Stock Market Liquidity and Stock Returns: Evidence from the London Stock Exchange

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Abstract

In this thesis, I investigate the effect of liquidity risk on stock returns using data from the London Stock Exchange. The main motivation behind this research is that most previous studies on this topic focus on the US stock market and very little is known about the link between liquidity and stock returns in the UK. Also, most studies only focus on one dimension of liquidity and ignore other illiquidity measures that capture different dimensions. This study employs eight different proxies of liquidity, namely bid-ask spread, effective spread, quoted spread, Liu's (2006) measure, dollar trading volume, turnover ratio, Amihud's (2002) RtoV ratio and Florackis et al.'s (2011) RtoTR ratio. Interestingly, the results based on the LSE do not support the existence of an illiquidity premium. In contrast, the results suggest a negative relationship between illiquidity and stock returns. As illiquidity increases, instead of seeing rises in stock returns, post-ranking returns decrease. This finding contradicts previous US evidence, which shows a positive relationship between illiquidity and stock returns.

Keywords: Stock Returns, Asset Pricing, Liquidity.

1. Introduction

In classical asset-pricing models, financial markets are assumed to have no frictions and thus the diverse features of liquidity are ignored. However, liquidity is important in investment as it affects portfolio investment performance and has significant implications for portfolio diversification strategies (Lesmond, Schill and Zhou, 2004). According to Amihud and Mendelson (1986a), liquidity affects the cross-sectional differences of asset returns (Brennan and Subrahmanyam, 1996; Amihud, 2002). It can also be regarded as a priced risk factor (Pastor and Stambaugh, 2003; Sadka, 2004; Acharya and Pedersen, 2005).

In general, liquidity is used to describe the ability to trade large quantities of shares in a given amount of time at a low cost. This is of interest for portfolio managers and risk management practitioners. Liquidity plays an important role at both macro- and micro-level. Liquidity at macro-level mainly refers to the central bank money supply provision and the availability of funds for participants in the financial markets. Micro-liquidity, on the other hand, refers to trading conditions. It is an important source of market friction and has first order effects on asset prices (Amihud and Mendelson, 1980). As liquidity is not observable, different economists have proposed various proxies for liquidity and models that test liquidity pricing on the market. According to Liu (2006), these trading conditions embrace trading quantity, trading speed, trading cost and price impact. Trading costs include the bid-ask spread, proposed by Amihud and Mendelson (1986a), relative spread (Amihud and Mendelson, 1986b), effective spread, suggested by Lee (1993) and amortized spread (Chalmers and Kadlec, 1998). Trading quantity includes trading volume (Brennan, Chordia and Subrahmanyam, 1998) and turnover rate (Datar, Naik and Radcliffe, 1998). Liu (2006) proposed a new measure of zero trading days to capture the dimension of trading speed, while the measures used by Amihud (2002) and Pastor and Stambaugh (2003) employ the concept of price impact to capture price reaction to trading volume.

The recent global financial crisis has highlighted the importance of liquidity. It is now well understood that a decline or, worse, evaporation of liquidity can cause substantial falls in asset prices that are not justified by their fundamentals (Florackis, Kontonikas and Kostakis, 2013). In addition, as liquidity is multidimensional, existing measures inevitably demonstrate a limited ability to capture liquidity risk fully and can be inaccurate even in the dimension they aim to capture. Given the limited number of liquidity proxies tested, the limited set of liquidity benchmarks compared and the absence of monthly proxies, it is not surprising that there are conflicting views about which measure is better. Yet, most studies on this topic are examined on the basis of the US stock market but only a few are based on the UK stock market. The objective of this study is to fill this gap in international stock market research and compare different dimensions of liquidity.

The main contribution of this research is in its investigation of the relationship between stock returns and liquidity on the London Stock Exchange (LSE). I examine whether these lead to different results and also whether UK-based results differ from US results. The use of a wide set of proxies helps to provide more comprehensive evidence on the relationship between liquidity and expected returns based on the UK dataset.

In particular, I employ a dataset from January 1991 to May 2011 for the LSE. The dataset contains 1823 stocks from the index that were traded across the whole time horizon. Each stock contains 252 observations.

The liquidity measures employed in this study include bid-ask spread, effective spread, quoted spread, dollar trading volume, turnover ratio, Liu's measure, Amihud's ratio and Florackis et al.'s (2011) RtoTR. Based on each illiquidity proxy, the dataset can be sorted into ten portfolios. Portfolio 1 (p1) includes stocks with the lowest value of illiquidity proxy while portfolio 10 (p10) includes stocks with the highest values of illiquidity proxy. Portfolios are formed both equal-weighted and value-weighted. Each portfolio return is regressed on a number of factors used in CAPM, Fama-French three-factor model and Carhart's (1997) four-factor models. The intercept from each regression is the excess return earned by trading based on liquidity risks. By examining the difference between the intercepts of the highest and lowest decile portfolios (p10-p1), the profit from a zero-investment cost trading strategy can be obtained.

The findings suggest a negative relationship between illiquidity and asset pricing. As illiquidity increases, post-ranking returns decline. This holds for all eight illiquidity proxies. Interestingly, this contradicts the results of previous studies for the US dataset. The empirical findings cannot account for liquidity premium; instead, the results suggest that liquidity stocks yield higher returns than illiquid stocks. The findings clearly have important implications for portfolio managers.

The remainder of the thesis is organized as follows: Section 2 presents the literature review on the topic of liquidity provides and the illiquidity proxies employed in this research. Section 3 describes the data, construction of the portfolios and descriptive statistics are presented. Section 4 describes the asset-pricing test considered and the empirical results in the time-series framework. Finally, the conclusion is presented in Section 5.

2. Related Literature

2.1 Liquidity and Asset Prices

The term 'liquidity' does not have a unique definition capturing all its properties, as it encompasses several dimensions. Empirical studies suggest that liquidity is the driving force behind organized markets, in which buyers and sellers organize through a common venue to reduce the search costs of finding someone to trade with. As a result, the more liquid an asset is, the easier it is to find a trading partner at a given piece. For instance, Keynes (1930) wrote that an asset is more liquid than another if it is more certainly realizable at short notice without loss. Acharya and Pedersen (2005) state that liquidity is risky and has commonality; it varies over time both for individual stocks and for the market as a whole (Chordia et al., 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 1999). Persaud (2003) noted that 'there is a broad belief among users of financial liquidity-traders, investors and central bankers – that the principal challenge is not the average level of financial liquidity, but its variability and uncertainty'.

The role of liquidity in empirical finance has grown rapidly over the past two decades. Liquidity has been shown to have an effect on market efficiency, corporate finance and asset pricing. It facilitates better risk sharing and trading efficiency. First, it is useful to consider its applications in market efficiency literature. DeBondt and Thaler (1985) found that trading strategies appear to generate significant abnormal returns. Jegadeesh and Titman (1993), Chan et al. (1996) and Rouwenhorst (1998) provided further evidence for these returns. However, Chordia et al. (2008) showed that the post-earnings announcement drift, the oldest trading strategy in the literature, couldn't produce returns greater than the Keim and Madhavan (1997) measures. In addition, liquidity plays an important role as it affects portfolio investment performance, as suggested by Holthausen, Leftwich and Mayers (1991), Keim (2004), Lesmond, Schill and Zhou (2004) and Korajczyk and Sadka (2004). It also has significant implications for portfolio diversification strategies (Domowitz and Wang, 2002; Harford and Kaul, 2005).

There is a growing need in finance research for useful monthly liquidity measures. Kalev, Pham and Steen (2003) provided evidence of a statistically significant relationship between under-pricing and various proxies for shareholding distribution and liquidity. This result remains robust after controlling for a number of underlying factors with potential to drive both under-pricing and ownership allocation decisions. Heflin and Shaw (2000) found that blockholder ownership is associated with reduced liquidity of stock. Specifically, they demonstrated a positive relationship between the magnitude of blockholders' stake and relative, effective and adverse selection spreads, coupled with a negative impact of block ownership on quoted depths. Moreover, Lipson and Mortal (2004b), Lerner and Schoar (2004) and numerous others have examined the influence of liquidity on capital structure, security issuance forms and other corporate finance decisions.

While some empirical studies cast doubt on the significance of liquidity as a priced factor, a number of more recent studies have uncovered a notable liquidity return relationship. For instance, Reinganum (1990) compared the size of the liquidity premium for a sample of Nasdaq and NYSE stocks and found a larger liquidity premium on the NYSE sample. Brennan and Subrahmanyam (1995) used intraday data and found that expected returns increased in both fixed and variable (information) costs. Consistent with the findings of Eleswarapu and Reinganum (1993), they also asserted that spread is negatively related to expected returns. Moreover, Eleswarapu (1997) also noted that the liquidity premium was statistically significant for a large sample of Nasdaq stocks.

A number of studies have focused on market-wide liquidity measures, particularly in the context of incorporating liquidity into asset-pricing models. Amihud and Mendelson (1986a) and Brennan and Subrahmanyam (1996) showed that liquidity, as a characteristic, affects the cross-sectional differences of asset returns. Chordia et al. (2000) documented a commonality in liquidity across stocks even after accounting for well-known firm-level liquidity determinants such as trading volume, volatility and price. Pastor and Stambaugh (2003) created a measure that essentially tries to associate lower liquidity with stronger volume-related return reversals. They created 'liquidity betas' and found that stocks with higher betas (higher sensitivity to aggregate liquidity shocks) offer higher expected returns. Moreover, O'Hara (2003) also argued that liquidity and the risks associated with price discovery need to be incorporated into asset-pricing models.

2.2 Liquidity Measures

While there is an increasing interest in the role of liquidity in equity markets, the basic question of how to measure liquidity remains largely unsolved. According to Kyle (1985), liquidity is not directly observable and involves a number of dimensions. It is doubtful that a single measure can capture all its aspects. Amihud (2002) also stated that liquidity is an elusive concept and is not observed directly but rather has a number of aspects that cannot be encompassed in a single measure. Amihud and Mendelson (1986a) were some of the first researchers to investigate the linkage between liquidity and stock returns. Since then, the liquidity effect is often examined through stocks' liquidity levels, measured using bid-ask spread, trading volume and trading frequency. Recently, researchers have shifted their focus towards variation of stocks' own liquidity attributes. For instance, a risk-based explanation is based on the view that investors are risk averse and thus requires a premium over volatility in liquidity (Chordia et al., 2001).

In testing whether returns are related to asset liquidity, a number of studies have constructed liquidity measures using low-frequency data as proxies for high-frequency-based transaction costs. Liquidity proxies based on high-frequency data have received a considerable amount of attention as desirable measures (for example, Amihud and Mendelson, 1986; Huang and Stoll, 1997; Chordia, Sarkar and Subrahmanyam, 2005). However, high-frequency data is available for a relatively short period of time. For instance, Brennan and Subrahmanyam (1996), who estimated price impact parameters with two years' data from ISSM, ran pooled regressions because of lack of data. It is therefore difficult to draw general conclusions about the illiquidity return relationship from the few previous studies using high-frequency data. Most of the illiquidity measures used in asset-pricing tests are therefore constructed from daily share price information. Part of the reason for this is that such information is easier to obtain in most markets around the world over long time frames, particularly in comparison to intraday data.

According to Liu (2006), liquidity can generally be described as the ability to trade large quantities quickly at low cost with little price impact and classified into four dimensions, namely trading quantity, trading speed, trading costs and price impact. The liquidity proxies will be discussed in detail within this four-dimension group.

2.2.1 Trading Costs

Trading activity incurs trading costs. Specifically, as potential traders buy securities at the asking price and sell securities at the bid price, traders suffer the spread between the bid and the ask. This spread arises because of the costs of maintaining inventories and order processing and traders act on private information, meaning that market makers require compensation for bearing those risks.

