UNIVERSITY OF EXETER

Essays on Stock Liquidity

by

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Declaration of Authorship

Submitted by Ozkan Haykir, to the University of Exeter as a thesis for the degree of Doctor of Philosophy in Finance, July 2017.

I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

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Abstract

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This thesis consists of three main empirical chapters on the effect of stock liquidity on exchange markets. The first (Chapter 2) investigates the pricing ability of an illiquidity measure, namely the Amihud measure (Amihud, 2002), in different sample periods. The second (Chapter 3) determines the causal link between two well-known market quality factors liquidity and idiosyncratic volatility adopting two-stage least squares methodology (2SLS). The last empirical chapter (Chapter 4) revisits the limits to arbitrage theory and studies the link between stock liquidity and momentum anomaly profit, employing the difference-in-differences approach. The overall contribution of this thesis is to employ causal techniques in the context of asset pricing in order to eliminate potential endogeneity problems while investigating the relation between stock liquidity and exchange markets.

Chapter 2 investigates whether the Amihud measure is priced differently if the investor is optimistic or, conversely, pessimistic about the future of the stock markets.

The results of the chapter show that Amihud measure is priced in the low-sentiment period and that there is illiquidity premium when investor sentiment is low.

Chapter 3 studies whether a change in stock liquidity has an impact on idiosyncratic volatility, employing causal techniques. Prior studies investigate the link between liquidity and idiosyncratic volatility but none focus on the potential problem of reverse causality. To overcome this reverse causality problem, I use the exogenous event of decimalisation as an instrumental variable and employ two-stage least squares approach to identify the impact of liquidity on idiosyncratic volatility. The results of the chapter suggest that an increase in illiquidity causes an increase in idiosyncratic volatility. As an additional result, my study shows that reduction in the tick size as a result of decimalisation improves firm-level stock liquidity.

Chapter 4 examines whether liquid stocks earn more momentum anomaly profits compare to illiquid stocks, using the implementation of different tick sizes for different price ranges in the American Stock Exchange (AMEX) between February 1995 and April 1997. This programme provides a plausibly exogenous variation to disentangle the endogeneity issue and allows me to examine the impact of liquidity on momentum, by clearly exploiting the difference-in-difference framework. The results of the chapter show that liquid stocks earn more momentum profit than illiquid stocks.

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Chapter 1

Introduction

Liquidity is a vital concept in the finance literature. The basic definition of liquidity is the ability to buy or sell a large amount of stock in a short period without significantly affecting its market price. There are four further aspects to the definition of stock liquidity. Harris (1991) summarises these as depth, immediacy, resiliency and width. Depth captures the number of shares that are traded at the certain bid and ask price. Immediacy refers to the speed of transaction at a given bid and ask price. Resiliency refers to the price impact or how quickly the market price adjusts itself after liquidity shock. Finally, width refers to the difference between the bid and ask price, which also reveals the ease of buying or selling a certain number of shares.

The importance of the liquidity on the stock markets is well documented in the asset pricing and market microstructure literature. Prior studies suggest that investors should demand a higher risk premium to hold illiquid stock in their portfolios. The reason for this is that investors bear more risk. In other words, the uncertainty of the outcome of holding an illiquid asset is higher when the investor comes to sell the asset. This phenomenon is known in the literature as the "illiquidity premium". Earlier papers establish that the illiquidity premium holds at both the firm and the aggregate market levels.

Theoretical and empirical papers study the impact of liquidity on expected return from two different angles. First, Amihud and Mendelson (1986) and Brennan, Chordia and Subrahmanyam (1998) study the terms of transaction costs and show that transaction costs of trading illiquid stock are higher than liquid stock. Thus, an investor should require higher expected returns for holding illiquid stocks since it will be costly when they decide to sell these assets. Second, Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) suggest that liquidity should be considered as a risk factor. Thus, increase in the sensitivity of the exposure of the risk of an asset will be compensated for by the higher expected return since the asset becomes riskier.

Liquidity is also considered one of the most important determinants of market quality. Thus, it has implications not only in the context of asset pricing but also in the context of corporate finance. Fang, Noe and Tice (2009) examine the impact of stock liquidity on firm performance, measured by Tobin's Q. Fang, Tian and Tice (2014) examine the impact of stock liquidity on corporate innovation. Nyborg and Wang (2014) study the impact of stock liquidity on corporate cash holdings. A more recent paper, Brogaard, Li and Xia (2017), shows that stock liquidity has the power to determine the bankruptcy risk of a firm.

1.1 Motivation of the Study

Even though the impact of stock liquidity is examined extensively in the finance literature, most of the studies are hampered by the issue of endogeneity. We know that endogeneity can cause a violation of the assumption of unbiasedness and leads to inconsistent estimates, therefore it is crucial to fix the problem to obtain accurate estimates. There are several reasons for the problem of endogeneity, including omitted variables, simultaneous causality and measurement errors. Researchers well understand the consequences of the endogeneity problem and have begun employing causal methodologies in their studies to solve it. These causal methods include instrumental variables, the difference-in-differences and regression discontinuity approaches. These methods require finding a source of exogenous variation to obtain the true coefficient of interest (Robert and Whited, 2011).

The motivation of this thesis is to solve the endogeneity problem by adopting causal econometric methodologies in the estimation of stock liquidity. Thus far, causal techniques have been widely used in the context of corporate finance but not so much in the context of asset pricing while understanding the role of stock liquidity. This is because it is not easy to find an exogenous shock to stock liquidity without affecting another asset pricing variable. In this thesis, I have used a regulation change in the US equity markets that enables me to handle the endogeneity problem. I use the change in the minimum price variation (tick size) in the US equity markets as an exogenous variation to estimate stock liquidity.

1.2 History of Exogenous Events

For a long time the minimum price variation remained at the same level, \$1/8, in the US equity markets. Nevertheless, at the beginning of 1990s, academicians and practitioners began discussing whether high tick size was harmful to market competitiveness and they suggested that the Security and Exchange Commission (SEC) should take responsibility for reinforcing the competitiveness of the US equity markets in relation to foreign equity markets.

In 1992, the SEC decreased the minimum price variation from \$1/8 to \$1/16 for stocks that were traded on the American Stock Exchange and were priced between \$1 and \$5. In 1995, this new rule included all stocks that were priced below \$10 on the American Stock Exchange. On May 1997, the minimum price variation was set at \$1/16 for all stocks in all US equity markets.

Around the same time, two US representatives (Oxley and Markey) proposed a new bill to switch the system of expression of stock prices in fractional terms to a decimal system. They believed that the new decimal pricing system would increase international competitiveness because most of the world's industrialised countries used decimal units. The SEC decided to implement the decimal pricing system in phases. The decimal pricing system was first introduced for only seven stocks in Phase I, and an additional 57 stocks and 94 stocks were included in Phase II and III, respectively. Finally, the decimal pricing system was introduced to all companies listed on the New York Stock Exchange (NYSE) and the American Stock Exchange

(AMEX) in January 2001, and companies listed on the National Association of Securities Dealers Automated Quotations (NASDAQ) in April 2001.

The effect on stock liquidity of changing the minimum price variation has been examined in the literature on not only on the US equity markets but also on international markets. Ahn, Cao and Choe (1996) examine the first change in the American Stock Exchange and find that trading costs declined by 18.9 per cent. Bacidore (1997) shows that adopting the decimal pricing system led to an increase in stock liquidity on the Toronto Stock Exchange. Ronen and Weaver (2001) also show that stock liquidity increased after decreasing tick size on the American Stock Exchange. Several researchers show that implementation of the decimal pricing system also led to rising stock liquidity (Chakravarty, Harris and Wood, 2001; Bessembinder, 2003; Furfine, 2003). As we have seen from the results of these early studies, changing minimum price variation therefore has an impact on stock liquidity. Moreover, the introduction of the decimal pricing system is used as an exogenous positive shock to stock liquidity in the corporate finance literature (Fang et al., 2009, 2014).

1.3 Contribution of the Thesis

Causal econometrics methodologies are extensively used in the empirical corporate finance literature but the use of these methods in asset pricing is limited. As we know, many concepts in asset pricing introduce the problem of reverse causality, which means that estimations are biased and inconsistent. The main contribution of this thesis is to employ causal econometrics methodologies in the context of asset pricing while estimating stock liquidity.

The first empirical chapter (Chapter 2) of this thesis investigates the pricing ability of an Amihud measure of stock liquidity at different levels of investor sentiment, captured by the investor sentiment index constructed by Baker and Wurgler (2006).

The importance of stock liquidity in finance is well defined but the question of which measure to use as a proxy for stock liquidity needs to be clarified. Currently, high-frequency (intraday) proxies of stock liquidity specifically, quoted and effective spread are extensively used in the market microstructure literature. Certainly, using high-frequency data will give a more accurate estimation of stock liquidity since they are captured by the bid and ask spread; however, there are two issues with using high-frequency data. First, the availability of the high-frequency data is limited. Due to high acquisition costs, it is not easy to access the data. Second, high-frequency data are not suitable for long time horizon analysis. Thus, it is important to find the best proxy of stock liquidity that gives a similar result to high-frequency measures. There are several low-frequency proxies of stock liquidity that have been used in finance, including the Amihud measure (Amihud, 2002), Roll's Impact (Chordia, Roll and Subrahmanyam, 2001), 'effective tick' estimator (Holden, 2009), Pastor and Stambaugh's gamma (Pastor and Stambaugh, 2003), Amivest liquidity ratio, Percentage of zero returns (Lesmond, Ogden and Trzcinka, 1999), Gibbs estimator (Hasbrouck, 2004), and the Corwin and Schultz (2012) measure. Goyenko, Holden and Trzcinka (2009) investigate which measure is the closest proxy, in terms of effectiveness, to high-frequency measures. First, they split the low-frequency measures into two categories: low-frequency spread proxies and low-frequency price impact proxies. They then examine these proxies to find the best low-frequency measure using the high-frequency measures as a benchmark. The overall result of their study suggests that the Amihud measure is the best proxy to capture the price impact compared to other low-frequency price impact proxies.

The Amihud measure interprets illiquidity of stock (a higher value indicates lower liquidity) and captures the price changes per dollar of volume unit of trade. The investor sentiment index determines the expectations of the stock market. If investors are optimistic about the future performance of the stock market, then the sentiment index is high. However, investor sentiment is low when investors are pessimistic about the future of the stock market. The theoretical studies suggest that there is a positive relation between investor sentiment and stock liquidity. When the investor sentiment goes up, stock liquidity also increases. Liu (2015) shows that investor sentiment index and stock liquidity are positively related and investor sentiment Granger-causes stock liquidity.

The contribution of Chapter 2 is to answer the question of whether the Amihud illiquidity measure is priced and the illiquidity premium is higher in the low sentiment period. I first employ sorting analysis by splitting the periods into two groups based on the median of the monthly investor sentiment index during the sample period. Then I employ Fama-MacBeth (1973) cross-sectional analysis to show that the results are consistent. Finally, I employ several robustness analyses to confirm my results after controlling for several other aspects.

The second empirical chapter of this thesis (Chapter 3) examines the causal link between stock liquidity and idiosyncratic volatility. A number of theoretical models suggest that stock liquidity and idiosyncratic volatility should be negatively related. Such models are also supported by empirical analysis. However, these empirical papers suffer from the problem of endogeneity to be more specific, reverse causality. Stock liquidity may have an impact on the idiosyncratic volatility of stock but at the same time, idiosyncratic volatility of stock may have an impact on stock liquidity. Thus, it is problematic to estimate the relation by ordinary least squares (OLS) methodology.

The importance of Chapter 3 is that stock liquidity and idiosyncratic volatility are the two most important indicators of market quality, and this chapter will help us to understand whether stock liquidity can be used as a tool for controlling idiosyncratic volatility. This is important since there has been a huge debate in the last decade on whether idiosyncratic volatility should be positively or negatively related with future expected return. Thus, if we can understand the link between liquidity and idiosyncratic volatility, we can eliminate the negative effect of idiosyncratic volatility.

The relation between idiosyncratic volatility and expected return is not as straightforward as stock liquidity. The theory goes back to the capital asset pricing model (CAPM) that suggests that unsystematic risk should not be priced since it can be well diversified. However, the investor may hold undiversified portfolios at some level in order to earn a higher expected return (Merton, 1987). According to Merton (1987), there should be a positive relation between unsystematic risk and expected stock return since investors bear more risk. Empirical studies find supporting evidence of this phenomenon (Goyal and Santa-Clara, 2003; Xu and Malkiel, 2006; Fu, 2009). On the other hand, Ang et al. (2006, 2009) show that investors earn less by holding undiversified portfolios not only in the US exchange markets but also in 23 developed international markets.

The contribution of Chapter 3 is to extend earlier findings and examine whether a change in stock liquidity has an impact on idiosyncratic volatility. To accomplish my aim to implement causal econometrics methods, I use the exogenous event of decimalisation that occurred in the US equity markets at the beginning of 2001 as an instrumental variable to estimate stock liquidity. By adopting causal methodology, I overcome the reverse causality problem, since decimalisation has no direct impact on idiosyncratic volatility, but has an indirect effect, and this indirect effect is through stock liquidity. I also provide evidence of the impact of decimalisation on stock liquidity.

The last empirical chapter of this thesis (Chapter 4) studies the impact of stock liquidity on anomaly profits. Why we have asset pricing anomalies is one of the biggest questions in the world of finance. Limits to arbitrage theory suggest that financial anomalies exist due to restrictions on the markets, such as short-selling constraint and illiquid markets. Thus, if these restrictions are eliminated then there should be no anomaly profit and the efficient market hypothesis should be captured. Several empirical papers study this phenomenon using changes in the markets. Chordia, Subrahmanyam and Tong (2014) suggest that after the implementation of decimal pricing the anomaly profits decrease, which is in line with limits to arbitrage theory.

Chu, Hirshleifer and Ma (2016) suggest that relaxation of the short-selling constraint will lead a 77 basis point decline in the 10 most well-known market anomalies per month. Therefore, limits to arbitrage theory is proven by the empirical studies that if we eliminate the restriction, anomalies will lose their power.

The contribution of Chapter 4 is to investigate whether liquid stocks earn higher momentum anomaly profits, by exploring the implementation of different tick sizes for different price ranges in the AMEX between February 1995 and April 1997. This programme provides a plausibly exogenous variation to disentangle the endogeneity issue and examine the impact of liquidity on momentum, clearly exploiting the difference-in-differences framework. As shown earlier, decreasing the minimum price variation causes the treatment group stocks to become liquid compared to the control group stocks that have a higher minimum price variation during the programme.

The reason for choosing momentum anomaly is that it is considered one of the most prominent asset pricing anomalies in finance. Jegadeesh and Titman (1993) show that stocks with high past performance outperform the low past performance stocks. Momentum strategy suggests buying (long) with high past performance stocks and selling (short) with low past performance stocks. Asness, Moskowitz and Pedersen (2013) show that the momentum anomaly still exists in the different time periods and in different asset classes. Thus, understanding what drives momentum anomaly is an important question to answer.

The outline of the thesis is organised as follows. Chapter 2, 3 and 4 includes the three empirical chapters. Chapter 5 concludes the thesis by explaining the limitations and offering suggestions for further research.

Chapter 2

Effect of Illiquidity on Expected Return: Evidence from the Sentiment Index

2.1 Introduction

The impact of stock liquidity on expected stock return at the firm and the aggregate market level has been at the centre of liquidity research for a long time. Many empirical papers argue that when a stock becomes illiquid the expected stock return should rise. The reason for this phenomenon is straightforward: investors require a higher risk premium to hold illiquid stocks in their portfolio (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Amihud, 2002). Moreover, earlier studies have documented that stock liquidity varies over time (Chordia et al., 2001; Hasbrouck and Seppi, 2001), and a recent paper written by Liu (2015) looks for the reason for this variation and shows that the sentiment index plays a significant role on stock liquidity. She finds that there is a positive relation between the sentiment index and market liquidity and that investor sentiment Granger-causes market liquidity. However, there is still a research gap on whether illiquidity premium exists in different states of the economy, which is determined by the investor sentiment index.

Figure 2.1 illustrates a time-series overview of stock illiquidity, constructed by the Amihud (2002) measure and investor sentiment index as well as National Bureau of Economic Research (NBER) recession periods (shaded areas). Equal-weighted market liquidity is calculated in each month and this measure is standardised. It can be clearly seen that sentiment index is decreasing at the beginning of NBER recession period until the end of the recession period, which is expected. And, illiquidity increases when the sentiment index is low. This supports the idea that stock liquidity dries up during the bad times and investors are willing to accept a higher risk premium during the crisis periods.[1]

[Insert Figure 2.1 near here]

In this chapter, I investigate whether stock's illiquidity is priced differently in different sentiment periods, which are determined using the investor sentiment index constructed by Baker and Wurgler (2006). The authors proposed an index to capture investors' view about future of the stock market. If investors are optimistic about the future then the sentiment index is high, and if investors are pessimistic about the future the sentiment index is low. Results show that firm-level stock's

[1]The correlation coefficient between market illiquidity and investor sentiment is -0.35.

illiquidity is positively priced only following a low sentiment period. This result holds for small-sized companies, controlling for idiosyncratic volatility and excluding financial and utility firms.

Even though there are several liquidity proxies have been used in the literature, the primary focus on this chapter is to understand the pricing ability of the Amihud measure only. The reason of this is that Amihud measure is well-accepted proxy of stock liquidity among the low-frequency proxies of stock liquidity which is empirically proven by the recent study written by Goyenko et al. (2009). They investigate which liquidity proxy (using daily data) gives the best result as intraday proxies. They find that the Amihud measure won the horserace in terms of capturing price impact. Another reason of focusing on Amihud measure is that intraday proxies of stock liquidity, namely, quoted and effective spread, are not easily accessible due to their high cost and the implications on the long time horizon.

The theoretical link between sentiment index and stock market liquidity is well defined in the literature. There are two channels through which the sentiment index may affect stock market liquidity. The first channel is the irrational investor during the high sentiment period. Baker and Stein (2004) show that there are more irrational investors on the market following a high sentiment period. These irrational investors will reduce the order flow due to overconfidence and this will lead to an increase in market liquidity. De Long et al. (1990) and Kyle (1985) explain the second channel. They suggest that during the high sentiment period there is greater "noise"[2] trading on the market and this causes market liquidity goes up.

There has been no attempt (to my knowledge) to show how stock's illiquidity is priced following the high and low sentiment periods. This chapter aims to fill this gap in the literature by conducting univariate and the cross-sectional analyses. The main cross-sectional analysis shows that a one standard deviation increase in the logarithm of Amihud illiquidity measure (3.29 in my sample period) is associated with a monthly return of 0.30 per cent in the entire estimation period, and more importantly a one standard deviation increase in the logarithm of Amihud illiquidity (3.30 in a low sentiment period) is associated with a monthly return of 0.39 per cent, which gives a 4.68 per cent return premium following a low sentiment period. This result is economically and statistically significant and supported by univariate analysis. Not surprisingly, after the high sentiment period, there is no risk premium for holding illiquid stock.

The rest of this chapter is organised as follows. Section 2.2 summarises earlier related research. Section 2.3 describes the empirical setting and data. Section 2.4 presents the empirical results. Section 2.5 reports the results of several robustness tests and Section 2.6 concludes the chapter.

[2] Stock market activity caused by programme trading, dividend payments or other phenomena that is not reflective of overall market sentiment (Black, 1986).

2.2 Related Literature

Stock liquidity is one of the main indicators of market quality (Chordia, Sarkar and Subrahmanyam, 2005) and its impact on expected return is well established in the finance literature (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Amihud, 2002). Researchers look at the importance of liquidity from two different theoretical perspectives. Amihud and Mendelson (1986) and Brennan et al. (1998) use the term transaction costs to determine the link between stock illiquidity and the expected return. They suggest that there is an illiquidity premium because the transaction costs of the trading illiquid asset are higher than liquid stocks, so an investor should demand a higher risk premium. Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) consider stock liquidity as a risk factor and explain the stock liquidity in terms of liquidity beta. They suggest that liquidity beta is positively related to the expected returns.

This study contributes to the literature by examining whether illiquidity premium is different in certain conditions. Recent papers begin by determining whether illiquidity premium is stronger in certain periods or conditions. Ben-Rephael, Kadan, and Wohl (2015) investigate how illiquidity premium has changed in recent times. They claim that stock liquidity has improved dramatically during the last two decades. Based on this increase, illiquidity premium has significantly declined. They conclude that the illiquidity premium that most papers claim, comes from an earlier time period, including 1960s and 1970s. Moreover, Naes, Skjeltorp and Odegaard

(2011) search for a link between stock market liquidity and the business cycle. They show that liquidity declines when there is a recession in the economy.

In this chapter, I use the investor sentiment index to distinguish the time periods. There are several papers that try to link investor sentiment index and stock market liquidity. Baker and Stein (2004) study the theoretical link between market liquidity and the sentiment index. They conclude that irrational investors are important players in high sentiment periods where liquidity of the market is high so, they use stock liquidity as an indication of the sentiment of the market. Baker and Wurgler (2006) construct an investor sentiment index and investigate its power to predict expected returns. Antoniou et al. (2015) also examine sentiment index by exploiting the relation between sentiment index and CAPM. They find that during the high sentiment period (optimistic periods) security market line exhibits upward slope curve and during the low sentiment period it exhibits downward sloping curve. They relate this finding with unsophisticated investors. They claim that during the high sentiment period unsophisticated investors play a significant role in the market but during the low sentiment period only the sophisticated investors' trade on the market. We could also think their results in the context of stock liquidity as Baker and Stein (2004) claim in their paper. This index has become one of the most popular indicators of investor sentiment and many researchers use this index. Empirical papers have been written to explain the theoretical link using real data. Liu (2015) uses this index and the institutional sentiment index to estimate the link between market illiquidity and investor sentiment. She empirically shows that when the investor sentiment rises, stock market liquidity increases as well. She also shows that investor sentiment Granger-causes market liquidity. Her paper focuses on the relationship between market liquidity and sentiment index. She tries to identify which one Granger-causes the other. On the other hand, this chapter mainly focuses on the relation between firm level stock liquidity and investor sentiment index and identify whether the pricing ability of Amihud (2002) measure is different during the different level of investor sentiment.

To capture the impact of the stock illiquidity, several proxies are used in the literature. There are high-frequency proxies effective and realised spread and low-frequency price impact proxies including, as outlined in the introductory chapter, Amihud (Amihud, 2002), Pastor and Stambaugh's gamma (Pastor and Stambaugh, 2003), Roll's Impact (Chordia et al., 2001), Amivest and Corwin-Schultz (2012). In this study, I only use Amihud's (2002) price impact proxy, since it is highly correlated with intraday data (Goyenko et al., 2009) and it produces a closer capture of the price impact as intraday data. Amihud (2002) captures the illiquidity of stocks: high Amihud proxy value is considered as low liquidity. The measure determines the price change per dollar of volume unit of trade.

2.3 Data and Variable Construction

The sample includes only common stocks (share codes 10 and 11) that are traded on NYSE and AMEX. NASDAQ companies are used for robustness analysis due to their inflated trading volume. The sample period is from January 1966 to December 2012. Daily and monthly return, price, share outstanding and volume data are downloaded from the Center for Research in Security Prices (CRSP). Compustat is used to obtain variables to construct book-to-market ratios. The monthly investor sentiment index is downloaded from Jeffrey Wurgler's website.[3] Daily and monthly Fama-French (2006) three-factors market premium (MKT), small-minus-big (SMB) and high-minus-low (HML) as well as momentum factor (winner-minus-loser, UMD) data are acquired from Kenneth French's personal website.[4]

The Amihud (2002) measure is used as a proxy for illiquidity in this chapter. In the literature it is extensively used to capture price impact. Lou and Shu (2016) state that between 2009 and 2013 more than 100 papers in the leading finance journals use the Amihud (2002) measure as a proxy for illiquidity in their papers.

The Amihud (2002) measure is formulated as follows:

$$Amihud_{im} = \frac{1}{D_{im}} \sum_{d=1}^{D_{im}} \frac{|Return_{id}|}{Dvol_{id}} \tag{2.1}$$

where D_{im} denotes the number of days in which stock has a valid ratio in month m for stock i. $Return_{id}$ is daily return in stock i on day d. $Dvol_{id}$ is the dollar value of trading volume on day d for stocks i. The measure captures the price impact since it is defined as the monthly average of the ratio of the absolute return of a stock divided by its volume traded in dollars and determined the price change per dollar of volume unit of trades. To clarify, the Amihud measure is interpreted as an illiquidity measure of a stock (a high number is considered as low liquidity). I follow earlier papers and calculate the Amihud measure if the stock has a valid daily

[3] http://people.stern.nyu.edu/jwurgler/.
[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

return and volume observation at least 10 days in a month. The Amihud measure is winsorised at the one per cent and 99 per cent levels each month to eliminate the effect of outliers in my sample. Following the earlier literature (e.g. Brennan, Huh and Subrahmanyam, 2013; Lou and Shu, 2016), I match illiquidity proxy in month $m-2$ with a stock return in month m.

In terms of investor sentiment index, I use one of the most commonly used indexes: the Baker and Wurgler (2006) investor sentiment index. The index captures investors' view of future stock market movements. When the investor sentiment index is high, investors are considered optimistic about future stock market performance. The measure is constructed using six proxies[5] and each proxy is orthogonalized with respect to common macroeconomic variables.[6] To be consistent with illiquidity measure sentiment index in month $m-2$ matches with a stock market return in month m.

In the cross-sectional analysis, I also control for common firm characteristics, such as book-to-market ratio, size, Return [-12 -2] and Return [-1]. The book-to-market ratio is defined as the book value of equity divided by market value of equity, where the book value of equity is defined following Lou and Shu (2016)[7] and the market value is market capitalisation of equity. The book value of each stock is calculated at the end of the fiscal year t and its market value is obtained at the end of the calendar year t. The book-to-market of stock i in year t is matched with the monthly

[5] After revision, they use only five proxies which are the closed-end fund discount, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium.

[6] Macro variables are industrial production index, nominal durables and nondurables consumption, nominal services consumption, NBER recession indicator, and employment.

[7] Book value of equity defined as stockholders' equity plus balance sheet deferred taxes plus investment tax credit minus the book value of preferred stock.

return of stock i from July of year $t+1$ to June of year $t+2$. The book-to-market ratio is winsorised at the one per cent and 99 per cent levels at the end of each year. Size is defined as the logarithm of the market capitalisation for stock i at the end of the estimation year t. Return [-12 -2] is defined as the cumulative return for stock i from month $m-12$ to $m-2$, and the Return [-1] is defined as the return of stock i in month $m-1$.

