2018; Hendricks and Singhal, 2001; Qian and Zhu, 2017; Sorescu *et al.*, 2017). We also include year dummies to account for unobservable time-specific effects (Jacobs *et al.*, 2015). We rely on β_9, β_{10}, and β_{11} to determine the effects of industry munificence, dynamism, and competition, respectively.

4. Results

4.1 The stock returns of 3DP implementation

(Insert Table 3 about here)

Table 3 presents the BHAR results based on three different matching approaches: industry-size match, industry-MTB match, and industry-size-MTB match. To alleviate the concern that other factors rather than 3DP implementation might affect firm performance, we test the BHARs during pre-implementation periods (Yang *et al.*, 2019). If significant BHARs are found even before 3DP is implemented, we might suspect that the significant BHARs, if any, detected during the post-implementation period are driven by other factors rather than 3DP implementation. The BHARs over three multi-month periods (i.e., month (-24, -1), (-24, -13), (-12, -1)) prior to 3DP implementation are not significant (p > 0.1) across the three matching approaches, indicating that the sample and control firms are comparable in terms of potential BHARs if the sample firms had not implemented 3DP.

We then look at the BHARs in the implementation periods within month (1, 12). In different time periods within month (1, 12), the BHARs are generally non-significant (p > 0.1) across the three matching approaches, except the BHAR over month (1, 12) with the industry-size-matched control firms, which is significant at the 10% level based on sign test. Overall, the non-significant test results confirm our expectation that it may take a few months for firms to implement 3DP and the value of 3DP implementation cannot emerge immediately following the announcement.

However, for longer time periods including the post-implementation periods of month (13, 24), there are significant positive changes in BHARs ($p < 0.1$) across the three matching approaches, especially when non-parametric tests are conducted. These positive results justify our choice of the long-term event study method and show the importance of focusing on 3DP's post-implementation periods. As we find significant positive BHARs after the implementation of 3DP, H1 is supported.

4.2 The moderating effect of environmental factors

(Insert Table 4 about here)

Table 4 presents the correlations among variables to be included in the regression analysis. For brevity in presenting and discussing our results, the regression analysis with the dependent variable of BHAR over month (1, 18) calculated with the industry-size-matched group is shown in Table 5. To check the sensitivity of the results, BHARs measured with alternative event window (1, 24) and matching approaches (industry-MTB match and industry-size-MTB match) are also tested and presented in Table 8.

(Insert Table 5 about here)

Model 1 is the basis model with a variety of control variables included. In Models 2-4, industry munificence, dynamism, and competition are added gradually. The value of R-squared increases with additional variables added to the regression, showing that each environmental factor explains a significant amount of variation in the BHAR. Specifically, the coefficient of industry munificence is positive and significant ($p < 0.01$) across Models 2-4, suggesting that the stock returns of 3DP implementation is more positive for firms operating in more munificent industries. H2 thus is supported. The coefficient of industry dynamism is positive and significant ($p < 0.05$) in Models 3 and 4, indicating that the BHAR is higher for firms operating in more dynamic industries. Therefore, H3 is supported. The coefficient of industry competition is negative and significant ($p < 0.05$) in Model 4, showing that firms operating in more competitive industries benefit less from 3DP implementation. As a result, H4a is rejected but H4b is supported. The hypothesis test results based on both event study and regression analysis are summarized in Figure 2.

(Insert Figure 2 about here)

4.3 Sensitivity analyses

We conduct several sensitivity analyses to check the robustness of our findings and to account for alternative explanations.

Propensity score matching (PSM). We employ the PSM approach to match each sample firm with a control firm that had a similar probability or propensity as the sample firm to implement 3DP but eventually did not implement 3DP. This matching approach enables us to control for other factors that may influence 3DP implementation and address possible self-selection bias (Austin, 2011; Ding *et al*., 2018). To implement PSM, we first construct a logistic regression model with 3DP implementation as the dependent variable while the independent variables include industry dummies, firm size, MTB ratio, return on asset, R&D intensity, industry velocity, industry munificence, industry dynamism, and industry competition. After running the logistic regression, the firms in the benchmark pool with the closest propensity scores to the sample firms are chosen as the control firms. The resulting BHARs based on the PSM approach shown in Table 6 reveal a consistent pattern as that found in our main analyses.

(Insert Table 6 about here)

Reduced sample size. The results shown in Table 3 suggest that our sample size drops significantly for longer event windows because about 45% of our announcements were made in 2016 and 2017. To check whether the decrease in sample size leads to biased estimation, we follow De Jong *et al.* (2014) and calculate the BHARs for the reduced sample across all the event windows. We focus on the subgroup of firms that have monthly stock return data over the longest time period of month (1, 24). The BHARs of this subsample generally follow a similar pattern as those of the firms in the full sample, as shown in Table 7. Specifically, the BHARs over three multi-month periods (i.e., month (-24, -1), (-24, -13), (-12, -1)) prior to the implementation are not significant ($p > 0.1$). However, over the post-implementation periods, especially for month (13, 18), (1, 18) and (1, 24), we find significant positive BHARs across all three matching approaches. In addition, the results show that this subsample enjoys greater gains in BHARs and earlier in time (e.g., month (7, 12), (1, 12)) compared with the full sample. One possible explanation is that these firms are early 3DP adopters, thus achieving greater benefits due to the first-mover advantage (Hendricks *et al.*, 2007).

(Insert Table 7 about here)

Alternative dependent variable. We also examine whether the results of regression analysis are consistent if BHAR with alternative event window and benchmark is used as the dependent variable. Table 8 presents the regression results with the BHAR calculated over month (1, 24) and with industry-MTB-matched and industry-size-MTB-matched benchmark groups. The coefficients of the three environmental factors are significant and consistent across different regression models, demonstrating the robustness of our regression results.

(Insert Table 8 about here)

5. Discussion and conclusions

Based on 232 announcements of 3DP implementation made by U.S.-listed firms from 2010 to 2017, we employ the event study method to examine the stock returns of 3DP implementation over two years after the announcements. The event study results show significant higher BHARs of sample firms compared with their non-implementation industry peers over the two-year post-implementation period. Our cross-sectional regression analysis further suggests that the stock returns due to 3DP implementation are more pronounced for firms operating in more munificent, more dynamic, and less competitive industry environments. Those findings are consistent with our CDC perspective which integrates the dynamic capabilities view with contingency theory. The empirical evidence documented and theoretical perspective adopted in our study provide important implications for practice and research, as discussed below.