Bid-ask Spread

Beginning with the pioneering work of Amihud and Mendelson (1986a), by focusing on the effect of the bid-ask spread, which relates to the trading cost dimension, this studies use monthly securities returns collected for NYSE stocks for the period from 1960 to 1979 and have generally found a positive relationship between stock return and stock illiquidity. More specifically, higher spread assets yield higher expected returns. However, using the same portfolio formation, Chen and Kan (1989) found an insignificant relationship. Additionally, Eleswarapu and Reinganum (1993), using the same proxy for liquidity as A & M, concluded that the relationship between stock returns and bid-ask spreads is significant, excluding the month of January by using portfolios of NYSE stocks during the period from 1961 to 1980. Brennan and Subrahmanyam (1996) adopted an innovative approach and segregated the cost of transacting into a variable and fixed component. In contrast, they did not find reliable evidence that bid-ask spreads were related to stock returns and also identified difficulty in obtaining such data over long time periods. In particular, they found a concave relationship between asset returns and transaction costs with respect to the variable cost component. Moreover, Eleswarapu (1997) examined the liquidity premium predicted by Amihud and Mendelson (1986a) by using Nasdaq data from 1973 to 1990. The results support the model and are much stronger than for the NYSE data as a result of dealers' inside spreads. In a recent study, Li et al. (2007) created an illiquidity metric based on a time-series of aggregate commission rates for NYSE trading, highly correlated with bid-ask spreads, and the result has significant explanatory power in cross-sectional regressions.

The principle theory in Amihud and Mendelson's (1986a) test revolves around the clientele effect, in which investors with short (long) holding periods prefer to hold assets with smaller (large) spreads. Empirical findings on the importance of the clientele effect of liquidity are mixed. Atkins and Dyl (1997) found evidence that the lengths of investors' holding periods are positively related to bid-ask spreads for NYSE stocks. Kryzanowski and Rubalcava (2005) also reported empirical findings supporting a generalized version of the investor clientele hypothesis of Amihud and Mendelson (1986). Others, however, have presented evidence that the clientele effect of liquidity does not hold. Brennan and Subrahmanyam (1996), using the Fama and French (1993) three-factor model, did not find a concave relationship between the fixed costs of transacting and investment horizons for NYSE stocks, which is inconsistent with Amihud & Mendelson's horizon clientele effect.

Effective Spread

Lee (1993) examined the effects of effective spread in NYSE and AMEX-listed firms and suggested that the execution price of similar adjacent trades can differ systematically depending on the location of execution. Even after controlling for trade security, the trade size and time of execution still show significant average execution price differences according to location. Heflin and Shaw (2000) documented a strong positive relationship between the percentage of outstanding shares held by blockholders and total effective spreads by using sample include 259 firms trading on NYSE and one firm trading on AMEX, Goyenko (2006) showed that various effective spread measures are priced significantly. Furthermore, Fujimoto (2003), Hasbrouck (2006), Korajczyk and Sadka (2004) and others have tested the pricing of effective spread measures. Roll (1984) developed an implicit measure of the effective bid-ask spread on the basis of serial covariance of daily price changes using data from weekly stock returns listed on the New York and American Exchanges from 1963 to 1982. The result related very negatively to firm size, thus supporting the notion that the measure is related to trading costs.

Quoted Spread

Amihud and Mendelson (1986b) used a quoted bid-ask spread as a measure of liquidity and tested the relationship between stock returns and liquidity during the period from 1961 to 1980. They found evidence consistent with the notion of liquidity premium. However, Petersen and Fialkowski (1994) found that less than 50% of trade on the NYSE actually occurs at the quoted bid or ask. Taking into account the price change after trade, Huang and Stoll (1996) estimated that the correlation between the realized and quoted spread is insignificantly different from zero.

However, these studies focus solely on the magnitude of the spread without consideration of the length of the holding period over which spreads are amortized. For example, Amihud and Mendelson (1986a), Chen and Kan (1989) and Eleswarapu and Reinganum (1993) all use closing bid-ask spreads as proxies for the expected cost of the spread. If stocks with similar spreads trade with different frequency, the magnitude of the spread is not a sufficient proxy for the amortized cost of the spread. According to Amihud et al. (2005), a risk neutral investor required return on security *i* is as:

$$E(r^i) = r^f + \mu \frac{C^i}{P^i} \tag{1}$$

where r^f is the risk free rate

C^i is the illiquidity cost of asset i

P^i is the price of asset i

μ is the trading intensity.

The proposition states that the expected excess returns depend not only on the transaction cost of the asset but also on its trading intensity, which is the probability of the cost incurred. The combined effect of transaction costs and trading frequency therefore determines the required return. This is also the case for risk adverse investors (Acharya and Pedersen, 2005) and, for this reason Chalmers and Kadlec (1998) stated that turnover ratio is also significant as it varies considerably across stocks. Alternatively, Chalmers and Kadlec (1998) used amortized effective spread as a measure of liquidity for AMEX and NYSE stocks over the period from 1983 to 1992, obtained from quotes and subsequent transactions, and reported evidence that the amortized rather than the regular spread is priced and positively affects stock returns. The amortized spread equals the product of the effective spread and the number of shares traded, summed over all trades for each day and expressed as an annualized fraction of equity value. This finding also suggests a contrasting result to the clientele effect of Amihud and Mendelson (1986a), whereby stocks with higher spreads should trade less frequently with lower turnovers. Moreover, bid-ask spreads obtained at a daily frequency may be uninformative as they are noisy and usually refer to end of day transactions. According to Acharya and Pedersen (2005), larger bid-ask spreads are indicative of illiquidity but do not provide any information about the 'depth' of the market. Quoted spread is also a poor proxy for actual transaction costs (Peterson and Fialkowski, 1994). There is an additional problem with some databases. For example, in the Thomson Datastream, bid-ask spreads appear as symmetric around the close price for most of the stocks, which makes relative spreads uninformative too. The maintained assumption of most empirical studies is that the available liquidity proxies capture the transaction costs of market participants. A number of studies have proposed liquidity measures but rarely test the hypothesis, which is that liquidity proxies are related to actual transaction costs. This assumption has not been tested because of the limited availability of actual trading costs. The consequences of not testing liquidity proxies on actual trading data include the fact that there is little in the way of consensus on which measures are better. In addition, there is limited evidence that any of the proposed measures are related to investor experience. Little is therefore known about whether transaction cost proxies measure what researchers claim they measure.

2.2.2 Trading Quantity

Schultz (2001) found that trading costs for larger trades in the over-the-counter corporate bond market are lower. In contrast, Easley and O'Hara (1987) argued that informed traders prefer to trade larger amounts at any given price. Market makers' pricing strategies therefore depend on trade size, with large trades made at less favourable prices for traders.

Trading Volume

It is possible that measures of trading volume capture more than a measure of a stock's liquidity, but trading volume may also contain information. For instance, empirical studies suggest that one common conjecture of trading volume is that it can act as a proxy for risk. For example, if a stock's recent trading volume is low, an investor may require an expected return premium for holding a stock that does not trade very frequently. An alternative conjecture is that trading volume measures may reflect information. For example, if a stock's recent trading volume is high, this can reflect new information coming to the market and an investor may therefore expect a higher return. Gervais et al. (2001) examined the impact of short-term changes in trading volume. They found that stocks that have had unusually high (low) trading volumes over the past day or week tend to experience a price increase (decrease) over the subsequent 20 trading days. This phenomenon is consistent with the notion that trading activity shocks affect the visibility of stock and in turn the subsequent demand. Hou et al. (2006) found that low volume stocks tend to under-react to earning news while high volume stocks tend to display over-reaction driven price momentum.

Brennan, Chordia and Subrahmanyam (1998) adopted trading volume as a liquidity proxy using monthly returns and other characteristics for a sample of the common stock of companies for the period from January 1996 to December 1995. Regardless of the method used to risk-adjust returns, they found a strong negative relation between average returns and trading volume, consistent with a liquidity premium in asset prices. Lee and Swaminathan (2000) investigated how the interaction between trading volume and past price momentum can predict cross-sectional return and found that past trading volume predicts both the magnitude and persistence of price momentum. Their findings confirm previous results but present new results not consistent with previous studies. Chordia, Subrahmanyam and Anshuman (2000) measured liquidity by trading volume and turnover ratio, which are in turn measured at firm level. They found that stocks with more volatile liquidity have lower expected returns. Dollar trading volume is related to how quickly a dealer expects to turn around his or her position and is positively related to liquidity in Stoll (1978). Glosten and Milgrom (1985) showed that stocks with high trading volume have lower levels of information asymmetry to the extent that information is revealed by prices. Brennan et al. (1998) used dollar-trading volume as a proxy for liquidity and demonstrated a negative relation between average returns and dollar trading volume.

Turnover

Turnover is defined as daily share trading volume divided by the number of total shares outstanding. It has also been a popular measure of liquidity. The theoretical motivation for using turnover as a liquidity proxy goes back to Demsetz (1968) and Glosten and Milgrom (1985). Demsetz (1968) showed that the price of immediacy would be smaller for stocks with high trading frequency as frequent trading can reduce the cost of inventory control. On the other hand, Glosten and Milgrom (1985) showed that stocks with high trading volume have lower levels of information asymmetry to the extent that information is revealed by prices. Moreover, as Hu (1997) has stated, volume data is more accessible because the commonly used quoted spread data does not measure actual transaction costs.

Trading quantity can be captured, according to Dater, Naik and Radcliffe (1998), by using turnover rate as a proxy for liquidity. Their study presented evidence of the significant role of liquidity in explaining the cross-sectional variation in stock returns, even after controlling firm size, book-to-market ratio and firm beta. Turnover rate is related to the representative investor's holding period and to liquidity in Amihud and Mendelson (1986a) and Chalmers and Kadlec (1998). By using trading turnover as a measure of liquidity for the 1976-1993 Tokyo Stock Exchange data, Hu (1997) found that stocks with higher turnover tend to have a lower expected return. This evidence is consistent with predictions from an Amihud–Mendelson type of transaction cost model. On the other hand, Lee and Swaminathan (2000) argued that turnover might be a less than perfect proxy for liquidity because the relationship between turnover and expected return depends on how stocks have performed in the past. However, Chordia et al. (2000) have documented a negative and significant cross-sectional relationship between average stock returns and share turnover. Nguyen et al. (2007) documented a negative relationship, arguing that stocks with high turnover ratios are characterized by greater trading speed and are more liquid, therefore indicating lower expected return. On the other hand, Brown et al. (2009) suggested that stocks with high turnover ratios have higher returns compared to stocks with low turnover ratios. Chan and Faff (2005) also presented mixed evidence of using turnover ratios as illiquidity proxies in the case of the Australian market.

2.2.3 Trading Speed

Little published research is devoted to capturing the trading speed dimension of liquidity. Liu (2006) used an alternative measure of liquidity for individual securities – the standardized turnover-adjusted number of zero daily trading volumes over the previous 12 months. This captures multiple dimensions of liquidity such as trading speed, trading quantity and trading cost, with particular emphasis on trading speed, using NYSE and AMEX stocks for the period from 1963 to 2003. Focus is therefore placed on the continuity of trading and potential delays or difficulties in executing orders. Consistent with the multidimensionality of liquidity, the new liquidity measure is highly correlated with the commonly used bid-ask spread, turnover and return to volume measures. The results suggest that this measure shows that less liquid tend to be low value, low turnover, high bid-ask spread and high return to volume stocks, consistent with intuition. Liu documented a significant liquidity premium robust to the CAPM and the Fama-French three-factor model, showing that liquidity is an important source of priced risk. A two-factor (market and liquidity) model clearly explains the cross-section of stock returns, describing the liquidity premium and subsuming documented anomalies associated with size, long-term contrarian investment and fundamental (cash flow, earnings and dividend) to price ratios. In particular, the two-factor model accounts for the book-to-market effect, which the Fama-French three-factor models fails to explain.

2.2.4 Price Impact

Price impact quantifies the change in a firm's stock price associated with its observed net trading quantities. Price impact captures the extent to which trade execution influences stock price: a perfectly liquid asset trades without any price impact while a perfectly illiquid asset cannot be traded at any price.

Amihud's Ratio

Amihud (2002) employed the concept of price impact to capture the price reaction to trading volume across NYSE stocks between 1964 and 1997. The illiquidity measure employed by Amihud was the daily ratio of absolute stock return to its dollar volume, averaged over some period and thus serving as a rough measure of price impact. The results showed that both across stocks and over time, expected market illiquidity has a positive and highly significant effect on expected return and unexpected illiquidity has a negative and significant effect on contemporaneous stock return. The negative effect of unexpected illiquidity is because higher realized illiquidity raises expected illiquidity; in turn, this leads to higher stock expected return. Stock prices should then decline to make the expected return rise. In addition, they found that these illiquidity effects are stronger for small firms' stock, suggesting variations over time in the 'size effect'. The ratio is widely accepted as one of the most appropriate and straightforward price impact measures to construct.