2.3.1 Summary Statistics

To give an overview of the relation between stock illiquidity and investor sentiment index, I present descriptive statistics in Table 2.1, which reports the descriptive statistics for three different sample periods. Panel A presents the relation in the entire period and Panel B and C cover only low and high sentiment period, respectively. I identify low and high sentiment periods based on the median of the index during the entire sample period. If the sentiment index of month m is lower than the median and the period is identified as low sentiment and if the index of month m has higher sentiment index than the median, the period is identified as high sentiment. Overall, I have 564 months in my sample period, where 282 months were used for the analysis of low and high sentiment periods separately.

In the entire sample period, I include 1,194,537 firm-month observations for the Amihud illiquidity measure and the number of firm-month observations is 601,000 and 593,537 for the low and high sentiment periods, respectively. At first glance, we can see that illiquidity increases during the low sentiment period compare with the high sentiment period, 5.640 and 2.254 respectively. This difference is more pronounced in the high quintiles of each period. When we compare the above median average for low and high sentiment period Amihud measures, in the low sentiment period stocks become more illiquid. This suggests that liquid stocks, in general, are not affected by the sentiment index but illiquid stocks become more illiquid in the low sentiment period. The result is in line with the theoretical explanation of the relation between stock illiquidity and investor sentiment index. During the low sentiment index, the investor becomes more sceptical and the demand for illiquid stock decreases more than the demand for liquid stocks. On the other hand, during the high sentiment period, overall optimism affects the investor's behaviour and they are not as afraid of the demand for illiquid stocks. Thus, stock liquidity dries up during the low sentiment period compare with the high sentiment period.

In addition to the Amihud measure, Table 2.1 reports other firm characteristics such as idiosyncratic volatility, book-to-market, size, price, return and Return [-12 -2] for the entire period as well as low and high sentiment period. Average raw return follows the same pattern as the Amihud measure. There is almost no difference below the median quintiles but higher quintiles show that average return is higher during the low sentiment period than during the high sentiment period. Since the demand of illiquid stock is lower in the low sentiment period, the investor who is willing to take the risk and hold illiquid stocks in his or her portfolio also demands a higher return to compensate for his or her risk of holding riskier stocks during the low sentiment period.

[Insert Table 2.1 near here]

Idiosyncratic volatility is defined as unsystematic risk and estimated based on the residuals from Fama-French's three-factor model. It is almost the same in the low and the high sentiment periods. Thus, we can say that the role of idiosyncratic volatility is not clear in obtaining different risk premiums in different sentiment periods.

2.4 Empirical Setting

The theoretical paper written by Baker and Stein (2004) proposes that investor sentiment and stock liquidity should be positively related. When sentiment goes up, liquidity of the stock market should increase as well, or to clarify with respect to my proxy of illiquidity, the Amihud measure should decrease due to decline in the price impact. Baker and Stein's explanation is that when investor sentiment is low, only highly trained people will trade on the market, so illiquidity will be high. On the other hand, when investor sentiment is high, irrational people play a significant role in the market, while trained or "smart" people do not actually trade that much. In this situation, irrational investors drive the illiquidity down, so that the market becomes liquid. Liu's (2015) recent paper investigates how market liquidity reacts when investor sentiment changes and finds that when the sentiment index goes up, stock market liquidity increases, which is in line with theoretical models proposed earlier.

The aim of this chapter is to present the link between investor sentiment and firm-level stock liquidity and to discover whether illiquidity premium is higher during the low sentiment period compared with the high sentiment period. The illiquidity premium is derived from holding an illiquid asset in a portfolio, which should lead to higher expected returns (higher yields). To test my hypothesis, I conduct univariate and cross-sectional analyses.

2.4.1 Univariate Analysis

First, I conduct sorting analysis. Stocks are sorted into quintiles in each month m based on their Amihud illiquidity measure at month $m-2$ and the equal-weighted portfolio return is calculated in each month and time series average of the portfolio returns are reported. In Table 2.2, I report the results using raw return and four-factor alphas. Fama-French's three-factors (MKT, SMB and HML) and momentum factor (UMD) are used to calculate four-factor alphas. The first group has the most liquid stocks and the last group has the most illiquid stocks. Column (6) shows the difference between the most illiquid stocks portfolio return and the most liquid stocks portfolio return and the last column shows t-statistics of this difference. I use Newey-West (1987) robust standard errors with six lags. Panel A presents the results from January 1966 to December 2012. This is to show that the illiquidity premium is observed in the period in which I have chosen to investigate my hypothesis. Panels B and C report the separate sorting analysis for the period where investor sentiment is low and high, respectively. Low and high sentiment periods are designated using the median of investor sentiment index following Stambaugh, Yu and Yuan (2012). If the sentiment index in month m is higher than the median of the index, I consider this month the high sentiment period and if the sentiment index in month m is lower than the median of the index, I consider this month as the low sentiment period.

As previous papers also establish, the raw return goes up when the illiquidity increases. The difference between illiquid and liquid portfolios is statistically significant with an associated t-statistic of 2.21. We see the same pattern when I use four-factor alphas. Panel B presents the same sorting analysis but using only the low sentiment periods. We see that the liquid stock portfolio return does not change much when we compare the result with entire period returns; however, the illiquid stock portfolio return becomes larger and leads to a larger difference between illiquid portfolios and liquid portfolios in the low sentiment period. This difference is statistically significant, with an associated t-statistic of 2.48 for raw return and 2.06 for four-factor alphas. On the other hand, Panel C, which shows the result of high sentiment period, indicates that there is no illiquidity premium.

[Insert Table 2.2 near here]

Liquid portfolio return is no different from during the low sentiment period but there is a large difference when we compare the return in the illiquid stocks portfolios. This is what we expected from the summary statistics. Smart investors play a role during the low sentiment period and require higher premiums for holding illiquid stocks. Unlike the low sentiment period, irrational investors join the market and increase the overall liquidity of the stock market, which leads to a decline in the return of holding illiquid stocks in the high sentiment period.

2.4.2 The Cross-Sectional Analysis

As a second analysis, I use Fama-MacBeth (1973) methodology to investigate the pricing ability of the Amihud measure in different sentiment periods. First, I run the cross-sectional regression to obtain estimated coefficients in each month. I then calculate the time-series average of the coefficients. T-statistics are calculated using Newey-West (1987) robust standard errors with six lags. Following the previous literature (e.g. Amihud, 2002; Brennan et al., 2013; Lou and Shu, 2016), I use the natural logarithm of the Amihud measure. I also use control variables, such as book-to-market, size, lagged return and cumulative past return.

Fama-French three-factor adjusted return is used as a dependent variable. Following Brennan et al. (1998) and Lou and Shu (2016), I construct Fama-French three-factor adjusted return as follows:

$$\begin{aligned} \text{FF-3 Adjusted Return}_{im} = (\mathrm{r}_{im} - rf_m) - (\hat{\beta_{im}}^{MKT} \times MKT_m + \\ \hat{\beta_{im}}^{SMB} \times SMB_m + \hat{\beta_{im}}^{HML} \times HML_m) \end{aligned} \tag{2.2}$$

where $\hat{\beta_{im}}^{MKT}$, $\hat{\beta_{im}}^{SMB}$, and $\hat{\beta_{im}}^{HML}$ are estimated factors. I firstly regress the monthly excess returns and Fama-French three factors using prior information from $m-60$ to $m-1$. As a condition, at least 24 valid observations are required to estimate the factors.

Table 2.3 reports the results of the Fama-MacBeth (1973) regression for the entire period from January 1966 to December 2012, low sentiment and high sentiment periods. Column (1) shows that the coefficient of the Amihud measure is 0.090 and it is statistically significant. Positive coefficient confirms the theory that higher illiquidity is associated with higher expected returns (Amihud, 2002). One standard deviation increase (standard deviation of ln(Amihud) is 3.29 in entire period) in the Log(Amihud) is associated with a 0.30 per cent expected return per month. Column (2) reports the result for the low sentiment period. The coefficient of the Amihud measure is 0.118 and it is statistically significant and has higher magnitude compared with entire period analysis. This means the illiquidity premium is more pronounced in the low sentiment period. One standard deviation increase (standard deviation of ln(Amihud) is 3.30 during low sentiment period) in the Log(Amihud) measure is associated with a 0.39 per cent expected return per month, which is consistent with four-factor alphas in the sorting analysis. The annual premium of holding illiquid stocks is around 4.68 per cent in the low sentiment period.

The result is consistent with my hypothesis that during the low sentiment period, illiquidity premium is higher than in other periods. This happens because the liquidity of the stock market dries up during the low sentiment period. Thus, the investor sells the most liquid stock and requires more premium for holding the illiquid stocks during the low sentiment period. Column (3) shows the high sentiment period analysis. Not surprisingly, there is no illiquidity premium in this period. The coefficient of interest is lower and statistically insignificant. The Log(Amihud) measure is 0.062. It is still positive, which means there is still a illiquidity premium but it is statistically insignificant. The reason for this result is straightforward: the market is very liquid and the investor can sell any asset in their portfolio, therefore, holding illiquid stock does not require a high premium. Return [-1], which is defined as lagged return, is negative and statistically significant in the entire period, low sentiment and high sentiment periods. On the other hand, Return [-12 -2], which is defined as cumulative return, is positive and statistically significant in the entire period and only the high sentiment period, but in the low sentiment period, it is positive but statistically insignificant.

[Insert Table 2.3 near here]

Overall, the results show that investors require an illiquidity premium during my sample period from January 1966 to December 2012. In the low sentiment period, this premium is more pronounced, and in the high sentiment period, the coefficient of interest is statistically insignificant even though the coefficient of the Amihud measure is positive. The results are in line with theoretical explanations of the link between investor sentiment index and stock liquidity. As mentioned before, this chapter uses only Amihud (2002) measure as a proxy for stock liquidity, but using other low-frequency price impact measures would give the similar results since the correlation between price impact measures is high. The results might be different if we use low-frequency spread measures as a proxy of stock liquidity, but this chapter only investigates the pricing ability of Amihud measure and does not examine low-frequency spread measures as a proxy of stock liquidity.

2.5 Robustness Analysis

2.5.1 NASDAQ Analysis

In the main analysis section, I only use companies that are traded on the NYSE and AMEX markets. The reason for that is that the dealer structure of NASDAQ is different from the other two markets. As stated in earlier papers, the volume of stocks in the NASDAQ has double-counting problems due to the inclusion of inter-dealer volume. To handle this issue, I divide the daily dollar value of volume by two as in Atkins and Dyl (1997) and Nagel (2005).

Table 2.4 reports the results of the NASDAQ companies. Column (1) shows the entire period, Column (2) and Column (3) show the low sentiment and the high sentiment periods results, respectively. Due to lack of availability of volume data for NASDAQ companies, the sample period begins January 1983 and ends December 2012. Overall results of this table suggest that Amihud has no pricing ability for the NASDAQ firms and even though the coefficient is positive it is insignificant. This is consistent with Lou and Shu's (2016) paper. They show that only the yearly Amihud measure has pricing ability for the NASDAQ market but the monthly measure has no power to explain the illiquidity premium. The low and high sentiment periods also follow the same pattern and show no significant evidence of pricing ability of the Amihud measure for the NASDAQ firms.[8]

[8] To make an appropriate comparison, I also adopt Fama-Macbeth regression for the NYSE and AMEX companies using same sample period as Table 2.4. The results show that the coefficient of interest is insignificant (The coefficient of interest is 0.031 and associated t-statistics is 0.84) for the entire sample. The magnitude is higher during the low sentiment period compare with the high sentiment period. (The coefficient of interest is 0.063 with 1.15 t-statistics for the low sentiment period and the coefficient of interest is -0.001 with -0.02 t-statistics for the high sentiment period).

[Insert Table 2.4 near here]

2.5.2 Size Analysis

Amihud (2002) demonstrates that market illiquidity is related to small firms more strongly than to large firms. Baker and Wurgler (2006) also show that small firms earn more expected return in the low sentiment period compared to the large firms. Thus, it is important to analyse small and large-size firms separately. I use market capitalisation at the end of each month to distinguish small and large-sized firms. Market capitalisation is defined as price multiplied by share outstanding for each firm i. I construct quintile portfolios in each month m based on the market capitalisation calculated on month $m-1$. I then use the first quintile as the smallest-size firms and the fifth quintile as the largest-size firms.

Table 2.5 presents the results of the size analysis using the Fama-MacBeth (1973) procedure with control variables. I drop the size variable from the regression since I control size by splitting the companies based on their market capitalisation. Panel A shows the small-size stocks, which include firms in the lowest market capitalisation quintile. The coefficient of the Amihud measure is positive and statistically significant, 0.284, and associated t-statistic is 4.57 in the entire period. We can see that the magnitude of the illiquidity coefficient increases greatly compared to earlier tables. This confirms the existing literature and shows that the effect of the Amihud measure is stronger for small capitalisation (small-cap) firms. Columns

This result is consistent with the earlier paper which states that illiquidity premium comes from the earlier sample period (the 60s and 70s).

(2) and (3) show that results hold in both periods in the low sentiment and the high sentiment periods for small-cap firms, even though the magnitude of the Amihud coefficient is slightly higher in the low sentiment periods relative to the high sentiment periods. Panel B shows the large-size stocks, which include firms in the highest market capitalisation quintile. The results show that the Amihud measure is not priced for large-cap stocks in any time periods. The coefficient of the Amihud measure is insignificant neither in the low sentiment period nor in the high sentiment period. This confirms that the effect of small-cap firms has a strong power to explain the results of this study. The results are consistent with the literature that small-cap stocks are more illiquid and when there is a down period in the economy these stocks suffer more.

[**Insert Table 2.5 near here**]

2.5.3 Excluding Financial and Utility Firms

As we know, financial and utility sectors are the ones that have more difficulties in down times on the market. Also, to some extent, the regulation of these sectors is different from other sectors. So, these sectors may play an important role in driving the illiquidity premium in low sentiment periods. Thus, excluding these sectors may give us clearer answers as to whether illiquidity premium is more pronounced in the low sentiment periods. Identification of financial and utility firms here is the same as in previous literature, which defines using financial sectors whose Standard

Industrial Classification (SIC) code is between 6000 and 6999 and utility sectors whose SIC code is between 4900 and 4999.

Table 2.6 reports the results of the same analysis as the in preceding tables but excludes financial and utility sectors. Column (1) indicates that we still have illiquidity premium in the entire period, the magnitude of the coefficient is almost the same as in our main analysis, 0.089, and it is statistically significant. We confirm similar results for low and high sentiment periods. Illiquidity premium is more pronounced in the low sentiment period. The coefficient is positive and statistically significant at 0.121, and associated t-statistic is 1.91. Column (3) shows that there is no illiquidity premium in the high sentiment period. Thus, I conclude that my result is not driven by financial and utility sectors. Illiquidity premium comes from the low sentiment period.

[Insert Table 2.6 near here]

2.5.4 Controlling for Idiosyncratic Volatility

Recent literature shows that not only does systematic risk have the power to explain variation in expected returns but that also unsystematic risk plays a role in explaining the expected returns (Goyal and Santa-Clara, 2003; Ang et al., 2006, 2009; Xu and Malkiel, 2006). Ang et al. (2006) is a cornerstone research paper on the impact of idiosyncratic volatility on expected returns. They show that there is a negative relation between idiosyncratic volatility and expected returns. Also, the correlation between illiquidity and idiosyncratic volatility is positive since both variables are driven by the same component in portfolio construction absolute return. Therefore, controlling for the effect of idiosyncratic volatility on expected returns is important. I follow the Ang et al. (2006) and estimate the following there-factor modes for returns:

$$(R_{id} - rf_d) = \alpha_{id} + \beta_1 \times MKT_d + \beta_2 \times SMB_d + \beta_3 \times HML_d + \epsilon_{id} \tag{2.3}$$

where $(R_{id} - rf_d)$ is the daily excess return of stock i in time d, MKT_d is the daily market risk premium in time d, SMB_d is the daily return difference between small and big sized companies based on market capitalisation in time d, and HML_d is the daily return difference between high and low book-to-market in time d. I estimate the three-factor model by OLS and use the standard deviation of the residuals as my estimate of idiosyncratic volatility within a month: Idiosyncratic Volatility$_{im} = \sqrt{Var(\epsilon_{id})}$.

Idiosyncratic Volatility of stock i in month $m - 1$ is matched with the monthly Fama-French three-factor adjusted return of stock i in month m.

Table 2.7 presents the results of Fama-MacBeth regression analysis including idiosyncratic volatility as an additional control variable. Column (1) shows that idiosyncratic volatility is negatively related to expected return, as previous literature suggests, and it does not affect the coefficient of interest, Amihud measure, significantly. The Amihud measure is still positive and statistically significant in the entire period. In column (2), I confirm that my result is consistent after controlling for idiosyncratic volatility. The coefficient of the Amihud measure is the same as in earlier results, 0.119, and associated t-statistic is 2.05 in the low sentiment period. Surprisingly, the inclusion of idiosyncratic volatility changes the magnitude of the Amihud measure in the high sentiment period. The coefficient of the Amihud is 0.076, which is higher than earlier tables and it is statistically significant at the 1 per cent level. Also, the magnitude of idiosyncratic volatility is higher in the high sentiment period than in the low sentiment period. This increase in the idiosyncratic volatility also drives the coefficient of the Amihud measure up in the high sentiment period. The reason for this might be the impact of idiosyncratic volatility is stronger than liquidity during the high sentiment period and the relation between idiosyncratic volatility and stock liquidity may drive the coefficient of stock liquidity become statistically significant at the 10 per cent level.

[Insert Table 2.7 near here]

2.5.5 January Effect

The effect of seasonality on stock prices, called the "January effect", on the concept of illiquidity premium is well established in the literature. Eleswarapu and Reinganum (1993) investigate this phenomenon and find that the illiquidity premium is significant only in January. Hasbrouck (2009) also supports this result. Market efficiency papers agree on the January effect, particularly on small-cap firms. The reason of this is the price of the stocks increases in January since investors typically sell their assets due to taxation which leads a decline in price due to taxation. I include this phenomenon in two ways. First (Panel A of Table 2.8) I exclude January from my sample period. Second, (Panel B) I use only January in my sample period.

Table 2.8 shows the Fama-MacBeth regression results to establish a January effect in my sample period. Panel A reports the results from excluding January for each year from my sample. Column (1) shows that the coefficient of the Amihud measure, 0.069, is lower than the main analysis in Table 2.3 (0.090), but it is still statistically significant. On the other hand, columns (2) and (3) show the positive relation between illiquidity and the expected return but they are statistically insignificant. Panel B presents the analysis of using only January of each year in my sample period. Overall, we can see that the magnitude of the coefficient of the Amihud measure is higher compared to Panel A. Columns (1) and (2) show that the illiquidity premium is positive and statistically significant the coefficient of Amihud measure is 0.322 and 0.551, respectively. However, column (3) shows that pricing ability of the Amihud measure does not present in the high sentiment period. Results confirm the effect of January on illiquidity premium. When I exclude January, I do not find any significant premium in the low and high sentiment periods, but I find a significant premium in the low sentiment period when I only use January of each year.[9]

[Insert Table 2.8 near here]

[9]Even though the chapter captures the January effect, the size effect outperforms the January effects. When I run a regression for only January and small-cap firms the coefficient is very strong and statistically significant for entire, low and high sentiment period; however, the coefficient is insignificant when I use large-cap companies.

2.5.6 Raw Return

To control the impact of price factors, I use Fama-French's three-factor adjusted return throughout, following Brennan et al. (1998). In this section, I use raw return as a dependent variable and replicate the Fama-MacBeth regression for the entire period as well as the low and the high sentiment periods.

Table 2.9 presents the results of raw return analysis. Column (1) shows there is still illiquidity premium when we consider raw return as the dependent variable using entire sample period, but the coefficient of the Amihud measure becomes insignificant in the low and high sentiment periods even though the coefficients are positive, 0.075 and 0.071, respectively.

[**Insert Table 2.9 near here**]

2.6 Conclusion

The aim of this chapter is to present new evidence of the impact of illiquidity on the expected returns in different time periods using the investor sentiment index created by Baker and Wurgler (2006). Theoretical and empirical papers suggest that sentiment index and stock market liquidity should be positively related. When investor sentiment index is low, the stock market illiquidity is high. This can be explained by the demand of the liquid stock during the bad times. As illustrated in Figure 2.1, the low sentiment period generally coincides with the NBER recession periods, and we know that during crisis periods the demand for the liquid stocks goes up, so that holding an illiquid asset in the portfolio becomes costlier for investors. Thus, investors require a higher premium for holding illiquid stocks in their portfolio during bad times.

Univariate and cross-sectional analyses show that there is an illiquidity premium associated with my choice of illiquidity proxy, Amihud (2002), in the sample period used. This result is consistent with earlier findings. More importantly, the illiquidity premium is significant in the low sentiment period but is insignificant in the high sentiment period. The result is robust, excluding financial and utility companies, considering January and small-cap anomalies, and controlling for idiosyncratic volatility.

This chapter contributes to the literature by exploring Novy-Marx's (2004) claims that it is not an illiquidity premium that investors earn; it is actually a premium from being exposed to the underlying risk of the stocks or periods. He suggests that illiquidity can be a good proxy for capturing this underlying risk factor resulting in what we call "illiquidity premium". This idea confirmed in this chapter in that illiquidity premium is only significant in the low sentiment period since underlying risk factors are strong in the low sentiment periods relative to the high sentiment periods where there is no illiquidity premium.

There are several ways in which this chapter could be extended. First, investor sentiment is a market-wide index that may not apply to each sector or individual firm. It would be useful therefore to use investor sentiment for each sector and see whether results change or not. Second, the choice of illiquidity proxy may play a role in explaining illiquidity premium. I only use Amihud (2002) as a proxy for illiquidity as it is widely used measure and is highly correlated with intraday data. However, it would be useful to use other illiquidity measures to study the same relation between sentiment index and illiquidity of stocks, since the results may be due to a particular feature of the Amihud. Last but not least, we should admit the problem of endogeneity in this analysis. Since earlier papers also show that low sentiment periods coincide with a recession period, we cannot easily explain the relation between liquidity and sentiment index. There might be other factors that drive this illiquidity premium during low sentiment periods. One way of solving this problem is to find an exogenous shock to the sentiment index; however, this is not easy. One suggestion might be to use a political event as a shock to sentiment such as Trump's election or the Brexit referendum. But, the problem is we that cannot use low-frequency data in this setting since the effect lasts only days.

2.7 Figure and Tables

Figure 2.1: Investor Sentiment and Market Illiquidity
The figure shows the time-series of illiquidity proxy and investor sentiment index from January 1966 to December 2012. Amihud (2002) illiquidity measure is constructed in each month using daily information for each stock. I then calculate equal-weighted market illiquidity for each month. Baker and Wurgler (2006) sentiment index is used as an indication of investor sentiment. The index is constructed in each month. Shaded areas show NBER recession periods.

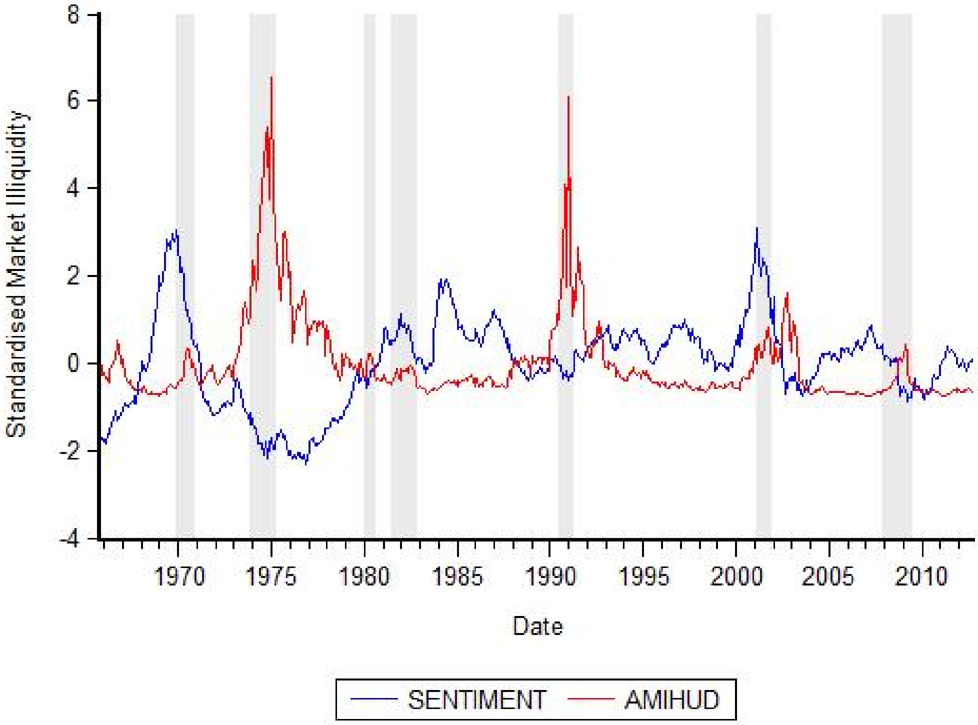

Table 2.1: Summary Statistics

The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX from November 1965 to October 2012. Panel A presents the summary statistics for the entire sample period. Panel B is the summary statistics for the low sentiment period and Panel C is the summary statistics for the high sentiment period. Low and high sentiment periods are defined as above and below the median in each month of Baker and Wurgler (2006) investor sentiment index. If the investor sentiment index in month m is lower than the median, I then identify the month m as the low sentiment period. If the investor sentiment index in month m is higher than the median, I then identify month m as the high sentiment period. Amihud is defined as the monthly average of a ratio of absolute return divided by price multiplies volume. Idiosyncratic volatility is the standard deviation of residuals which are obtained by regressing firms' daily excess return on daily Fama-French three factors. Size is the logarithm of the market capitalisation of equity. The book-to-market ratio is the book value of equity divided by the market capitalisation of equity. Return [-12 -2] is cumulative return from month $m - 12$ to $m - 2$. Return is the raw return and price is the price of a stock i in month m. Amihud and Book-to-Market are winsorised at 1 and 99 percentage points in each month cross-sectional. The Amihud measure is multiplied by 10^6.