5.1 Managerial contribution

Although 3DP has received extensive public attention in recent years, the current level of adoption of the technology is still relatively low. Such a low adoption rate is partly due to practitioners' lack of the knowledge of 3DP and difficulties to quantify its impact (Ernst & Young, 2016). Our study represents one of the first research efforts examining the impact of 3DP implementation in terms of stock returns. We employ the event study method to provide an objective documentation of the positive stock returns due to 3DP implementation, which helps resolve the controversy over the business value of 3DP and encourage firms to implement 3DP to reap the financial benefits. The positive stock returns documented in our research also enable firms to convince their shareholders or investors to support their 3DP implementation. However, firms should realize that 3DP is not a "quick fix" solution as we cannot find significant positive stock returns in the first few months following the announcements of 3DP implementation. This can be attributed to the fact that 3DP implementation is a complex process and it takes time for firms to overcome various barriers (e.g., technical issues, human resources, quality concerns) in order to implement 3DP (Shukla *et al.*, 2018; Thomas-Seale *et al.*, 2018). Instead, our research suggests that the positive stock returns become more significant in the long run (about two years after the announcements of 3DP implementation). Therefore, managers (and also investors) should be patient with 3DP implementation, allowing

3DP's value to emerge in the post-implementation periods.

While we encourage firms to implement 3DP based on the positive stock returns documented in our research, we also urge them to pay attention to the industry environments in which the 3DP is implemented. This is because our research shows that the stock returns due to 3DP implementation vary across different industry environments. In particular, our research suggests that firms can benefit more from 3DP implementation in munificent and dynamic industries. Munificent industries are characterized by their sufficient resources to support firms' growth, which are important to 3DP implementation. Various critical barriers such as "education, cost, software, material, mechanical properties, validation and finishing" (Thomas-Seale *et al.*, 2018, p. 108) have limited the broader applications of 3DP. The resources available in munificent industries can help firms overcome those barriers and support the effective implementation of 3DP. On the other hand, in dynamic industries with fluctuating market demands and changing customer preferences, 3DP enables firms to gain a competitive advantage due to its ability to help firms improve manufacturing flexibility and product variety (Dong *et al.*, 2017; Shukla *et al.*, 2018). For example, in the highly dynamic apparel industry, Nike was able to implement 3DP to slash the time required for manufacturing and testing and better accommodate the ever-changing fashion (Jopson, 2013). Therefore, we urge firms operating in munificent and dynamic industries to take advantage of their operating environments to reap more benefits from 3DP implementation.

However, our research suggests that firms operating in competitive industries with a large number of competitors may not benefit from 3DP implementation. Although implementing 3DP can enable a firm to differentiate itself from its competitors in competitive industries, it is difficult for the firm to gain sufficient resources to support its 3DP implementation due to the intensive competition for resources among firms in such industries. Our research shows that the negative effect due to weak support for 3DP implementation overweighs the positive effect arising from strong demand for 3DP implementation, resulting in lower benefits gained from 3DP implementation in competitive industries. This finding provides important implications for policy makers. In particular, for industries with strong demand but weak support for 3DP implementation, governments can provide better financial (e.g., tax incentives) and non-financial resources (e.g., education and trainings) to support 3DP implementation, enabling 3DP adopters to gain competitive advantage in such industries.

5.2 Theoretical contribution

Our CDC perspective provides a comprehensive and complementary theoretical explanation of the 3DP implementation-stock returns relationship. On the one hand, we deploy the dynamic capabilities view (Barreto, 2010; Schilke *et al.*, 2018) to theorize how 3DP implementation enhances firms' manufacturing capabilities through broadening their operational scopes without cost penalties, ultimately leading to improved competitive advantage and resulting in positive stock returns. This theorization enables us to link firms' practices or strategies such as 3DP implementation to their performance in terms of stock returns. On the other hand, we adopt contingency theory (Reinking, 2012; Sousa and Voss, 2008) to reject the one-size-fits-all assumption and explore the possible fit between 3DP-enahnced manufacturing capabilities and firms' operating environments in terms of industry munificence, dynamism, and competition. We theorize how these industry variables represent different levels of environmental support and environmental requirement for 3DP implementation, thus moderating the impact of 3DP implementation on stock returns. Taken together, this CDC perspective advances our understanding of the 3DP implementation-stock returns relationship as it considers not only the direct impact of 3DP implementation on stock returns but also the indirect moderating role of firms' operating environments. We believe this CDC perspective can serve as a useful theoretical foundation for future 3DP research. In particular, it urges researchers to shift their focus from the discussion of 3DP's technological features and industrial applications (Lam *et al.*, 2002; Ventola, 2014; Williams *et al.*, 2010) to a more strategic view on 3DP implementation, exploring its ability to enhance firms' manufacturing capabilities and its potential to contribute to firms' competitive advantage. Moreover, it also reminds researchers about the importance of taking firms' operating environments in which the 3DP is implemented into account. While our research is focused on industry munificence, dynamism, and competition, future research can adopt the CDC logic to further explore other environmental characteristics that may exhibit varying levels of alignment with 3DP implementation and thus affect its performance impact.

Our research contributes to the literature on dynamic capabilities and contingency theory in several ways. First, we extend the dynamic capabilities view to consider the role of other dimensions of firms' operating environments beyond environmental dynamism. In addition to confirming the dynamic capabilities view that stresses the importance of developing dynamic capabilities to satisfy the requirements arising from "rapidly changing environments" (Teece *et al.*, 1997, p. 516) or dynamic environments, our research suggests it is also crucial for the environments to provide sufficient support for firms to develop such capabilities in order to gain a competitive advantage. Specifically, our research shows that munificent environments with sufficient resources and support available for firms to implement 3DP enable them to gain higher stock returns. Moreover, our research on industry competition further suggests that environmental support may be even more critical than environmental requirement when there is a conflict between them. Specifically, although competitive environments exhibit the requirement or demand for developing dynamic capabilities, such environments with a large number of competitors may not possess sufficient resources to support firms to develop the required dynamic capabilities, thus preventing them from gaining competitive advantage in such environments. Therefore, our research highlights the limitations of focusing only on environmental requirement in general and environmental dynamism in particular and encourages future dynamic capabilities research to explore the roles of other dimensions of firms' operating environments.

On the other hand, while the contingency literature has considered many different environmental variables that may moderate the performance outcomes of firms' practices or strategies, it has been criticized for relying too much on the "it all depends" notion without more theoretical classifications of those external factors (Reinking, 2012). Our research helps address this concern by characterizing firms' operating environments in terms of environmental support and environmental requirement. We believe such classifications should be beneficial to future contingency research for explaining the performance variation due to the fit between other firm strategies beyond 3DP implementation and other environmental variables beyond munificence, dynamism, and competition. In particular, researchers can adopt our classifications to theorize whether the specific environmental variables considered in their research indicate different levels of environmental support and/or environmental requirement for the specific firm strategies concerned, thus affecting the extent to which such strategies impact on firm performance.