Pastor and Stambaugh (2003) also captured liquidity associated with the strength of volume-related return reversals using daily data on the NYSE and AMEX and found that smaller stocks are less liquid and have high sensitivities to aggregate liquidity. Fujimoto (2003), Hasbrouck (2006), Korajczyk and Sadka (2006) and others have tested the pricing of both effective spread and price impact measures. Brennan and Subrahmanyam (1996) measured liquidity by price impact of order flow from the Glosten–Harris regression and reported an additional return of 6.6% per year for the lowest against the highest liquidity portfolio. On the other hand, Bekaert, Harvey and Lundblad (2007) found that, consistent with liquidity being a priced factor, unexpected liquidity shocks are positively correlated with contemporaneous return shocks and negatively correlated with shocks to the dividend yield. Florackis et al. (2011), using stocks listed on the LSE, found that stocks with high *RtoV* values lead to higher expected returns in comparison to stocks with low *RtoV* values. This is consistent with previous studies.

Compared to traditional illiquidity proxies, Amihud's ratio has several advantages. First, without resorting to detailed, high quality microstructure data that are difficult to obtain, it is easy to calculate over long periods as volume and returns data are widely available. Secondly, as trading volume is related to liquidity (Brennan et al., 1998; Chordia et al., 2001), the ratio directly measures the impact of a unit of monetary trading volume on stocks return and translates this into transaction cost (Acharya and Pedersen, 2005). The greater the response of returns, the more illiquid this stock is considered to be.

Moreover, Amihud's ratio is closely related to the Amivest measure, which is roughly the sum of the daily volume to the sum of the absolute return (Amihud, Mendelson and Lauterbach, 1997). The Amivest ratio is popular among professional investors (Khan and Baker, 1993). Furthermore, Amihud's ratio has an empirical foundation in Kyle's (1985) lambda (Hasbrouck, 2005). Large buy/sell orders for illiquid stocks lead to wide short-term stock price movements because of adverse selection and inventory costs that partly 'bounce back' in the following days as the larger order shock is being absorbed (Amihud and Mendelson, 1980). It also has a 'price discovery' component as trading activity may be motivated by information or expectations about future stock price movement (Cochrane, 2005; Daniel, Hirshleifer and Subrahmanyam, 1998a). The ratio can also be interpreted as a measure of disagreement among investors (Amihud, 2002).

Amihud's ratio, however, has two major shortcomings. First, small capitalization stocks are bound to exhibit lower trading volume than large capitalization stocks, even when they have the same turnover ratio. As a result, Amihud's ratio is not comparable across stocks with different market capitalization and therefore suffers a significant size bias. Based on the ratio, small capitalization stocks are therefore automatically characterized as illiquid stocks because of their size (Cochrane, 2005). Secondly, Amihud's ratio ignores the stock holding horizons of investors. The combined effect of transaction costs and trading frequency determines the required premium, not each in isolation. Although the ratio attempts to proxy the cost of transacting, this is not appropriate without respect to the frequency at which this cost is incurred. It assumes that trading frequency is similar across stocks and does not affect liquidity. The ratio is also an alternative choice for the amortized spread (Chalmers and Kadlec, 1998), but does not need information on bid and ask price data.

RtoTR

Florackis, Gregoriou and Kostakis (2011) proposed an alternative price impact ratio to Amihud (2002), using an average monthly ratio of daily absolute stock return to its turnover ratio from the LSE over the period from 1991 to 2008 and providing evidence of a compound effect of trading frequency and transaction cost that matters for asset pricing. They reported that stocks with the lowest *RtoTR* yield much higher risk-adjusted returns than stocks with the highest *RtoTR*s. More specifically, stocks with very high turnover ratios and hence very low *RtoTR*s command high abnormal returns even if the price impact of trading activity is relatively low. This finding suggests that the trading frequency effect overwhelmingly dominates the transaction cost effect in determining the corresponding premium. Compared to Amihud's ratio, it replaces trading volume with turnover ratio. The use of turnover indicates a measure of trading activity, enabling comparability across assets. As it does not require price level or exchange rate adjustments, it is also comparable across different stock markets and countries. Moreover, it is free of any size bias. The measure has a very neat theoretical foundation as the expected excess returns depend not only on the transaction cost of the asset but also on its trading intensity, or the probability according to which this cost is incurred (Amihud and Mendelson, 1986a).

As liquidity is multidimensional, existing measures inevitably demonstrate a limited ability to capture liquidity risk fully and may be inaccurate even in the dimension they aim to capture. The literature has proposed different types of liquidity proxies designed to capture different liquidity benchmarks (for example, effective spread, realized spread and price impact). Given the limited number of liquidity proxies tested, the limited set of liquidity benchmarks compared and the absence of monthly proxies, it is not surprising that there are conflicting views about which measure is better. A handful of studies by Lesmond, Ogden, and Trzcinka (1999), Lesmond (2005) and Hasbrouck (2006) have tested whether a few of the available liquidity proxies as constructed on an annual or quarterly basis from daily return data are related to annual or quarterly liquidity computed from transactions data. Hasbrouck (2009) tested how three annual percent–cost proxies and one annual cost-per-volume proxy are related to the benchmarks of the percent effective spread and the slope of the price function lambda as computed from high-frequency US trade and quote data. On the other hand, Goyenko, Holden and Trzcinka (2009) tested how nine annual and monthly percent–cost proxies are related to annual and monthly percent–cost effective spreads and percent realized spreads, also computed from high-frequency US trade and quote data.

Nevertheless, most of the empirical studies are presented on the basis of the US stock market. There is little research for the UK stock market. Using stocks on the LSE for the period from 1996 to 2001, Galariotis and Giouvris (2009) investigated the relationship between systematic liquidity and excess returns. Using bid-ask spread as an illiquidity proxy, the results showed that systematic liquidity is an important factor in asset pricing. Gregoriou, Ioannidis and Zhu (2011) investigated commonality in liquidity on the LSE for the period from 2005 to 2009, suggesting a co-movement in liquidity on the UK stock market. The commonality is significant for both periods before and after the financial crisis. Foran, Hutchinson and O'Sullivan (2010) have also suggested that liquidity is an important factor for stock returns. However, most of these studies have limited ability to fully capture liquidity risk as they only use proxies for the dimensions they aim to capture. The main purpose of this research is therefore to investigate stock exchange for the relationship between return and liquidity on the LSE, based on several different proxies and, in turn, to investigate which proxies can better explain the relationship between liquidity and expected returns.

2.3 Construction of the Illiquidity Proxies

Liquidity is multidimensional and thus difficult to define and measure. The difficulty encountered in capturing liquidity explains the existence of various proxies for liquidity. This paper employs several liquidity proxies, which capture different aspects of liquidity. According to Liu (2006), liquidity can generally be described as the ability to trade large quantities quickly at low cost with little price impact and classified into four dimensions, namely trading quantity, trading speed, trading cost and price impact.

2.3.1 Trading Cost-Based Proxies

The first illiquidity measure used in this study is the bid-ask spread. Amihud and Mendelson (1986a) were early investigators of the linkage between liquidity and stock returns. The principal theory in their test revolved around the clientele effect, in which investors with short (long) holding periods prefer to hold assets with smaller (large) spreads. The liquidity effect is examined through stocks' liquidity levels, measured by bid-ask spreads. For a given time interval *s*, the bid-ask spread is defined as

$$\textit{Bid-ask spread}_s = Ask_s - Bid_s \qquad (2)$$

where

Ask_s is the best ask quote in that time interval

Bid_s is the best bid quote in that time interval

The next illiquidity proxy used was effective spread. Effective bid-ask spread was proposed by Lee (1993) in order to capture transaction costs. For a particular stock on the k^{th} trade, it is defined as twice the absolute value of the difference between a transaction price and the midpoint of the bid and ask quotes in effect at the time of the transaction.

$$\textit{Effective spread}_k = 2\ (ln(P_k) - ln(M_k)) \qquad (3)$$

where

P_k is the price of the k^{th} trade

M_k is the midpoint of the consolidated BBO (Best-Bid-Or-Offer) prevailing at the time of the k^{th} trade. For a particular stock aggregated over a time interval, a stock's effective spread is the local currency volume weighted average of effective spread computed over all trades in month *i*.

Quoted spread is also named as relative spread. Amihud and Mendelson (1986b) proposed quoted/relative bid-ask spread as a liquidity measure. For a given time interval *s*, the quoted spread is defined as the ask price minus the bid price, divided by the average of the bid and ask prices.

$$\textit{Percent quoted spread} = (Ask_s - Bid_s) / ((Ask_s + Bid_s)/2) \qquad (4)$$

where

Ask_s is the best ask quote

Bid_s is the best bid quote in that time interval
Over month *I*, the stock's quoted spread is the time-weighted average of quoted spread, computed over all time intervals in the month.

2.3.2 2.3.2 Trading Quantity-Based Proxies

Brennan and Subrahmanyam (1995) found that trading volume is an important determinant of the measure of liquidity. Dollar trading volume is related to how quickly a dealer expects to turn around his or her position and positively related to liquidity in Stoll (1978). Brennan et al. (1998) used dollar-trading volume as a proxy for liquidity and demonstrated a negative relationship between average returns and dollar trading volume.

$$Dollar\ trading\ volume_{i,t} = v_{i,t} \times p_{i,t} \qquad (5)$$

where
$v_{i,t}$ is the total trading volume for stock *i* in month *t*
$p_{i,t}$ is the average price for stock *i* in month *t*

Turnover ratio has been a popular liquidity measure in previous literature (Rouwenhorst, 1999; Chordia and Swaminathan, 2000; Dennis and Strickland, 2003). Lesmond (2005) proposed turnover ratio to capture trading quantity. Theory suggests that higher turnover means stocks can be traded quickly with low time delay costs. Thus, it is negatively related to bid-ask spread and expected returns. As a proxy of liquidity, it is assigned with a negative sign.

Stock turnover is calculated as the ratio of trading volume to the number of shares outstanding as

$$turnover_{i,t} = \frac{v_{i,t}}{share_{i,t}} \qquad (6)$$

where
$v_{i,t}$ is the total trading volume for stock *i* in month *t*
$share_{i,t}$ is the number of shares outstanding of stock *i* in month *t*

2.3.3 Trading Speed-Based Proxies

Liu (2006) proposed a standardized turnover-adjusted number of zero daily trading volumes over the previous x months (x =12), defined as

$$LMx = \left[Number\ of\ zero\ daily\ volumes\ in\ previous\ x\ months + \frac{1/(x\text{−}month\ turnover)}{Deflator}\right] \times \frac{21x}{NoTD}$$

(9)

where

$x - month\ turnover$ is the turnover over the previous x months

$NoTD$ is the total number of trading days in the market over the previous x months

Deflator is chosen such that

$$0 < \frac{1/(x\text{−}month\ turnover)}{Deflator} < 1 \qquad (10)$$

for all sample stocks[1].