Panel A: Entire Period (Between November 1965 and October 2012)									
	Mean	Std. Dev.	Skewness	Kurtosis	Q10	Q25	Q50	Q75	Q90
Amihud	3.958	21.660	18.344	650.465	0.001	0.007	0.101	0.928	5.596
Idiosyncratic Volatility	0.023	0.022	13.746	1195.55	0.009	0.012	0.018	0.028	0.042
Size	5.189	2.285	0.160	-0.422	2.246	3.458	5.127	6.831	8.175
Book-to-Market	0.996	0.940	3.724	25.453	0.252	0.441	0.751	1.232	1.934
Price	39.116	1167.30	86.163	7925.57	3.500	8.310	18.000	31.500	47.860
Return	0.012	0.146	4.872	241.183	-0.129	-0.059	0.001	0.069	0.154
Return [-12 -2]	0.135	0.550	6.233	160.627	-0.379	-0.157	0.069	0.322	0.656
Panel B: Low Sentiment Period									
	Mean	Std. Dev.	Skewness	Kurtosis	Q10	Q25	Q50	Q75	Q90
Amihud	5.640	27.482	15.745	467.619	0.001	0.016	0.187	1.547	8.975
Idiosyncratic Volatility	0.024	0.022	18.958	1944.37	0.009	0.012	0.019	0.029	0.044
Price	36.241	1163.97	90.220	8511.05	3.152	7.500	16.500	29.500	45.500
Return	0.015	0.151	5.223	285.899	-0.128	-0.058	0.001	0.073	0.163
Return [-12 -2]	0.130	0.569	5.598	120.146	-0.395	-0.172	0.054	0.317	0.676
Panel C: High Sentiment Period									
	Mean	Std. Dev.	Skewness	Kurtosis	Q10	Q25	Q50	Q75	Q90
Amihud	2.254	13.178	18.036	516.625	0.001	0.004	0.052	0.515	3.048
Idiosyncratic Volatility	0.023	0.021	7.057	150.701	0.008	0.012	0.017	0.027	0.041
Price	42.023	1170.65	82.128	7346.55	3.813	9.350	19.750	33.500	50.000
Return	0.009	0.141	4.422	180.656	-0.130	-0.059	0.001	0.067	0.146
Return [-12 -2]	0.140	0.529	7.023	214.334	-0.362	-0.141	0.084	0.326	0.636

Table 2.2: Sorting Analysis

Panel A reports the monthly percentage returns of quintile portfolios and the difference between illiquid and liquid quintiles. The sample includes only common stocks (share code 10 and 11) that are listed on NYSE and AMEX from January 1966 to December 2012. Panel A presents the sorting analysis for the entire sample period. Panel B and C present sorting analysis for the low sentiment period and the high sentiment period, respectively. Low and high sentiment periods are defined as above and below the median in each month of Baker and Wurgler (2006) investor sentiment index. If the investor sentiment index in month m is lower than the median, I then identify month m as the low sentiment period. If the investor sentiment index in month m is higher than the median, I then identify the month m as the high sentiment period. Stocks are sorted into quintiles in month m based on the Amihud illiquidity measure of each stock calculated in $m-2$. Then equal-weighted portfolios returns are calculated in each month for each quintile. Time-series average of each quintile return and four-factor alphas are reported. Fama-French's three-factors (MKT, SMB and HML) and momentum factor (UMD) are used. Newey-West (1987) robust standard errors are used to calculate t-statistics. *, **, *** represent statistical significance at the 10, 5, and 1 per cent levels, respectively.

Panel A: Entire Sample Period (January 1966 - December 2012)							
	Liquid	2	3	4	Illiquid	Illiquid-Liquid	T-Statistics
Raw Return	0.951	1.117	1.216	1.228	1.482	0.531**	(2.21)
Four-Factor Alpha	-0.007	0.043	0.062	0.089	0.364	0.371**	(2.35)
Panel B: Low Sentiment Period							
	Liquid	2	3	4	Illiquid	Illiquid-Liquid	T-Statistics
Raw Return	0.908	1.193	1.342	1.549	1.882	0.973**	(2.48)
Four-Factor Alpha	-0.055	0.040	0.064	0.226	0.444	0.499**	(2.06)
Panel C: High Sentiment Period							
	Liquid	2	3	4	Illiquid	Illiquid-Liquid	T-Statistics
Raw Return	0.994	1.041	1.090	0.907	1.082	0.088	(0.31)
Four-Factor Alpha	-0.031	-0.059	-0.002	-0.097	0.221	0.252	(1.24)

Table 2.3: Fama-MacBeth Regression Analysis

Monthly Fama-MacBeth cross-sectional regression is used to estimate. The dependent variable is Fama-French's three-factor adjusted return and independent variables are the natural logarithm of the Amihud measure, size, book-to-market, Return [-12 -2] and Return [-1]. Sample period is between January 1966 and December 2012. Common stocks that are listed on NYSE and AMEX are used in this analysis. Low and high sentiment periods are defined as above and below the median in each month of Baker and Wurgler (2006) investor sentiment index. If the investor sentiment index in month m is lower than the median, I then identify month m as the low sentiment period. If the investor sentiment index in month m is higher than the median, I then identify month m as the high sentiment period. Size is the logarithm of the market capitalisation of equity. The book-to-market ratio is the book value of equity divided by the market capitalisation of equity. Return [-12 -2] is cumulative return from month $m-12$ to $m-2$. Return [-1] is the lagged return. Newey-West (1987) robust standard errors are used to calculate t-statistics. *, **, *** represent statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Dependent Variable: FF-3 Adjusted Return		
	Entire Period (1966-2012)	Low Sentiment Period	High Sentiment Period
Log(Amihud)	0.090**	0.118**	0.062
	(2.46)	(2.00)	(1.49)
Size	0.061	0.048	0.074
	(1.57)	(0.81)	(1.54)
Book-to-Market	0.080*	0.102*	0.058
	(1.91)	(1.75)	(0.99)
Return [-12 -2]	0.616***	0.328	0.905***
	(3.30)	(0.98)	(5.50)
Return [-1]	-5.788***	-7.154***	-4.422***
	(-12.25)	(-10.52)	(-7.61)
Adjusted R^2	0.030	0.034	0.027
# of Observations	1654	1651	1658
# of Months	564	282	282

Table 2.4: Fama-MacBeth Regression Analysis (NASDAQ Companies)
Monthly Fama-MacBeth cross-sectional regression is used to estimate. The dependent variable is Fama-French's three-factor adjusted return and independent variables are the natural logarithm of the Amihud measure, size, book-to-market, Return [-12 -2] and Return [-1]. Sample period is January 1983 to December 2012. Common stocks that are listed on NASDAQ are used in this analysis. Low and high sentiment periods are defined as above and below the median in each month of the Baker and Wurgler (2006) investor sentiment index. If the investor sentiment index in month m is lower than the median, I then identify month m as the low sentiment period. If the investor sentiment index in month m is higher than the median, I then identify month m as the high sentiment period. Size is the logarithm of the market capitalisation of equity. The book-to-market ratio is the book value of equity divided by the market capitalisation of equity. Return [-12 -2] is cumulative return from month $m-12$ to $m-2$. Return [-1] is the lagged return. Newey-West (1987) robust standard errors are used to calculate t-statistics. *, **, *** represent statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Dependent Variable: FF-3 Adjusted Return		
	Entire Period (1983-2012)	Low Sentiment Period	High Sentiment Period
Log(Amihud)	0.328	-0.200	0.086
	(0.74)	(-0.31)	(1.57)
Size	-0.129	-0.324**	0.066
	(-1.38)	(-2.08)	(0.73)
Book-to-Market	0.235***	0.001	0.462***
	(2.80)	(0.07)	(4.08)
Return [-12 -2]	0.313*	-0.025	0.651***
	(1.83)	(-0.09)	(4.00)
Return [-1]	-5.023***	-4.587***	-5.458***
	(-11.39)	(-7.22)	(-9.88)
Adjusted R^2	0.023	0.024	0.023
# of Observations	2544	2437	2652
# of Months	360	180	180

Table 2.5: Size Analysis

Monthly Fama-MacBeth cross-sectional regression is used to estimate. The dependent variable is Fama-French's three-factor adjusted return, and independent variables are the natural logarithm of the Amihud measure, book-to-market, Return [-12 -2] and Return [-1]. Sample period is January 1966 to December 2012. Common stocks that are listed on NYSE and AMEX are used in this analysis. Panel A reports the analysis for small-cap companies, and Panel B reports the analysis for large-cap companies. Each stock sorted into quintiles based on their market capitalisation in month $m-1$. Stocks in the lowest quintiles are used in the small-cap analysis and stocks in the highest quintiles are used in the large-cap analysis. Low and high sentiment periods are defined as above and below the median in each month of the Baker and Wurgler (2006) investor sentiment index. If the investor sentiment index in month m is lower than the median, I then identify month m as the low sentiment period. If the investor sentiment index in month m is higher than the median, I then identify month m as the high sentiment period. The book-to-market ratio is the book value of equity divided by the market capitalisation of equity. Return [-12 -2] is cumulative return from month $m-12$ to $m-2$. Return [-1] is the lagged return. Newey-West (1987) robust standard errors are used to calculate t-statistics. *, **, *** represent statistical significance at the 10, 5, and 1 per cent levels, respectively.

Panel A: Small Size Companies			
	Dependent Variable: FF-3 Adjusted Return		
	Entire Period (1966-2012)	Low Sentiment Period	High Sentiment Period
Log(Amihud)	0.284***	0.298***	0.269***
	(4.57)	(2.85)	(4.48)
Book-to-Market	0.175***	0.017	0.233***
	(2.70)	(1.25)	(2.61)
Return [-12 -2]	0.473*	-0.039	0.985***
	(1.77)	(-0.08)	(4.66)
Return [-1]	-8.923***	-11.143***	-6.702***
	(-11.79)	(-9.48)	(-8.06)
Adjusted R^2	0.035	0.041	0.029
# of Observations	330	330	331
# of Months	564	282	282
Panel B: Large Size Companies			
	Dependent Variable : FF-3 Adjusted Return		
	Entire Period (1966-2012)	Low Sentiment Period	High Sentiment Period
Log(Amihud)	0.010	0.024	-0.005
	(0.39)	(0.66)	(-0.20)
Book-to-Market	-0.162**	-0.100	-0.224**
	(-2.50)	(-1.18)	(-2.26)
Return [-12 -2]	0.443**	0.143	0.743***
	(2.11)	(0.42)	(3.03)
Return [-1]	-4.553***	-4.488***	-4.619***
	(-8.03)	(-5.94)	(-5.38)
Adjusted R^2	0.051	0.055	0.047
# of Observations	330	329	330
# of Months	564	282	282

Table 2.6: Exclude Financial and Utility Sectors
Monthly Fama-MacBeth cross-sectional regression is used to estimate. The dependent variable is Fama-French's three-factor adjusted return and independent variables are the natural logarithm of the Amihud measure, size, book-to-market, Return [-12 -2] and Return [-1]. Sample period is January 1966 to December 2012. Financial and utility firms are excluded from the analysis. Sectors are identified based on their SIC code. Financial sectors' SIC code is between 6000 and 6999 and utility sectors' SIC code is between 4900 and 4999. Common stocks listed on the NYSE and AMEX are used in this analysis. Low and high sentiment periods are defined as above and below the median in each month of the Baker and Wurgler (2006) investor sentiment index. If the investor sentiment index in month m is lower than the median, I identify month m as the low sentiment period. If the investor sentiment index in month m is higher than the median, I identify the month m as the high sentiment period. Size is the logarithm of the market capitalisation of equity. The book-to-market ratio is the book value of equity divided by the market capitalisation of equity. Return [-12 -2] is cumulative return from month $m-12$ to $m-2$. Return [-1] is the lagged return. Newey-West (1987) robust standard errors are used to calculate t-statistics. *, **, *** represent statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Dependent Variable: FF-3 Adjusted Return		
	Entire Period (1966-2012)	Low Sentiment Period	High Sentiment Period
Log(Amihud)	0.089**	0.121*	0.058
	(2.24)	(1.91)	(1.23)
Size	0.066	0.057	0.075
	(1.53)	(0.88)	(1.33)
Book-to-Market	0.119***	0.145**	0.093
	(2.60)	(2.54)	(1.32)
Return [-12 -2]	0.586***	0.310	0.864***
	(3.18)	(0.94)	(5.09)
Return [-1]	-5.925***	-7.398***	-4.452***
	(-12.41)	(-10.80)	(-7.50)
Adjusted R^2	0.031	0.035	0.027
# of Observations	1344	1367	1322
# of Months	564	282	282

Table 2.7: Idiosyncratic Volatility as an Additional Control Variable
Monthly Fama-MacBeth cross-sectional regression is used to estimate. The dependent variable is Fama-French's three-factor adjusted return and independent variables are the natural logarithm of the Amihud measure, size, book-to-market, Return [-12 -2], Return [-1] and idiosyncratic volatility. Sample period is January 1966 to December 2012. Common stocks listed on the NYSE and AMEX are used in this analysis. Low and high sentiment periods are defined as above and below the median in each month of the Baker and Wurgler (2006) investor sentiment index. If the investor sentiment index in month m is lower than the median, I identify month m as the low sentiment period. If the investor sentiment index in month m is higher than the median, I identify month m as the high sentiment period. Size is the logarithm of the market capitalisation of equity. The book-to-market ratio is the book value of equity divided by the market capitalisation of equity. Return [-12 -2] is cumulative return from month $m-12$ to $m-2$. Return [-1] is the lagged return. Idiosyncratic volatility is the standard deviation of residuals that are obtained by regressing firms' daily excess return on the daily Fama-French three factors. Newey-West (1987) robust standard errors are used to calculate t-statistics. *, **, *** represent statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Dependent Variable: FF-3 Adjusted Return		
	Entire Period (1966-2012)	Low Sentiment Period	High Sentiment Period
Log(Amihud)	0.097***	0.119**	0.076*
	(2.72)	(2.05)	(1.88)
Size	0.028	0.016	0.041
	(0.81)	(0.30)	(0.93)
Book-to-Market	0.053	0.093	0.014
	(1.27)	(1.64)	(0.23)
Return [-12 -2]	0.584***	0.374	0.792***
	(3.36)	(1.20)	(5.15)
Return [-1]	-5.725***	-7.150***	-4.299***
	(-11.65)	(-9.99)	(-7.19)
Idiosyncratic Volatility	-15.763***	-11.874**	-19.654***
	(-4.96)	(-2.51)	(-4.35)
Adjusted R^2	0.037	0.039	0.034
# of Observations	1654	1651	1658
# of Months	564	282	282

Table 2.8: January Effect
Monthly Fama-MacBeth cross-sectional regression is used to estimate. The dependent variable is Fama-French's three-factor adjusted return and independent variables are the natural logarithm of the Amihud measure, size, book-to-market, Return [-12 -2] and Return [-1]. Sample period is January 1966 to December 2012. Common stocks listed on the NYSE and AMEX are used in this analysis. Panel A reports the analysis excluding January in each year, and Panel B reports the analysis using only January in each year. Low and high sentiment periods are defined as above and below the median in each month of the Baker and Wurgler (2006) investor sentiment index. If the investor sentiment index in month m is lower than the median, I identify month m as the low sentiment period. If the investor sentiment index in month m is higher than the median, I identify month m as the high sentiment period. Size is the logarithm of the market capitalisation of equity. The book-to-market ratio is the book value of equity divided by the market capitalisation of equity. Return [-12 -2] is cumulative return from month $m-12$ to $m-2$. Return [-1] is the lagged return. Newey-West (1987) robust standard errors are used to calculate t-statistics. *, **, *** represent statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Panel A: January Excluded		
	Dependent Variable: FF-3 Adjusted Return		
	Entire Period (1966-2012)	Low Sentiment Period	High Sentiment Period
Log(Amihud)	0.069**	0.080	0.058
	(1.97)	(1.41)	(1.55)
Size	0.097***	0.065	0.128***
	(2.71)	(1.15)	(3.21)
Book-to-Market	0.044	0.072	0.017
	(1.05)	(1.24)	(0.29)
Return [-12 -2]	0.857***	0.552*	1.163***
	(4.59)	(1.68)	(7.18)
Return [-1]	-5.091***	-6.397***	-3.781***
	(-10.82)	(-9.67)	(-6.36)
Adjusted R^2	0.027	0.031	0.024
# of Observations	1654	1650	1658
# of Months	517	259	258
	Panel B: Only January		
	Dependent Variable: FF-3 Adjusted Return		
	Entire Period (1966-2012)	Low Sentiment Period	High Sentiment Period
Log(Amihud)	0.322**	0.551***	0.102
	(2.15)	(3.23)	(0.58)
Size	-0.334*	-0.148	-0.512*
	(-1.67)	(-0.75)	(-1.68)
Book-to-Market	0.469**	0.439***	0.497
	(2.36)	(3.14)	(1.48)
Return [-12 -2]	-2.032***	-2.200***	-1.871***
	(-4.23)	(-4.17)	(-4.31)
Return [-1]	-13.450***	-15.672***	-11.320***
	(-8.98)	(-5.93)	(-8.51)
Adjusted R^2	0.064	0.072	0.057
# of Observations	1659	1661	1657
# of Months	47	23	24

Table 2.9: Dependent Variable Raw Return
Monthly Fama-MacBeth cross-sectional regression is used to estimate. The dependent variable is raw return and independent variables are the natural logarithm of the Amihud measure, size, book-to-market, Return [-12 -2] and Return [-1]. Sample period is January 1966 to December 2012. Common stocks listed on the NYSE and AMEX are used in this analysis. Low and high sentiment periods are defined as above and below the median in each month of the Baker and Wurgler (2006) investor sentiment index. If the investor sentiment index in month m is lower than the median, I then identify month m as the low sentiment period. If the investor sentiment index in month m is higher than the median, I then identify month m as the high sentiment period. Size is the logarithm of the market capitalisation of equity. The book-to-market ratio is the book value of equity divided by the market capitalisation of equity. Return [-12 -2] is cumulative return from month $m-12$ to $m-2$. Return [-1] is the lagged return. Newey-West (1987) robust standard errors are used to calculate t-statistics. *, **, *** represent statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Dependent Variable: Raw Return		
	Entire Period (1966-2012)	Low Sentiment Period	High Sentiment Period
Log(Amihud)	0.073*	0.075	0.071
	(1.83)	(1.29)	(1.30)
Size	-0.024	-0.119	0.070
	(-0.36)	(-1.17)	(0.87)
Book-to-Market	0.221***	0.154	0.287***
	(2.93)	(1.47)	(2.68)
Return [-12 -2]	0.571**	0.343	0.798***
	(2.33)	(0.76)	(4.03)
Return [-1]	-5.232***	-6.366***	-4.098***
	(-10.42)	(-7.94)	(-6.85)
Adjusted R^2	0.050	0.057	0.043
# of Observations	1654	1651	1658
# of Months	564	282	282

Chapter 3

Impact of Stock Illiquidity on Idiosyncratic Volatility: Evidence from Decimalisation

3.1 Introduction

Several theoretical models suggest that stock liquidity and idiosyncratic volatility should be negatively related (see, e.g., Ho and Stoll, 1980, 1981; Spiegel and Subrahmanyam, 1995). Specifically, the strategy inventory control model argues that market makers supply the liquidity to investors. When there is high uncertainty, reflected in higher idiosyncratic volatility, the market makers choose to provide less liquidity to investors to reduce the cost of adverse selection. Thus, higher liquidity is associated with less idiosyncratic volatility. In other words, the difference between bid and offer price compensates market makers for holding risky assets in their portfolio since high spread causes stocks to become riskier.

While liquidity and idiosyncratic volatility have received considerable attention in the literature individually, there is relatively little evidence concerning the relationship between them, which is the focus of this study. Spiegel and Wang (2005) and Han and Lesmond (2011) examine this relation to some extent. On the one hand, Spiegel and Wang (2005) show that when idiosyncratic volatility increases, stock illiquidity increases; on the other, Han and Lesmond (2011) present evidence that shows that when stock illiquidity increases, idiosyncratic volatility increases. However, both studies ignore the issue of reverse causality. Thus, they are unable to shed light on the direction of causality between two variables.

In this chapter, I test whether a change in stock illiquidity *causes* a change in idiosyncratic volatility. Figure 3.1 displays the long run relationship between illiquidity and idiosyncratic volatility.[10] Standardised average illiquidity and idiosyncratic volatility from January 1960 to December 2014 is presented in Figure 3.1. We can easily see that the positive relationship holds for the entire period. When the stock illiquidity increases, idiosyncratic volatility goes up too, which is a visualisation of earlier theoretical and empirical studies.

[**Insert Figure 3.1 near here**]

Since I would like to test whether liquidity affects idiosyncratic volatility, it may be the case that, in turn, idiosyncratic volatility may affect illiquidity. For instance, a stock can be illiquid because the idiosyncratic risk of the stock is high, or idiosyncratic risk of a stock is high because the stock is illiquid. To eliminate this

[10] High-low estimator is used as a proxy for stock illiquidity in Figure 3.1. The correlation coefficient between market illiquidity and idiosyncratic volatility is around 0.65.

reverse causality problem, I employ the instrumental variable approach using the exogenous event of decimalisation that occurred in the US equity markets at the beginning of 2001. The introduction of the change in tick size across the three major markets, NYSE, AMEX and NASDAQ, allows us to identify the causal effect and thus eliminate the reverse causality problem. Previous papers find that decimalisation decreases the illiquidity significantly (Bessembinder, 2003; Furfine, 2003).

To capture the true effect of stock liquidity, intraday proxies, such as effective and realised spread, are used extensively in the literature. However, using intraday proxies has some disadvantages. First, I cannot use a long time horizon with intraday data due to a computational problem. Second, it is difficult to obtain the data due to the high cost. Hence, I decide to use proxies based on daily data. The main stock liquidity proxy used in this analysis is based on the high-low estimator proposed by Corwin and Schultz (2012). They construct a liquidity proxy from the ratio of daily low and high prices by removing the volatility component. This proxy can be considered as bid-ask spread since the low(high) prices are generally sell(buy) trade. Since I aim to show the impact of stock liquidity, it would be desirable to have a consistent result with several liquidity proxies. Thus, I use two sets of liquidity proxies: low-frequency price impact proxies (Amihud, 2002), and turnover-based and low-frequency spread proxies (bid-ask spread and percentage of zero return).[11] As a proxy for idiosyncratic volatility, I follow the standard procedure and use the

[11] I interpret my liquidity proxies as an illiquidity since they actually capture illiquidity. In other words, when we see an increase in the liquidity proxies I interpret them as an increase in illiquidity.

standard deviation of the residuals from the Fama-French three-factor model as a proxy of idiosyncratic volatility.

To illustrate my hypothesis, I plot the estimated standardised monthly average of idiosyncratic volatility between January 1999 and January 2003 in Figure 3.2. The vertical line indicates the period in which decimalisation occurred. The figure shows that after decimalisation, there was a decline in idiosyncratic volatility. My main hypothesis is that this decline in idiosyncratic volatility was due to a decline in illiquidity arising from the reduction in the tick size that was associated with decimalisation.

[**Insert Figure 3.2 near here**]

I report two main findings. First, changes in liquidity do indeed cause changes in idiosyncratic volatility. I show that a one per cent increase in illiquidity is associated with a 1.23 per cent increase in the standard deviation of the idiosyncratic component of returns. Second, the reduction in the tick size in the three major US equity markets that occurred because of decimalisation indeed improved stock liquidity. My results are robust to alternative measures of stock illiquidity, including Amihud, turnover, zero return and the spread. They are also robust to the use of fixed effects and clustered standard error. As a further robustness check, I employ a difference-in-differences analysis following Fang et al. (2009) and my conclusions are unchanged.

The remainder of this chapter is organised as follows. Section 3.2 summarises the related literature. Section 3.3 describes the data and background of the exogenous event. Section 3.4 reports the empirical results. Section 3.5 reports the results of several robustness tests. Section 3.6 summarises the chapter and offers some concluding comments and suggestions for future research.

3.2 Related Literature

There are two theoretical approaches to the analysis of stock liquidity. The first treats liquidity as a determinant of the expected stock return in the form of transaction costs (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Brennan et al., 1998). The second treats it as a risk factor (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005). Empirically, Amihud (2002) shows that when a stock becomes less liquid, its expected stock return increases. Pastor and Stambaugh (2003) explain the impact of liquidity on the expected stock return in terms of its liquidity beta, that is, the sensitivity of the stock return to changes in stock liquidity. They find that the liquidity beta is positively related to expected return, suggesting that investors require greater compensation for holding stocks that are less liquid.

A separate strand of the literature has considered the relationship between idiosyncratic volatility and returns. Under the capital asset pricing model (CAPM), only systematic risk is priced, since idiosyncratic risk is diversifiable and so investors should not be compensated for bearing this risk. However, Merton (1987) presents evidence that investors may be willing to hold undiversified portfolios in order to gain a higher expected return. The empirical evidence on the relationship between idiosyncratic volatility and returns is mixed. On the one hand, Goyal and Santa-Clara (2003), Xu and Malkiel (2006), and Fu (2009) report a positive correlation between idiosyncratic volatility and expected return. On the other, Ang et al. (2006, 2009) show that idiosyncratic volatility is negatively correlated with expected stock returns not only in the US market but also in 23 other developed international markets. Anderson, Bianchi and Goldberg (2015) take one step further and investigate aggregate volatility as a risk factor following Ang et al. (2006) study. They suggest that a single outlier drives the results of the importance of aggregate volatility. When the observation for October 1987 is excluded from the sample, standard error of the estimated coefficient is increased and the results are no longer statistically significant. But, in this chapter, I mainly focus on firm level idiosyncratic volatility which is still in the centre of the most of the research.

Unlike the individual effect of stock liquidity and idiosyncratic volatility on the expected stock return, the link between these factors gets less attention in the empirical finance literature. Spiegel and Wang (2005) examine the pricing ability of stock liquidity and idiosyncratic volatility and show that when they control for idiosyncratic volatility, stock liquidity loses its explanatory power. They also support the theoretical literature regarding the negative link between liquidity and idiosyncratic volatility using various liquidity proxies. On the other hand, Lesmond and Han (2011) analyse the pricing ability of idiosyncratic volatility and find that there is a liquidity bias in the estimation of idiosyncratic volatility. They use the bid-ask bounce[12] to estimate idiosyncratic volatility instead of closing return and show that

[12]Where the price of a stock or other asset bounces rapidly back and forth within the very limited range between the bid price and ask price.

the pricing ability of idiosyncratic volatility disappears after controlling the liquidity bias. Therefore, it is important to identify the link between these two factors to infer their pricing ability on the stock market.

The impact of adopting new tick size on market quality has been examined extensively in the US markets as well as international markets. Prior studies suggest that when the tick size declines, the bid-ask spread should go down and stocks become more liquid. Bacidore (1997) documents that adopting decimal pricing in the Toronto Stock Exchange reduced the spread. Harris (1997) documents a summary of the all tick size change studies in the US context as well as international exchange markets. Furfine (2003) shows that decimalisation decreases the transaction costs by narrowing the bid-ask spread. Bessembinder (2003) and Furfine (2003) show that decimalisation positively affects liquidity, especially for more actively traded stocks. These findings have allowed researchers to use decimalisation as a natural experiment to determine the causal effect of liquidity of stock on various quantities. For example, Fang et al. (2014) examine the causal effect of liquidity on firm innovation using decimalisation as an exogenous shock and employ difference-in-differences methodology. Nyborg and Wang (2014) use decimalisation to study the impact of liquidity on corporate cash holdings, while Brogaard et al. (2017) use decimalisation to address the causal link between liquidity and the bankruptcy risk of a firm.