Finally, our research sheds some light on the structure-conduct-performance framework that has been frequently adopted in the operations management literature to study manufacturing capabilities (Terjesen *et al.*, 2011). In particular, prior research has relied on this framework to view environmental conditions as a driver of firms' manufacturing strategies and capabilities, which in turns lead to firm performance (Mellor *et al.*, 2014; Ward and Duray, 2000). Although we do not reject this causal sequencing explanation, our CDC perspective stresses the overlooked moderating role of environmental conditions in the manufacturing capabilities-firm performance relationship. To put it another way, our research suggests that structure can be viewed not only as a driver but also as a moderator in the conduct-performance relationship. Our research thus enriches the structure-conduct-performance framework by encouraging future research to consider the multiple roles that structure plays in the conduct-performance relationship.

5.3 Limitations and future research

Our research suffers from several limitations which in turn create new opportunities for future research. First, our research is focused on U.S. publicly listed firms, which may limit the generalizability of our findings to private firms and firms located in other counties. Indeed, private firms should possess less resources compared with publicly listed firms, which may affect their 3DP implementation. Similarly, firms located in different counties may receive different levels of environmental support to implement 3DP, thus reaping different benefits from 3DP implementation. Therefore, it would be interesting for future research to examine the benefits of 3DP implementation for other firms (e.g., private firms) and in different contexts (e.g., developing countries).

Moreover, we study the impact of 3DP implementation in terms of stock returns. Although stock returns represent overall firm value and better capture the full performance impact due to 3DP implementation (Joshi and Hanssens, 2010; Sorescu *et al.*, 2017), it is unclear whether 3DP implementation influences stock returns "through top-line impact, bottom-line impact, or both" (De Jong *et al.*, 2014, p. 131). It thus is worth investigating how 3DP implementation may affect other dimensions of firm performance such as sales growth, cost reduction, and profitability improvement (De Jong *et al.*, 2014; Orzes *et al*., 2017) in order to gain a more comprehensive understanding of the performance implications of 3DP implementation. Such investigations can also help verify the conclusions drawn in our research based on abnormal stock returns.

Finally, following contingency theory that emphasizes the fit between firm strategies and external environments (Reinking, 2012; Sousa and Voss, 2008), our research considers the moderating role of several factors at the industry level rather than at the firm or individual level. However, firm-level and individual-level factors may also affect 3DP's implementation and thus its performance impact. For example, firms with larger sizes may possess more resources to implement 3DP while CEOs with technical backgrounds may be more likely to support 3DP implementation, both of which may affect the effectiveness of 3DP implementation. Therefore, future research on 3DP implementation can explore the moderating role of other non-industry-level factors.

References

Anand, G. and Ward P.T. (2009), "Fit, flexibility and performance in manufacturing: coping with dynamic environments", *Production and Operations Management,* Vol. 13 No. 4, pp. 369-385.

Attaran, M. (2017), "Additive manufacturing: the most promising technology to alter the supply chain and logistics", *Journal of Service Science and Management,* Vol. 10 No. 3, pp. 189-206.

Atzeni, E., and Salmi, A. (2012), "Economics of additive manufacturing for end-usable metal parts", *International Journal of Advanced Manufacturing Technology*, Vol. 62 No. 9-12, pp. 1147-1155.

Austin, P.C. (2011), "An introduction to propensity score methods for reducing the effects of confounding in observational studies", *Multivariate Behavioral Research*, Vol. 46 No. 3, pp. 399-424.

Azadegan, A., Patel, P.C., Zangoueinezhad, A. and Linderman, K. (2013), "The effect of environmental complexity and environmental dynamism on lean practices", *Journal of Operations Management,* Vol. 31 No. 4, pp. 193-212.

Barber, B.M. and Lyon, J.D. (1997), "Detecting long-run abnormal stock returns: the empirical power and specification of test statistics", *Journal of Financial Economics,* Vol. 43 No. 3, pp. 341-372.

Barreto, I. (2010), "Dynamic capabilities: a review of past research and an agenda for the future", *Journal of Management*, Vol. 36 No. 1, pp. 256-280.

Benjamini, Y. and Hochberg, Y. (1995), "Controlling the false discovery rate: a practical and powerful approach to multiple testing", *Journal of the Royal Statistical Society: Series B (Methodological)*, Vol. 57 No. 1, pp. 289-300.

Bloomberg (2017), "Henry Schein Announces North American Marketing Partnership with GuardLab during Yankee Dental Congress", available at https://www.bloomberg.com/research/stocks/private/snapshot.asp?privcapId=260615611/ (accessed 10 August 2018).

Business Wire (2015), "Autodesk and Mattel Team Up to Bring New Digital and 3D Printing Experiences to Kids and Families", available at http://investors.autodesk.com/news-releases/news-release-details/autodesk-and-mattel-team-bring-new-digital-and-3d-printing/ (accessed 10 August 2018).

Carey, N. (2016), "Sensing Threat, UPS Plans to Expand its 3D Printing Operations", available at https://www.reuters.com/article/us-united-parcel-3dprint/sensing-threat-ups-plans-to-expand-its-3d-printing-operations-idUSKCN11M2AL (accessed 28 July 2019).

Chari, M.D.R., Devaraj, S. and David, P. (2007), "The impact of information technology investments and diversification strategies on firm performance", *Management Science,* Vol. 54 No. 1, pp. 224-234.

Chavez, R., Gimenez, C., Fynes, B., Wiengarten, F. and Yu, W. (2013), "Internal lean practices and operational performance: the contingency perspective of industry clockspeed", *International Journal of Operations & Production Management*, Vol. 33 No. 5, pp. 562-588.

Chen, Y., Wang, Y., Nevo, S., Jin, J., Wang, L., and Chow, W.S. (2014), "IT capability and organizational performance: the roles of business process agility and environmental factors", *European Journal of Information Systems*, Vol. 23 No. 3, pp. 326-342.

Clark, J.R. and Huckman, R.S. (2011), "Broadening focus: spillovers, complementarities, and specialization in the hospital industry", *Management Science*, Vol. 58 No. 4, pp. 708-722.

Corbett, L.M. and Claridge, G.S. (2002), "Key manufacturing capability elements and business performance", *International Journal of Production Research*, Vol. 40 No. 1, pp. 109-131.

d'Aveni, R. (2015), "The 3-D printing revolution", *Harvard Business Review,* Vol. 93 No. 5, pp. 40-48.

De Jong, P., Paulraj, A., and Blome, C. (2014), "The financial impact of ISO 14001 certification: top-line, bottom-line, or both?", *Journal of Business Ethics*, Vol. 119 No. 1, pp. 131-149.