2.3.4 Price Impact-Based Proxies

The term 'price impact' has been used in a variety of ways in the literature and corresponding benchmarks have been constructed. A static price impact is the slope of the price function at a moment in time. The first illiquidity measure is a price impact measured by Amihud (2002). Following Kyle (1985), Amihud (2002) developed the illiquidity ratio to capture the price impact of order flows or trading volume. The main concept of Amihud (2002) was that stocks with high (low) price movement at a given amount of trades have lower (greater) capacity to absorb large orders. Thus, they are more (less) illiquid. Liquidity studies, for example that of Acharya and Pedersen (2005), using Amihud's (2002) measure, generally document a positive relationship between this measure and stock returns. The illiquidity ratio is defined as

$$ILLIQ_t^i = \frac{1}{D_t^i}\sum_{d=1}^{D_t^i}\frac{\left|R_{td}^i\right|}{V_{td}^i} \qquad (7)$$

where

[1] I use a deflator of 11,000 in constructing *LM12,* as suggested by Liu (2006)

$\left|R_{td}^{i}\right|$ is the absolute returns of stock i in day d of month t

V_{td}^{i} is the trading volume (in millions of dollars) for the stock on day i of month t

D is the total trading days for the stock in month t

Another price impact illiquidity proxy used is Florackis et al.'s (2011) RtoTR. Florackis, Gregoriou and Kostakis (2011) proposed a new price impact ratio as an alternative to the widely used Amihud's ratio. The Return-to-Turnover ratio (RtoTR) essentially modifies the RtoV ratio by substituting trading volume in its denominator with the turnover ratio for each security. It is defined as

$$R\ to\ TR_{t}^{i} = \frac{1}{D_{t}^{i}} \sum_{d=1}^{D_{t}^{i}} \frac{\left|R_{td}^{i}\right|}{TR_{td}^{i}} \tag{8}$$

where

TR_{td}^{i} is the turnover ratio of stock i at day d

$\left|R_{td}^{i}\right|$ is the absolute returns of stock i in day d of month t

D is the total trading days for the stock in month t

3. Data and Descriptive Statistics

3.1 Data

All common stocks listed on the LSE from January 1991 to May 2011 are considered in the initial sample. The sample covers both active stocks (presently listed stocks) and dead stocks (stocks of firms that were de-listed for various reasons). As a result, the sample is free from any potential survivorship bias. In order to minimize the impact of outliers, the following screening criteria have been imposed. First, stocks with a market value of less than ten million pounds have been excluded. Secondly, stocks for which it is not possible to obtain price data for more than 36 consecutive months have been excluded because of the impossibility of calculating beta values. Stocks are also required to have at least 100 positive trading volume days (Chordia, Roll and Subrahmanyam, 2000). Furthermore, following Fletcher and Kihanda (2005), unit trusts, investment trusts and ADRs have been excluded from the analysis. The final data therefore contain 1823 stocks listed on the LSE.

The fundamental hypothesis is that useful monthly liquidity measures going back in time can be constructed from low-frequency (daily) stock returns and volume data, where such data are available. A handful of studies such as those by Lesmond, Ogden and Trzcinka (1999), Lesmond (2005) and Hasbrouck (2006) have tested whether a few of the available liquidity proxies constructed on an annual or quarterly basis from daily return data are related to annual or quarterly liquidity computed from transactions data. However, from previous empirical studies, the majority of the literature that uses liquidity proxies is based on monthly data. This suggests a need to test monthly proxies, partly because the percent-cost and cost-per-volume liquidity proxies provide considerable advantage for global research, spanning a large cross-section of countries over a long time-series.

I use the Thomson DataStream to obtain data on several variables, including share price (opening, closing, bid, ask and mid share price), return index, trading volume (number of shares traded for a stock on a particular day), turnover ratio (ratio of trading volume to number of shares outstanding), total trading days for stock in a month, market value and price-to-book value (share price-to-book value per share). The different liquidity proxies can then be calculated from these data.

For the estimation of asset-pricing models, FTSE All share is used as market index and the one-month UK interbank rate is adopted as risk-free rate. The size factor and value factor suggested in the Fama-French three-factor asset-pricing model have also been created. Size factor can first be formed by sorting all listed stocks according to their market capitalization at month t-1, then the top 30% of value-weighted stocks can be assigned to the 'big size' portfolio and the bottom 30% of stocks to the 'small size' portfolio. The difference between the returns of these two portfolios at month t yields the size factor (SMB) return. The value factor is calculated as the spread between the monthly returns of the MSCI UK Growth and the MSCI UK Value indices following Cuthbertson, Nitzsche and O'Sullivan (2008). The momentum factor suggested in Carhart's four-factor model could be produced by ranking all traded stocks at month t-1 according to their returns from month t-13 to t-2. The top 30% value-weighted of the stocks is classified as 'winners'' stocks and the bottom 30% as' losers'' stocks. Alternatively, rather than following the methodology discussed above, these factors can be obtained directly from the study of Gregory, Tharayan and Christidis (2013).[2] For the analysis I used both sets of factors and obtained consistent results.

Furthermore, the stocks have been classified into deciles portfolios according to individual illiquidity proxies. Specifically, at the end of month *t-1*, stocks are alternatively sorted according to their average illiquidity proxies' values in that month into ten portfolios. Portfolio 1 includes stocks with the smallest values of illiquidity proxy while portfolio 10 includes stocks with the highest values of illiquidity proxy; their excess return in month *t* is then calculated.

Both equally-weighted and value-weighted portfolio excess returns in each month t are calculated. Portfolios are rebalanced on a monthly basis. According to Chordia, Shivakumar and Subrahmanyam (2004), aggregate market liquidity is more strongly reflected in large firms than in small firms in the US markets, while the equal-weighted scheme has the benefit of preventing over-representation of large stock liquidity in market liquidity. Alternatively, Cremers, Petajisto and Zitzewitz (2010) have criticized the construction of the Fama-French factors and followed their proposal on value-weighted rather than equal-weighted individual component portfolios of the Fama-French factors.

3.2 Descriptive Statistics

Table 1 presents summary statistics for the main liquidity proxies used in this study for stocks listed in the LSE over the period from January 1980 to May 2011. Liu's measure has an average of 58.7, which means that, on average, there were 58.7 zero trading volume days over the previous 12 months (252 trading days). As expected, Liu's measure is negatively but relatively low correlated

[2] The data are available from the XFI EXETER website. The factors can be download at: http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/

with the turnover ratio at -0.048, which supports Liu (2006) that the measure can capture the trading quantity feature of liquidity. It is also negatively correlated with size at -0.055, implying that small firms are less liquid. Trading volume is the average daily trading volume over the previous 12 months and is highly correlated with MV, which is 0.783. The spearman correlation coefficient between the RtoTR price impact ratio and MV is -0.108 and the correlation between the RtoV price impact ratio and MV is -0.059, which indicates that the price impact ratio does not exhibit inherent size bias (see Florackis et al., 2011). RtoTR is positively correlated with bid-ask spread with a coefficient of 0.142 and negatively correlated with turnover ratio with a coefficient of -0.147. However, this is not the case for Amihud's ratio (RtoV ratio); the results indicate a negative correlation between the RtoV ratio and turnover ratio at -0.057 but also a negative correlation between the RtoV ratio and bid-ask spread at -0.009. These findings support those of Florackis, Gregoriou and Kostakis (2011) that this price impact ratio is likely to capture two different dimensions of illiquidity, namely trading cost and trading frequency. The correlation coefficient between bid-ask spread and turnover is -0.125, which is negative but relatively low. This is consistent with the view that these two variables are likely to capture two different dimensions of liquidity. It may therefore help to capture some important information which conventional measures are unable to adequately incorporate in isolation.

Table 2 presents the performances and characteristics of the ten portfolios constructed on the basis of eight different illiquidity proxies for the period January 1991 to December 2010. Interestingly, for trading cost-based illiquidity proxies, the results based on bid-ask spread for the period indicate that, as the spread increases from p1 to p10, the portfolios are becoming more illiquid and the equal-weighted return decreases. The level of this differential is -12.649% p.a. and the t-statistic is -4.950. This result suggests a negative relationship between the bid-ask spreads and the expected returns. This pattern also holds for value-weighted portfolios' returns. The result shows a larger differential of -13.312% p.a. with a t-test value of -6.157. These results contradict earlier evidence on the relationship between bid-ask spread and returns based on the

US market. The results based on effective spread also indicate a negative relationship between effective spread and both equal-weighted and value-weighted returns. The difference between portfolio 10 and portfolio 1 of equal-weighted returns is -8.728% p.a. (t-statistic is -4.219) and the difference between p10 and p1 of value-weighted returns is -7.574% p.a. (t-statistic is -2.570). This is also against conventional evidence for the US market. The relationship between quoted spread and equal-weighted returns is significantly negative; the difference between p10 and p1 is -17.853% p.a. (t=-5.220). The relationship between quoted spread and value-weighted returns is also significantly negative; the difference between p10 and p1 is -18.853% p.a. with a t value of -4.810. All three trading cost illiquidity proxies indicate a negative relationship between illiquidity and expected return. As the spread increases, the expected return declines. These results are consistent for both equal-weighted and value-weighted returns.

Moreover, for trading quantity-based illiquidity proxies, I found that by using dollar-trading volume as a proxy, as it increases from p1 to p10, the equal-weighted returns increase co-responsibly. The p10 to p1 spread is positive and statistically significant at 12.140% p.a., with a t statistic 3.467. This is also the case for value-weighted returns. The difference between p10 and p1 is 11.188% p.a. with a t statistic of 2.850. The results show that, as the stocks become more liquid, the expected returns, and both equal-weighted and value-weighted, increase as well. The use of turnover ratio as a proxy also suggests a positive relationship between turnover ratio and equal-weighted returns. The difference from p10 to p1 is 17.787% p.a. with t= 5.670. The relationship between turnover ratio and value-weighted returns is again positive (except portfolios 7 and 9). The differential from p10 to p1 is 11.094% p.a. (t=2.843). Turnover ratio proxy indicates a negative relationship between illiquidity and expected return, for both equal-weighted and value-weighted returns. In general, by using trading quantity-based illiquidity proxies (dollar trading volume and turnover ratio), the results support a negative link between illiquidity and stock returns. In sum, these results are consistent with those obtained from spread measures and suggest a positive link between liquidity and stock returns.

In general, a common finding across many liquidity studies is that trading volume measures may act as proxies for risk. Little attention has been given to the effect of trading on the second moment of returns, especially to control of fundamental information. More specifically, higher investor participation and trading volume leads to better price discovery, therefore leading to prices that are closer to fundamental values; thus, more trading reduces estimation noise and reduces the volatility of returns. The existing literature indicates that the concept of trading volume does not only relate to liquidity, but also to momentum and information. Pastor and Stambaugh (2003) referred to liquidity as a 'broad and elusive concept'. It is entirely possible that different forces dominate at different levels of trading and thus the resulting market equilibrium critically depends on volume of trading. Dichev, Huang and Zhou (2011) summarized that the benefits of increased liquidity and trading are not a one-way street. Brown, Crocker and Foerster (2009) indicate that for relatively liquid (typically larger) stocks, momentum and information effects can dominate and result in a positive relationship between trading volume and stock returns. They used portfolios from the S & P 500 Index and found that large capitalization stocks sorted on higher trading volume and turnover tend to have higher subsequent returns than those with lower trading volume.

By using trading speed-based proxy (Liu's measure), it can be shown that, moving from the most liquid decile (p1) to the least liquid decile (p10), the mean portfolio holding equal-weighted return decreased. This indicates a negative relationship between illiquidity and the expected equal-weighted return. The differential is -8.398% with a t statistic of -2.609. It is also the case for the relationship between Liu's zero trading days and value-weighted returns. The p10 to p1 difference is -6.435, but the result is insignificant with a 1% significance level (t=-1.838). Consistent with the positive relationship between turnover ratio and expected return identified earlier, Liu's measure based on UK stock also differs from the results found in Liu's empirical studies based on a US dataset. The results therefore once again indicate that, as the stocks become more liquid, the expected equal-weighted return increases co-responsibly. These results are consistent with the results based on trading costs and trading quantity proxies.

I then move to the results for price impact ratios. As a result of the reverse result of dollar trading volume and equal-weighted and value-weighted returns, the relationship between Amihud's ratio and returns is also opposite to that identified in previous empirical studies based on a US dataset. Moving from p1 to p10, the average portfolio returns decrease considerably for both equal-weighted and value-weighted returns. The level of this differential is 21.321% p.a. (t=-6.104) for equal-weighted returns and -21.389% p.a. (t=-5.234) for value-weighted returns. Again, the results indicate a negative link between illiquidity and stock returns. As Amihud's ratio increases, stock returns decline. This is the case for both equal-weighted and value-weighted expected returns. The results also differ from the findings of Florackis, Gregoriou and Kostakis (2011), who use daily data from all stocks listed on the LSE over the period from 1991 to 2008. Amihud's ratio is positively related to average portfolio returns. Another price impact ratio, RtoTR, proposed by Florackis, Gregoriou and Kostakis (2011), suggests a negative relationship between the RtoTR and average portfolio returns. P1 yields a much higher average return than p10 for both equal- and value-weighted returns. For equal-weighted returns, the difference from p10 to p1 is -24.282% p.a. with a t statistic of -8.626. The difference from p10 to p1 for value-weighted returns is -12.317% p.a. (t=-3.042). These results differ from the empirical findings of Florackis, Gregoriou and Kostakis (2011). In sum, the use of price impact ratios to capture illiquidity leads to findings that differ from previous US evidence. I find a negative relationship between illiquidity and stock returns, which holds for both equal-weighted and value-weighted returns.