3.3 Data and Variable Construction

My full sample comprises ordinary common stocks (share codes 10 and 11) that are listed on the three main markets, NYSE, AMEX and NASDAQ, and covers the period January 1999 and January 2003. I use the NYSE and AMEX for the main analysis, and use NASDAQ to assess the robustness of my results.[13] The choice of the sample period is designed to avoid other fractional pricing changes prior to 1999, as well as the effect of the sharp increase in algorithmic trading in early 2003.[14]

I use several sources of data. Daily and monthly price, return, shares outstanding and volume are taken from the Center for Research in Security (CRSP). Compustat and Moody's are used as sources for constructing the market-to-book ratio. Daily and monthly Fama-French factors, that is, market premium (MKT), small-minus-big (SMB) and high-minus-low (HML) factors are downloaded from Kenneth French's website.[15]

Following the existing literature, I impose various data requirements on the stocks in my sample. To construct the monthly high-low estimators, Corwin and Schultz (2012), Amihud (2002) and idiosyncratic volatility, I require at least 10 days of valid daily return and volume data each month.[16] Following Amihud and Mendelson (2015), I delete observations for which the stock price is less than $5 or stock price exceeds $999 per share or for which the volume traded is lower than 100. To be

[13] Decimalisation occurred on January 29, 2001 on the NYSE and AMEX and on April 9, 2001 on NASDAQ.

[14] Hendershott, Jones and Menkveld (2011) examine the impact of algorithmic trading on liquidity and find that it increases liquidity for NYSE stocks.

[15] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[16] I also construct idiosyncratic volatility without any restriction on the data, but results are unchanged.

included in the sample, a stock must have a valid monthly return for the whole sample period and not switch exchange during the sample period. My final sample comprises 34,008 observations before decimalisation and 34,008 observations after decimalisation.

3.3.1 Liquidity

Liquidity is defined as the ability to buy or sell a large quantity of a stock without affecting its market price significantly. I determine liquidity using low-frequency proxies since transaction data is not easy to access and not suitable to for use with a long time horizon.

My primary proxy for liquidity is the high-low estimator proposed by Corwin and Schultz (2012). They develop the high-low estimator using information on intraday high and low prices. They note that the intraday high(low) price is almost always the result of a buy(sell) trade, and so the intraday high-low range reflects both the variance of the stock and its bid-ask spread. The variance is proportional to the return interval, but the bid-ask spread is not, and so an estimate of the stock's bid-ask spread can be obtained by comparing the high-low range over one-day and two-day intervals. Specifically, they first construct the sum of the squared logarithm of the one-day high-low price ratio over two consecutive days:

The final closed form of the solution of their high-low estimator is as follows:

$$S = \frac{2 \times (e^{\alpha - 1})}{1 + e^{\alpha}} \tag{3.1}$$

Thus, spread estimates can be obtained for each consecutive two-day period, and then averaged over each month. Corwin and Schultz (2012) propose two versions of this measure: for the first, negative estimated values are set to zero, while for the second, negative estimated values are omitted. I use both versions in my empirical analysis. Both measures are adjusted for overnight price changes.[17] An advantage of the high-low estimator proxy is that it allows us to estimate liquidity based on transaction costs without the need to use intraday data. Using simulation, Corwin and Schultz (2012) show that the high-low estimator provides an accurate estimate of the true bid-ask and compares favourably to estimators that are calculated using intraday or daily data and the correlation between intraday data and their proxy is around 0.9.

One of the most widely used measures of liquidity is the proxy proposed by Amihud (2002). The Amihud measure is defined as the monthly average of the ratio of the absolute return of a stock divided by its volume traded in dollars. Interpreted as the price change per dollar of trading volume, the Amihud measure can be seen to reflect price impact. The definition of the Amihud measure of stock i in month m is given by:

$$Amihud_{im} = \frac{1}{D_{im}} \sum_{d=1}^{D_{im}} \frac{|Return_{id}|}{Dvol_{id}} \tag{3.2}$$

where D_{im} denotes the number of days in which stock has a valid ratio in month m for stock i. $Return_{id}$ is daily return in stock i on day d. $Dvol_{id}$ is the dollar value of trading volume on day d for stocks i. The measure captures the price impact since it is defined as the monthly average of the ratio of the absolute return of a stock

[17] I am grateful to the authors for sharing their code on their website.

divided by its volume traded in dollars and interpreted as the price change per dollar of trading volume. Following advice from Atkins and Dyl (1997) and Nagel (2005), I divide the reported daily dollar value of volume by two for NASDAQ stocks to eliminate the double-counting problem that occurs due to the dealer structure of NASDAQ.

I also consider a turnover-based Amihud measure:

$$Turnover_{im} = \frac{1}{D_{im}} \sum_{d=1}^{D_{im}} \frac{|Return_{id}|}{TO_{id}} \tag{3.3}$$

where $Turnover_{im}$ is the turnover-based Amihud measure ratio of stock i on month m, TO_{id} which is constructed as the daily share volume of stock i on day d divided by the shares outstanding of stock i on day d.

Lesmond et al. (1999) propose a new version of liquidity measure, namely percentage of zero return. They argue two main points: first, illiquid stocks tend to have zero-return days with zero volume, and second that even with positive volume, they may also have zero return due to high transaction costs. Zero return measure of stock i in month m is given by:

$$Zeros_{im} = \frac{\#\ of\ zero\ returns\ day}{D} \tag{3.4}$$

where D is the number of the trading days in month m for stock i.

Alternatively:

$$Zeros\_2_{im} = \frac{\#\ of\ positive\ volume\ days\ with\ zero\ return}{D} \tag{3.5}$$

To check the robustness of my results, I consider an alternative measure of liquidity, namely the spread. I construct the spread using the end of day bid and ask prices obtained from CRSP. The spread of stock i in month m is given by:

$$Spread_{im} = \frac{1}{D_{im}} \sum_{d=1}^{D_{im}} 2 \times \frac{Ask_{id} - Bid_{id}}{Ask_{id} + Bid_{id}} \tag{3.6}$$

where Ask_{id} is the ask price at the end of day d of stock i and Bid_{id} is bid price at the end of day d of stock i and D_{im} denotes the number of days in which stock has a valid ratio in month m. Following standard practice in the literature, the liquidity measures are winsorised at the one per cent and 99 per cent levels each month to eliminate the effect of outliers in our sample.

3.3.2 Idiosyncratic Volatility

The total risk of a stock has two components: systematic risk and idiosyncratic (or unsystematic) risk. Modern portfolio theory asserts that idiosyncratic risk should not affect expected returns since it is diversifiable. However, recent research has shown that this is not the case empirically and that, in practice, expected returns are related to idiosyncratic volatility (Goyal and Santa-Clara, 2003; Ang et al., 2006; Xu and Malkiel, 2006). The most common approach to the estimation of idiosyncratic volatility is to first estimate a factor model for returns, such as the single factor model implied by the CAPM, or the Fama-French three-factor model. The standard deviation of the residuals from this model is then used as a measure of idiosyncratic volatility (see, for example, Ang et al., 2006; Bali and Cakici, 2008; Han and Lesmond, 2011).

To estimate idiosyncratic volatility, I, therefore, estimate the following three-factor model for returns:

$$(R_{id} - rf_d) = \alpha_{id} + \beta_1 \times MKT_d + \beta_2 \times SMB_d + \beta_3 \times HML_d + \epsilon_{id} \tag{3.7}$$

where $(R_{id} - rf_d)$ is the daily excess return of stock i on day d, MKT_d is the daily market risk premium on day d, SMB_d is the daily return difference between small and big sized companies based on market capitalisation on day d, and HML_d is the daily return difference between high and low book-to-market on day d. I estimate the three-factor model by OLS and use the standard deviation of the residuals as my estimate of idiosyncratic volatility within a month: Idiosyncratic Volatility$_{im} = \sqrt{Var(\epsilon_{id})}$.

3.3.3 Control Variables

In my regressions, I include the following control variables: market-to-book ratio, Return [-12 -2] and Return [-1]. The market-to-book ratio is defined as the market value of equity divided by book value of equity, where the market value of equity is market capitalisation, and book value of equity is defined as stockholders' equity plus balance sheet deferred taxes plus investment tax credit minus the book value of preferred stock.[18] The book value of each stock is obtained at the end of the fiscal year t and its market value is obtained at the end of the calendar year t. The market-to-book of stock i in year t is matched with the monthly return of stock i

[18]Detailed definitions of the variables used in the construction of the book value of equity are given in the Appendix.

from July of year $t+1$ to June of year $t+2$. The market-to-book ratio is winsorised at the one per cent and 99 per cent levels at the end of each year. Return [-12 -2] captures the momentum, and is defined as the cumulative return for stock i from month $m-12$ to $m-2$. Return [-1] captures short-term reversal and is defined as the lagged return for stock i on month $m-1$. Since there is not yet any paper on the relation between stock liquidity and idiosyncratic volatility, control variables are selected based on their link on stock liquidity due to the importance of precise estimation of stock liquidity. Prior studies confirm the influence of the market-to-book ratio and past returns while they examine stock liquidity (Spiegel and Wang, 2005; Han and Lesmond, 2011).

3.3.4 Background of Event, Decimalisation

Prior to decimalisation, the US stock markets used fractional pricing. This put the US markets at a disadvantage relative to foreign markets, many of which had already adopted decimal pricing. In view of this, the SEC started the process of moving away from fractional pricing. In 1992, the AMEX reduced the tick size from $1/8 to $1/16 for stocks with trading prices between $0.25 and $5.00, and in 1997 this was extended to all AMEX stocks. The rule was subsequently applied to all stocks on the NYSE and NASDAQ.

In 1997, two US representatives (Oxley and Markey) proposed a new bill to change the fractional pricing system to a decimal pricing in all US markets, with the intention of increasing international competitiveness because of a reduction in the tick size (see Harris, 1997). The SEC decided to implement decimalisation in phases, and for a limited sample of companies, to determine the effect of the new pricing system. Specifically, the decimal pricing system was introduced for seven stocks in August 2000 (Phase I), additional 57 stocks in September 2000 (Phase II) and a further 94 stocks in December 2000 (Phase III).[19] Following the success of these trials, decimal pricing was implemented for all stocks listed on the NYSE and AMEX on January 29, 2001, and for those listed on NASDAQ on April 9, 2001. Subsequent research suggests that decimalisation led to a reduction in both the quoted spread and the effective spread (Chakravarthy et al., 2001; Bacidore, Battalio and Jennings, 2003; Bessembinder, 2003). Decimalisation is also extensively used as an exogenous positive shock to liquidity (Fang et al., 2009; Nyborg and Wang, 2014; Brogaard, et al., 2017).

3.3.5 Summary Statistics

Here I examine how liquidity and idiosyncratic volatility change during my sample period. Table 3.1 reports summary statistics before (Panel A) and after (Panel B) the implementation of decimal pricing on the NYSE and AMEX. Consistent with the findings of previous studies, the mean of high-low estimator decreases from 0.015 before decimalisation to 0.012 after decimalisation, equivalent to a decrease in illiquidity of approximately 20 per cent. The mean of Amihud also decreases from 0.141 to 0.110. The biggest impact of decimalisation can be seen in the spread, which decreases by 52 per cent following decimalisation. Zero return proxies and turnover give similar results.

[19] Following prior research, these stocks are excluded from my sample.

[Insert Table 3.1 near here]

Figure 3.3 illustrates the relationship between stock illiquidity and decimalisation between January 1999 and January 2003.[20] The vertical line indicates the month in which decimalisation took place. We can see that illiquidity displays a downward-sloping pattern after decimal pricing was implemented. This supports my use of decimalisation as an instrument for liquidity. Moreover, when I compare Figures 3.2 and 3.3, we see that in general, they follow a similar pattern. For example, in Figure 3.3, on average, stock illiquidity increases sharply in the first quarter of 2000 and the last quarter of 2002. In the same period we also see an increase in idiosyncratic volatility in Figure 3.2, which supports the idea that illiquidity and idiosyncratic volatility are positively correlated.

[Insert Figure 3.3 near here]

Although the summary statistics and Figure 3.3 show that illiquidity certainly decreases after decimalisation, I also provide univariate analysis to confirm that the change in illiquidity before and after the decimalisation period is statistically significant. Table 3.2 reports the statistical significance of the mean difference before and after decimalisation for each of the liquidity proxies. The decrease in illiquidity following decimalisation is statistically highly significant for all the liquidity proxies.

[Insert Table 3.2 near here]

[20] H-L Spread estimator is used as a proxy for stock illiquidity in Figure 3.3.

The prior literature suggests that idiosyncratic volatility is positively correlated with illiquidity. In other words, when the illiquidity of a stock decreases, its idiosyncratic volatility risk should decrease. Table 3.3 reports the correlations between the various proxies of stock illiquidity and idiosyncratic volatility. Column (8) shows the correlation coefficient of our primary proxies of illiquidity with idiosyncratic volatility, namely the high-low estimator, Amihud, percentage of zero return and spread, are positively correlated with idiosyncratic volatility, consistent with the existing literature. As we see, the high-low estimator has the highest correlation with idiosyncratic volatility. This also confirms that our primary choice of liquidity proxy is appropriate.

[**Insert Table 3.3 near here**]

3.4 Empirical Analysis

Previous studies that have examined the relationship between idiosyncratic volatility and stock liquidity have tended to use ordinary least squares (OLS). For example, Spiegel and Wang (2005) regress idiosyncratic volatility on various stock liquidity proxies using pooled OLS, while Lesmond and Han (2011) regress stock liquidity, measured by either the Amihud or the bid-ask spread, on idiosyncratic volatility using the Fama-MacBeth (1973) methodology. Both studies find a statistically significant relationship between liquidity and idiosyncratic volatility. However, as is clear from the different choices of dependent variable in each of these regressions, liquidity and idiosyncratic volatility are jointly determined, and so there is a reverse causality problem. Thus, OLS is an inconsistent estimator of the parameters of either regression.

3.4.1 Univariate Analysis

In Figure 3.1, I presented the positive long-run relationship between illiquidity and idiosyncratic volatility. I support this positive relationship with sorting analysis in Table 3.4. Stocks are divided into quintiles using monthly illiquidity proxies. The first group has liquid stocks and the last group has illiquid stocks in each month. After dividing stocks into five portfolios, equal-weighted idiosyncratic volatility of each portfolio is obtained in each month. Time-series averages of each portfolio are calculated to examine the results. Idiosyncratic volatility increases monotonically with stock illiquidity. All seven liquidity proxies show that illiquid stocks have higher idiosyncratic volatility and the difference between illiquid and liquid portfolios is statistically significant when I use Newey-West (1987) robust standard errors. This analysis confirms the positive relation between illiquid stocks and idiosyncratic volatility at the univariate level. Therefore, examining the causal impact of stock illiquidity on idiosyncratic volatility is essential to explain this positive relationship in more detail.

[Insert Table 3.4 near here]

3.4.2 Exogeneity and Instrumental Variable Approach

As stated in earlier sections and visualised by earlier figures, liquidity is certainly related to idiosyncratic volatility, and, so far, this relationship has been examined by multivariate analysis. However, the multivariate analysis does not eliminate the concern of reverse causality. It is possible that lower liquidity causes stock to have high volatility, or, the other way around. If lower liquidity causes the stock to have high volatility, similarly, high volatility causes the stock to have less liquidity. In addition, the interpretation of the impact may be different for regulators compared with investors. Investors may be concerned about idiosyncratic volatility rather than liquidity but regulators may be concerned about liquidity rather than idiosyncratic volatility. Hence, it is problematic to answer whether lower stock liquidity leads to higher idiosyncratic volatility since the relationship can go both ways. Imagine that an investor wants to sell his or her shares of a stock in the market at a certain price level, but there is no buyer at that price level, so the investor needs to lower the price of the stock step by step until sellers and buyers reach a tradable price level. If the stock is liquid then the seller should not decrease the price too much; however, if the stock is illiquid then the seller needs to decrease the price drastically so that he or she can sell his or her shares of the stock, causing an increase in idiosyncratic volatility of the stock. This illustration can be stated the opposite way. It may be that the stock is risky, so that no one wants to buy it at its initial price, which makes the stock illiquid. To address this issue, we need a source of exogenous variation that allows us to capture the causal relation between the two factors.

To present statistical evidence regarding endogeneity, I use the Wu-Hausman (Wu, 1973; Hausman, 1978) test to demonstrate the existence of the endogeneity problem and needs to be taken care of before making any inference regarding the relationship between stock illiquidity and idiosyncratic volatility. The Wu-Hausman procedure includes two steps. In the first step, I run an OLS regression, where the dependent variable is my illiquidity proxies, with my instrumental variable and store the residuals. In the second step, I use predicted residuals and run another OLS where the dependent variable is idiosyncratic volatility. Each column of Table 3.5 shows that predicted residuals are statistically significant, therefore, I confirm statistically that the endogeneity problem exists.

[**Insert Table 3.5 near here**]

The identification strategy that I use to disentangle the reverse causality problem is to use the instrumental variable approach, which yields consistent estimates of the regression parameters and allows us to draw conclusions about the causal effect of liquidity on idiosyncratic volatility. The instrumental variables method allows us to eliminate the variation in liquidity that is exogenous and use it to capture the effect of liquidity on idiosyncratic volatility. To undertake the instrumental variable approach, a valid instrument must cause a variation in stock liquidity and at the same time it must be uncorrelated with idiosyncratic volatility. Therefore, I use decimalisation as my instrument since it is exogenous (i.e. uncorrelated with idiosyncratic volatility) but, as shown above and in previous studies, it is correlated with liquidity. Intuitively, reducing the minimum tick size will lead to an increase in a spread in a competitive market setting.

To implement the instrumental variable approach, I define a dummy variable denoted $Decimalisation_m$, which is set to one if the period is after decimalisation and zero before decimalisation. I exclude the month that decimalisation occurred (January 2001) from my analysis since it took place part way through the month. In order to use instrumental variable approach, I implement the two-stages least squares methodology. In the first stage, I regress my measures of liquidity on the instrument $Decimalisation_m$, to yield fitted values of the liquidity measures. In the second stage, I regress the fitted value of liquidity derived from the first stage on idiosyncratic volatility. The first-stage regression will also provide us with additional evidence on whether liquidity decreased or increased following decimalisation. This will supplement existing studies that examine the impact of decimalisation on liquidity using the various low-frequency proxies of liquidity. The second-stage regression will be used to test our hypothesis that increase in illiquidity causes a rise in idiosyncratic volatility. To be consistent with the literature, I use the natural logarithm version of both measures of liquidity and idiosyncratic volatility. To summarise, the two-stage least squares approach is given by the following:

First-stage regression:

$$Log(Liquidity_{im}) = \alpha_0 + \alpha_1 \times Decimalisation_m + \upsilon_{im} \tag{3.8}$$

Second-stage regression:

$$\text{Log(Idiosyncratic Volatility}_{im})=\beta_0+\beta_1\times Log(\widehat{Liquidity}_{im})+\epsilon_{im} \tag{3.9}$$

where $Decimalisation_m$ is a time dummy variable that is set to one if the time period is after decimalisation and zero otherwise.

Panel A of Table 3.6 reports the results of the second-stage regression given by equation (3.9), while Panel B reports the results of the first-stage regression given by equation (3.8). For reference, Panel C reports the results of OLS estimation. Column (1), which reports results using the high-low estimator, reveals a strong relationship between illiquidity and idiosyncratic volatility, with an estimated coefficient of 1.229 and a corresponding t-statistic of 24.92. This coefficient suggests that a one per cent increase in illiquidity is associated with a 1.229 per cent increase in the standard deviation of idiosyncratic returns. The coefficient is considerably larger than in the OLS estimated regression reported in Panel C, suggesting that OLS does indeed suffer from a reverse causality problem that leads to a reduction in the magnitude of the estimated parameter. From Panel B, which reports the results of the first stage regression, we can see that illiquidity decreased by 12.7 per cent on average, following the implementation of decimal pricing. This is consistent with existing studies on the impact of decimalisation on liquidity. In Column (2), I use similar liquidity proxy as Column (1).[21] The estimated coefficient is positive and statistically significant as another proxy. This coefficient suggests that a

[21]Column (1) reports the result by using high-low estimator which is defined as the high-low estimator estimates with negative estimates set to zero and column (2) shows the results of high-low estimator which is defined as the high-low estimator estimates with negative estimates set to missing.

one percent increase in illiquidity is associated with a 1.427 percent increase in the standard deviation of idiosyncratic returns.

Column (3) reports the results using the original version of the Amihud measure as a proxy for illiquidity. The results are supportive of my hypothesis that an increase in illiquidity leads a rise in idiosyncratic volatility. This increase is statistically and economically significant. One per cent increase in illiquidity is associated with a 0.386 per cent increase in the standard deviation of idiosyncratic returns.

Column (4) reports the estimation results using the turnover measure of illiquidity. This confirms the findings reported for the high-low estimator and Amihud measure: the estimated coefficient is of a similar order of magnitude, and statistically highly significant.

Columns (5) and (6) report the results of the percentage of zero return proxies of liquidity. These proxies have the highest magnitude of the estimated coefficient, which is anticipated due to the return relationship of idiosyncratic volatility.

In column (7), I use spread as a proxy for illiquidity. Similar to the results obtained using the other proxies of illiquidity, Panel A shows that the relationship between the illiquidity and idiosyncratic volatility is positive and statistically significant. In particular, one per cent increase in spread leads to an increase in the standard deviation of the idiosyncratic volatility of 0.258 per cent. From Panel B, we can see that the use of the spread as a measure of illiquidity yields the highest adjusted R-squared of all measures, reflecting the reduction in the tick size that accompanied decimalisation. These results suggest that my results are not driven by the choice of liquidity measure.

Overall, the results in Table 3.6 suggest a statistically and economically significant effect of illiquidity on idiosyncratic volatility. When stocks become more illiquid, their idiosyncratic volatility increases, and this result does not depend on the choice of illiquidity proxies. I disentangle the reverse causality problem by employing instrumental variable methodology, using the exogenous event of decimalisation as our instrumental variable. My results also provide further evidence that decimalisation had a significant impact on liquidity, with stocks becoming more liquid on average.

[**Insert Table 3.6 near here**]

3.4.3 Instrumental Variable Approach with Control Variables

To determine the true effect of decimalisation on liquidity I need to include additional control variables to ensure that my results do not suffer from omitted variables bias. Following the existing literature, I extend my analysis by including additional control variables in both stages of the instrumental variable estimation. I include Return [-12 -2], Return [-1] and market-to-book ratio to improve the precision of my estimation.

First stage regression:

$$Log(Liquidity_{im}) = \alpha_0 + \alpha_1 \times Decimalisation_m + \Gamma' X_{im} + \upsilon_{im} \tag{3.10}$$

Second stage regression:

$$\text{Log(Idiosyncratic Volatility}_{im}\text{)}=\beta_0 + \beta_1 \times Log(\widehat{Liquidity_{im}}) + \theta' X_{im} + \epsilon_{im} \tag{3.11}$$

where $Decimalisation_m$ is a time dummy variable that is set to one if the time period is after decimalisation and zero otherwise. X_{im} presents a $k \times 1$ vector of control variables and Γ' and θ' are $k \times 1$ vectors of parameters. The control variables are the market-to-book ratio, Return [-12 -2] and Return [-1].

The estimation results including control variables are reported in Table 3.7, with the second-stage regression in Panel A, the first-stage regression in Panel B, and the estimation results for OLS in Panel C. We should first note that the inclusion of the control variables leads to a very considerable increase in the explanatory power of the first-stage regression, with the adjusted R-squared coefficient rising from one per cent to 17 per cent for the specification employing the Amihud proxy in column (3). A similar increase in adjusted R-squared coefficient is seen for other specifications in columns (1) to (7). In all specifications, the Return [-12 -2] and market-to-book ratio are positive and statistically significant in the second-stage regression, but negative and statistically significant in the first-stage regression. The Return [-1] is significant in the first-stage regression, but insignificant in the second-stage regression for Amihud and turnover-based liquidity estimation. Overall, my findings appear to be robust to the inclusion of the control variables, with a one per cent increase in the high-low estimator proxy of illiquidity leading to a 1.306 per cent increase in idiosyncratic standard deviation, with a t-statistic of 23.91. In column (3) the magnitude of the estimated coefficient of Amihud slightly decreases by including control variables, to 0.342. Similarly, from the first-stage regression using the Amihud measure, decimalisation causes a reduction in illiquidity of 59.2 per cent. This result holds when I use other proxies for illiquidity in columns (1) to (7).

[**Insert Table 3.7 near here**]

Even though earlier studies and this study show that decimalisation has certain impact on stock liquidity, there is one extra condition which must statistically be proven before I clearly confirm the validity of the usage of two-stage least squares estimation, namely weak instrument problem. One of the most important properties that instrumental variable approach must eliminate is weak instrument condition. If one has a weak instrument than the two-stage least squares estimation will be inconsistent which will lead an incorrect interpretation of the result of the two-stage least squares estimation. Earlier studies built a rule of thumb to examine the weak instrumental problem. Staiger and Stock (1997) suggest that instrument can be considered as a weak instrument if F-statistic of the first-stage of 2SLS estimation is less than 10.

F-statistics in the first-stage of 2SLS estimation for each stock liquidity proxies is presented in Table 3.7. We could easily see that all the F-statistics are higher than

10, so that I can conclude that my instrument is not weak; therefore, adopting 2SLS estimation will produce consistent estimation of β.

3.4.4 The Difference-in-Differences Approach

In addition to the instrumental variable approach, I follow the literature and adopt the difference-in-differences methodology to confirm the impact of liquidity on idiosyncratic volatility around decimalisation. Since decimalisation was implemented for all companies on the NYSE and AMEX at the same time, I cannot construct a standard difference-in-differences framework owing to the lack of a control group. Instead, I follow Fang et al. (2009), who examine the impact of liquidity on Tobin's Q, which they consider a proxy for firm performance. They use a two-year window ($t-1$ to $t+1$) to capture the impact of decimal pricing on liquidity. I adopt their identification strategy using the change in liquidity from the month before decimalisation to the month after decimalisation as the independent variable and the change in idiosyncratic volatility over the same period as the dependent variable. The impact of the implementation of decimal pricing can be captured efficiently in the shorter horizon; therefore, I limit my sample period to the month before decimalisation and the month after decimalisation.

The regression equation can be expressed as follows:

$$\Delta\text{Log}(\text{Idiosyncratic Volatility}_i)=\gamma_0 + \gamma_1 \times \Delta\text{Log}(\text{Liquidity}_i)+\epsilon_i \tag{3.12}$$

where ΔLog(Idiosyncratic Volatility$_i$) indicates the difference in the logarithm of idiosyncratic volatility of stock i between values in the month after decimalisation and values in the month before decimalisation. Similarly, ΔLog(Liquidity$_i$) is the difference in the logarithm of various stock liquidity measures of stock i from over the same period.[22]

Table 3.8 reports the results of the difference-in-differences estimation. The primary measures of stock illiquidity are positive and statistically significant, with coefficients of 0.175 and 0.270 as shown in columns (1) and (3), respectively. We see the same pattern when I use either turnover or spread as a proxy for stock illiquidity. In column (5), the percentage of zero return proxy is statistically insignificant and the similar measure in column (6) is marginally significant. The reason for this might be that the impact of decimalisation can take effect over several months. Since my period is limited to one month before and after decimalisation, the effect of the decline in tick size is no longer supported for these proxies. Another reason could be that since this regression is still OLS, there may still be an endogeneity problem that renders this coefficient insignificant.