Dess, G.G. and Beard, D.W. (1984), "Dimensions of organizational task environments", *Administrative Science Quarterly,* Vol. 29 No. 1, pp. 52-73.

Ding, L., Lam, H.K., Cheng, T.C.E., and Zhou, H. (2018), "A review of short-term event studies in operations and supply chain management", *International Journal of Production Economics*, Vol. 200, pp. 329-342.

Dong, L., Shi, D. and Zhang, F. (2017), "3D printing vs. traditional flexible technology: implications for operations strategy", Working Paper, Washington University, St. Louis.

Ernst & Young (2016), "How Will 3D Printing Make Your Company the Strongest Link in the Value Chain", available at https://www.ey.com/Publication/vwLUAssets/EY-3d-druck-studie-executive-summary/$FILE/ey-how-will-3d-printing-make-your-company-the-strongest-link-in-the-value-chain.pdf/ (accessed 10 August 2018).

Eyers, D.R., Potter, A.T., Gosling, J. and Naim, M.M. (2018), "The flexibility of industrial additive manufacturing systems", *International Journal of Operations & Production Management,* Vol. 38 No. 12, pp. 2313-2343.

Ferguson, C., Finn, F., Hall, J. and Pinnuck, M. (2010), "Speculation and e-commerce: the long and the short of IT", *International Journal of Accounting Information Systems,* Vol. 11 No. 2, pp. 79-104.

Ford, S., and Despeisse, M. (2016), "Additive manufacturing and sustainability: an exploratory study of the advantages and challenges", *Journal of Cleaner Production*, Vol. 137, pp. 1573-1587.

Grant, R.M., Krishnan, R., Shani, A.B. and Baer, R. (1991), "Appropriate manufacturing technology: a strategic approach", *Sloan Management Review,* Vol. 33 No. 1, pp. 43-55.

Gross, D. (2013), "Obama's Speech Highlights Rise of 3-D Printing", available at: https://edition.cnn.com/2013/02/13/tech/innovation/obama-3d-printing/index.html/ (accessed 10 August 2018).

Helfat, C.E., Finkelstein, S., Mitchell, W., Peteraf, M.A., Singh, H., Teece, D.J. and Winter, S.G. (2007), *Dynamic Capabilities: Understanding Strategic Change in Organizations*. Blackwell, Malden, MA.

Hendricks, K.B. and Singhal, V.R. (2001), "The long-run stock price performance of firms with effective TQM programs", *Management Science,* Vol. 47 No. 3, pp. 359-368.

Hendricks, K.B., Singhal, V.R. and Stratman, J.K. (2007), "The impact of enterprise systems on corporate performance: a study of ERP, SCM, and CRM system implementations", *Journal of Operations Management,* Vol. 25 No. 1, pp. 65-82.

Hitt, M.A., Hoskisson, R.E. and Kim, H. (1997), "International diversification: effects on innovation and firm performance in product-diversified firms", *Academy of Management Journal,* Vol. 40 No. 4, pp. 767-798.

Holmström, J., Holweg, M., Khajavi, S.H. and Partanen, J. (2016), "The direct digital manufacturing (r)evolution: definition of a research agenda", *Operations Management Research*, Vol. 9 No. 1-2, pp. 1-10.

Huang, S.H., Liu, P., Mokasdar, A. and Hou, L. (2012), "Additive manufacturing and its societal impact: a literature review", *International Journal of Advanced Manufacturing Technology,* Vol. 67 No. 5-8, pp. 1191-1203.

Jacobs, B.W., Swink, M. and Linderman, K. (2015), "Performance effects of early and late Six Sigma adoptions", *Journal of Operations Management,* Vol. 36, pp. 244-257.

Jansen, J.J., Van Den Bosch, F.A. and Volberda, H.W. (2006), "Exploratory innovation, exploitative innovation, and performance: effects of organizational antecedents and environmental moderators", *Management Science,* Vol. 52 No. 11, pp. 1661-1674.

Jia, F., Wang, X., Mustafee, N. and Hao, L. (2016), "Investigating the feasibility of supply chain-centric business models in 3D chocolate printing: a simulation study", *Technological Forecasting and Social Change,* Vol. 102 No. 202-213, pp. 202-213.

Jiang, W., Mavondo, F.T. and Matanda, M.J. (2015), "Integrative capability for successful partnering: a critical dynamic capability", *Management Decision*, Vol. 53 No. 6, pp. 1184-1202.

Jopson, B., (2013), "New Stamping Ground for Nike and Adidas as 3D Shoes Kick Off", available at https://www.ft.com/content/1d09a66e-d097-11e2-a050-00144feab7de/ (accessed 10 August 2018).

Joshi, A. and Hanssens, D.M. (2010), "The direct and indirect effects of advertising spending on firm value", *Journal of Marketing*, Vol. 74 No. 1, pp. 20-33.

Kim, J.S. and Arnold, P. (1993), "Manufacturing competence and business performance: a framework and empirical analysis", *International Journal of Operations & Production Management*, Vol. 13 No. 10, pp. 4-25.

Kothari, S.P. and Warner, J.B. (2007), "Econometrics of Event Studies", in Eckbo, B.E. (Ed.), *Handbook of Empirical Corporate Finance*, Elsevier, pp. 3-36.

Kovach, J.J., Hora, M., Manikas, A. and Patel, P.C. (2015), "Firm performance in dynamic environments: the role of operational slack and operational scope", *Journal of Operations Management,* Vol. 37, pp. 1-12.

Lam, C.X.F., Mo, X.M., Teoh, S.H. and Hutmacher, D.W. (2002), "Scaffold development using 3D printing with a starch-based polymer", *Materials Science and Engineering: C,* Vol. 20 No. 1, pp. 49-56.

Lam, H. K. (2018), "Doing good across organizational boundaries: sustainable supply chain practices and firms' financial risk", *International Journal of Operations & Production Management*, Vol. 38 No. 12, pp. 2389-2412.

Lyon, J.D., Barber, B.M. and Tsai, C.L. (1999), "Improved methods for tests of long-run abnormal stock returns", *Journal of Finance,* Vol. 54 No. 1, pp. 165-201.

McCue, T.J., (2015), "3D Print Your Favorite Ford Vehicle - With New Ford 3D Store", Available at https://www.forbes.com/sites/tjmccue/2015/06/11/3d-print-your-favorite-ford-vehicle-with-new-ford-3d-store/#5343bfda5e29 (accessed 28 July 2019).

Mellor, S., Hao, L. and Zhang, D. (2014), "Additive manufacturing: a framework for implementation". *International Journal of Production Economics*, Vol. 149, pp. 194-201.

Melville, N., Kraemer, K. and Gurbaxani, V. (2004), "Information technology and organizational performance: an integrative model of IT business value", *MIS Quarterly,* Vol. 28 No. 2, pp. 283-322.