Overall, the descriptive statistics suggest that different illiquidity proxies can all provide evidence of the existence of illiquidity effects on both equal-weighted and value-weighted returns. Based on stocks listed in the LSE, the results of using eight different illiquidity measures indicate a negative relationship between illiquidity and stock returns for both equal-weighted and value-weighted returns. The findings are consistent for all proxies based on trading cost measures, trading quantity measures, trading speed measures and price impact measures. These results differ from previous evidence on the link between liquidity and stock returns for the US market.

4. Asset-Pricing Tests

4.1 Test Methodology

The relationship between liquidity risks and stock returns is usually tested within a time-series context (see Pastor and Stambaugh, 2003; Sadka, 2004 and Liang and Wei, 2005). This setting allows for interpretation of the economic magnitude of liquidity risks. In order to test and compare abnormal performance of the portfolios constructed on the basis of the different illiquidity proxies, I estimate correspondingly using three commonly used asset-pricing models.

The test involves individual stocks as a test asset as individual stocks have several advantages. First, as the test results vary according to test assets applied, using individual stocks may prevent controversy. Moreover, it gives more power to the tests because of the large number of observations. On the other hand, it can be noisy to estimate betas at individual stock level. Individual stocks will be allocated into portfolios based on different illiquidity proxies and betas estimated at portfolio level. According to Fama and French (1992), this can reduce noise and furthermore present individual stock level betas.

The sample stocks are sorted into ten decile portfolios each year based on different illiquidity measures mentioned in the previous section. Portfolio 1 contains stocks with the smallest range of proxy value and portfolio 10 includes stocks with the highest range of illiquidity proxy value. Portfolios are formed both as equal-weighted and value-weighted averages. Each portfolio return is regressed based on CAPM, the Fama and French three-factor model and Carhart's four-factor model. These models are analytically explained below.

The Capital Asset-Pricing Model (CAPM)

First, we estimate Jensen's alpha using the classic CAPM model:

$$r_{it} - r_{ft} = \alpha_i + \beta_{i,MKT} MKT_t + \varepsilon_{it} \quad (11)$$

where i = 1,2,...,10 denoting ten portfolios (low numbered portfolio is formed based on small illiquidity measure). r_{it} is the equally-weighted or value-weighted return of portfolio i in month t, r_{ft} is the risk-free rate for month t, MKT_t is the excess market portfolio return which is equal to $r_{mt} - r_{ft}$ and r_{mt} is the market portfolio return in month t.

The Fama- French Model

Next Fama-French alpha, i.e. the intercept of the three-factor Fama-French (1993) model is computed as follows:

$$r_{it} - r_{ft} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{it} \quad (12)$$

where SMB_t stands for the size factors and HML_t is the value risk factor respectively.

Carhart's Model

Furthermore, the intercept of the four-factor Carhart (1997) is estimated as follows as Carhart's alpha:

$$r_{it} - r_{ft} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \beta_{i,MOM} MOM_t + \varepsilon_{it} \quad (13)$$

where MOM_t is the momentum risk factor.

The intercept from each regression is the excess return gained from trading based on different illiquidity risks that are not explained by commonly used CAPM, the Fama-French model and Carhart's model. The difference between the intercepts of the highest and lowest decile portfolios (p10 to p1 spread) is obtained as the profit from a zero-investment cost trading strategy. A statistically significant p10 to p1 spread implies that the illiquidity risk is priced.

4.2 Results

Table 3 reports the abnormal performance of equal-weighted decile portfolios constructed on the basis of eight different illiquidity proxies: bid-ask spread, effective spread, quoted spread, dollar trading volume, turnover ratio, Liu's measure, Amihud's ratio and Florackis et al.'s (2011) RtoTR. All stocks listed on the LSE during the period from January 1991 to December 2010 are sorted into ten decile portfolios. Table 4 reports the abnormal performance of ten value-weighted decile portfolios constructed on the basis of eight different illiquidity proxies for the period from January 1991 to December 2010.

For trading cost-based illiquidity proxies, the equal-weighted alpha of CAPM, using bid-ask spread sorted portfolios, accounts for the spread being related to bid-ask spread, except portfolio 1 (p1), portfolio 2 (p2) and portfolio 3 (p3), which are insignificant at 1% significant level. P1 yields the highest alpha at -3.184% p.a. and p10 yields the lowest alpha at -15.132% p.a. The spread from p10 to p1 is -11.949% p.a. with a t statistic of -3.260. The alphas of the Fama-French model give significant results except p1. Moving from p1 to p10, the alpha decreases from -4.091% p.a. to -15.565% p.a., yielding a differential of -11.472% p.a. (t=-3.213). The Carhart alphas yield a spread of -11.301% p.a. between p10 and p1. The alphas of the portfolios account significantly except p1. For the value-weighted CAPM, the alphas of p1, p3, p4, p5 and p6 are insignificant at 1% significant level. P1 yields the highest alpha at 0.393% p.a. and p10 yields the lowest alpha at -13.046% p.a., which yields 13.439% p.a. differential with a t statistic of -2.950. The alphas for Fama-French and Carhart suggest similar results. In particular, the Fama-French alpha for the p10 to p1 spread is -13.196% p.a. (t=-3.089) and the alphas for p10 to p1 for Carhart yield -12.065% p.a. (t=-2.992).

The equal-weighted alpha of CAPM, using effective spread sorted portfolios, account for significant spread. The alpha of p1 is insignificant at 1% significant level. With the exception of this, all portfolios hold significant value for alphas. Moving from p1 to p10, the alpha of CAPM decreases from -4.095% p.a. to -13.356% p.a. The difference from p10 to p1 is -9.261% p.a. (t=-3.319). The alpha of the Fama-French model shows similar results. P1 has the highest alpha of -5.078 (t=-2.710) and p10 has the lowest alpha of -14.317% p.a. (t=-5.258). The difference between p10 and p1 is -9.239% p.a. with a t statistic of -3.406. Moreover, the alpha of the Carhart model shows an even larger portfolio difference of -11.740 % p.a. (the difference between -14.585% p.a. and -2.845% p.a.) with a t statistic of -4.392. For the value-weighted portfolios, the alpha of CAPM decreased from -2.221% p.a. to -9.365% p.a., moving from p1 to p10. The difference between p10 and p1 is -7.144% p.a. However, the result is insignificant at 1% significant level. The alphas for p1, p3, p4, p8 and p9 are also insignificant. The alpha of the Fama-French model provides a similar result. The alphas for p1, p4 and p9 are insignificant. The alphas decrease from -2.504% p.a. to -10.185% p.a., moving from p1 to p10. The spread yield from p10 to p1 is -7.682% p.a. but insignificant at 1% significant level. The alpha of Carhart provides a different result. Although it is still insignificant for alphas of p1, p4 and p9, the spread p10-p1 yields a significant value of -10.178% p.a. (t=-2.595).

For equal-weighted portfolios sorted according to quoted spread, the alphas of the CAPM declined from p1 from -4.140% p.a. (t=-3.053) to -20.989% p.a. (t=-4.566). The p10 to p1 is -16.849 with a t value of -3.742. Nonetheless, the results are not significant for all decile portfolios. The alphas of the Fama-French model lead into a significant spread. P1 has the highest alpha value of -4.512% p.a. and p10 has the lowest alpha value of -21.842% p.a. The spread is -17.330% p.a. with a t statistic of -4.665. The Carhart model also accounts for a premium of 19.741% p.a. (t=-5.008), the largest of all three models. For the value-weighted portfolios, p1 yields the highest estimated alpha for all three asset-pricing models considered. Moving from p1 to p10, alpha estimates are substantially reduced, though not monotonically. The premium estimate of p10 to p1 for the

CAPM is -17.360% p.a. (t=-4.008). For the Fama-French model, this figure is -18.338% p.a. (t=-5.64) and for the Carhart model it is -20.994% p.a. (t=-6.290).

In general, the trading cost-based illiquidity proxies show more statistically significant results for equal-weighted portfolios. By using the CAPM, Fama-French model and Carhart's four-factor model, all three proxies' bid-ask spread, effective spread and quoted spread lead to a significant spread moving from p1 to p10. However, this is not the case for value-weighted portfolios. The alphas sorted according to bid-ask spread proxy and quoted spread proxy can have significant premium by using the CAPM, Fama-French model and Carhart's four-factor model as regression models. However, effective spread only accounts for a significant spread at a 1% significant level by using Carhart's four-factor model as a regression model. The results differ from those of previous studies based on a US dataset, showing negative p10 to p1 spreads in both equal-weighted and value-weighted portfolios. The results cannot support the existence of a liquidity premium. Instead, they show a negative relationship between illiquidity and stock returns.

In terms of the trading quantity-based illiquidity proxies, alphas of dollar trading volume sorted equal-weighted portfolios increases from p1 to p10 for all three asset-pricing models. The alphas of the CAPM yield a positive premium (p10 to p1) of 10.286% p.a., yet with a t statistic of 2.428 that is insignificant at 1% level. Moving from p1 to p10, the alphas of the Fama-French model increase from -16.480% p.a. (t=-4.948) to -5.739% p.a. (t=-4.163). P10 to p1 gives a 10.741% p.a. (t=-2.958) premium. The alphas of the Carhart model increase from -17.437% p.a. (t=-4.630) for p1 to -4.278% p.a. (t=-3.254), corresponding with a spread from p10 to p1 of 13.158% p.a. with a t statistic of 3.278. The alphas of value-weighted portfolios, on the other hand, cannot completely show significant premium. Moving from p1 to p10, the alphas of the CAPM increase from -14.642% p.a. (t=-2.647) to -4.626% p.a. (t=-4.063). However, the alphas of p3, p4, p6, p7, p8 and p9 are all insignificant at a 1% significant level. The spread from p10 to p1 is 10.016 (t=1.738), which is insignificant at a 1% significant level. The alphas of the Fama-French model also increase from p1 to p10, though not monotonically. P1 yields the lowest alpha and p10 yields the highest estimated alpha. The premium is 11.020% p.a., which is positive but insignificant, under a 1% significant level (t=2.294). Moving from p1 to p10, the estimated alphas of the Carhart model increase from -17.020% p.a. (t=-3.254) to -4.207% p.a. (t=-4.124). The spread from p10 to p1 is positive (12.813), with t statistics of 2.352.

For equal-weighted portfolios sorted according to turnover ratio, the alphas of all three models cannot account for a premium of illiquidity risk. P1 yields the lowest estimated alphas for all three asset-pricing models considered and p10 yields the highest estimated alphas. The p10 to p1 spread for the alphas of CAPM is 16.061% p.a. (t=3.675), the spread for the Fama-French model is 16.286% p.a. (t=3.750) and Carhart yields the highest premium of 17.340% p.a. with a t value of 3.474. For the value-weighted portfolios, the alphas of the CAPM increase from -14.577% p.a. for p1 to -4.344% p.a. for p10. However, the alphas of p2, p3, p6, p7, p9 and p10 are all insignificant at a 1% significant level. The spread is therefore 10.233% p.a., which is insignificant (t=1.993) at a 1% significant level. The alphas of the Fama-French model are also insignificant for portfolios p2, p3, p6, p7, p9 and p10. The premium of p10 to p1 is insignificant (10.878% p.a.) with a t value of 2.205. The Carhart model indicates similar results. P1 yields the lowest estimated alpha of -16,054% p.a. (t=3.763) and p10 yields the highest estimated alpha of -4.702% p.a. (t=-2.329). The difference between p10 and p1 is 11.352% p.a., which is insignificant from null at 1% level.