[Insert Table 3.8 near here]

[22]When I use percentage of zero return as a proxy for liquidity, I do not use the logarithm version of it since the measure is already in percentage.

3.5 Robustness Analysis

3.5.1 Clustering Analysis

I repeat the instrumental variable regression analysis, clustering the standard errors at the industry level using the Fama-French 48-industry classification.[23] Clustering at the industry level allows the errors to be correlated within each industry but assumes that they are uncorrelated between industries. Since clustering the data only affects the standard errors, the magnitudes of the estimated coefficients do not change. Table 3.9 reports the results of the instrumental variable regression with robust clustered standard errors. I focus on only the stock illiquidity proxies in this analysis, and so for brevity I only report the estimated coefficients of the second stage. Columns (1) to (7) of Table 3.9 show that after controlling for industry effects, my results are still significant at one per cent level. This is true for all the proxies of illiquidity.[24]

[Insert Table 3.9 near here]

In addition to cluster data in industry level, I adopt a different strategy and use industry dummy variables for each industry and cluster my data at firm level. I also include a month dummy variable to capture any seasonality effect if it exists. Table 3.10 reports the results of the second stage of the instrumental variable analysis with

[23] I also clustered the standard errors at the firm level but the estimated coefficients have higher significance levels than industry-level clustering.

[24] The results of the instrumental variable analysis with robust clustered standard errors without control variables lead me to similar results.

robust clustered standard errors at firm level and including month and industry dummy variables as well as control variables.[25]

[Insert Table 3.10 near here]

As a further robustness check, following Fang, Noe and Tice (2009), I add industry fixed effects to our difference-in-difference analysis, using the Fama-French 48 industry classifications. The results are reported in Table 3.11. Adding fixed effects and robust standard errors do not have a significant impact on the relationship between illiquidity and idiosyncratic volatility: the estimated coefficient remains positive and statistically significant in each column except the columns (5) and (6).

[Insert Table 3.11 near here]

3.5.2 Different Time Horizon

To examine the robustness of the instrumental variable approach, I repeat the analysis using alternative time intervals around decimalisation. As shown in Table 3.6, my time interval covers the period from two years before decimalisation to two years after decimalisation. In Table 3.12, I report the results of my analysis with control variables, clustering the robust standard errors at the industry level, using the sample period of one year, six months and three months either side of decimalisation. Panel A of Table 3.12 covers the period between January 2000 and January 2002. The estimated coefficients are positive and statistically significant for all illiquidity

[25]For simplicity, I do not present the coefficients of month and industry dummy variables as well as other control variables.

proxies. The magnitudes of the coefficients are even stronger than using two-year time windows. Similar results can be seen in Panels B and C when I use six- and three-month time windows, respectively.

[Insert Table 3.12 near here]

3.5.3 Excluding Financial and Utility Sectors

I control for financial and utility sectors by excluding companies in these sectors. Controlling these sectors will give us clearer evidence that our results are not driven by these sectors. Table 3.13 reports the results of the second stage of instrumental variable estimation by excluding financial and utility companies.[26] I also include control variables and cluster the standard errors at the industry level as with prior results. Each column supports the results shown in the previous analyses. The magnitude of coefficients slightly decreases in the first two columns, but slightly increases in the other columns.

[Insert Table 3.13 near here]

3.5.4 The Size Effect

The results may be driven by either large or small companies. To eliminate the effect of company size I follow Nyborg and Wang (2014) and orthogonalize each of

[26] SIC code for financial companies is between 6000-6999 and for utility companies is between 4900-4999.

my illiquidity proxies for firm i and year t by running following OLS regression:

$$Liquidity_{it} = \gamma_0 + \gamma_1 \times FirmSize_{it} + \eta_{it} \tag{3.13}$$

where firm size is defined as the logarithm of total assets from the Compustat database. Since firm size is a yearly measure, I decided to use the yearly construction of illiquidity proxies to obtain the residuals from equation (3.13). I also use industry-clustered standard errors. I shrink my period to one year before decimalisation (2000) and one year after decimalisation (2002). I match the yearly residuals by monthly measures of idiosyncratic volatility and control variables. Using residual illiquidity proxies leads to similar results. All the illiquidity proxies are statistically significant from columns (1) to (7). The magnitude of illiquidity proxies increases in each column and last three columns decrease; thus, the overall result of Table 3.14 supports my results. Since the turnover proxy of illiquidity already takes care of size effect of the firm, the magnitude of this coefficient is very small but it is still statistically significant in column (4).

[**Insert Table 3.14 near here**]

3.5.5 NASDAQ Analysis

Decimal pricing was introduced in the NASDAQ market in April 2001, two months later than in the NYSE and AMEX. I can therefore test the robustness of my findings by examining the impact of decimalisation on the idiosyncratic volatility of NASDAQ stocks. I present only the instrumental variable approach results with industry fixed effects and robust standard errors; as with the NYSE and AMEX, the other approaches lead to very similar conclusions. The sample covers the period April 1999 to April 2003. I delete the month (April 2001) in which decimalisation took place. I also cluster my data at the industry level. Table 3.15 reports the result of the analysis for NASDAQ stocks. From column (1), we can see that there is an even stronger relationship between idiosyncratic volatility and stock illiquidity for NASDAQ than there is for the NYSE and AMEX stocks. A one per cent change in stock illiquidity leads to a 0.905 per cent change in idiosyncratic standard deviation. The results using other proxies of illiquidity are similar.

[**Insert Table 3.15 near here**]

3.6 Conclusion

Understanding the determinants of market quality is an important aspect of research in the finance literature. Several studies have examined the role of liquidity and idiosyncratic volatility in this context, and have shown that both are related to the expected stock returns. However, the link between these two factors has received relatively less attention. Inventory control model suggests that there should be a positive relationship between stock illiquidity and idiosyncratic volatility, and this relation is supported by empirical studies. On the one hand, Spiegel and Wang (2005) show that when idiosyncratic volatility increases, stock illiquidity increases; on the other hand, Han and Lesmond (2011) present evidence that shows that when stock illiquidity increases, idiosyncratic volatility increases. However, these empirical studies are a lack of giving the causality between stock liquidity and idiosyncratic volatility of return. In other words, high liquidity may cause idiosyncratic volatility to decline or high idiosyncratic volatility may lead a decline in stock liquidity as well.

In this chapter, I investigate the causal relationship between liquidity and idiosyncratic volatility. First, I confirm the positive relation between illiquidity and idiosyncratic volatility using graphical and univariate analysis. Second, I show that increase in stock illiquidity leads to increase on idiosyncratic volatility. To control for potential reverse causality problem, I estimate the relationship between liquidity and idiosyncratic volatility with the instrumental variable approach, using the exogenous change in the tick size that occurred because of decimalisation as an instrumental variable for liquidity. I use a range of different proxies of illiquidity, and measure idiosyncratic volatility as the standard deviation of the residuals from the Fama-French three factors model.

The results show that an increase in illiquidity leads to an economically and statistically significant increase in idiosyncratic volatility: using my primary proxy of illiquidity, a one per cent increase in illiquidity leads to an increase in the standard deviation of idiosyncratic returns of about 1.229 per cent. Consistent with the previous finding, I also show that decimalisation resulted in a significant decline in illiquidity. My results are robust to the inclusion of industry effects, control variables and to alternatives estimation methods.

The economic importance of the finding can be that since this study examines the link at the firm level, for any reason that a stock becomes illiquid this can be a signal for investors who should consider holding the stock to diversify their portfolio to eliminate unsystematic risk since the stock become riskier. In other words, when a stock becomes illiquid this will increase the overall risk of the portfolio, thus investor re-evaluates his risk of the overall portfolio. Another takeaway from this study can be that the pricing ability of idiosyncratic volatility indeed comes from controlling stock liquidity as shown Lesmond and Han (2011). Therefore, we may consider controlling liquidity before estimating idiosyncratic volatility.

There are several ways in which the research reported in this chapter could be extended. First, it would be interesting to examine how the relationship between liquidity and idiosyncratic volatility is affected by the level of trading activity since prior research shows that decimalisation has a greater impact on stocks that are more actively traded. Second, it would be useful to establish whether our results hold using even more accurate proxies of liquidity, such as those based on intraday quoted spreads. Finally, while the focus of this chapter is to examine how changes in liquidity impact idiosyncratic volatility, a natural line of enquiry would be whether causality also runs in the opposite direction, from idiosyncratic volatility to liquidity.

3.7 Figures and Tables

Figure 3.1: Market Illiquidity and Idiosyncratic Volatility
The figure shows the time-series of illiquidity proxy and idiosyncratic volatility from January 1960 to December 2014. H-L Spread illiquidity measure is constructed in each month using daily information for each stock. I then calculate equal-weighted market illiquidity for each month. I follow same construction procedure for idiosyncratic volatility. Both variables are standardised.

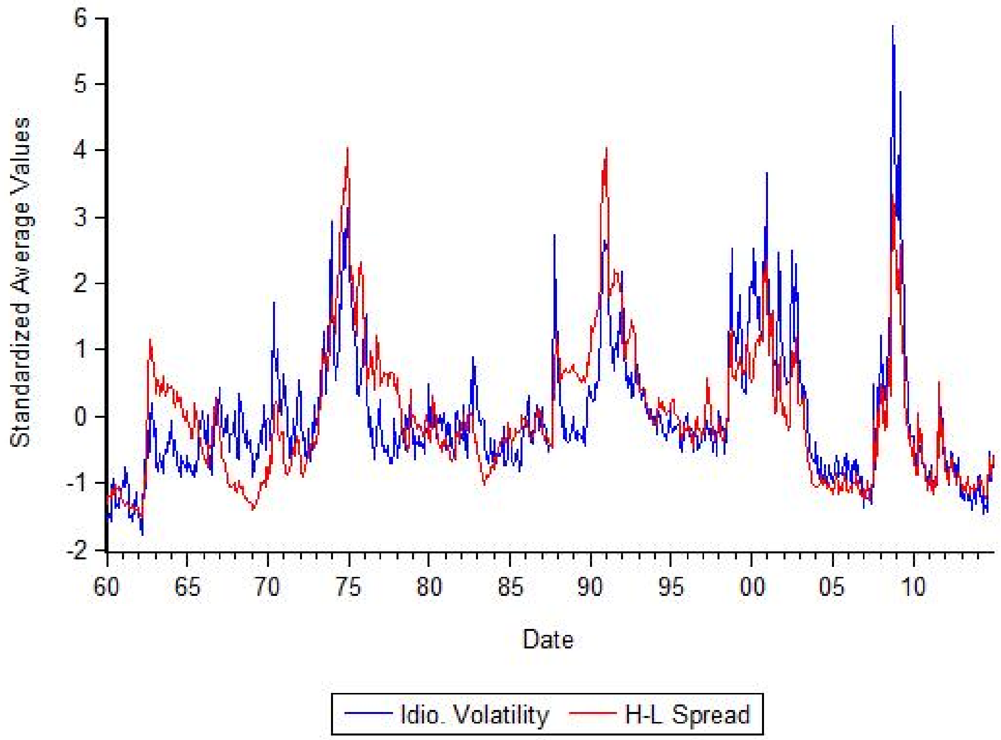

Figure 3.2: Standardised Average Idiosyncratic Volatility
The figure shows the time-series of idiosyncratic volatility around decimalisation, from January 1999 to January 2003. Idiosyncratic Volatility is constructed in each month using daily information for each stock. I then calculate equal-weighted idiosyncratic volatility for each month. Idiosyncratic volatility is standardised.

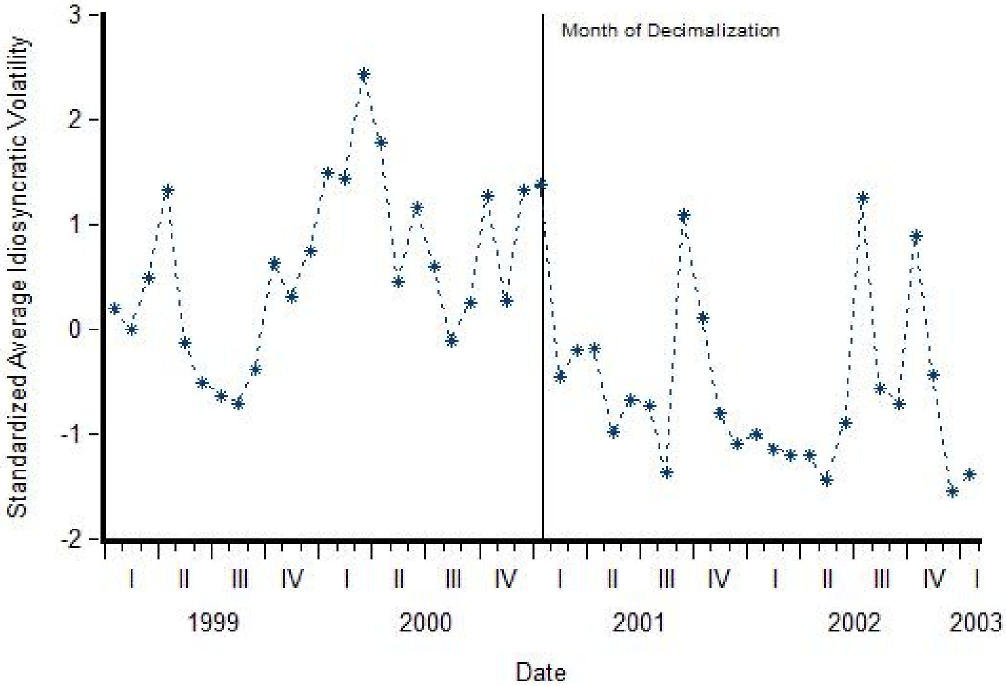

Figure 3.3: Standardised Market Illiquidity
The figure shows the time-series of market illiquidity around decimalisation, from January 1999 to January 2003. Market illiquidity is constructed in each month using daily information for each stock. I then calculate equal-weighted market illiquidity for each month. H-L Spread is used as a proxy for stock illiquidity. Market illiquidity is standardised.

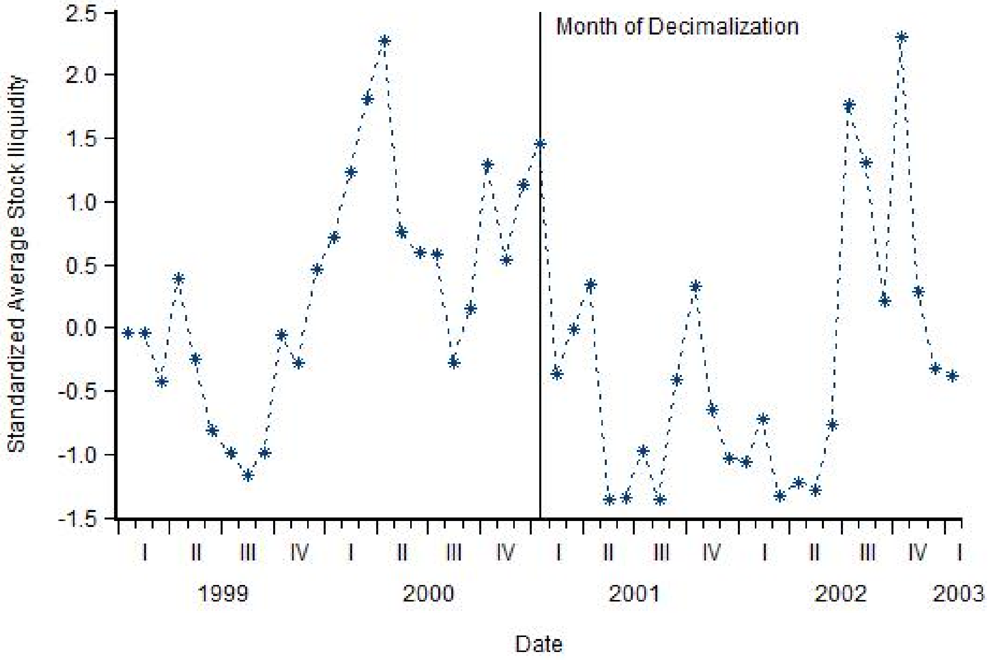

Table 3.1: Summary Statistics

The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX from January 1999 to January 2003. Panel A presents summary statistics for companies before decimalisation and Panel B shows the summary statistics for companies after decimalisation period. H-L Spread, estimated using Corwin and Schultz (2012), is defined as the high minus low spread estimate with negative estimates set to zero. H-L Spread_M is defined as the high minus low spread estimate with negative estimates set to missing. Amihud is defined as the monthly average of a ratio of absolute return divided by price multiplies volume. Turnover is defined as the monthly average of a ratio of absolute return divided by turnover where turnover is defined as daily share volume divided by shares outstanding. Zero Return (%) is defined as the number of zero return days divided by the trading days in the same month. Zero Return_2 (%) is defined as the number of zero return days with positive volume divided by the trading days in the same month. Spread is the monthly average of the ratio of the end of the day bid-ask spread divided by the midpoint of spread. Idiosyncratic volatility is a standard deviation of residuals which are obtained by regressing firms' daily excess return on daily Fama-French three factors. Market-to-Book ratio is market capitalisation of equity divided by book value of equity. Return [-12 -2] is a cumulative return from month $m-12$ to $m-2$. Return [-1] is lagged return of securities. Amihud, Turnover, Spread, H-L Spread, H-L Spread_M and Market-to-Book ratio are winsorised at 1 and 99 percentage points in each month cross-sectional. Amihud is multiplied by 10^6 and Turnover is multiplied by 10^3.

Panel A: Before Decimalisation									
	Mean	Std. Dev.	Skewness	Kurtosis	Q10	Q25	Q50	Q75	Q90
H-L Spread	0.015	0.021	4.417	22.718	0.004	0.006	0.009	0.014	0.027
H-L Spread_M	0.021	0.023	4.064	19.984	0.007	0.010	0.014	0.021	0.037
Amihud	0.141	0.456	7.198	79.119	0.000	0.001	0.008	0.055	0.350
Turnover	15.672	25.237	5.300	41.219	3.313	4.736	7.403	15.127	34.910
Zero Return (%)	0.118	0.129	1.446	1,788	0.000	0.000	0.053	0.150	0.250
Zero Return_2 (%)	0.102	0.108	1.451	2.071	0.000	0.000	0.053	0.150	0.250
Spread	0.025	0.016	0.833	-0.260	0.008	0.012	0.020	0.035	0.050
Idiosyncratic Volatility	0.028	0.020	4.151	39.330	0.012	0.016	0.022	0.032	0.047
Return [-12 -2]	0.032	0.581	6.764	122.858	-0.433	-0.261	-0.067	0.173	0.524
Return [-1]	0.006	0.149	1.868	18.502	-0.148	-0.077	-0.005	0.073	0.170
Market-to-Book	2.732	3.010	3.611	17.154	0.748	1.123	1.822	3.121	5.438
Panel B: After Decimalisation									
	Mean	Std. Dev.	Skewness	Kurtosis	Q10	Q25	Q50	Q75	Q90
H-L Spread	0.012	0.017	5.086	32.414	0.004	0.005	0.008	0.012	0.021
H-L Spread_M	0.018	0.019	4.493	26.497	0.007	0.009	0.013	0.019	0.031
Amihud	0.110	0.374	7.027	70.531	0.000	0.001	0.004	0.035	0.254
Turnover	12.524	22.307	5.121	37.375	2.082	3.098	5.124	11.412	28.842
Zero Return (%)	0.057	0.095	2.352	5.923	0.000	0.000	0.000	0.067	0.182
Zero Return_2 (%)	0.042	0.067	2.173	5.209	0.000	0.000	0.000	0.050	0.136
Spread	0.012	0.009	2.195	6.584	0.004	0.006	0.009	0.015	0.023
Idiosyncratic Volatility	0.024	0.022	6.947	145.820	0.009	0.013	0.019	0.028	0.044
Return [-12 -2]	0.131	0.490	2.835	23.051	-0.357	-0.138	0.800	0.311	0.624
Return [-1]	0.008	0.145	1.554	14.598	-0.142	-0.065	0.002	0.071	0.152
Market-to-Book	2.319	2.716	3.818	20.431	0.518	0.901	1.493	2.601	4.752

Table 3.2: Mean Difference of Illiquidity Measures
The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX from January 1999 to January 2003. The table presents the mean difference before and after decimalisation period. H-L Spread, estimated using Corwin and Schultz (2012), is defined as the high minus low spread estimate with negative estimates set to zero. H-L Spread_M is defined as the high minus low spread estimate with negative estimates set to missing. Amihud is defined as the monthly average of a ratio of absolute return divided by price multiplies volume. Turnover is defined as the monthly average of a ratio of absolute return divided by turnover where turnover is defined as daily share volume divided by shares outstanding. Zero Return (%) is defined as the number of zero return days divided by the trading days in the same month. Zero Return_2 (%) is defined as the number of zero return days with positive volume divided by the trading days in the same month. Spread is the monthly average of the ratio of the end of the day bid-ask spread divided by the midpoint of spread. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

Pre and Post Decimalisation Mean Difference				
	Pre	Post	Difference	T-statistics
H-L Spread	0.015	0.012	-0.002***	(-16.37)
H-L Spread_M	0.022	0.018	-0.003***	(-15.97)
Amihud	0.141	0.110	-0.031***	(-8.89)
Turnover	15.672	12.524	-3.148***	(-15.78)
Zero Return (%)	0.118	0.057	-0.061***	(-70.25)
Zero Return_2 (%)	0.102	0.042	-0.600***	(-86.34)
Spread	0.025	0.012	-0.013***	(-115.51)

Table 3.3: Correlation Analysis
The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX from January 1999 to January 2003. The table presents Pearson correlation coefficients between liquidity measures and idiosyncratic volatility. H-L Spread, estimated using Corwin and Schultz (2012), is defined as the high minus low spread estimate with negative estimates set to zero. H-L Spread_M is defined as the high minus low spread estimate with negative estimates set to missing. Amihud is defined as the monthly average of a ratio of absolute return divided by price multiplies volume. Turnover is defined as the monthly average of a ratio of absolute return divided by turnover where turnover is defined as daily share volume divided by shares outstanding. Zero Return (%) is defined as the number of zero return days divided by the trading days in the same month. Zero Return_2 (%) is defined as the number of zero return days with positive volume divided by the trading days in the same month. Spread is the monthly average of the ratio of the end of the day bid-ask spread divided by the midpoint of spread. Idiosyncratic volatility is a standard deviation of residuals which obtained by regressing firms' daily excess return on daily Fama-French three factors.