Oliver, C. and Holzinger, I. (2008), "The effectiveness of strategic political management: a dynamic capabilities framework", *Academy of Management Review*, Vol. 33 No. 2, pp. 496-520.

Orzes, G., Jia, F., Sartor, M. and Nassimbeni, G. (2017), "Performance implications of SA8000 certification". *International Journal of Operations & Production Management*, Vol. 37 No. 11, pp. 1625-1653.

Park, N.K. and Mezias, J.M. (2005), "Before and after the technology sector crash: the effect of environmental munificence on stock market response to alliances of e-commerce firms", *Strategic Management Journal,* Vol. 26 No. 11, pp. 987-1007.

Petrick, I.J. and Simpson, T.W. (2013), "Point of view: 3D printing disrupts manufacturing:

how economies of one create new rules of competition", *Research-Technology Management,* Vol. 56 No. 6, pp. 12-16.

Prajogo, D.I. and Oke, A. (2016), "Human capital, service innovation advantage, and business performance: the moderating roles of dynamic and competitive environments", *International Journal of Operations & Production Management*, Vol. 36 No. 9, pp. 974-994.

Qian, J.Q. and Zhu, J.L. (2017), "Return to invested capital and the performance of mergers and acquisitions", *Management Science,* Vol. 64 No. 10, pp. 4814-4834.

Ramdas, K. (2009), "Managing product variety: an integrative review and research directions", *Production and Operations Management,* Vol. 12 No. 1, pp. 79-101.

Reinking, J. (2012), "Contingency theory in information systems research", in Dwivedi, Y.K., Wade, M.R. and Schneberger, S.L. (Eds), *Information Systems Theory*, Springer, New York, NY, pp. 247-263.

Schilke, O., Hu, S. and Helfat, C.E. (2018), "Quo vadis, dynamic capabilities? a content-analytic review of the current state of knowledge and recommendations for future research", *Academy of Management Annals*, Vol. 12 No. 1, pp. 390-439.

Schniederjans, D.G. (2017), "Adoption of 3D-printing technologies in manufacturing: a survey analysis", *International Journal of Production Economics,* Vol. 183, pp. 287-298.

Shamsie, J., Martin, X. and Miller, D. (2009), "In with the old, in with the new: capabilities, strategies, and performance among the Hollywood studios", *Strategic Management Journal*, Vol. 30 No. 13, pp. 1440-1452.

Shukla, M., Todorov, I. and Kapletia, D. (2018), "Application of additive manufacturing for mass customisation: understanding the interaction of critical barriers", *Production Planning & Control,* Vol. 29 No. 10, pp. 814-825.

Sorescu, A., Warren, N.L. and Ertekin, L. (2017), "Event study methodology in the marketing literature: an overview", *Journal of the Academy of Marketing Science,* Vol. 45 No. 2, pp. 186-207.

Sousa, R. and Voss, C.A. (2008), "Contingency research in operations management practices", *Journal of Operations Management*, Vol. 26 No. 6, pp. 697-713.

Stoel, M. and Muhanna, W.A. (2009), "IT capabilities and firm performance: A contingency analysis of the role of industry and IT capability type", *Information & Management,* Vol. 46 No. 3, pp. 181-189.

Swink, M. and Jacobs, B.W. (2012), "Six Sigma adoption: operating performance impacts and contextual drivers of success", *Journal of Operations Management,* Vol. 30 No. 6, pp. 437-453.

Teece, D.J., Pisano, G. and Shuen, A. (1997), "Dynamic capabilities and strategic management", *Strategic Management Journal*, Vol. 18 No. 7, pp. 509-533.

Terjesen, S., Patel, P.C. and Covin, J.G. (2011), "Alliance diversity, environmental context and the value of manufacturing capabilities among new high technology ventures", *Journal of Operations Management,* Vol. 29 No. 1, pp. 105-115.

Thomas-Seale, L.E.J., Kirkman-Brown, J.C., Attallah, M.M., Espino, D.M. and Shepherd, D.E.T. (2018), "The barriers to the progression of additive manufacture: perspectives from UK industry", *International Journal of Production Economics,* Vol. 198, pp. 104-118.

Van Dusen, M. (2017), "GE's 3D-Printed Airplane Engine Will Run This Year", available at https://www.ge.com/reports/mad-props-3d-printed-airplane-engine-will-run-year/ (accessed 10 August 2018).

Ventola, C.L. (2014), "Medical applications for 3D printing: current and projected uses", *Pharmacy and Therapeutics*, Vol. 39 No. 10, pp. 704-711.

Ward, P.T. and Duray, R. (2000), "Manufacturing strategy in context: environment, competitive strategy and manufacturing strategy", *Journal of Operations Management*, Vol. 18 No. 2, pp. 123-138.

Weller, C., Kleer, R. and Piller, F.T. (2015), “Economic implications of 3D printing: market structure models in light of additive manufacturing revisited”, *International Journal of Production Economics,* Vol. 164, pp. 43-56.

White, G.P. (1996), “A meta-analysis model of manufacturing capabilities”, *Journal of Operations Management*, Vol. 14 No. 4, pp. 315-331.

Wilden, R., Gudergan, S.P., Nielsen, B.B. and Lings, I. (2013), “Dynamic capabilities and performance: strategy, structure and environment”, *Long Range Planning*, Vol. 46 No. 1-2, pp. 72-96.

Williams, C.B., Cochran, J.K. and Rosen, D.W. (2010), “Additive manufacturing of metallic cellular materials via three-dimensional printing”, *International Journal of Advanced Manufacturing Technology,* Vol. 53 No. 1-4, pp. 231-239.

Wong, C.Y., Boon-Itt, S. and Wong, C.W. (2011), “The contingency effects of environmental uncertainty on the relationship between supply chain integration and operational performance”, *Journal of Operations management*, Vol. 29 No. 6, pp. 604-615.

Xia, Y., Singhal, V.R. and Zhang, G.P. (2016), “Product design awards and the market value of the firm”, *Production and Operations Management,* Vol. 25 No. 6, pp. 1038-1055.

Yang, Y., Orzes, G., Jia, F. and Chen, L. (2019), “Does GRI sustainability reporting pay off? An empirical investigation of publicly listed firms in China”, *Business & Society*, in press.

Zhang, D., Linderman, K. and Schroeder, R.G. (2012), “The moderating role of contextual factors on quality management practices”, *Journal of Operations Management*, Vol. 30 No. 1-2, pp. 12-23.