Overall, for equal-weighted portfolios of trading quantity-based proxies, almost all results suggest significant spread between the alpha of p10 and the alpha of p1 for both proxies and for all three asset-pricing models, the CAPM, Fama-French model and Carhart's four-factor model. On the other hand, for value-weighted portfolios, both dollar trading volume and turnover ratio fail to explain a significant premium from p10 to p1 for all three asset-pricing models. Consistent with my previous findings, trading quantity-based proxies provides positive p10 to p1 spreads, suggesting a negative relationship between illiquidity risk and stock returns.

The equal-weighted alphas of the CAPM, using Liu's measure, sorted portfolios cannot account for a liquidity premium. Moving from p1 to p10, the alphas of CAPM decrease from -8.099% p.a. (t=-3.541) to -14.698% p.a. (t=-3.652). The difference from p10 to p1 is negative (-6.660), but not statistically significant. The spread yield by the Fama-French model is -6.630 and is also insignificant from null at a 1% significant level. The alphas of the Carhart model yield a different result. Moving from p1 to p10, the estimated alphas decrease from -7.204% p.a. (-4.134) to -16.672% p.a. (t=-5.131). The premium from p10 to p1 is -9.468% p.a. (t=-2.605). For the value-weighted portfolios' alphas of the CAPM, the value decreases from p1=-4.880% p.a. (t=-2.324) to p10=-9.908% p.a. (t=-2.647). P10 to p1 yields a negative spread of -5.028% p.a. However, it is insignificant from null at a 1% level of significance. The Fama-French model also yields a negative (-5.243% p.a.) yet insignificant value of alphas of premium. By using the Carhart model, moving from p1 to p10, the alphas decrease from -4.334% p.a. (t=-2.594) to -12.516% p.a. (t=-4.445). The difference between p10 and p1 is -8.182% p.a. with a t value of 2.632. For trading speed-based illiquidity proxy (Liu's measure), the alphas for equal-weighted and value-weighted portfolios provide similar outcomes. The results do not support the existence of illiquidity using the CAPM and the Fama-French model. However, Carhart's four-factor model shows significant premium for both equal-weighted and value-weighted portfolios. Moreover, the results also contrast with those of Liu (2006), who shows a negative relationship between illiquidity risk and asset pricing.

The other illiquidity dimension is that of price impact, which is measured using Amihud's ratio and Florackis et al.'s (2011) RtoTR. For equal-weighted portfolios sorted according to Amihud's ratio, the alphas of all three models cannot account for a premium of illiquidity risk. P1 yields the highest estimated alphas for all three asset-pricing models considered and p10 yields the lowest estimated alphas for all three models. The spread under the CAPM is -20.263% p.a. (t=-4.271) and -20.551% p.a. (t=-4.950) under the Fama-French model. The Carhart model yields a spread of -22.322% p.a. with a t statistic of -4.973. For value-weighted portfolios sorted according to Amihud's ratio, the alphas of none of the three models can account for a significant premium of illiquidity risk. The spread yield using the CAPM is -21.009% p.a. (t=-4.368) and the spread yield using the Fama-French model is -22.005% p.a. (t=-5.453). The Carhart model has a spread of -22.475% p.a. with a t value of -4.950.

Alphas of RtoTR sorted equal-weighted portfolios decreased from p1 to p10 for all three asset-pricing models though not monotonically. The alphas of the CAPM decreased from 0.305% p.a. (t=0.135, insignificant from null), for p1 to -24.173% p.a. (t=-5.472) for p10. The spread is negative and yields -24.479% p.a. with a t statistic of -5.916, which cannot indicate the existence of illiquidity risk. The alphas of the Fama-French model yield a spread of -24.807% p.a. with a t statistic of -6.446. The premium for p10 to p1 for the Carhart model gives -24.318% p.a. (t=-6.657). Moreover, the use of RtoTR sorted value-weighted portfolios yields a decrease trend from p1 to p10. From p1 to p10, the alphas of the CAPM decreased from -2.207% p.a. (insignificant at a 1% significant level) to -15.436% p.a. (t=-3.047). The spread is therefore -13.230% p.a. (t=-2.820), relatively small compared to equal-weighted portfolio spreads. The Fama-French model decreases from -2.135% p.a. (insignificant at a 1% level of significance) to -15.900% p.a. (t=-3.755). The premium of p10 to p1 is -13.766% p.a. with a t statistic of -3.498. The Carhart model shows similar results, with a spread yield from p10 to p1 of -14.182% p.a. (t=-3.353). None of the three asset-pricing models indicate a premium of illiquidity risk.

Overall, the results-based illiquidity proxies that include Amihud's ratio and Florackis et al.'s (2011) RtoTR do not support the existence of illiquidity risk. The results show that for both equal-weighted and value-weighted portfolios, liquid stocks yield higher returns, and these results are consistent for all three asset-pricing models. Again, the results differ from those in previous studies based on a US dataset, showing negative p10 to p1 spreads in both equal-weighted and value-weighted portfolios.

Overall, by using stocks listed on the LSE, none of the illiquidity proxies provided in this paper indicate evidence of the existence of illiquidity risk. Instead, the results suggest a negative relationship between illiquidity and stock returns. In particular, the findings show that liquid stock actually yields higher returns than illiquid stocks. The results are inconsistent with previous empirical findings based on US stock market data.

5. Conclusions

This paper investigates the relationship between stock returns and stock market liquidity for the UK market. Using daily data for all listed companies on the LSE over the period from January 1991 to May 2011, this paper empirically examines the importance of various illiquidity proxies for asset pricing. The different illiquidity proxies examined in this paper include trading cost-based illiquidity proxies (bid-ask spread, effective spread and quoted spread), trading quantity-based proxies (dollar trading volume and turnover ratio), trading speed-based proxy (Liu's measure) and price impact-based proxies (Amihud's ratio and RtoTR). For the estimation, I used time-series tests based on the CAPM, the Fama-French three-factor model and Carhart's four-factor model. For robustness purposes, I conducted my analysis using both equal-weighted and value-weighted returns.

Overall, this study is intended to analyse whether liquidity has an impact on asset pricing on the UK stock market. The empirical findings cannot account for liquidity premium; instead, the results suggest that liquidity stocks yield higher returns than illiquid stocks. These findings clearly have important implications for portfolio managers. Interestingly, the findings suggest a negative relationship between illiquidity and asset pricing. As illiquidity increases, instead of rises in stock returns, post-ranking returns decrease. The outcomes are consistent with all eight illiquidity proxies. Tests based on liquidity measures of price impact ratio best demonstrate the influence of illiquidity risk on stock returns. By using the CAPM, the Fama-French model and Carhart's four-factor model, all three trading costs-based proxies show significant spread moving from p1 to p10 for both equally-weighted and value-weighted portfolios except effective spread. Liu's (2006) measure provides insignificant results for illiquidity effect for the use of the CAPM and the Fama-French model. Trading quantity-based proxies, on the other hand, fail to explain a significant spread for all three asset-pricing models when the portfolios are formed on a value-weighted basis. This finding contradicts previous US evidence, which suggests a positive relationship between illiquidity and stock returns. It is an important consideration in any quantitatively based investment strategy.

Given the results in this paper, several questions arise. Most importantly, why is there a reverse relationship result between illiquidity measures and expected returns in the UK? Reasons vary and relate to the different levels of goodness of each measure and different aspects of liquidity as measure proxies.

First of all, this paper assumes that investors have the same holding period of one month. The impact of different holding periods on liquidity has therefore not been considered (Amihud and Mendelson, 1986a; Constantinides, 1986). DeLong, Shleifer, Summers and Waldmann (1990) developed a model showing positive correlation of stock returns at shorter horizons when positive feedback traders respond to past price increases by entering the market, therefore creating higher trading volume. Pastor and Stambaugh (2003) referred to liquidity as a 'broad and elusive concept'. It is entirely possible that different forces dominate at different levels of trading and thus the resulting market equilibrium critically depends on volume of trading. Dichev, Huang and Zhou (2011) summarized that the benefits of increased liquidity and trading are not a one-way street. Brown, Crocker and Foerster (2009) indicated that for relatively liquid (typically larger) stocks, momentum and information effects may dominate and result in a positive relationship between trading volume and stock returns.

Moreover, trading activity shocks affect a stock's visibility and, in turn, subsequent demand. There is a solid argument that higher investor participation leads to better price discovery and therefore to prices that are closer to fundamental values. More trading thus reduces estimation noise and reduces the volatility of returns. Daniel, Hirshleifer and Subrahmanyam (1998a) presented a model indicating that investors can become over-confident when receiving confirming public information (for example, resulting in an increase in trading volume) and cause prices to over-react in the short term. Gervais, Kaniel and Mingelgrin (2001) found that stocks with unusually high (low) trading volume over the past day or week tend to experience a price increase (decrease) over the subsequent 20 trading days. Hou, Peng and Xiong (2006) found that low volume stocks tend to under-react to earnings news and that high volume stocks tend to display over-reaction-driven price momentum. Brown, Crocker and Foerster (2009) suggested that we might look at trading volume not only as a cost of trading (for example, related to liquidity) but also as a source of information.

This paper has a number of caveats. Firstly, proxies of trading costs used in this paper are noisy measures as manifested in previous studies (Goyenko, Holden, Lundblad and Trzcinka, 2005; Lesmond, 2005). Also, trading volume and turnover are not necessarily strictly related to liquidity. Third, as in many studies, the results are specific to particular periods of analysis; further research can be carried out to investigate other periods. Possible directions for future research studies include further analyses of liquidity risk on asset pricing on other UK stock exchanges, with more liquidity measures and for different periods.

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Tables

Table 1. Summary statistics of illiquidity proxies

This table reports descriptive statistics for the main liquidity proxy used in the study. RtoV12 (in millions) is the liquidity measure of Amihud (2002), which is the Amihud's ratio over the previous 12 months; BA12 is the average daily bid-ask spread over the prevopis 12 months; and ER12 is average daily effective spread over the previous 12 months. LM12 is based on Liu's measure, which is the standardized turnover-adjusted number of zero daily trading volumes over the previous 12 months; QS12 is the daily average quoted spread over the previous 12 months. RtoTR12 is the liquidity measure of Florackis et al.'s (2011) RtoTR ratio over the previous 12 months. TV12 is the average daily trading volume over the previous 12 months and TO12 is the average daily turnover over the previous 12 months. This table presents the results on the sample including LSE ordinary common stocks over the period from January 1980 to May 2011. The descriptive statistics are based on these 252 months' time-series cross-sectional averages

Descriptive statistics

	RtoV12 (m)	BA12	ER12	LM12	QS12	RtoTR12	TV12	TO12
Mean	6.209	-63.866	0.003	58.749	0.170	479615.3	3395226	0.225
Min.	0	-167628.4	-3.546	5.55e-11	-0.004	0	-0.003	0
Median	5.67e-06	-3.553	0	0.006	0.045	20.804	78303.4	0.002
Max.	39806.7	2.192	7.642	35348.73	37224.51	4.50e+10	8.24e+08	6106.616
25% percentile	2.42e-07	-6.256	0	0.000	0.021	8.126	13497.92	0.001
75% percentile	.0000	-1.812	0.002	9.618	0.094	64.792	551004.8	0.004
Standard deviation	477.301	1764.361	0.041	240.459	58.493	9.17e+07	1.92e+07	36.460

Spearman rank correlation

	MV (m)	TV12	TO12	RtoV12 (m)	LM12	BA12	QS12	RtoTR12	ER12
MV (m)	1								
TV12	0.783	1							
TO12	0.079	0.211	1						
RtoV12 (m)	-0.059	-0.060	-0.057	1					
LM12	-0.055	-0.059	-0.048	-0.012	1				
BA12	-0.075	-0.100	-0.125	-0.009	0.018	1			
QS12	-0.225	-0.235	-0.153	-0.326	0.039	0.108	1		
RtoTR12	-0.108	-0.124	-0.147	-0.410	-0.004	0.142	0.305	1	
ER12	-0.039	-0.046	-0.039	-0.028	0.101	-0.061	0.171	0.0	1

Table 2. Performance and characteristics of deciles portfolios

This table reports the characteristics of portfolios constructed on the basis of eight different illiquidity proxies, bid-ask spread, effective spread, quoted spread, dollar trading volume, turnover ratio, Liu's measure, Amihud's ratio and Florackis et al.'s (2011) RtoTR. All stocks listed on the LSE during the period from January 1991 to December 2010 are sorted at month *t-1* in ascending order and assigned to ten portfolios. P1 is the deciles portfolio containing the stocks with the lowest illiquidity proxy and P10 is the deciles portfolio containing the stocks with the highest. P10-p1 is the spread between p10 and p1. The excess returns of these portfolios at month *t* are calculated. EW returns (% p.a.) are the annualized average monthly returns of the equal-weighted portfolios. VW returns (% p.a.) are the annualized average monthly returns of the value-weighted portfolios.