Correlation Analysis								
	H-L Spread	H-L Spread_M	Amihud	Turnover	Zero Return (%)	Zero Return_2 (%)	Spread	Idiosyncratic Volatility
H-L Spread	1							
H-L Spread_M	0.981	1						
Amihud	0.346	0.229	1					
Turnover	0.102	0.034	0.565	1				
Zero Return (%)	0.517	0.471	0.421	0.332	1			
Zero Return_2 (%)	0.313	0.291	0.279	0.271	0.849	1		
Spread	0.317	0.262	0.367	0.328	0.493	0.482	1	
Idiosyncratic Volatility	0.534	0.608	0.028	0.019	0.190	0.219	0.267	1

Table 3.4: Sorting Analysis
The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX from January 1960 to December 2014. Stocks are divided into five different portfolios by highest liquid stocks in the first portfolio and the lowest liquid stocks in the last portfolio in each month. Then, equal-weighted idiosyncratic volatility in each portfolio calculated. H-L Spread, estimated using Corwin and Schultz (2012), is defined as the high minus low spread estimate with negative estimates set to zero. H-L Spread_M is defined as the high minus low spread estimate with negative estimates set to missing. Amihud is defined as the monthly average of a ratio of absolute return divided by price multiplies volume. Turnover is defined as the monthly average of a ratio of absolute return divided by turnover where turnover is defined as daily share volume divided by shares outstanding. Zero Return (%) is defined as the number of zero return days divided by the trading days in the same month. Zero Return_2 (%) is defined as the number of zero return days with positive volume divided by the trading days in the same month. Spread is the monthly average of the ratio of the end of the day bid-ask spread divided by the midpoint of spread. Idiosyncratic volatility is a standard deviation of residuals which obtained by regressing firms' daily excess return on daily Fama-French three factors. I use Newey and West (1987) robust standard errors. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Portfolios Sorted on Illiquidity Measures						
	Liquid	2	3	4	Illiquid	Illiquid-Liquid	T-statistics
	Panel A: Sorted on High-Low Spread Measures						
Sorted on H-L Spread							
Idiosyncratic Volatility	1.289	1.546	1.863	2.375	4.124	2.84***	(27.44)
Sorted on H-L Spread_M							
Idiosyncratic Volatility	1.182	1.493	1.858	2.412	4.251	3.07***	(29.71)
	Panel B: Sorted on Amihud Measures						
Sorted on Amihud							
Idiosyncratic Volatility	1.368	1.645	1.812	2.009	2.274	0.91***	(35.42)
Sorted on Turnover							
Idiosyncratic Volatility	1.865	1.735	1.747	1.834	1.928	0.06**	(1.96)
	Panel C: Sorted on Spread Measure						
Sorted on Spread							
Idiosyncratic Volatility	1.372	1.735	1.926	2.207	2.532	1.13***	(22.70)
	Panel D: Sorted on Zero Return (%) Measures						
Sorted on Zero Return (%)							
Idiosyncratic Volatility	1.926	1.948	2.126	2.404	2.953	1.03***	(15.79)
Sorted on Zero Return_2 (%)							
Idiosyncratic Volatility	1.976	1.986	2.134	2.316	2.939	0.96***	(17.00)

Table 3.5: Testing for Endogeneity (Hausman-Wu Test)
The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX from January 1999 to January 2003. The dependent variable in each regression is the logarithm of idiosyncratic volatility. H-L Spread, H-L Spread_M, Amihud, Turnover, Zero Return (%), Zero Return_2 (%) and Spread are used as liquidity measure respectively in column (1) to (7). Predicted Residual is obtained from an OLS regression of liquidity measures on an instrumental variable, decimalisation. All liquidity measures (except zero return measures) and idiosyncratic volatility are in logarithm form. T-Statistics are presented in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

Hausman-Wu Test of Endogeneity							
	Dependent Variable: Log(Idiosyncratic Volatility)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.284***	2.560***	-2.641***	-5.294***	-4.173***	-4.122***	-2.924***
	(13.98)	(16.04)	(-89.26)	(-188.56)	(-442.61)	(-516.70)	(-125.20)
Log(H-L Spread)	1.308***						
	(37.75)						
Log(H-L Spread_M)		1.518***					
		(40.38)					
Log(Amihud)			0.342***				
			(46.35)				
Log(Turnover)				0.583***			
				(46.14)			
Zero Return (%)					2.787***		
					(32.83)		
Zero Return_2 (%)						2.897***	
						(32.91)	
Log(Spread)							0.259***
							(46.79)
Predicted Residual	-0.892***	-0.958***	-0.322***	-0.578***	-2.581***	-2.327***	-0.063***
	(-25.66)	(-25.38)	(-43.27)	(-44.98)	(-29.19)	(-24.93)	(-9.78)

Table 3.6: Two Stage Least Squares Estimation
The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX from January 1999 to January 2003. Panel A represents my main result, the second stage of my 2SLS regression where the dependent variable is the logarithm of idiosyncratic volatility and the independent variable is the logarithm of stock liquidity. Panel B shows the first stage of 2SLS regression where the dependent variable is the logarithm of stock liquidity and the independent variable is the instrument, decimalisation. Panel C presents Pooled OLS regression where the dependent variable is logarithm version of idiosyncratic volatility and the independent variable is the logarithm of stock liquidity measures in each column. H-L Spread, H-L Spread_M, Amihud, Turnover, Zero Return (%), Zero Return_2 (%) and Spread are used as liquidity measures respectively in column (1) to (7). I have an intercept in the Pooled OLS regression but I do not report for simplicity. Decimalisation is a time dummy variable which equals to one when the period is after decimalisation and zero before decimalisation. All liquidity measures (except zero return measures) and idiosyncratic volatility are in logarithm form. T-statistics are presented in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

Panel A: The Second Stage of 2SLS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	1.934***	2.173***	-2.075***	-5.121***	-4.079***	-4.043***	-2.859***
	(8.32)	(9.68)	(-24.31)	(-141.13)	(-517.66)	(-625.50)	(-122.74)
Log(H-L Spread)	1.229***						
	(24.92)						
Log(H-L Spread_M)		1.427***					
		(26.85)					
Log(Amihud)			0.386***				
			(31.89)				
Log(Turnover)				0.567***			
				(31.89)			
Zero Return (%)					2.549***		
					(30.00)		
Zero Return_2 (%)						2.611***	
						(31.41)	
Log(Spread)							0.258***
							(47.86)
Panel B: The First Stage of 2SLS							
	Log(H-L Spread)	Log(H-L Spread_M)	Log(Amihud)	Log(Turnover)	Zero Return (%)	Zero Return_2(%)	Log(Spread)
Constant	-4.647***	-4.170***	-4.651***	2.204***	0.118***	0.102***	-3.928***
	(-1099.1)	(-1135.3)	(-314.59)	(383.49)	(192.29)	(208.19)	(-932.49)
Decimalisation	-0.127***	-0.109***	-0.510***	-0.348***	-0.061***	-0.060***	-0.769***
	(-21.18)	(-21.00)	(-24.13)	(-42.30)	(-70.30)	(-86.34)	(-127.57)
Adjusted R^2	0.007	0.006	0.010	0.030	0.068	0.099	0.232
Panel C: Ordinary Least Squares							
Illiquidity	0.448***	0.593***	0.018***	0.024***	0.634***	1.207***	0.199***
	(169.70)	(210.09)	(22.27)	(11.50)	(30.40)	(47.20)	(77.07)

Table 3.7: Two Stage Least Squares Estimation (Include Control Variables) The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX from January 1999 to January 2003. Panel A represents the main result, the second stage of my 2SLS regression where the dependent variable is the logarithm of idiosyncratic volatility and the independent variable is the logarithm of stock liquidity measures. Panel B shows the first stage of 2SLS regression where the dependent variable is the logarithm of stock liquidity and the independent variable is the instrument, decimalisation. Panel C presents Pooled OLS regression where the dependent variable is logarithm version of idiosyncratic volatility and the independent variable is the logarithm of stock liquidity measures. H-L Spread, H-L Spread_M, Amihud, Turnover, Zero Return (%), Zero Return_2 (%) and Spread are used as liquidity measures respectively in column (1) to (7). I have an intercept in the Pooled OLS regression but I do not report for simplicity. Decimalisation is a time dummy variable which equals to one when the period is after decimalisation and zero before decimalisation. Market-to-Book ratio is market capitalisation of equity divided by book value of equity. Return [-12 -2] is a cumulative return from month $m-12$ to $m-2$ and Return [-1] is lagged return of securities. All liquidity measures (except zero return measures) and idiosyncratic volatility are in logarithm form. F-statistics has been reported. T-statistics are presented in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

Panel A: The Second Stage of 2SLS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.278***	2.554***	-2.641***	-5.294***	-4.173***	-4.122***	-2.924***
	(8.84)	(10.13)	(-48.92)	(-125.71)	(-405.79)	(-492.99)	(-124.70)
Log(H-L Spread)	1.306***						
	(23.91)						
Log(H-L Spread_M)		1.516***					
		(25.54)					
Log(Amihud)			0.342***				
			(25.40)				
Log(Turnover)				0.583***			
				(30.76)			
Zero Return (%)					2.786***		
					(30.08)		
Zero Return_2 (%)						2.897***	
						(31.40)	
Log(Spread)							0.259***
							(46.60)
Return [-12 -2]	0.160***	0.106***	0.209***	0.196***	0.058***	0.046***	0.111***
	(15.58)	(13.09)	(21.48)	(25.25)	(10.46)	(8.39)	(25.94)
Return [-1]	0.216***	0.208***	-0.017	0.007	-0.111***	-0.122***	-0.080***
	(7.38)	(7.64)	(-0.55)	(0.27)	(-5.79)	(-6.67)	(-4.89)
Market-to-Book	0.015***	0.007***	0.121***	0.043***	0.017***	0.010***	0.019***
	(10.18)	(6.05)	(25.84)	(26.66)	(14.07)	(9.66)	(24.11)
Panel B: The First Stage of 2SLS							
	Log(H-L Spread)	Log(H-L Spread_M)	Log(Amihud)	Log(Turnover)	Zero Return (%)	Zero Return_2 (%)	Log(Spread)
Constant	-4.650***	-4.188***	-3.691***	2.385***	0.135***	0.112***	-3.777***
	(-895.13)	(-923.07)	(-208.66)	(329.21)	(183.14)	(191.82)	(-702.68)
Decimalisation	-0.129***	-0.111***	-0.592***	-0.347***	-0.061***	-0.058***	-0.786***
	(-21.07)	(-20.78)	(-28.58)	(-40.90)	(-69.52)	(-84.21)	(-125.06)
Return [-12 -2]	-0.135***	-0.081***	-0.390***	-0.207***	-0.027***	-0.023***	-0.221***
	(-23.89)	(-16.32)	(-19.62)	(-25.51)	(-33.40)	(-9.69)	(-9.38)
Return [-1]	-0.309***	-0.261***	-0.364***	-0.253***	-0.027***	-0.023***	-0.221***
	(-14.93)	(-14.44)	(-4.67)	(-7.94)	(-9.36)	(-9.69)	(-9.38)
Market-to-Book	-0.017***	-0.009***	-0.338***	-0.065***	-0.009***	-0.006***	-0.053***
	(-15.67)	(-10.13)	(-96.76)	(-45.42)	(-56.51)	(-48.46)	(-50.40)
F-Statistic	34.44	30.91	19.20	23.51	23.55	14.26	15.52
Adjusted R^2	0.026	0.018	0.171	0.081	0.137	0.157	0.281
Panel C: Ordinary Least Squares							
Illiquidity	0.422***	0.567***	0.025***	0.024***	0.407***	0.826***	0.212***
	(138.62)	(173.97)	(26.48)	(10.30)	(17.07)	(28.15)	(76.73)
Control Variables	YES	YES	YES	YES	YES	YES	YES

Table 3.8: Difference-in-Difference Estimation

The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX. The dependent variable in each regression is changed in the logarithm of idiosyncratic volatility from December 2000 to February 2001, and independent variables are changed in the logarithm of stock liquidity measures from December 2000 to February 2001. H-L Spread, H-L Spread_M, Amihud, Turnover, Zero Return (%), Zero Return_2 (%) and Spread are used as liquidity measures respectively in column (1) to (7). All liquidity measures (except zero return measures) and idiosyncratic volatility are in logarithm form. T-statistics are presented in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Dependent Variable: Δ Log(Idiosyncratic Volatility)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-0.290***	-0.237***	-0.226***	-0.246***	-0.013***	-0.012***	-0.298***
	(-21.50)	(-17.14)	(-14.94)	(-16.98)	(-16.42)	(-15.68)	(-15.57)
ΔLog(H-L Spread)	0.175***						
	(8.59)						
ΔLog(H-L Spread_M)		0.334***					
		(14.41)					
ΔLog(Amihud)			0.270***				
			(11.72)				
ΔLog(Turnover)				0.278***			
				(11.11)			
ΔZero Return (%)					0.004		
					(0.73)		
ΔZero Return_2 (%)						0.012*	
						(1.86)	
ΔLog(Spread)							0.074***
							(2.84)
Adjusted R^2	0.035	0.092	0.085	0.077	0.0003	0.001	0.007

Table 3.9: Two Stage Least Squares Estimation (Cluster Standard Errors) The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX from January 1999 to January 2003. The dependent variable in each regression is the logarithm of idiosyncratic volatility and independent variables are the logarithm of stock liquidity measures. H-L Spread, H-L Spread_M, Amihud, Turnover, Zero Return (%), Zero Return_2 (%) and Spread are used as liquidity measures respectively in column (1) to (7). Standard errors are robust and clustered industry level. Fama-French 48 industry classification is used to cluster data at the industry level. All liquidity measures (except zero return measures) and idiosyncratic volatility are in logarithm form. T-statistics are presented in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	The Second Stage of 2SLS						
	Dependent Variable: Log(Idiosyncratic Volatility)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.258***	2.536***	-2.643***	-5.293***	-4.172***	-4.121***	-2.927***
	(3.63)	(3.74)	(-22.14)	(-34.44)	(-80.94)	(-81.64)	(-26.17)
Log(H-L Spread)	1.302***						
	(10.14)						
Log(H-L Spread_M)		1.512***					
		(9.70)					
Log(Amihud)			0.342***				
			(10.74)				
Log(Turnover)				0.583***			
				(9.56)			
Zero Return (%)					2.777***		
					(9.74)		
Zero Return_2 (%)						2.888***	
						(9.36)	
Log(Spread)							0.259***
							(12.00)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Industry Clustered	YES	YES	YES	YES	YES	YES	YES

Table 3.10: Two Stages Least Squares Estimation (Industry and Month Dummies

The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX from January 1999 to January 2003. The dependent variable in each regression is the logarithm of idiosyncratic volatility and independent variables are the logarithm of stock liquidity measures. H-L Spread, H-L Spread_M, Amihud, Turnover, Zero Return (%), Zero Return_2 (%) and Spread are used as liquidity measures respectively in column (1) to (7). Control variables are a market-to-book ratio, Return [-12 -2] and Return [-1]. Standard errors are robust and clustered firm level. Fama-French 48 industry classification is used to create a dummy variable for each industry. Monthly dummy variables are also included. I do not report the coefficients of my industry and month dummy variables for brevity. All liquidity measures (except zero return measures) and idiosyncratic volatility are in logarithm form. T-statistics are presented in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	The Second Stage of 2SLS						
	Dependent Variable: Log(Idiosyncratic Volatility)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	1.305*	1.686**	-3.374***	-5.139***	-4.270***	-4.002***	-2.927***
	(1.72)	(2.19)	(-32.24)	(-50.21)	(-48.05)	(-59.48)	(-42.41)
Log(H-L Spread)	1.288***						
	(12.85)						
Log(H-L Spread_M)		1.503***					
		(13.10)					
Log(Amihud)			0.332***				
			(17.48)				
Log(Turnover)				0.560***			
				(18.59)			
Zero Return (%)					2.773***		
					(17.05)		
Zero Return_2 (%)						2.894***	
						(17.17)	
Log(Spread)							0.255***
							(25.89)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Month Dummies	YES	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES	YES
Firm Clustered	YES	YES	YES	YES	YES	YES	YES

Table 3.11: Difference-in-Difference Estimation (Industry Fixed Effect)
The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX. The dependent variable in each regression is changed in logarithm of idiosyncratic volatility from December 2000 to February 2001, and independent variables are changed in logarithm of stock liquidity measures from December 2000 to February 2001. H-L Spread, H-L Spread_M, Amihud, Turnover, Zero Return (%), Zero Return_2 (%) and Spread are used as liquidity measures respectively in column (1) to (7). Control variables are a market-to-book ratio, Return [-12 -2] and Return [-1]. Industry fixed effect and robust standard deviation are used. Fama-French 48 industry classification is used for fixed effect. All liquidity measures (except zero return measures) and idiosyncratic volatility are in logarithm form. T-statistics are presented in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Dependent Variable: ΔLog(Idiosyncratic Volatility)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-0.294***	-0.241***	-0.227***	-0.248***	-0.013***	-0.012***	-0.297***
	(-37.92)	(-26.38)	(-20.36)	(-32.00)	(-32.92)	(-24.96)	(-86.69)
ΔLog(H-L Spread)	0.165***						
	(6.60)						
ΔLog(H-L Spread_M)		0.323***					
		(11.41)					
ΔLog(Amihud)			0.266***				
			(7.44)				
ΔLog(Turnover)				0.273***			
				(8.07)			
ΔZero Return (%)					0.002		
					(0.32)		
ΔZero Return_2 (%)						0.009	
						(1.01)	
ΔLog(Spread)							0.047**
							(2.04)
Industry Fixed Effect	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.035	0.092	0.085	0.077	0.0002	0.001	0.007

Table 3.12: Two Stage Least Squares (Shorten Time Periods)
The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX. Table covers the period between January 2000 and January 2002; July 2000 and July 2001 and October 2000 and April 2001 in Panel A, B and C, respectively. The dependent variable in each regression is the logarithm of idiosyncratic volatility. Control variables are a market-to-book ratio, Return [-12 -2] and Return [-1]. Standard errors are robust and clustered industry level. Fama-French 48 industry classification is used to cluster data at the industry level. T-statistics are presented in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

Panel A: The Second Stage of 2SLS (Period Covers Between 2000:01/2002:01)							
	Dependent Variable: Log(Idiosyncratic Volatility)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.425*	0.399**	-1.769***	-6.069***	-4.290***	-4.207***	-2.101***
	(1.84)	(2.09)	(-9.23)	(-25.12)	(-60.78)	(-63.76)	(-23.24)
Log(H-L Spread)	0.912***						
	(18.50)						
Log(H-L Spread_M)		1.007***					
		(22.77)					
Log(Amihud)			0.554***				
			(10.60)				
Log(Turnover)				0.931***			
				(10.56)			
Zero Return (%)					4.121***		
					(11.09)		
Zero Return_2 (%)						4.225***	
						(11.52)	
Log(Spread)							0.457***
							(19.49)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Industry Clustered	YES	YES	YES	YES	YES	YES	YES

Panel B: The Second Stage of 2SLS (Period Covers Between 2000:07/2001:07)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.247	0.197	-1.608***	-5.875***	-4.223***	-4.159***	-1.573***
	(0.85)	(0.73)	(-4.36)	(-21.02)	(-61.35)	(-63.35)	(-8.51)
Log(H-L Spread)	0.883***						
	(14.32)						
Log(H-L Spread_M)		0.966***					
		(15.46)					
Log(Amihud)			0.602***				
			(5.90)				
Log(Turnover)				0.825***			
				(8.05)			
Zero Return (%)					3.016***		
					(9.31)		
Zero Return_2 (%)						3.132***	
						(9.69)	
Log(Spread)							0.599***
							(12.66)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Industry Clustered	YES	YES	YES	YES	YES	YES	YES

Table 3.11: Two Stage Least Squares (Shorten Time Periods) (cont.)

Panel C: The Second Stage of 2SLS (Period Covers Between 2000:10/2001:04)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	1.851***	1.441***	-1.003*	-6.131***	-4.219***	-4.145***	3.306*
	(3.55)	(4.17)	(-1.92)	(-19.06)	(-60.96)	(-64.54)	(1.83)
Log(H-L Spread)	1.236***						
	(10.75)						
Log(H-L Spread_M)		1.273***					
		(15.15)					
Log(Amihud)			0.761***				
			(5.23)				
Log(Turnover)				0.935***			
				(7.89)			
Zero Return (%)					3.498***		
					(10.18)		
Zero Return_2 (%)						3.594***	
						(10.78)	
Log(Spread)							1.950***
							(3.96)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Industry Clustered	YES	YES	YES	YES	YES	YES	YES

Table 3.13: Two Stage Least Squares Estimation (Exclude Financial and Utility Sectors)

The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX from January 1999 to January 2003. I exclude financial and utility companies (SIC code between 6000 and 6999 for financial stocks and SIC code between 4900 and 4999 for utility stocks). The dependent variable in each regression is the logarithm of idiosyncratic volatility and the independent variables are the logarithm of stock liquidity measures. H-L Spread, H-L Spread_M, Amihud, Turnover, Zero Return (%), Zero Return_2 (%) and Spread are used as liquidity measures respectively in column (1) to (7). Control variables are a market-to-book ratio, Return [-12 -2] and Return [-1]. Fama-French 48 industry classification is used to cluster data at the industry level. All liquidity measures (except zero return measures) and idiosyncratic volatility are in logarithm form. I use Newey and West (1987) robust standard errors. T-statistics are presented in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	The Second Stage of 2SLS						
	Dependent Variable: Log(Idiosyncratic Volatility)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.050***	2.312***	-2.587***	-5.285***	-4.083***	-4.029***	-2.829***
	(4.48)	(4.58)	(-20.61)	(-29.95)	(-117.63)	(-122.75)	(-46.09)
Log(H-L Spread)	1.260***						
	(12.99)						
Log(H-L Spread_M)		1.467***					
		(12.27)					
Log(Amihud)			0.346***				
			(9.67)				
Log(Turnover)				0.621***			
				(9.43)			
Zero Return (%)					2.727***		
					(13.47)		
Zero Return_2 (%)						2.840***	
						(13.50)	
Log(Spread)							0.264***
							(19.40)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Industry Clustered	YES	YES	YES	YES	YES	YES	YES

Table 3.14: Size Analysis (Orthogonalize by Size)
The sample includes only common stocks (share code 10 and 11) which are listed on NYSE and AMEX from January 2000 to December 2002. I exclude 2001 to eliminate the impact of decimalisation on liquidity measures. I orthogonalize liquidity measures by firm size. Firm size is defined as the logarithm of total asset. I run OLS regression liquidity on firm size and get residuals from this OLS regression. Use the fitted residuals as liquidity measures and employ 2SLS approach. All liquidity measures are residuals. The dependent variable in each regression is the logarithm of idiosyncratic volatility and the independent variables are the residuals of stock liquidity measures. H-L Spread, H-L Spread_M, Amihud, Turnover, Zero Return (%), Zero Return_2 (%) and Spread are used as liquidity measures respectively in column (1) to (7). Control variables are market-to-book ratio, Return [-12 -2] and Return [-1]. Standard errors are robust and clustered industry level. Fama-French 48 industry classification is used to cluster data at the industry level. T-statistics are presented in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent, respectively.

	The Second Stage of 2SLS						
	Dependent Variable: Log(Idiosyncratic Volatility)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.025***	0.024***	0.018***	0.019***	0.026***	0.026***	0.022***
	(20.45)	(20.12)	(21.04)	(24.59)	(21.84)	(21.76)	(25.82)
R(H-L Spread)	3.132***						
	(6.62)						
R(H-L Spread_M)		2.406***					
		(7.94)					
R(Amihud)			0.341***				
			(2.63)				
R(Turnover)				0.004***			
				(4.59)			
R(Zero Return (%))					0.241***		
					(8.27)		
R(Zero Return_2 (%))						0.223***	
						(8.16)	
R(Spread)							1.386***
							(7.57)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Industry Clustered	YES	YES	YES	YES	YES	YES	YES

Table 3.15: Two Stage Least Squares (NASDAQ)
The sample includes only common stocks (share code 10 and 11) which are listed on NASDAQ from April 1999 to April 2003. The second stage of 2SLS regression results where the dependent variable is the logarithm of idiosyncratic volatility and independent variables are the logarithm of stock liquidity measures and control variables are presented in this table. Decimalisation is a time dummy variable which equals to one the period after decimalisation and zero before decimalisation. Control variables are market-to-book ratio, Return [-12 -2] and Return [-1]. All liquidity measures (except zero return measures) and idiosyncratic volatility are in logarithm form. T-statistics are presented in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

The Second Stage of 2SLS							
	Dependent Variable: Log(Idiosyncratic Volatility)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.188	0.222	-3.129***	-5.988***	0.026***	0.028***	-1.945***
	(0.56)	(0.74)	(-12.94)	(-18.27)	(8.08)	(8.39)	(-22.47)
Log(H-L Spread)	0.905***						
	(12.45)						
Log(H-L Spread_M)		0.984***					
		(13.37)					
Log(Amihud)			0.441***				
			(18.84)				
Log(Turnover)				0.804***			
				(12.51)			
Zero Return (%)					0.093***		
					(7.76)		
Zero Return_2 (%)						0.097***	
						(9.53)	
Log(Spread)							0.414***
							(19.76)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Industry Clustered	YES	YES	YES	YES	YES	YES	YES

Chapter 4

Does a Decline in Tick Size Affect Momentum Profits? Evidence from the American Stock Exchange

4.1 Introduction

The limits to arbitrage theory suggests that when the market experiences a liquid period, there should be fewer anomaly profits due to lower arbitrage activities, also suggested by the efficient market hypothesis. Empirical studies investigate this phenomenon and their results support the theory (see, for example, Chordia et al., 2014). In contrast, a recent study by Avramov, Cheng and Hameed (2016) shows that the relation between market illiquidity and momentum profit is negative. In other words, when the market is liquid, investors expect to earn higher profits from the long-minus-short portfolio created based on momentum anomaly.

In this chapter, I investigate whether liquid stocks earn *higher* momentum profit exploiting plausibly exogenous variation created by the tick size change in the US markets. The SEC announced a decline in the minimum price variation for AMEX companies during the period February 1995 to May 1997. Specifically, if the share price of a stock was between \$5 and \$10, the minimum tick size increments changed from \$1/8 to \$1/16. The reason for focusing only on momentum anomaly is because it is the most persistent anomaly across all different market conditions, stock characteristics and time horizons and, more importantly, there is a lack of consensus regarding the impact of liquidity on momentum profit.

The theoretical link between liquidity and anomaly returns can be understood by the notion of the limits to arbitrage theory as explained by Shleifer and Vishny (1997). They claim that limits to arbitrage affect sophisticated investors' trading in the stock market and eliminate inefficiency due to constraints on wealth flow from irrational investors. Sophisticated investors' objective is to increase the net profits of their investments after costs. This can be achieved when trading is easy on the market or, in other words, when the market experiences a liquid period. The increase in the liquidity will lead to an increase in arbitrage activities and this will eliminate the inefficiency of the stock markets. In other words, investor should not earn an abnormal return using any strategy when the market is liquid. On the other hand, increasing liquidity may also allow investors to implement strategies more easily due to the availability of capital. Therefore, the price of the liquid stocks should rise and cause higher momentum profits for investors, as explained by the notion of behavioural bias. Another explanation concerns the relation between liquidity and expected stock return. As stated in prior literature, when the stock is liquid, the investor expects to get less future return due to less risk exposure (Amihud and Mendelson, 1986). In this experiment, since the treatment group stocks become liquid on average during the event period, the short leg should bring less future return than the prior event period and this should cause a rise in the long-minus-short portfolio. Thus, we should anticipate a positive relation between liquidity and momentum profits.

Unlike previous studies, this study relies on a peculiar market design that is created by regulators by decreasing the minimum price variation for stocks in the price range between \$5 and \$10. This design allows me to adopt a reliable identification strategy to show causality between liquidity and momentum profits since the decline in the tick size increases the stock liquidity for the treatment group compared with the control group. The decline in tick size will make the bid-ask spread narrower, which will lead to a rise in the liquidity of the stocks.

Contradicting the limits to arbitrage theory, my finding is in line with the notion of the positive link between liquidity and momentum profits, as Avramov et al. (2016) present in their study. Difference-in-differences analysis shows that long-minus-short portfolio returns of the treatment group companies experience a three per cent higher return than the control group per month and this result is statistically significant at the one per cent level. The result is consistent after employing several robustness tests, such as including time fixed effects, adopting placebo analysis, using different control groups and different time horizons.

The remainder of this chapter is organised as follows. Section 4.2 summarises the prior related literature. Section 4.3 describes the empirical setting and data. Section 4.4 reports the empirical results. Section 4.5 reports the results of several robustness tests. Section 4.6 concludes the chapter and offers some comments and suggestions for further research.

4.2 Prior Studies

Asset pricing anomalies are considered an inefficiency of the stock market. When investors do not react as they should to new information, the price of the stocks does not fully adjust itself immediately, thus financial anomalies occur. There have been plenty of studies that try to determine what should be considered financial market anomalies, since some of the anomalies disappear after a short period or when controlling for other factors. One of the most prominent asset pricing anomalies is momentum anomaly. Jegadeesh and Titman (1993) claim that high-return recent-past stocks outperform the low-return recent-past stocks, and this holds in different market conditions and asset classes (e.g. Asness, Moskowitz and Pedersen, 2013). Momentum strategy suggests buy(long) with high past performance stocks and sell(short) with low past performance stocks. Because of this trading strategy, the long-minus-short portfolio should bring positive profits for the investor.

Not only historical stock data but also corporate finance information is used to predict subsequent stock returns. Sloan (1996) shows that low-accrual firms earn higher returns. Hirshleifer et al. (2004) document that stocks with low net operating assets outperform stocks with high net operating assets. Titman, Wei and Xie (2004) show that increasing capital investment brings negative returns. Fama and French (2006) find that earnings can be used to estimate stock returns. Cooper, Gulen and Schill (2008) document that asset growth is one of the important components in predicting cross-sectional stock returns. Novy-Marx (2013) shows that gross profits have the power to estimate cross-sectional return and that high-profit firms outperform less profitable firms. They suggest that high asset growth brings low returns.

In addition to using corporate finance information to predict future return, several predictions of issuing stock are used to understand cross-sectional return. Loughran and Ritter (1995) show that there is a negative relation between net stock issues and stock returns, which is further documented by Pontiff and Woodgate (2008). Daniel and Titman (2006) show that there is also a negative relation, but between stock returns and composite equity. Contrary to the capital asset pricing model (CAPM), Ang et al. (2006) document that low idiosyncratic volatility firms earn higher returns than high idiosyncratic volatility firms. In this chapter, I focus only on the momentum anomaly since it is well-accepted and is extensively used as an investment strategy.