Table 1 Descriptive statistics

Panel A: Distribution of 3DP implementation announcements across years		
Year	Frequency	Percentage
2010	4	2%
2011	5	2%
2012	9	4%
2013	25	11%
2014	42	18%
2015	41	18%
2016	61	26%
2017	45	19%
Total	232	100%

Panel B: Distribution of 3DP implementation announcements across industries			
Industry	SIC	Frequency	Percentage
Agriculture, Mining, Construction	0100-1999	5	2%
Food, textiles, furniture, paper, and chemicals	2000-2999	34	15%
Rubber, leather, stone, metals, machinery, and equipment	3000-3569, 3580-3659,3800-3999	57	25%
Computers, electronics, communications, and defense	3570-3579, 3660-3699, 3760-3789	37	16%
Automobile, aircraft, and transportation manufacturing	3700-3759, 3790-3799	24	10%
Transportation, communications, wholesaling and retailing	4000-5999	22	9%
Services and non-classifiable	6000-9999	53	23%
Total		232	100%

Panel C: Characteristics of 3DP implementation announcing firms				
Firm characteristics	Mean	Standard deviation	Maximum	Minimum
Market value ($ million)	72160.8	108860.4	647506.9	20.2
Total assets ($ million)	34618.8	150870.0	751216	15.8
Sales ($ million)	37442.5	46791.1	233715	0.38
Net Income ($ million)	3235.9	6491.83	53394	-6127

Table 2 Measurement of variables

Variable Type	Variable Name	Measurement	Data Source	Reference
Dependent Variable	BHAR	Abnormal buy-and-hold stock return calculated with monthly return $\text{BHAR} = \prod_{t=1}^{T}(1+R_{it}) - \prod_{t=1}^{T}(1+R_{bt})$	CRSP	(Lyon *et al.*, 1999)
Explanatory variables	Industry munificence	Slope coefficient obtained by regressing sales over the time period of 2010-2017 / mean sales over the same time period	Compustat	(Jacobs *et al.*, 2015)
	Industry dynamism	Standard error of the slope coefficient obtained by regressing sales over the time period of 2010-2017 / mean sales over the same time period	Compustat	(Jacobs *et al.*, 2015)
	Industry competition	1-Herfindahl index = 1- $\sum_{i}^{N}(\frac{Sales_i}{Total\ Sales\ of\ firms\ in\ the\ same\ industry})^2$	Compustat	(Xia *et al.*, 2016)
Control variables	Firm size	Natural logarithm of market value of equity in the most recent fiscal year before the announcement year	Compustat	(Hendricks and Singhal, 2001)
	MTB ratio	Market value of equity / Book value of equity in the most recent fiscal year before the announcement year	Compustat	(Lam, 2018)
	R&D intensity	R&D expenses / Sales in the most recent fiscal year before the announcement year	Compustat	(Jacobs *et al.*, 2015)
	Prior performance	Sample firm ROA – Median ROA of firms with the same 3-digit SIC code	Compustat	(Swink and Jacobs, 2012)
	Capital structure	Total liabilities / Sales in the most recent fiscal year before the announcement year	Compustat	(Chari *et al.*, 2007)
	Momentum	Buy-and-hold return of sample firms from 6 months to 1 month prior to the announcement month	CRSP	(Qian and Zhu, 2017)
	Velocity	Fast velocity industries (SIC = 284, 367, 737) = 1 Other industries = 0	Compustat	(Jacobs *et al.*, 2015)
	Manufacturing	Manufacturing industries = 1 Service and other industries = 0	Compustat/ Announcements	(Swink and Jacobs, 2012)
	Year dummies	Years of 3DP implementation announcements	Announcements	(Lam, 2018)

Table 3 Buy-and-hold abnormal returns of sample firms

Start Month	End Month	No. of observations	BHAR mean	p-value (*t*-test)	BHAR median	p-value (WSR)	BHAR positive	p-value (sign test)
Industry-size-matched control firms								
-24	-1	184	-31.26%	0.076	-4.52%	0.393	46%	0.338
-24	-13	184	-7.87%	0.056	-0.80%	0.493	49%	0.941
-12	-1	192	-6.51%	0.176	2.55%	0.863	55%	0.220
0	0	198	0.05%	0.946	0.27%	0.973	51%	0.943
1	6	179	-1.71%	0.429	-0.02%	0.768	49%	0.881
7	12	145	3.36%	0.132	2.80%	0.158	56%	0.184
1	12	145	3.28%	0.323	2.76%	0.157	59%	0.030*
13	18	120	3.22%	0.186	3.30%	0.041	61%	0.022*
1	18	120	8.27%	0.111	9.30%	0.014*	61%	0.022*
1	24	94	14.56%	0.033	18.45%	0.004**	63%	0.017*
Industry-MTB-matched control firms								
-24	-1	161	-21.84%	0.275	2.08%	0.486	50%	1.000
-24	-13	162	-2.74%	0.573	5.18%	0.466	53%	0.480
-12	-1	179	-6.99%	0.177	-3.73%	0.447	47%	0.550
0	0	192	0.20%	0.834	-0.22%	0.850	49%	0.942
1	6	171	1.17%	0.689	4.98%	0.089	57%	0.066
7	12	135	3.17%	0.350	4.64%	0.064	55%	0.302
1	12	135	6.27%	0.171	3.06%	0.068	56%	0.168
13	18	112	8.98%	0.001***	9.34%	0.000***	66%	0.001***
1	18	112	14.64%	0.027	12.09%	0.004**	63%	0.010**
1	24	88	20.73%	0.051	24.48%	0.004**	66%	0.004**
Industry-size-MTB-matched control firms								
-24	-1	176	-27.14%	0.140	3.24%	0.878	52%	0.598
-24	-13	177	-7.52%	0.091	-1.41%	0.591	49%	0.881
-12	-1	189	-3.12%	0.472	1.96%	0.941	52%	0.663
0	0	198	0.14%	0.883	-0.22%	0.937	49%	0.831
1	6	182	-1.57%	0.532	2.00%	0.755	52%	0.711
7	12	146	1.83%	0.381	-0.05%	0.646	50%	1.000
1	12	146	0.13%	0.973	2.35%	0.718	53%	0.563
13	18	121	7.74%	0.002**	5.24%	0.004**	62%	0.011*
1	18	121	9.54%	0.049	7.17%	0.084	58%	0.101
1	24	93	20.26%	0.015*	17.35%	0.009**	65%	0.007*

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests; significance is adjusted using Benjamini and Hochberg's (1995) approach).