Bid-ask spread												
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1	t-test
EW returns (% p.a.)	5.998	4.203	3.350	1.786	0.288	-1.505	-2.500	-1.367	-4.617	-6.651	-12.649	-4.950
VW returns (% p.a.)	9.798	4.278	5.099	8.510	2.537	-4.142	-0.422	-0.284	--2.921	-3.514	-13.312	-6.157

Effective spread												
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1	t-test
EW returns (% p.a.)	4.329	1.414	-1.201	-0.371	-1.025	-1.194	-1.032	2.914	-0.566	-4.399	-8.728	-4.219
VW returns (% p.a.)	7.514	4.732	4.638	2.296	0.682	1.591	2.814	4.544	3.817	-0.061	-7.574	-2.570

Quoted spread												
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1	t-test
EW returns (% p.a.)	5.091	7.289	4.912	3.585	0.972	0.958	0.012	-5.401	-6.537	-12.762	-17.853	-5.220
VW returns (% p.a.)	4.846	7.235	5.279	2.384	0.570	-1.083	-1.585	-2.820	-6.262	-13.764	-18.610	-4.810

Dollar Trading Volume												
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1	t-test
EW returns (% p.a.)	-7.781	-9.004	-3.602	-3.277	-2.509	1.872	1.440	4.027	5.021	4.360	12.140	3.467
VW returns (% p.a.)	-6.307	-6.323	-0.196	1.594	2.324	5.418	3.982	5.694	6.648	4.881	11.188	2.850

Turnover ratio												
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1	t-test
EW returns (% p.a.)	-13.327	-5.255	-2.283	-2.501	-0.358	-0.015	1.584	3.239	3.099	4.461	17.787	5.670
VW returns (% p.a.)	-5.320	-0.610	5.896	-1.158	2.528	4.315	7.811	4.436	7.303	5.774	11.094	2.843

Liu's												
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1	t-test
EW returns (% p.a.)	1.996	3.589	4.133	2.546	-0.157	-0.075	-3.456	-4.356	-5.096	-6.402	-8.398	-2.609
VW returns (% p.a.)	5.129	5.888	5.816	3.885	2.957	1.376	4.092	0.773	2.537	-1.306	-6.435	-1.838

Amihud's ratio												
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1	t-test
EW returns (% p.a.)	3.116	5.661	6.342	3.976	3.083	2.443	0.138	-7.066	-8.736	-18.205	-21.321	-6.104
VW returns (% p.a.)	5.500	4.764	4.289	5.395	2.464	3.989	3.909	-3.780	-8.079	-15.889	-21.389	-5.234

Florackis et al.'s (2011) RtoTR												
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1	t-test
EW returns (% p.a.)	9.473	7.153	4.370	3.179	-0.281	-0.472	-3.891	-4.370	-9.519	-14.808	-24.282	-8.626
VW returns (% p.a.)	7.067	5.945	6.250	1.122	2.452	-0.448	2.392	4.745	--5.064	-5.250	-12.317	-3.042

Table 3. Alphas of equal-weighted portfolios

This table reports the abnormal performance of ten equal-weighted deciles portfolios constructed on the basis of eight different illiquidity proxies, bid -ask spread, effective spread, quoted spread, dollar trading volume, turnover ratio, Liu's measure, Amihud's ratio and Florackis et al.'s (2011) RtoTR. All stocks listed on the LSE during the period from January 1991 to December 2010 are sorted at month *t-1* in ascending order and assigned to ten portfolios. P1 is the deciles portfolio containing the stocks with the lowest illiquidity proxy and p10 is the deciles portfolio containing the stocks with the highest. P10-p1 is the spread between p10 and p1. CAPM alpha is the annualized alpha estimate derived from the Capital Asset Pricing Model. Fama-French alpha is the annualized alpha estimate derived from the Fama-French three-factor model. Carhart alpha is the annualized alpha estimate from the Carhart four-factor model. *t-statistics* are reported in parentheses. *** Indicate that the corresponding alpha coefficient is statistically significant at 1% significant level.

	Bid-ask spread										
	DECILE PORTFOLIO										
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-3.184	-4.954	-5.783	-7.379	-8.727	-10.239	-11.342	-10.087	-13.287	-15.132	-11.949
	(-0.905)	(-1.727)	(-2.276)	(-2.920***)	(-3.190***)	(-3.502***)	(-3.619***)	(-3.343***)	(-4.380***)	(-4.263***)	(-3.260***)
Fama-French alpha (% p.a.)	-4.091	-5.932	-6.741	-8.143	-9.547	-11.072	-12.016	-10.823	-14.001	-15.565	-11.472
	(-1.491)	(-3.428***)	(-4.675***)	(-4.921***)	(-4.749***)	(-5.666***)	(-4.811***)	(-4.9930***)	(-6.463***)	(-5.879***)	(-3.213***)
Carhart alpha (% p.a.)	-3.968	-5.855	-5.928	-7.305	-9.368	-11.321	-11.784	-10.829	-13.695	-15.270	-11.301
	(-1.380)	(-3.137***)	(-3.669***)	(-3.796***)	(-4.149***)	(-5.059***)	(-4.117***)	(-4.586***)	(-5.485***)	(-5.957***)	(-3.145***)

Effective spread											
DECILE PORTFOLIO											
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-4.095	-8.959	-8.886	-8.004	-10.377	-10.028	-10.374	-6.490	-9.660	-13.356	-9.261
	(-1.733)	(-3.030***)	(-3.095***)	(-2.301)	(-3.456***)	(-3.389***)	(-3.628***)	(-2.340)	(-3.121***)	(-3.733***)	(-3.319***)
Fama-French alpha (% p.a.)	-5.078	-9.510	-9.609	-8.704	-11.061	-10.767	-10.986	-7.354	-10.667	-14.317	-9.239
	(-2.710***)	(-4.130***)	(-5.116***)	(-3.236***)	(-4.875***)	(-5.125***)	(-5.377***)	(-3.816***)	(-5.356***)	(-5.258***)	(-3.406***)
Carhart alpha (% p.a.)	-2.845	-9.187	-9.054	-9.592	-11.280	-10.976	-11.149	-7.284	-9.442	-14.585	-11.740
	(-1.566)	(-4.159***)	(-4.573***)	(-2.982***)	(-4.345***)	(-4.195***)	(-4.712***)	(-3.767***)	(-4.319***)	(-4.718***)	(-4.392***)

Quoted spread											
DECILE PORTFOLIO											
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-4.140	-1.900	-4.321	-5.407	-7.816	-7.614	-8.603	-13.734	-14.798	-20.989	-16.849
	(-3.053***)	(-0.893)	(-1.865)	(-1.922)	(-2.771***)	(-2.700***)	(-2.389)	(-3.807***)	(-3.755***)	(-4.566***)	(-3.742***)
Fama-French alpha (% p.a.)	-4.512	-2.725	-5.280	-6.392	-8.808	-8.634	-9.584	-14.710	-15.889	-21.842	-17.330
	(-3.659***)	(-1.839)	(-3.929***)	(-3.404***)	(-4.636***)	(-4.245***)	(-3.600***)	(-5.478***)	(-5.340***)	(-6.278***)	(-4.665***)
Carhart alpha (% p.a.)	-3.554	-2.304	-4.894	-5.042	-8.432	-7.869	-9.378	-15.211	-15.604	-23.296	-19.741
	(-3.002***)	(-1.661)	(-3.549***)	(-2.485)	(-3.771***)	(-3.311***)	(-3.132***)	(-4.882***)	(-5.008***)	(-6.161***)	(-5.008***)

Dollar Trading Volume											
	DECILE PORTFOLIO										
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-15.711	-17.351	-12.284	-12.062	-11.846	-7.698	-8.208	-5.775	-4.799	-5.425	10.286
	(-3.614***)	(-4.267***)	(-3.254***)	(-3.929***)	(-3.616***)	(-2.974***)	(-3.083***)	(-2.580***)	(-2.581***)	(-3.876***)	(2.428)
Fama-French alpha (% p.a.)	-16.480	-18.090	-13.078	-12.833	-12.776	-8.549	-9.170	-6.718	-5.386	-5.739	10.741
	(-4.948***)	(-6.611***)	(-5.062***)	(-6.092***)	(-4.958***)	(-4.753***)	(-4.295***)	(4.468***)	(-2.781***)	(-4.163***)	(-2.958***)
Carhart alpha (% p.a.)	-17.437	-18.694	-13.915	-13.093	-12.163	-8.221	-8.526	-5.340	-4.611	-4.278	13.158
	(-4.630***)	(-6.106***)	(-4.671***)	(-5.651***)	(-4.158***)	(-4.151***)	(-3.904***)	(-3.754***)	(-2.247)	(-3.254***)	(3.278***)

Turnover ratio											
	DECILE PORTFOLIO										
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-21.626	-13.852	-8.994	-11.496	-9.540	-9.133	-7.886	-6.383	-6.561	-5.566	16.061
	(-4.955***)	(-4.268***)	(-2.959***)	(-4.250***)	(-3.315***)	(-3.625***)	(-3.414***)	(-2.826***)	(-3.026***)	(-1.915)	(3.675***)
Fama-French alpha (% p.a.)	-22.454	-14.576	-9.748	-12.245	-10.401	-9.960	-8.743	-7.134	-7.266	-6.168	16.286
	(-6.764***)	(-6.648***)	(-4.655***)	(-6.410***)	(-4.851***)	(-5.706***)	(-5.834***)	(-4.444***)	(-4.017***)	(-2.360)	(3.750***)
Carhart alpha (% p.a.)	-23.033	-14.677	-9.479	-12.075	-9.678	-9.255	-8.749	-7.313	-6.168	-5.692	17.340
	(-6.076***)	(-5.865***)	(-4.204***)	(-5.324***)	(-3.744***)	(-4.260***)	(-5.249***)	(-4.138***)	(-3.407***)	(-2.046)	(3.474***)

Liu's											
	DECILE PORTFOLIO										
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-8.099	-6.157	-5.442	-6.952	-9.377	-9.178	-12.289	-13.047	-13.664	-14.698	-6.660
	(-3.541***)	(-2.994***)	(-2.839***)	(-2.712***)	(-3.520***)	(-2.968***)	(-3.761***)	(-4.243***)	(-3.485***)	(-3,652***)	(-1.905)
Fama-French alpha (% p.a.)	-8.870	-6.931	-6.221	-7.872	-10.285	-9.948	-13.046	-13.829	-14.303	-15.500	-6.630
	(-4.969***)	(-4.023***)	(-4.382***)	(-4.274***)	(-5.051***)	(-4.413***)	(-5.510***)	(-6.696***)	(-5.455***)	(-5.305***)	(-1.974)
Carhart alpha (% p.a.)	-7.204	-5.482	-5.455	-7.324	-9.163	-10.005	-12.981	-13.800	-14.933	-16.672	-9.468
	(-4.134***)	(-3.203***)	(-3.421***)	(-3.637***)	(-3.796***)	(-4.104***)	(-4.493***)	(-6.320***)	(-4.941***)	(-5.131***)	(-2.605***)