Why do financial market anomalies not attenuate over time since markets are efficient? This question is longstanding in the history of finance and researchers have been trying to answer it for many years. Researchers examine the conditions where limits to arbitrage are relaxed in the markets. Schwert (2003) states that anomalies can be considered an indication of either profit opportunities or that asset pricing models are not adequately defined to explain the behaviour of the stock market. He claims, after reviewing the anomalies documented in the 1980s, that when arbitrage opportunities increase, anomaly returns should be attenuated. Korajczyk and Sadka (2004) investigate the link between trading cost and momentum and find that reduction in trading costs increases arbitrage opportunities, which causes fewer momentum profits. Mashruwala, Rajgopal and Shevlin (2006) examine the impact of liquidity on the accrual anomaly. They suggest that low liquidity firms bring the highest accrual anomaly profits.

Stambaugh et al. (2012) investigate the impact of investor sentiment on asset pricing anomalies. Their hypothesis is that high investor sentiment results in high mispricing, which increases the profits of the long-minus-short portfolios. Chu, Hirshleifer and Ma (2016) investigate the circumstances in US exchange markets where regulators can relax the limits to arbitrage by allowing short selling. Short selling is one of the most acceptable limits to arbitrage since investors should short sell for the lowest-performance stocks. In 2005, the SEC decided to allow investors to short sell stocks when the stock price went down for a certain number of companies (removing the uptick rule, Regulation SHO).[27] This pilot programme enabled authors to investigate the impact of the relaxation of short selling on market anomalies. They use 10 well-known anomalies and find that relaxation of short selling constraints decreases the combined anomaly returns. Pilot group firms experienced 77 basis

[27]A trading restriction that states that short selling in only allowed on an uptick. In the pilot programme, between May 2005 and August 2007, the SEC removed the uptick rule for companies arbitrarily chosen from the Russell 3000 index.

points less long-minus-short portfolio returns compared with the non-pilot group during the event period per month. This chapter contributes to the literature in a similar way by examining the impact of liquidity on momentum anomaly.

Liquidity is considered the cornerstone of the financial markets. It is used to determine the quality of the markets. It is defined as the market's ability to trade an asset quickly without significantly affecting its market price. Its effect on financial market anomalies has also been examined. According to the theory, an increase in market liquidity should decrease anomaly returns. Chordia et al.'s (2014) recent empirical paper presents supporting evidence of earlier researchers exploiting decimalisation as an exogenous event that increases overall liquidity by decreasing the minimum tick size variation from \$1/16 to a penny in the US stock exchanges. They show that when the market is liquid, most of the anomalies (8 out of 12 anomalies) economically decline after adopting the decimal pricing system and 5 of these 12 anomalies disappear.[28] One of the caveats to this paper is that they use a very wide time horizon: before decimalisation between 1976 and 2000 and after decimalisation between 2001 and 2011. Hence, it does not provide clear evidence that financial anomalies attenuated due to an increase in liquidity.

In contrast, Avramov et al. (2016) investigate the link between market liquidity and momentum anomaly and find a contradictory result. They find their results ”surprising” and show that the momentum profit is larger when the market is liquid. Therefore, they claim that there is a positive relation between market liquidity

[28] Chordia et al. (2014) consider size, book-to-market, lagged return, momentum, turnover, illiquidity, accruals, asset growth, new issues, idiosyncratic volatility, gross profitability and standardised unexpected earnings as financial anomalies.

and momentum profit. They use the Amihud (2002) illiquidity measure as a proxy for market liquidity to show that when market illiquidity increases, the long-minus-short portfolio return decreases. They suggest that their results hold when they control for macroeconomic conditions, return dispersion and investor sentiment. They also provide supporting evidence by examining Japan and Eurozone as additional analyses. Avramov et al. (2016) mainly focus on the relationship between market liquidity and momentum profit, but in this analysis, I have investigated the impact of the tick size on momentum return and explain my result mentioning stock liquidity. Also, my study uses well-established econometrics technique to eliminate potential endogeneity biases.

The lack of consensus regarding the impact of liquidity on momentum anomaly is the motivation for investigating this issue in more detail using the decline in the tick size as a proxy for liquidity. The impact of adopting a new tick size on market quality has been examined extensively in the US markets as well as international markets. Prior studies suggest that when the tick size declines, the bid-ask spread should go down and stocks become more liquid. Ahn et al. (1996) investigate the tick size change in the AMEX and find that trading costs decline by 18.9 per cent. Bacidore (1997) documents that adopting decimal pricing in the Toronto Stock Exchange reduced the spread. Harris (1997) summarises all tick size change studies in the US context as well as international exchange markets. Ronen and Weaver (2001) find that decreasing the tick size from \$1/16 to \$1/8 narrows the bid-ask spread and leads to an increase in market quality on the AMEX. Goldstein and Kavajecz (2000) investigate the change in the NYSE after decreasing the minimum price increments from \$1/8 to \$1/16, and find that liquidity increases after this change. Furfine (2003) shows that decimalisation decreases the transaction costs by narrowing the bid-ask spread.

Another important point that needs to be clarified is the importance of the size of the firms on momentum anomaly. Since the treatment group firms are relatively small market capitalisation companies compared with the control group firms, one should question whether this issue might drive the result. However, Israel and Moskowitz (2013) study this issue in depth. They claim that there is no substantial difference in momentum profits across different sized firms. They also suggest that there is no monotonic relation between size and momentum strategy: mid-size quintile firms earn the highest momentum profits. Therefore, I can rely on my identification strategy that momentum profit is driven by the change in liquidity, not the size of the firms.

4.3 Empirical Setting and Data

In the long history of the US exchange markets, the minimum price variation stayed at the same level, \$1/8. Public discussion of decreasing this price variation amplified at the beginning of 1990s. Academicians and practitioners suggested that the regulator should step up and decrease the minimum price increment to reinforce the competitiveness of the US exchange markets, and the SEC began considering changing the minimum price variation in the mid-1990s.

In 1992, the SEC made its first move. The AMEX reduced the minimum price variation (tick size) from $1/8 to $1/16 for stocks priced between $1 and $5 on September 3, 1992.[29] Following this change there was an extension to the rule. On February 1, 1995, the minimum price variation of $1/16 was also applied to stocks priced between $5 and $10.[30] In May 1997, the SEC decided to implement the $1/16 rule for all companies trading on the AMEX, NYSE and the NASDAQ.[31] Finally, after much debate, on January 29, 2001 the SEC abandoned the fractional system and adopted the decimal pricing system in the AMEX and the NYSE.[32]

4.3.1 Sample Construction

My full sample comprises all ordinary common stocks (share codes 10 and 11) listed on the AMEX, and data are obtained from the Center for Research in Security Prices (CRSP). Monthly Fama-French factors, that is, the market premium (MKT), small-minus-big (SMB) and high-minus-low (HML) factors, are downloaded from Kenneth French's website.[33] The sample period covers January 1980 to April 1997, after which the SEC decided to implement the $1/16 tick size rule for all companies in the three major markets: the NYSE, the AMEX and the NASDAQ. Treatment and control groups are distinguished based on the closing daily price on the last trading day, January 31, 1995.[34] If the closing price of a stock is between $5 and $10,

[29]AMEX Rule 127 Minimum Fractional Changes, 57 Federal Register 40484 (September 3, 1992).

[30]Continuation of AMEX Rule 127 Federal Register 16894 Vol. 60, No. 63 (April 3, 1995).

[31]Order Granting Approval of Proposed Rule Change Relating to Trading in $1/16, 62 Federal Register 25682 (May 9, 1997).

[32]Three months later the NASDAQ also adopted the decimal pricing system (April, 2001).

[33]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[34]Since the SEC pilot programme began on February 1, 1995.

which are appointed to implement lower minimum price increments, the company is selected for the treatment group; if the closing price of a stock is above \$10, the company is selected for the control group. To follow traditional anomaly papers, I exclude the stocks priced below \$5 on the last trading day. My final sample includes 148 companies in the treatment group and 193 companies in the control group.

I construct the momentum anomaly in the traditional way following Jegadeesh and Titman (1993), who introduced momentum for the first time. Momentum anomaly is one of the most consistent anomalies in the history of asset pricing and because of that receives much credit. The theory behind the anomaly is simple; it states that the highest past performance stocks will continue to outperform the lowest past performance stocks in subsequent months.

In this study, the portfolio formation period is between month $m-12$ and $m-2$ and I skip the most recent past return $m-1$ to eliminate the short-term reversal effect. Momentum return is the cumulative returns during the formation period. Stocks are sorted into quintile portfolios based on formation period return at time m. I rebalance the quintile portfolios in each month. The reason for sorting stocks into quintile portfolios is the lack of the number of companies in each portfolio.[35] Each portfolio's returns are calculated based on equal-weighted portfolios in this analysis. If the stock is in the highest(lowest) past performance quintile, then it is considered a long(short) leg. Finally, I create a zero-cost portfolio with the long-minus-short portfolio in the traditional way: buying the highest performance quintile and selling

[35] As a robustness check, I sort stocks into deciles and results are unchanged.

the lowest performance quintile. I require the stock to have a valid monthly return for the entire formation period to include the stock in my sample.

Following standard practice in the literature, I winsorised momentum return at the one per cent and 99 per cent levels in each month to eliminate the impact of outliers in my sample.

4.3.2 Summary Statistics

Table 4.1 records the descriptive statistics of each portfolio as well as the long-minus-short portfolios for the entire sample, treatment, and control group separately. To analyse the momentum anomaly between treatment and control group, I report the raw return, the CAPM alpha, the Fama-French three-factors alpha, and CAPM beta, as well as two liquidity proxies, namely Amihud (2002) and Corwin-Schultz (2012) in each quintile. The sample period spans January 1980 and December 2000 in Table 4.1.

Panel A of Table 4.1 shows the full sample quintile portfolio construction based on the equal-weighted momentum return. The long portfolio has the highest momentum return and the short portfolio has the lowest momentum return, as established in the prior literature. It is essential to show that the momentum anomaly actually exists during the sample period in this study. The long-minus-short portfolio is positive, at 1.08 per cent, and statistically significant at the one per cent level, which suggests that the momentum anomaly exists during the sample period. After we control for the risk-adjusted return based on the CAPM and the Fama-French three-factor model, momentum return remains at the same level and is statistically significant.

Panels B and C of Table 4.1 record each quintile's portfolio returns and the long-minus-short portfolio return for the treatment and control group separately. By doing so, I can ensure that there is no systematic difference between the treatment and the control groups that drives my result. When I partition the entire sample into treatment and control groups, long-minus-short portfolio return remains around the same level and is statistically significant, which means that there is no systematic difference between treatment and control group in terms of momentum return. This is also important since the treatment group companies are small-size companies compared with the control groups. Hence, the result eliminates the possibility of a small-size anomaly effect, as explained by Banz (1981).[36]

[Insert Table 4.1 near here]

In addition to portfolio returns, I provide the portfolio average liquidity based on two well-known proxies of liquidity, Amihud (2002) and Corwin-Schultz (2012). The Amihud measure is defined as the monthly average of the ratio of absolute return of a stock divided by its volume traded in dollars. The definition of the Amihud measure of stock i in month m is given by:

$$Amihud_{im} = \frac{1}{D_{im}} \sum_{d=1}^{D_{im}} \frac{|Return_{id}|}{Dvol_{id}} \tag{4.1}$$

[36]Smaller firms will earn more profits than larger companies.

where D_{im} denotes the number of days in which stock has a valid ratio in month m for stock i. $Return_{id}$ is daily return in stock i on day d. $Dvol_{id}$ is the dollar value of trading volume on day d for stocks i. The measure captures the price impact since it is defined as the monthly average of the ratio of the absolute return of a stock divided by its volume traded in dollars and interpreted as the price change per dollar of trading volume.

The results of the liquidity characteristics of each portfolio are consistent with Avramov et al.'s (2016) study. Short leg has the highest illiquid portfolio and long leg has the lowest illiquid portfolio. Specifically, the Amihud measure is 8.68 in portfolio (1), which is substantially higher than in portfolio (5), at 1.94. The results are similar when we use Corwin-Schultz (2012) as an additional proxy for liquidity.[37]

Another point about Table 4.1 is that the treatment group companies consistently have higher average illiquidity in each portfolio than the control group. Hence, it is essential to report how illiquidity proxies changed in each portfolio and compare the treatment and control groups. This can also provide an interpretation of the parallel trend assumption of the difference-in-differences estimation. Table 4.2 reports the result of the average of the two proxies of liquidity before and after, separately for treatment and control groups, and show the difference-in-differences at the last column. Both liquidity proxies are decreasing during the tick size change period for treatment and control groups, but in the last column, the difference-in-differences

[37] Amihud (2002) and Corwin and Schultz (2012) proxies are winsorised at one per cent and 99 per cent levels in each month.

result shows that treatment group companies become more liquid by adopting lower minimum price variation.[38]

[Insert Table 4.2 near here]

Even though I report long-minus-short portfolio returns as positive and statistically significant in the entire period from January 1980 to December 2000, it is essential to provide evidence that the long-minus-short portfolio returns are statistically significant before the tick size change. Table 4.3 reports the equal-weighted average long-minus-short portfolio returns as well as risk-adjusted factor alphas, the CAPM, and the Fama-French three-factor model, between January 1980 and December 1994 for all companies in my sample. Results are consistent with Table 4.1; therefore, we verify that the momentum anomaly exists before the tick size change for companies in my sample.

[Insert Table 4.3 near here]

4.4 Empirical Analysis

The main hypothesis is that liquid stocks earn more momentum anomaly compared with illiquid stocks. To test my hypothesis, I exploit the difference-in-differences estimation technique. The change in the minimum price variation for a certain group,

[38]The percentage decline of Amihud measure for treatment and control group is 72% and 59%, respectively and the percentage decline of high-low spread measure for treatment and control group is 32% and 11%, respectively.

stocks priced between \$5 and \$10, will allow me to exploit the traditional difference-in-differences framework. First, I split my stocks into treatment and control groups based on the last trading price before the tick size change, on January 31, 1995. Second, I sort stocks into quintiles based on momentum and calculate the equal-weighted portfolio returns for each portfolio for only the treatment group. Third, I consider the highest performing portfolio as long leg and the lowest performing portfolio as short leg and calculate the long-minus-short portfolio returns. I do the same for the control group as well. I then investigate whether the long-minus-short portfolio returns are different between the treatment and control groups during the period they have a different tick size, adopting the difference-in-differences estimation procedure.

4.4.1 The Difference-in-Differences Estimation

The main identification strategy is formulated as follows:

$$Ret_{im} = \alpha + \beta Pilot_i \times During_m + \beta_1 Pilot_i + \beta_2 During_m + \epsilon_{im} \tag{4.2}$$

Ret_{im} is the monthly return of portfolio i, which can be long leg, short leg or the long-short portfolio of momentum anomaly, in month m; $Pilot_i$ is a dummy variable which is equal to one if portfolio i is formed on treatment firms, and zero otherwise; $During_m$ is a dummy variable, which equals one if month m is between February 1995 and April 1997.

The main coefficient of interest is β in equation (4.2). The coefficient will determine the impact of the tick size change on momentum return of the treatment group compared with the control group. Following Hirshleifer et al. (2016), I also include time fixed effects to eliminate the unobserved factors that can affect both treatment and control group in each year. By including time fixed effects, I drop the $During_m$ since time fixed effect captures all the impact:

$$Ret_{im} = \alpha_m + \beta Pilot_i \times During_m + \beta_1 Pilot_i + \epsilon_{im} \tag{4.3}$$

Throughout the chapter, all my interpretations are according to the time fixed effects analysis as stated in equation (4.3), even though I present the results of equation (4.2) as well. One should note that adding time fixed effects does not change the magnitude of the coefficients; it will only affect the significance level. I report the result of the long leg, short leg and long-minus-short leg portfolios using equation (4.2) and (4.3) separately.

Table 4.4 reports the results of the difference-in-differences estimations; first three columns show the results of equation (4.2) and last three columns show the results of equation (4.3). Overall, long-minus-short portfolio results suggest that the treatment group has 3 per cent more anomaly profits than the control group during the tick size programme per month. This result is in line with the notion that there is a positive relation between momentum anomaly and stock liquidity proposed by Avramov et al. (2016) and suggests that liquid stocks bring more long-minus-short portfolio returns.

The magnitude of the β coefficient in the short leg is negative and relatively high even though it is not significant. This happens because the treatment group companies become liquid during the period compared with the control group companies. As stated earlier, when stocks become liquid, the expected stock return should decrease. Due to the rise in overall liquidity in the treatment group, shorting the lowest performing portfolio should bring less momentum return for the treatment group compared with the control group and this should cause a higher long-minus-short portfolio return for the treatment group companies. This supports the notion of why one should expect to earn higher momentum returns when liquidity increases.

Another point that needs a close interpretation is to look at other coefficients β_1, namely $Pilot_i$. This gives us the difference in the long-minus-short portfolio returns between treatment and control groups before the tick size change happened. If size anomaly drives my results, we should expect to see positive and significant coefficients. However, the long-minus-short portfolio returns are negative and statistically significant, which indicates that before the tick size change happens, the control group firms earn more momentum returns compared with the treatment group. This is supportive of the idea that liquid firms earn more momentum profits compared with illiquid firms, since before the tick size change control group firms are more liquid than treatment group, as presented in Table 4.1.

[**Insert Table 4.4 near here**]

To claim the power of my identification strategy, I follow Hirshleifer et al.'s (2016) study and show that during the tick size change period, the average long-minus-short portfolio returns are still there for the control group. I present equal-weighted average of raw return, CAPM and Fama-French three-factor alphas from momentum anomaly during the tick size change period, from February 1995 to April 1997, for the control group only. Table 4.5 reports the results of this analysis. It is clear and consistent that momentum anomaly is there and statistically significant for control group companies during the tick size change period.

[**Insert Table 4.5 near here**]

4.4.2 Value-Weighted Portfolio Returns

In the main analysis, I have used equal-weighted portfolio returns. To confirm my results are not driven by the size, I construct my portfolio return based on the weights of each stock in the previous month. Table 4.6 presents the results of value-weighted portfolio returns analysis and confirms my earlier results that lower tick size stocks earn higher momentum anomaly return than higher tick size stocks.

[**Insert Table 4.6 near here**]

4.5 Robustness Analysis

4.5.1 Benchmark Adjusted Portfolio Returns

In the main analysis, I used raw return as a dependent variable. Now, I follow Hirshleifer et al. (2016) and adjust portfolio returns with the CAPM and the Fama-French three-factor model to test my hypothesis. I adopt their methodology and obtain benchmark-adjusted returns first by regressing the time series of raw return on the CAPM and the Fama-French three-factors and obtaining intercept and residuals for each month. I then sum intercept and residuals to get monthly benchmark-adjusted returns.

Table 4.7 reports the result of benchmark-adjusted return analysis. As we expect, the result does not change, thus the analysis confirms that my main results hold with benchmark-adjusted returns.

[**Insert Table 4.7 near here**]

4.5.2 The Effect of Ending of Different Tick Size Period

After much debate, SEC decided to implement the new tick size, $1/16 for all stocks traded on the US exchange markets. This new tick size was used until the SEC approved the decimal pricing system in January 2001. To be able to justify that my results are driven by the liquidity difference between the treatment and the control groups, I conduct the difference-in-differences analysis by extending the period. By doing so, I expect no significant difference in the anomaly return between treatment and control groups. Since until decimalisation all companies used the same tick size, my sample period for this analysis spans January 1980 and December 2000.

My main identification strategy, as shown in equation (4.3) can be represented as follows:

$$Ret_{im} = \alpha_m + \beta Post_m \times Pilot_i + \beta_1 Pilot_i \times During_m + \beta_2 Pilot_i + \epsilon_{im} \tag{4.4}$$

Ret_{im} is the monthly return of portfolio i, which can be long leg, short leg or the long-short portfolio of an anomaly in month m; $Pilot_i$ is a dummy variable which is equal to one if portfolio i is formed on treatment firms, and zero otherwise; $During_m$ is a dummy variable, which equals one if month m is between February 1995 and April 1997; $Post_m$ is a dummy variable, which equals one if month m is between April 1997 and December 2000. Time fixed effect is also included.

Table 4.8 shows the result of this analysis. The main coefficient of interest is β in equation (4.4), long-minus-short portfolio returns, and it presents insignificant results with and without controlling for time fixed effect. This is confirmation that the difference between long-minus-short portfolio returns is driven by the different tick size that treatment and control groups use. We should also note that $During_m$ is insignificant. This is because there is no difference in the tick size for the control group before February 1992.

[Insert Table 4.8 near here]

4.5.3 Placebo Analysis

To justify the validity of my result, I conduct placebo test analysis. By doing so, I avoid the correlation between the intervention and unobserved shocks that may affect treatment and control groups differently. In other words, if results are driven by another factor such as size anomaly, I should also get a significant result in the falsification tests. There are several ways of doing placebo tests (falsification tests), and I will adopt two ways in this section, using pseudo-period and using different markets.

One of the most commonly used falsification tests is to use a pseudo-period and examine the difference-in-differences estimation based on this pseudo-period. Specifically, I assume that tick size change happened in 1991 and construct a pseudo-event window from February 1991 to April 1993. I retain the same treatment and control group companies and exploit the difference-in-differences estimation as follows:

$$Ret_{im} = \alpha_m + \beta Pilot_i \times PseudoDuring_m + \beta_1 Pilot_i + \epsilon_{im} \tag{4.5}$$

Ret_{im} is the monthly return of portfolio i, which can be long leg, short leg or the long-short portfolio of an anomaly in month m; $Pilot_i$ is a dummy variable which is equal to one if portfolio i is formed on treatment firms, and zero otherwise; $PseudoDuring_m$ is a dummy variable, which equals one if month m is between February 1991 and April 1993. Time fixed effect is also included.

Table 4.9 reports the results of the first falsification test. The coefficient of interest is again β in equation (4.5). As stated earlier, I expect to see an insignificant result to justify that there are no unobservable shocks that affect treatment and control groups differently. The coefficient of the long-minus-short portfolio returns with and without time fixed effects is insignificant, which is in line with my hypothesis that the difference in portfolio returns between treatment and control group is driven by liquidity.

[**Insert Table 4.9 near here**]

A second falsification methodology is to use a different exchange market that is not affected by any change during the same period of tick size change as happened in the AMEX. I use the NYSE for this analysis. I distinguish the treatment and control groups in the same way I constructed them in the main analysis section. On January 31, 1995, stocks priced between $5 and $10 are identified as the treatment group and stocks priced between $10 and $15 are identified as the control group. The reason for restricting the control group stocks to a certain price range is to have a comparable number of firms in each group. There are 194 firms in the treatment group and 222 firms in the control group. My sample period is between January 1980 and April 1997.

The results of the second falsification test are reported in Table 4.10. The coefficient of interest shows that there is no difference between the treatment and control groups during the period that AMEX adopted a different tick size for a different price range. Hence, both of my falsification tests provide evidence that the results of my analysis are not driven by some other unobservable shock that affects the treatment and control groups differently.

[Insert Table 4.10 near here]

4.5.4 Different Control Groups

There may be concern with regard to construction of the treatment and control groups since I have chosen the last trading day closing price to distinguish the treatment and the control group stocks. In my main analysis, I formed my groups in the following way: if the stock is priced between $5 and $10 then the firm is in the treatment group, and if stock is priced above $10, the firm is in the control group. There is a potential issue with this analysis: a noise estimation of the potential outcome of the difference between treatment and control groups, since the company may switch groups during the period. To control this noise, I use different criteria to form my treatment and control groups. First, I follow Ahn et al. (1996) and use NYSE firms that are priced between $5 and $10 as a control group. Second, I follow Bacidore (1997) and take the three months' average of the pre-event window daily price and construct my treatment and control groups. Last, I follow Ahn et al. (1996) and take the three months' average of the pre-event window daily price and the three months' average of the post-event daily price and construct treatment and control groups.

In the first analysis, the treatment group is the same as the main analysis's AMEX stocks, which are priced between $5 and $10 on the last trading day before the programme begins, and my control group is the NYSE stocks that are priced in the same range as the AMEX stocks, between $5 and $10 on the last trading day before the programme begins. There are 148 stocks in the treatment group and 194 stocks in the control group. I use the same identification strategy as shown in equations (4.2) and (4.3). Table 4.11 reports the results of this analysis. Even though magnitude of the coefficient decreases slightly, it is still significant at the 5 per cent level of significance. The difference in the long-minus-short portfolio return in treatment group is that it has a 2.39 per cent higher monthly return compared with the control group during the different tick size period.

[Insert Table 4.11 near here]

Second, I use the AMEX companies as in the main analysis but using different identification. I take the average daily closing price of the last 90 days before the tick size change. If the average price of the stock is between \$5 and \$10 then this stock is labelled as the treatment group, and if the average price of stocks is above \$10 then it is labelled as the control group. The treatment group includes 158 stocks and the control group includes 209 stocks. The identification strategy is same as shown in equations (4.2) and (4.3). Table 4.12 presents the results of this analysis. Using three months' average to construct treatment and control groups does not have an impact on the estimation results. The monthly average of the long-minus-short portfolio returns of treatment group is 3.27 per cent higher than the control group during the difference tick size period.

[Insert Table 4.12 near here]

Last, I use the AMEX companies and take the average daily closing price of the last 90 days before the tick size change and the average daily closing price of the following 90 days after tick size change, separately. Then I retain only the stock that stays in the same price range before and after. If the stock price 90 days before and after average is between $5 and $10 then the stock is in the treatment group; if the price is above $10 then the stock is in the control group. The treatment group consists of 124 companies and the control group consists of 186 companies. The identification strategy is still the same as in equations (4.2) and (4.3). Table 4.13 presents the results of this analysis. Even though the magnitude of the coefficient of interest decreases, it is still statistically significant at the 10 per cent level when we use the time fixed effects.

[**Insert Table 4.13 near here**]

Overall, the main result of my analysis is unchanged, when I use different treatment and control groups. Therefore, the positive relation between liquidity of stock and momentum anomaly exists and it does not depend on the choice of the treatment and the control groups.

4.5.5 Shorten the Sample Period

Another concern might be that the impact may come from the time horizon used in this study. Hence, it is worth presenting evidence that the main results do not depend on the time horizon. I exploit the difference-in-differences estimation as in equations (4.2) and (4.3) between January 1990 and April 1997.

Table 4.14 reports the results of the different periods' analysis. The magnitude of coefficient loses its power (β is 2.44 per cent), but the result is still statistically significant at the 10 per cent level with t-statistic of 1.83 in the last column. Since most of the anomaly studies suggest using enough time periods to observe the anomaly return, it is expected to have a lower magnitude of the coefficient. This result again verifies that treatment group long-minus-short portfolio return created based on momentum anomaly is higher than the control group.