Table 4 Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12
1. BHAR(%)	1											
2. Firm size	0.20**	1										
3. MTB ratio	0.02	0.05	1									
4. R&D intensity	0.01	-0.17*	-0.06	1								
5. Prior performance	-0.04	0.27***	0.09	-0.23**	1							
6. Capital structure	0.03	0.30***	-0.14	0.38***	-0.17*	1						
7. Momentum	0.05	0.08	-0.05	0.00	-0.10	0.00	1					
8. Velocity	-0.20**	0.10	-0.07	-0.03	0.37***	-0.19**	0.03	1				
9. Manufacturing	-0.10	-0.11	-0.19**	0.05	-0.05	0.27***	-0.05	-0.42***	1			
10. Munificence	0.33***	0.03	0.25***	0.03	0.04	-0.25***	-0.09	-0.09	-0.01	1		
11. Dynamism	0.08	-0.24***	-0.04	-0.08	-0.08	-0.05	-0.18*	-0.21**	0.05	-0.08	1	
12. Competition	-0.29***	-0.22**	-0.13	0.09*	0.16	-0.14	-0.03	0.51***	-0.20**	-0.20**	0.32***	1
Mean	0.08	10.14	5.05	0.23	0.04	1.03	-0.03	0.26	0.71	0.01	0.01	0.74
Standard deviation	0.56	1.87	6.78	1.92	0.07	0.97	0.32	0.44	0.46	0.04	0.01	0.24

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests).

Table 5 Regression analysis

Independent variables	Model 1		Model 2		Model 3		Model 4	
	Estimated Coefficients	$\sqrt{VIF}$	Estimated Coefficients	$\sqrt{VIF}$	Estimated Coefficients	$\sqrt{VIF}$	Estimated Coefficients	$\sqrt{VIF}$
Intercept	0.67 (0.96)		0.68 (1.03)		0.51 (0.78)		1.11 (1.62)	
Control variables								
Firm size	0.09 (2.76)***	1.14	0.07 (2.13)**	1.14	0.09 (2.61)**	1.16	0.07 (2.05)**	1.18
MTB ratio	-0.01 (-0.71)	1.04	-0.01 (-1.41)	1.05	-0.01 (-1.25)	1.05	-0.01 (-1.17)	1.05
R&D intensity	0.03 (0.84)	1.09	0.00 (0.14)	1.10	0.01 (0.37)	1.11	0.02 (0.79)	1.11
Prior performance	-0.03 (-0.03)	1.14	0.00 (0.06)	1.14	0.15 (0.17)	1.14	0.26 (0.30)	1.14
Capital structure	-0.07 (-0.98)	1.19	0.00 (0.06)	1.22	0.01 (0.13)	1.22	0.00 (0.03)	1.22
Momentum	0.16 (0.87)	1.09	0.22 (1.26)	1.09	0.32 (1.85)*	1.11	0.36 (2.12)**	1.11
Velocity	-0.52 (-3.64)***	1.13	-0.45 (-3.33)***	1.13	-0.41 (-3.04)***	1.14	-0.20 (-1.26)	1.25
Manufacturing	-0.31 (-2.27)**	1.13	-0.34 (-2.55)**	1.03	-0.34 (-2.64)***	1.13	-0.33 (-2.60)**	1.13
Year dummies	Included	1.03	Included	1.07	Included	1.04	Included	1.04
Explanatory variables								
Munificence			4.06 (3.40)***	1.07	4.20 (3.60)***	1.07	3.80 (3.29)***	1.08
Dynamism					17.05 (2.46)**	1.09	24.88 (3.28)***	1.15
Competition							-0.68 (-2.31)**	1.23
No. of observations	119		119		119		119	
R-squared	21.49%		29.48%		33.47%		36.85%	
Adjusted *R*-squared	10.05%		18.41%		22.27%		25.49%	
F-statistic	1.88**		2.66***		2.99***		3.24***	
Δ*R*-squared			7.99%		4.00%		3.38%	
Δ*F*			12.65***		6.33**		5.35**	

Notes: The dependent variable is the BHAR based on the industry-size matching approach with an event window of month (1, 18). *t*-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests).

Table 6 Buy-and-hold abnormal returns of sample firms based on propensity score matching

Start Month	End Month	No. of observations	BHAR mean	p-value (*t*-test)	BHAR median	p-value (WSR)	BHAR positive	p-value (sign test)
-24	-1	158	-0.48%	0.915	-1.77%	0.942	48%	0.691
-24	-13	158	3.84%	0.259	2.71%	0.241	53%	0.474
-12	-1	170	-6.60%	0.085	-3.60%	0.325	44%	0.145
0	0	174	1.24%	0.072	0.37%	0.228	51%	0.820
1	6	172	0.82%	0.692	0.96%	0.447	53%	0.402
7	12	171	0.38%	0.861	1.61%	0.536	54%	0.359
1	12	171	2.34%	0.405	5.64%	0.218	60%	0.014*
13	18	156	2.06%	0.328	2.57%	0.235	55%	0.230
1	18	156	7.40%	0.059	10.32%	0.015*	63%	0.002**
1	24	128	8.58%	0.107	9.97%	0.017*	61%	0.017*

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests; significance is adjusted using Benjamini and Hochberg's (1995) approach).

Table 7 Buy-and-hold abnormal returns of subsample firms

Start Month	End Month	No. of observations	BHAR mean	p-value (*t*-test)	BHAR median	p-value (WSR)	BHAR positive	p-value (sign test)
Industry-size-matched control firms								
-24	-1	88	-49.43%	0.164	-0.83%	0.631	50%	1.000
-24	-13	88	-12.42%	0.091	4.97%	0.590	53%	0.594
-12	-1	92	-11.81%	0.159	4.76%	0.970	57%	0.251
0	0	94	-0.27%	0.794	-0.58%	0.502	45%	0.353
1	6	94	1.14%	0.625	3.40%	0.907	53%	0.606
7	12	94	5.63%	0.028	3.90%	0.040*	61%	0.049*
1	12	94	6.56%	0.091	6.06%	0.025*	63%	0.017**
13	18	94	5.21%	0.052	4.30%	0.009**	65%	0.005**
1	18	94	12.28%	0.029	12.24%	0.001***	64%	0.010**
1	24	94	14.56%	0.033	18.45%	0.004**	63%	0.017**
Industry-MTB-matched control firms								
-24	-1	78	-42.66%	0.290	2.55%	0.511	50%	1.000
-24	-13	79	-6.56%	0.434	10.03%	0.413	56%	0.368
-12	-1	84	-7.52%	0.352	-2.13%	0.648	49%	0.913
0	0	90	0.67%	0.642	0.44%	0.615	51%	0.916
1	6	90	4.13%	0.276	5.19%	0.039*	59%	0.113
7	12	89	5.58%	0.086	4.64%	0.046*	56%	0.289
1	12	89	9.01%	0.096	6.07%	0.017**	61%	0.056
13	18	88	12.49%	0.000***	12.68%	0.000***	69%	0.000***
1	18	88	18.55%	0.014*	15.16%	0.000***	67%	0.002***
1	24	88	20.73%	0.051	24.48%	0.004**	66%	0.004**
Industry-size-MTB-matched control firms								
-24	-1	85	-45.74%	0.218	4.67%	0.661	53%	0.665
-24	-13	86	-7.92%	0.336	8.39%	0.633	57%	0.235
-12	-1	93	-9.44%	0.216	-2.08%	0.462	47%	0.679
0	0	96	1.18%	0.305	-0.22%	0.727	49%	0.919
1	6	96	-1.44%	0.671	-0.67%	0.946	48%	0.760
7	12	95	3.10%	0.246	1.64%	0.345	52%	0.838
1	12	95	1.59%	0.741	2.32%	0.493	53%	0.682
13	18	94	11.01%	0.000***	10.31%	0.000***	67%	0.001**
1	18	94	13.49%	0.010*	9.16%	0.020*	60%	0.079
1	24	93	20.26%	0.015*	17.35%	0.009**	65%	0.007**