Amihud's ratio											
	DECILE PORTFOLIO										
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-6.593	-4.060	-3.289	-5.526	-6.089	-6.494	-8.702	-15.910	-17.379	-26.856	-20.263
	(-3.125***)	(-4.131***)	(-4.365***)	(-5.269***)	(-4.271***)	(-2.246)	(-3.125***)	(-4.131***)	(-4.365***)	(-5.269***)	(-4.271***)
Fama-French alpha (% p.a.)	-7.129	-4.697	-3.910	-6.429	-6.964	-7.241	-9.377	-16.819	-18.288	-27.551	-20.551
	(-4.946***)	(-3.221***)	(-3.510***)	(-3.270***)	(-3.344***)	(-3.520***)	(-4.672***)	(-6.663***)	(-6.743***)	(-7.148***)	(-4.950***)
Carhart alpha (% p.a.)	-5.929	-4.126	-3.128	-5.753	-5.867	-7.159	-9.642	-17.113	-18.917	-28.251	-22.322
	(-4.148***)	(-2.642***)	(-2.739***)	(-2.849***)	(-2.696***)	(-2.966***)	(-4.058***)	(-5.920***)	(-6.247***)	(-6.672***)	(-4.973***)

Floracks et al.'s (2011) RtoTR										
	DECILE PORTFOLIO										
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	0.305	-2.312	-5.250	-6.112	-9.386	-9.349	-12.920	-13.182	-18.572	-24.173	-24.479
	(0.135)	(-1.500)	(-2.433)	(-2.212)	(-2.941***)	(-3.249***)	(-4.172***)	(-4.224***)	(-5.007***)	(-5.472***)	(-5.916***)
Fama-French alpha (% p.a.)	-0.194	-2.810	-6.075	-6.947	-10.208	-10.136	-13.675	-14.002	-19.538	-25.002	-24.807
	(-0.010)	(-1.805)	(-4.493***)	(-3.230***)	(-4.418***)	(-4.783***)	(-6.599***)	(-5.858***)	(-7.007***)	(-7.517***)	(-6.446***)
Carhart alpha (% p.a.)	-0.147	-2.020	-5.710	-6.331	-11.480	-9.956	-13.420	-13.385	-19.003	-24.466	-24.318
	(-0.079)	(-1.223)	(-3.923***)	(-2.756***)	(-4.228***)	(-3.835***)	(-5.226***)	(-5.466***)	(-6.445***)	(-7.250***)	(-6.657***)

Table 4. Alphas of value-weighted portfolios

This table reports the abnormal performance of ten value-weighted deciles portfolios constructed on the basis of eight different illiquidity proxies, bid -ask spread, effective spread, quoted spread, dollar trading volume, turnover ratio, Liu's measure, Amihud's ratio and Florackis et al.'s (2011) RtoTR. All stocks listed on the LSE during the period from January 1991 to December 2010 are sorted at month *t-1* in ascending order and assigned to ten portfolios. P1 is the deciles portfolio containing the stocks with the lowest illiquidity proxy and p10 is the deciles portfolio containing the stocks with the highest. P10-p1 is the spread between p10 and p1. CAPM alpha is the annualized alpha estimate derived from the Capital Asset Pricing Model. Fama-French alpha is the annualized alpha estimate derived from the Fama-French three-factor model. Carhart alpha is the annualized alpha estimate from the Carhart four-factor model. *t-statistics* are reported in parentheses. *** indicate that the corresponding alpha coefficient is statistically significant at 1% significant level.

					Bid-ask spread						
					DECILE PORTFOLIO						
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	0.393	-4.767	-4.062	-1.152	-7.613	-5.224	-9.909	-9.276	-12.336	-13.046	-13.439
	(0.176)	(-2.790***)	(-1.994)	(-0.551)	(-2.411)	(-1.839)	(-4.762***)	(-4.931***)	(-3.834***)	(-3.630***)	(-2.950***)
Fama-French alpha (% p.a.)	0.050	-4.914	-4.081	-1.393	-7.849	-5.780	-10.136	-9.707	-12.804	-13.146	-13.196
	(0.023)	(-2.772***)	(-1.966)	(-0.714)	(-2.573)	(-2.196)	(-4.969***)	(-6.828***)	(-4.233***)	(-4.179***)	(-3.089***)
Carhart alpha (% p.a.)	-1.107	-3.848	-3.963	-1.939	-8.632	-5.234	-10.228	-10.137	-12.280	-13.172	-12.065
	(-0.649)	(-2.165)	(-2.091)	(-0.094)	(-2.780***)	(-1.954)	(-5.053***)	(-6.901***)	(-3.791***)	(-3.743***)	(-2.992***)

Effective spread											
DECILE PORTFOLIO											
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-2.221	-5.782	-4.864	-5.035	-9.207	-7.832	-6.929	-5.125	-3.878	-9.365	-7.144
	(-1.041)	(-3.112***)	(-2.402)	(-1.722)	(-2.845***)	(-3.215***)	(-2.625***)	(-2.493)	(-1.287)	(-2.744***)	(-1.758)
Fama-French alpha (% p.a.)	-2.504	-5.986	-5.175	-5.511	-9.655	-8.542	-7.224	-5.524	-4.586	-10.185	-7.682
	(-1.268)	(-3.322***)	(-3.114***)	(-2.116)	(-3.511***)	(-4.938***)	(-3.131***)	(-3.117***)	(-1.916)	(-3.257***)	(-2.007)
Carhart alpha (% p.a.)	-1.079	-5.983	-5.378	-6.476	-10.858	-9.933	-8.034	-5.999	-3.420	-11.257	-10.178
	(-0.516)	(-3.160***)	(-3.147***)	(-2.411)	(-3.708***)	(-5.029***)	(-3.778***)	(-3.433***)	(-1.498)	(-3.351***)	(-2.595***)
Quoted spread											
DECILE PORTFOLIO											
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-4.402	-2.084	-4.103	-6.880	-8.680	-10.297	-11.014	-11.721	-14.974	-21.762	-17.360
	(-4.168***)	(-1.260)	(-1.725)	(-2.816***)	(-2.921***)	(-3.423****)	(-2.780***)	(-3.255***)	(-3.524***)	(-5.124***)	(-4.008***)
Fama-French alpha (% p.a.)	-4.339	-2.593	-4.833	-7.681	-9.511	-11.277	-11.765	-12,543	-15.815	-22.676	-18.338
	(-4.151***)	(-1.774)	(-3.127***)	(-3.887***)	(-3.795***)	(-4.693***)	(-4.131***)	(-4.043***)	(-4.438***)	(-6.997***)	(-5.64***)
Carhart alpha (% p.a.)	-4.027	-3.304	-5.098	-7.413	-8.876	-10.445	-12.564	-12.882	-16.123	-25.021	-20.994
	(-4.171***)	(-2.322)	(-3.395***)	(-3.128***)	(-3.288***)	(-3.670***)	(-4.069***)	(-3.667***)	(-4.651***)	(-7.534***)	(-6.290***)

Dollar trading volume											
DECILE PORTFOLIO											
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-14.642	-14.435	-8.601	-6.939	-6.661	-3.824	-5.390	-3.813	-2.816	-4.626	10.016
	(-2.647***)	(-3.725***)	(-2.509)	(-2.274)	(-2.619***)	(-1.597)	(-2.213)	(-1.654)	(-1.925)	(-4.063***)	(1.738)
Fama-French alpha (% p.a.)	-15.567	-15.116	-9.359	-7.535	-7.444	-4.558	-6.160	-4.512	-3.161	-4.547	11.020
	(-3.357***)	(-5.626***)	(-4.138***)	(-3.661***)	(-4.022***)	(-2.937***)	(-2.967***)	(-2.609***)	(-2.206)	(-4.027***)	(2.294)
Carhart alpha (% p.a.)	-17.020	-16.045	-9.908	-8.603	-7.632	-4.577	-6.617	-4.285	-3.810	-4.207	12.813
	(-3.254***)	(-5.426***)	(-3.632***)	(-3.803***)	(-3.610***)	(-2.543)	(-3.047***)	(-2.281)	(-2.708***)	(-4.124***)	(2.352)
Turnover ratio											
DECILE PORTFOLIO											
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-14.577	-10.189	-3.400	-10.689	-6.807	-5.214	-1.358	-4.751	-2.078	-4.344	10.233
	(-3.055***)	(-2.440)	(-0.919)	(-4.565***)	(-2.634***)	(-1.637)	(-0.930)	(-3.160***)	(-1.294)	(-1.647)	(1.993)
Fama-French alpha (% p.a.)	-15.247	-10.544	-3.812	-11.016	-7.326	-5.614	-1.513	-4.811	-2.309	-4.369	10.878
	(-3.663***)	(-2.435)	(-1.159)	(-5.167***)	(-3.016***)	(-1.815)	(-1.041)	(-3.316***)	(-1.289)	(-1.945)	(2.205)
Carhart alpha (% p.a.)	-16.054	-10.886	-3.728	-12.178	-6.299	-4.464	-2.859	-5.220	-1.080	-4.702	11.352
	(3.763***)	(-2.308)	(-1.165)	(-5.028***)	(-2.566)	(-1.346)	(-1.779)	(-3.212***)	(-0.558)	(-2.329)	(2.261)

Liu's											
DECILE PORTFOLIO											
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-4.880	-3.641	-3.225	-5.630	-6.314	-8.035	-5.224	-8.438	-6.195	-9.908	-5.028
	(-2.324)	(-2.269)	(-2.136)	(-2.894***)	(-2.309)	(-2.688***)	(-1.850)	(-2.674***)	(-1.518)	(-2.647***)	(1.401)
Fama-French alpha (% p.a.)	-5.664	-3.847	-3.241	-5.831	-6.831	-8.705	-5.664	-9.235	-6,663	-10.297	-5.243
	(-2.545)	(-2.325)	(-2.201)	(-2.872***)	(-2.608***)	(-3.527***)	(-2.409)	(-3.892***)	(-1.916)	(-3.865***)	(-1.666)
Carhart alpha (% p.a.)	-4.334	-3.576	-3.450	-6.038	-7.160	-9.575	-5.623	-9.434	-7.856	-12.516	-8.182
	(-2.594***)	(-2.119)	(-2.386)	(-3.031***)	(-2.634***)	(-3.772***)	(-2.029)	(-3.886***)	(-2.106)	(-4.445***)	(2.632***)

Amihud's ratio											
DECILE PORTFOLIO											
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-3.896	-4.852	-5.246	-3.920	-6.842	-5.049	-5.022	-12.801	-17.032	-24.905	-21.009
	(-2.446)	(-4.228***)	(-2.932***)	(-1.593)	(-2.547)	(-1.868)	(-1.826)	(-3.594***)	(-4.105***)	(-4.806***)	(-4.368***)
Fama-French alpha (% p.a.)	-3.878	-5.013	-5.444	-4.486	-7.439	-5.736	-5.683	-13.768	-17.979	-25.883	-22.005
	(-2.502)	(-4.042***)	(-3.032***)	(-2.430)	(-3.676***)	(3.266***)	(-2.574)	(-5.996***)	(-6.265***)	(-6.061***)	(-5.453***)
Carhart alpha (% p.a.)	-3.603	-5.106	-5.066	-4.308	-7.837	-5.657	-6.625	-14.254	-18.779	-26.078	-22.475
	(-2.482)	(-4.338***)	(-2.684***)	(-2.454)	(-3.416***)	(-2.692***)	(-2.466)	(-5.200***)	(-6.119***)	(-5.439***)	(-4.950***)

Floracksis et al.'s (2011) RtoTR											
	DECILE PORTFOLIO										
	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p10-p1
CAPM alpha (% p.a.)	-2.207	-3.471	-3.665	-8.371	-7.274	-10.003	-7.117	-4.558	-14.835	-15.436	-13.230
	(-1.254)	(-2.494)	(-2.020)	(-2.812***)	(-2.171)	(3.841***)	(-2.384)	(-1.882)	(-4.342***)	(-3.047***)	(-2.820***)
Fama-French alpha (% p.a.)	-2.135	3.691	-2.936	-8.717	-7.753	-10.523	-7.442	-5.326	-15.464	-15.900	-13.766
	(-1.205)	(-2.511)	(-2.094)	(-2.970***)	(-2.544)	(-4.228***)	(-2.834***)	(3.013***)	(-4.687***)	(-3.755***)	(3.498***)
Carhart alpha (% p.a.)	-2.368	-3.790	-3.739	-7.136	-8.149	-11.209	-7.796	-5.299	-14.210	-16.551	-14.182
	(-1.474)	(-2.525)	(-2.113)	(-2.443)	(-2.478)	(-3.640***)	(-3.016***)	(-2.810***)	(-4.529***)	(-3.768***)	(-3.353***)