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests; significance is adjusted using Benjamini and Hochberg's (1995) approach).

Table 8 Regression analysis with alternative BHAR as dependent variable

Models	Munificence	Dynamism	Competition	*N*	Adjusted *R*-squared	*F*-statistic
Industry-size-matched group; Event window = (1, 24)	3.49 (2.07)**	19.25 (1.70)*	-0.91 (-2.39)**	93	20.65%	2.33***
Industry-MTB-matched group; Event window = (1, 18)	3.99 (2.80)***	28.57 (3.02)***	-0.75 (-2.06)**	109	23.88%	3.12***
Industry-size-MTB-matched group; Event window = (1, 18)	4.69 (4.23)***	11.75 (1.67)*	-0.64 (-2.25)**	120	19.69%	2.62***

Notes: *t*-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests).

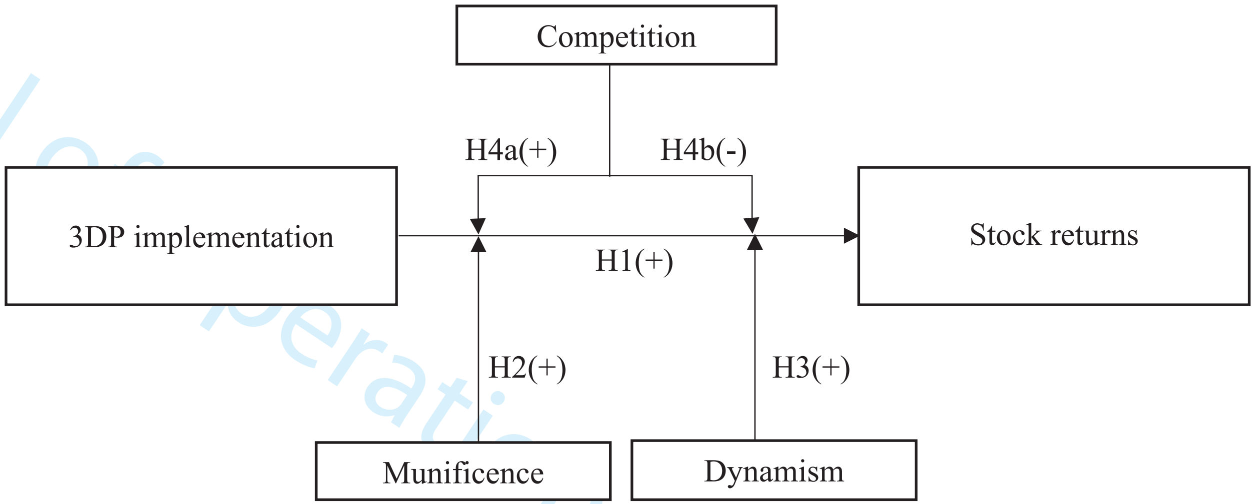

Figure 1 Research model

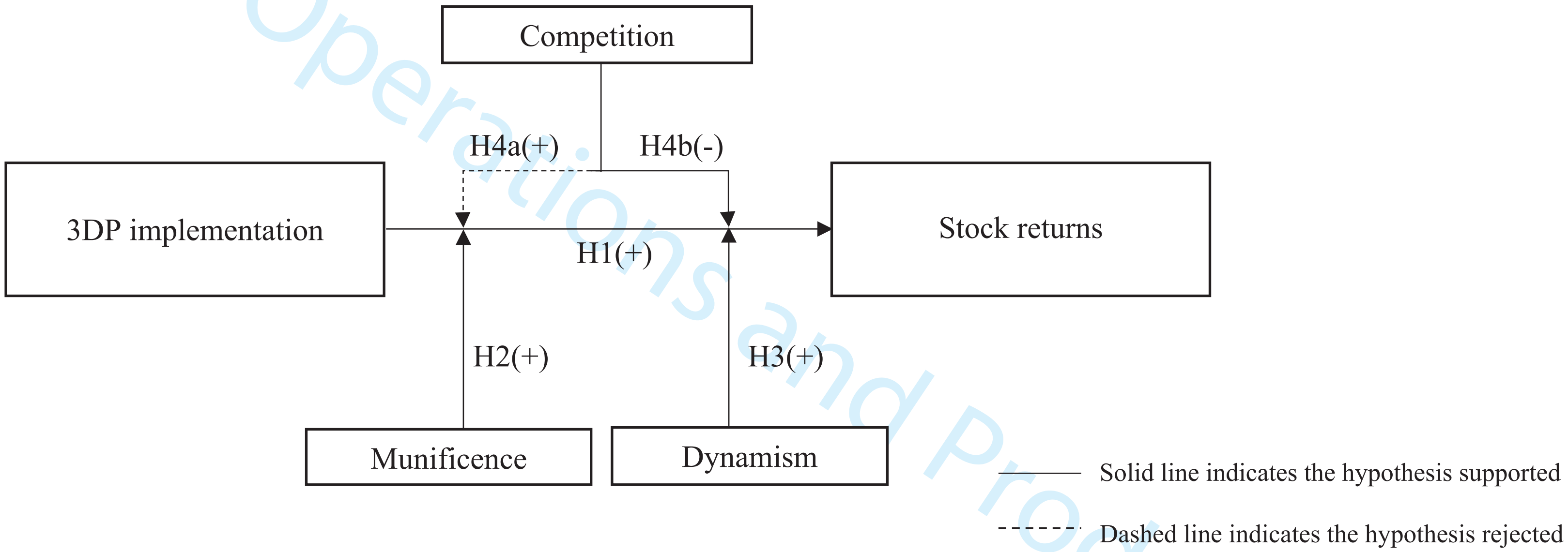

Figure 2 Hypothesis test results