[Insert Table 4.14 near here]

4.5.6 Decile Portfolios Analysis

The main analyses in this chapter use quintile portfolios due to lack of the number of companies in the treatment and control group; however, it is still important to show that the result does not depend on the choice of the portfolios. Hence, I sort stocks into deciles for each group separately and exploit the same estimation methodology as presented earlier in equations (4.2) and (4.3). Bear in mind that by doing this, I do not have many observations in each portfolio, so the estimation results may not be meaningful in a statistical sense, but it is still important to see the magnitude of the coefficient.

Table 4.15 shows that the magnitude of the coefficient is in a similar range to the main result. The β coefficient is 2.92, which suggests that the treatment group companies have a 2.92 per cent higher long-minus-short portfolio return compared with the control group during the period between January 1980 and April 1997.

Even though the magnitude of the coefficient is more important in this exercise, the coefficient is marginally significant at 10 per cent level, and with t-statistic of 1.64 in the last column.

[Insert Table 4.15 near here]

To summarise, several robustness analyses provide evidence consistent with that presented in the main analysis. First, I control for the effect of ending the use of different tick size and show that the coefficient of interest becomes insignificant as predicted, as when the treatment and the control group begin using the same tick size the difference disappears. Second, I provide two falsification tests. First I use a different period as a pseudo-time horizon, and second I use the NYSE companies during the same period the actual tick size difference occurs in the AMEX. Both falsification tests show that there are no statistically significant results. Third, to address the issue of constructing the treatment and the control groups, I identify them in several different ways: using the NYSE stocks that are priced between $5 and $10 during the same period; taking the three months' pre-event daily price average; and taking the three months' pre-event and post-event average separately and retaining the companies that remain in the same group. Using different treatment and control groups do not have an impact on my result. Fourth, I control the choice of the time horizon since the pre-event window is longer than the post-event window in the main analysis, but the results are still unchanged. Finally, I sort stocks into deciles instead of quintiles. Even though the significance level decreases, the magnitude of the coefficient of interest remains at the same level.

4.6 Conclusion

The limits to arbitrage theory suggests that when the market is liquid, there should not be an anomaly return. Chordia et al. (2014) investigate this phenomenon in the context of changing fractional pricing to decimal pricing in the US exchange markets. They find that decimalisation increases the liquidity by decreasing the tick size in the market and this increase leads to a decline in several well-known market anomalies' returns, consistent with the theory. On the other hand, a recent paper published by Avramov et al. (2016) looks at this concept from a different perspective and examines only momentum anomaly. They suggest that the relation between momentum anomaly and market liquidity is positive. In other words, when the market is liquid, a long-minus-short portfolio created by momentum anomaly brings more return.

This chapter contributes to the literature by exploiting the causal link between liquidity and momentum anomaly since prior literature lacks evidence of causality. The SEC decided to implement a different tick size for the different price ranges in the AMEX between February 1995 and April 1997. Specifically, if the stock price was between \$5 and \$10 then the tick size was \$1/16 and if the stock price was above \$10 then the tick size was \$1/8 during the period. As prior literature suggests, lower tick size generally induces a higher liquidity, and this programme provides a plausibly exogenous variation in which to examine the impact of liquidity on momentum, clearly exploiting the difference-in-differences framework. The treatment group is the stocks priced between \$5 and \$10 and the control group is the stocks priced above \$10. I find that treatment group stocks have around 3 per cent more long-minus-short portfolio return compared with the control group during the programme, which suggests that there is a positive relation between liquidity and momentum anomaly. This result is consistent after controlling with several robustness analyses.

A first explanation may be that when stocks become liquid, implementation of the momentum strategy will become easier for investors. Therefore, the demand for the liquid stocks will increase and cause an increase in their price. This will lead to an increase in momentum anomaly return. This follows the notion of behavioural bias. The second and more plausible explanation is that when liquidity difference between the highest quintile portfolio and the lowest quintile portfolio decreases, there should be more anomaly profits. Since anomaly profits are mostly driven by a short leg, when the stocks in the short leg become liquid they should bring less return and cause an increase in the long-minus-short portfolio return. As we have seen that the lowest quintile portfolio (short leg) has the highest illiquid stocks, and the highest quintile portfolio (long leg) has the lowest illiquid stocks, and during the programme the treatment group firms become more liquid overall as shown in the summary statistics, I may expect to see less short leg return, which leads to more long-minus-short profits for the treatment group during the programme (Avramov et al., 2016).

There are some limitations to this chapter that need to be highlighted. First, selection of the companies into the treatment and the control groups is not randomised. There is a certain threshold that distinguishes the treatment and the control groups.

Second, maintaining the same treatment and control groups may not be feasible. In this analysis, I identify the treatment and the control groups based on the daily price on the last trading day before the event begins. Hence, there may be some companies that switch groups during the period. I use several different construction techniques to control for the effect of this and the main result remains at the same level. There was an equal trend in the treatment and the control groups prior to the event so the application of the difference-in-differences estimation is a most appropriate technique to adopt in this chapter.

This result is also important from policy-makers' perspective since there is a new pilot programme where the SEC has increased the tick size for small capitalisation firms in the US exchange market. On May 6, 2015, the SEC approved a new tick size pilot programme to analyse whether increasing the tick size for small capitalisation stocks will have an impact on market quality, which brings to the debate once more the notion of the optimal tick size.[39] A further extension of this chapter could be to investigate other anomalies exploiting the different price variation since I only examine momentum anomaly.

[39]The new tick size pilot programme is designed to increase the tick size from $0.01 to $0.05 for firms that have market capitalisation less than $3 billion or whose average volume is less than $1 million each day, or whose volume-weighted average price is higher than $2.00 in a trading day.

4.7 Tables

Table 4.1: Summary Statistics

This table reports the descriptive statistics of the momentum portfolio in my sample between 1980 and 2000. Momentum anomaly is constructed in a traditional way: portfolio formation period is between month $m-12$ and $m-2$, and skip the most recent past return month $m-1$ and holding period return in month m is calculated from the equal-weighted average of stock returns in each quintile. All common stocks in the AMEX are used and companies are sorted into quintiles based on formation period return. Each quintile portfolio and long-minus-short portfolio momentum profits are presented. Raw return and risk-adjusted alphas based on CAPM and Fama-French three-factor model are presented as well as CAPM beta. Amihud (2002) define as the monthly average of a ratio of absolute return divided by price multiplies volume. Corwin and Schultz (2012) define as the high-minus-low spread estimate with negative values set to zero. Panel A present the entire sample and Panel B and C present the results of the treatment and the control groups, respectively. Liquidity measures are winsorised at 1 and 99 percentage points in each month cross-sectional. Raw Return, CAPM and FF-3 alphas are in percentage. Amihud measure is multiplied by 10^6. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Short	2	3	4	Long	Long-Short
	Panel A: All Companies					
Raw Return	1.05	1.18	1.31	1.56	2.13	1.08***
CAPM α	-0.21	-0.70	0.12	0.33	0.75	0.96***
FF-3 α	-0.36	-0.17	-0.02	0.21	0.72	1.08***
CAPM β	0.88	0.78	0.79	0.86	1.02	0.14
Amihud	8.68	3.70	2.61	2.19	1.94	-6.74
Corwin&Schultz	0.03	0.02	0.01	0.01	0.01	-0.02
	Panel B: Treatment Group Companies					
Raw Return	0.82	1.40	1.00	1.38	1.86	1.04**
CAPM α	-0.50	0.18	-0.20	0.04	0.50	1.00***
FF-3 α	-0.59	0.01	-0.31	-0.18	0.48	1.07***
CAPM β	0.95	0.81	0.78	0.95	0.98	0.03
Amihud	15.04	7.89	5.76	4.73	3.53	-11.51
Corwin&Schultz	0.04	0.03	0.02	0.02	0.02	-0.02
	Panel C: Control Group Companies					
Raw Return	1.07	1.22	1.43	1.74	2.30	1.23***
CAPM α	-0.15	0.11	0.27	0.50	0.91	1.06***
FF-3 α	-0.30	-0.10	0.14	0.42	0.88	1.18***
CAPM β	0.84	0.73	0.77	0.87	1.05	0.21
Amihud	2.55	1.55	1.21	1.07	0.94	-1.61
Corwin&Schultz	0.02	0.01	0.01	0.009	0.009	-0.01

Table 4.2: Comparing Pilot and Non-Pilot Firms: Illiquidity Variables
This table reports the average liquidity measures pre and post for the treatment and the control groups separately as well as the difference between pre and post for each group. Diff-in-Diff provides the differences-in-differences between the treatment and the control groups during the period between January 1980 and April 1997. Pre is defined as the sample period before February 1995, and post defines as the sample period between February 1995 and April 1997, when an actual event happen. Amihud (2002) define as the monthly average of a ratio of absolute return divided by price multiplies volume. Corwin and Schultz (2012) define as the high minus low spread estimate with negative values set to zero. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Treatment Group			Control Group			
	Pre	Post	Difference	Pre	Post	Difference	Diff-in-Diff
Amihud	9.391	2.667	-6.724***	1.602	0.661	-0.941***	-5.783***
Corwin&Schultz	0.025	0.017	-0.009***	0.009	0.008	-0.001***	-0.007***

Table 4.3: Momentum Returns
This table shows the average monthly the long, the short and the long-minus-short portfolios raw return, the CAPM, and the Fama-French three-factor alphas constructed based on momentum anomaly during the sample period between January 1980 and December 1994 for all firms. Stocks sorted into quintile portfolios based on their momentum return. Long-minus-short portfolio return is constructed by buying the highest performing quintile and shorting the lowest performing quintile. Raw Return, CAPM and FF-3 alphas are in percentages. Robust t-statistics are in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Raw Return	CAPM α	Fama-French-3 α
Long	2.12***	1.46***	1.41***
	(4.70)	(5.43)	(7.31)
Short	1.41***	0.77**	0.63**
	(2.84)	(2.23)	(2.50)
Long-Short	0.72**	0.69**	0.78**
	(2.16)	(2.14)	(2.27)

Table 4.4: The Main Difference-in-Difference Results

This table presents the main results of the difference-in-differences estimation for the long leg (the highest performing quintile), short leg (the lowest performing quintile) and long-minus-short portfolio return. The period is between January 1980 and April 1997. The pilot is a dummy variable that is equal to one if portfolio i is formed on the treatment group, zero otherwise. During this is a time dummy variable equal to one if month m is between February 1995 and April 1997, zero otherwise. I distinguish firms based on the daily closing price on January 31, 1995. If the stock has a share price between \$5 and \$10 then it will be in the treatment group; if the stock share price is above \$10 then the stock will be in the control group. Equal-weighted portfolios are constructed based on the momentum variable. Momentum anomaly is constructed in the traditional way: portfolio formation period is between month $m-12$ and $m-2$, and I skip the most recent past return month $m-1$, and holding period return in month m is calculated from the equal-weighted average of stock returns in each quintile. All common stocks in the AMEX are used and companies are sorted into quintiles based on formation period return. I also use time fixed effect as a second estimation. Results are presented in the last three columns. All coefficients are in percentage. Robust t-statistics are in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Long	Short	Long-Short	Long	Short	Long-Short
Pilot $\times$During	1.251	-1.764	3.015**	1.251	-1.764	3.015***
	(0.88)	(-1.04)	(2.16)	(1.33)	(-1.59)	(2.59)
Pilot	-0.919	0.154	-1.073*	-0.919***	0.154	-1.073**
	(-1.35)	(0.19)	(-1.72)	(-2.68)	(0.33)	(-1.98)
During	-0.818	-0.767	-0.051	-	-	-
	(-0.87)	(-0.77)	(-0.06)			
Constant	2.435***	1.271***	1.164***	2.329***	1.171***	1.158***
	(5.36)	(3.00)	(3.60)	(14.57)	(5.44)	(4.73)
Time Fixed Effect	NO	NO	NO	YES	YES	YES

Table 4.5: Control Group Momentum Return During the Program
This table shows the average monthly the long, the short and the long-minus-short portfolios raw return, the CAPM, and the Fama-French three-factor alphas constructed based on momentum anomaly during the sample period between February 1995 and April 1997 for only the control firms. Stocks are sorted into quintile portfolios based on their momentum return. Long-minus-short portfolio return is constructed by buying the highest performing quintile and shorting the lowest performing quintile. Raw return, CAPM and FF-3 alphas are in percentages. Robust t-statistics are in parentheses. *, **, *** represent statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Raw Return	CAPM α	Fama-French-3 α
Long	1.62*	0.05	-0.30
	(1.96)	(0.06)	(-0.52)
Short	0.50	-1.60**	-2.08***
	(0.56)	(-2.72)	(-3.13)
Long-Short	1.11**	1.65*	1.78**
	(1.44)	(1.87)	(2.00)

Table 4.6: The Main Difference-in-Difference Results (Value-Weighted Portfolio Returns)
This table presents the main results of the difference-in-differences estimation for the long leg (the highest performing quintile), short leg (the lowest performing quintile) and long-minus-short portfolio return. The period is between January 1980 and April 1997. The pilot is a dummy variable that is equal to one if portfolio i is formed on the treatment group, zero otherwise. During is a time dummy variable that is equal to one if month m is between February 1995 and April 1997, zero otherwise. I distinguish firms based on the daily closing price on January 31, 1995. If the stock has a share price between \$5 and \$10 then it will be in the treatment group; if the stock share price is above \$10 then the stock will be in the control group. Value-weighted portfolios are constructed based on the momentum variable. Momentum anomaly is constructed in the traditional way: portfolio formation period is between month $m-12$ and $m-2$, and I skip the most recent past return month $m-1$, and holding period return in month m is calculated from the equal-weighted average of stock returns in each quintile. All common stocks in the AMEX are used and companies are sorted into quintiles based on formation period return. All coefficients are in percentage. Robust t-statistics are in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Long	Short	Long-Short	Long	Short	Long-Short
Pilot ×During	2.523	-0.620	3.143	2.523	-0.620	3.143*
	(1.31)	(-0.37)	(1.54)	(1.63)	(-0.62)	(1.81)
Pilot	-0.789	-1.300	0.512	-0.789*	-1.300**	0.512
	(-0.99)	(-1.56)	(0.62)	(-1.70)	(-2.45)	(0.71)
During	-0.841	-0.115	-0.726	-	-	-
	(-0.73)	(-0.10)	(-0.62)			
Constant	1.929***	0.544	1.385**	-0.488	-4.419***	3.931***
	(3.56)	(1.02)	(2.59)	(-0.66)	(-10.47)	(4.97)
Time Fixed Effect	NO	NO	NO	YES	YES	YES

Table 4.7: The Main Difference-in-Difference Results (Benchmark Adjusted Return)

This table presents the main results of the difference-in-differences estimation for the long leg (the highest performing quintile), short leg (the lowest performing quintile) and long-minus-short portfolio return. The period is between January 1980 and April 1997. The pilot is a dummy variable that is equal to one if portfolio i is formed on the treatment group, zero otherwise. During is a time dummy variable that is equal to one if month m is between February 1995 and April 1997, zero otherwise. I distinguish firms based on the daily closing price on January 31, 1995. If the stock has a share price between $5 and $10 then it will be in the treatment group; if the stock share price is above $10 then the stock will be in the control group. Equal-weighted portfolios are constructed based on the momentum variable. Momentum anomaly is constructed in the traditional way: portfolio formation period is between month $m-12$ and $m-2$, and skip the most recent past return month $m-1$, and holding period return in month m is calculated from the equal-weighted average of stock returns in each quintile. Dependent variable is CAPM and Fama-French three-factor adjusted returns in Panel A and Panel B, respectively. All common stocks in the AMEX are used and companies are sorted into quintiles based on formation period return. All coefficients are in percentage. Robust t-statistics are in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

Panel A: CAPM Adjusted Return						
	Long	Short	Long-Short	Long	Short	Long-Short
Pilot ×During	1.321	-1.923	3.245**	1.321	-1.923*	3.245***
	(1.17)	(-1.48)	(2.33)	(1.42)	(-1.73)	(2.79)
Pilot	-0.809*	-0.011	-0.798	-0.809**	-0.011	-0.798
	(-1.78)	(-0.02)	(-1.29)	(-1.38)	(-0.02)	(-1.52)
During	-1.881***	-1.713***	-0.168	-	-	-
	(-2.75)	(-2.62)	(-0.20)			
Constant	1.732***	0.686**	1.047***	-7.628***	-10.981***	3.353***
	(6.87)	(2.47)	(3.30)	(-17.66)	(-21.74)	(6.47)
Time Fixed Effect	NO	NO	NO	YES	YES	YES
Panel B: FF-3 Adjusted Return						
	Long	Short	Long-Short	Long	Short	Long-Short
Pilot ×During	1.561*	-1.433	2.993**	1.561*	-1.433	2.993***
	(1.77)	(-1.12)	(2.12)	(1.65)	(-1.39)	(2.65)
Pilot	-0.897**	-0.045	-0.850	-0.897***	-0.047	-0.850
	(-2.49)	(-0.10)	(-1.39)	(-2.73)	(-0.11)	(-1.62)
During	-1.304**	-1.147	-0.158	-	-	-
	(-2.57)	(-1.57)	(-0.19)			
Constant	1.709***	0.593***	1.116***	-1.521***	-3.956***	2.434***
	(8.46)	(2.74)	(3.53)	(-3.44)	(-8.51)	(4.87)
Time Fixed Effect	NO	NO	NO	YES	YES	YES

Table 4.8: The Effect of End if Using Different Tick Size
This table presents the results of the difference-in-differences estimation for the long leg (the highest performing quintile), short leg (the lowest performing quintile) and long-minus-short portfolio return after the difference in tick size is removed. The period is between January 1980 and December 2000. The pilot is a dummy variable that is equal to one if portfolio i is formed on the treatment group, zero otherwise. During is a time dummy variable that is equal to one if month m is between February 1995 and April 1997, and is equal to zero if month m is before February 1995. The post is a time dummy variable that is equal to one if month m is between May 1997 and December 2000, zero otherwise. I distinguish firms based on the daily closing price on January 31, 1995. If the stock has a share price between \$5 and \$10 then it will be in the treatment group; if the stock share price is above \$10 then the stock will be in the control group. Equal-weighted portfolios are constructed based on the momentum variable. Momentum anomaly is constructed in the traditional way: portfolio formation period is between month $m-12$ and $m-2$, and I skip the most recent past return month $m-1$, and holding period return in month m is calculated from the equal-weighted average of stock returns in each quintile. All common stocks in the AMEX are used and companies are sorted into quintiles based on formation period return. All coefficients are in percentage. Robust t-statistics are in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Long	Short	Long-Short	Long	Short	Long-Short
Pilot ×Post	1.609	-0.255	1.864	1.609	-0.255	1.864
	(0.99)	(-0.12)	(0.91)	(1.63)	(-0.20)	(1.28)
Pilot ×During	1.251	-1.764	3.015**	1.251	-1.764	3.015***
	(0.88)	(-1.04)	(2.16)	(1.33)	(-1.59)	(2.59)
Pilot	-0.919	0.154	-1.073*	-0.919***	0.154	-1.073**
	(-1.35)	(0.19)	(-1.72)	(-2.67)	(0.33)	(-1.98)
Post	-0.541	-1.086	0.545	-	-	-
	(-0.52)	(-1.11)	(0.56)			
During	-0.818	-0.767	-0.509	-	-	-
	(-0.86)	(-0.76)	(-0.06)			
Constant	2.435***	1.271***	1.164****	2.253***	1.000***	1.254***
	(5.36)	(2.99)	(3.60)	(14.56)	(4.87)	(5.36)
Time Fixed Effect	NO	NO	NO	YES	YES	YES

Table 4.9: Results of Placebo Test

This table presents the placebo test. I assume that an actual event happens in the period and creates a pseudo-event window. The pseudo-event window is between February 1991 and April 1993. The main identification strategy is used in placebo test as well: the difference-in-differences estimation for the long leg (the highest performing quintile), short leg (the lowest performing quintile) and long-minus-short portfolio returns. The period is between January 1980 and April 1993. The pilot is a dummy variable equal to one if portfolio i is formed on the treatment group, zero otherwise. During is a time dummy variable that is equal to one if month m is between February 1991 and April 1993, zero otherwise. I distinguish firms based on the daily closing price on January 31, 1991. If the stock has a share price between \$5 and \$10 then it will be in the treatment group; if the stock share price is above \$10 then the stock will be in the control group. Equal-weighted portfolios are constructed based on the momentum variable. Momentum anomaly is constructed in the traditional way: portfolio formation period is between month $m-12$ and $m-2$, and I skip the most recent past return month $m-1$, and holding period return in month m is calculated from the equal-weighted average of stock returns in each quintile. All common stocks in the AMEX are used and companies are sorted into quintiles based on formation period return. All coefficients are in percentage. Robust t-statistics are in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Long	Short	Long-Short	Long	Short	Long-Short
Pilot ×During	2.283	0.814	1.469	2.283**	0.814	1.469
	(1.26)	(0.39)	(0.82)	(1.99)	(0.65)	(1.05)
Pilot	-1.216	0.178	-1.393*	-1.216***	0.178	-1.393**
	(-1.53)	(0.19)	(-1.94)	(-3.29)	(0.32)	(-2.18)
During	0.704	1.444	-0.740	-	-	-
	(0.63)	(1.30)	(-0.79)			
Constant	2.322***	0.947*	1.375***	2.435***	1.179***	1.256***
	(4.27)	(1.88)	(3.71)	(13.69)	(4.72)	(4.39)
Time Fixed Effect	NO	NO	NO	YES	YES	YES

Table 4.10: Results of the Second Placebo Test (NYSE Companies)
This table presents the second placebo test. I only use NYSE firms in this test and distinguish firms based on the daily closing price on January 31, 1995. If the stock has a share price between $5 and $10 then it will be in the treatment group; if the stock share price is above $10 then the stock will be in the control group. The main identification strategy is used in second placebo test as well: the difference-in-differences estimation for the long leg (the highest performing quintile), short leg (the lowest performing quintile) and long-minus-short portfolio return. The period is between January 1980 and April 1997. The pilot is a dummy variable that is equal to one if portfolio i is formed on the treatment group, zero otherwise. During is a time dummy variable that is equal to one if month m is between February 1995 and April 1997, zero otherwise. Equal-weighted portfolios are constructed based on the momentum variable. Momentum anomaly is constructed in the traditional way: portfolio formation period is between month $m-12$ and $m-2$, and I skip the most recent past return month $m-1$, and holding period return in month m is calculated from the equal-weighted average of stock returns in each quintile. All common stocks in the AMEX are used and companies are sorted into quintiles based on formation period return. All coefficients are in percentage. Robust t-statistics are in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Long	Short	Long-Short	Long	Short	Long-Short
Pilot ×During	0.539	0.880	-0.341	0.539	0.880	-0.341
	(0.42)	(0.55)	(-0.28)	(0.98)	(1.14)	(-0.38)
Pilot	-0.529	-0.207	-0.323	-0.529*	-0.207	-0.323
	(-0.75)	(-0.27)	(-0.56)	(-1.93)	(-0.53)	(-0.70)
During	0.261	-1.067	1.328*	-	-	-
	(0.29)	(-1.07)	(1.65)			
Constant	1.960***	1.007**	0.953**	2.378***	0.849***	1.125***
	(3.96)	(2.17)	(2.51)	(25.02)	(4.98)	(5.43)
Time Fixed Effect	NO	NO	NO	YES	YES	YES

Table 4.11: NYSE as a Control Group
This table presents the results of the difference-in-differences estimation for the long leg (the highest performing quintile), short leg (the lowest performing quintile) and long-minus-short portfolio return. The period is between January 1980 and April 1997. The pilot is a dummy variable that is equal to one if portfolio i is formed on the treatment group, zero otherwise. During is a time dummy variable that is equal to one if month m is between February 1995 and April 1997, zero otherwise. I distinguish firms based on the daily closing price on January 31, 1995. If the stock has a share price between $5 and $10 and stock is trading on the AMEX, then it will be in the treatment group; if the stock share price is between $5 and $10 and it is trading on the NYSE then it will be in the control group. Equal-weighted portfolios are constructed based on the momentum variable. Momentum anomaly is constructed in the traditional way: portfolio formation period is between month $m-12$ and $m-2$, and I skip the most recent past return month $m-1$ and holding period return in month m is calculated from the equal-weighted average of stock returns in each quintile. All common stocks in the AMEX and NYSE are used and companies are sorted into quintiles based on formation period return. All coefficients are in percentage. Robust t-statistics are in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Long	Short	Long-Short	Long	Short	Long-Short
Pilot ×During	0.056	-2.332	2.389*	0.056	-2.332**	2.389**
	(0.04)	(-1.24)	(1.63)	(0.06)	(-2.51)	(2.25)
Pilot	-0.251	0.631	-0.883	-0.251	0.631	-0.883
	(-0.34)	(0.71)	(-1.31)	(-0.70)	(1.34)	(-1.56)
During	0.124	-0.445	0.570	-	-	-
	(0.13)	(-0.35)	(0.65)			
Constant	2.125***	0.989*	1.136***	2.141***	0.931***	1.210***
	(4.03)	(1.73)	(2.82)	(13.07)	(4.40)	(4.78)
Time Fixed Effect	NO	NO	NO	YES	YES	YES

Table 4.12: Three Months Pre-Event Average Price to Construct Groups
This table presents the results of the difference-in-differences estimation for the long leg (the highest performing quintile), short leg (the lowest performing quintile) and long-minus-short portfolio return. The period is between January 1980 and April 1997. The pilot is a dummy variable that is equal to one if portfolio i is formed on the treatment group, zero otherwise. During is a time dummy variable that is equal to one if month m is between February 1995 and April 1997, zero otherwise. I distinguish firms based on the average three months' daily closing price before the event starts. If the average share price of the stock is between $5 and $10 then it will be in the treatment group; if the average share price of the stock is above $10 it will be in the control group. Equal-weighted portfolios are constructed based on the momentum variable. Momentum anomaly is constructed in the traditional way: portfolio formation period is between month $m-12$ and $m-2$, and I skip the most recent past return month $m-1$, and holding period return in month m is calculated from the equal-weighted average of stock returns in each quintile. All common stocks in the AMEX and NYSE are used and companies are sorted into quintiles based on formation period return. All coefficients are in percentage. Robust t-statistics are in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Long	Short	Long-Short	Long	Short	Long-Short
Pilot ×During	1.582	-1.687	3.268**	1.582*	-1.687	3.268***
	(1.10)	(-0.99)	(2.35)	(1.70)	(-1.50)	(2.91)
Pilot	-1.031	-0.051	-0.980*	-1.031***	-0.051	-0.980**
	(-1.50)	(-0.07)	(-1.71)	(-3.38)	(-0.11)	(-2.07)
During	-0.955	-0.637	-0.318	-	-	-
	(-1.06)	(-0.65)	(-0.39)			
Constant	2.513***	1.353***	1.160***	-2.772***	-6.875***	4.104***
	(5.60)	(3.22)	(3.76)	(-16.52)	(-6.15)	(5.17)
Time Fixed Effect	NO	NO	NO	YES	YES	YES

Table 4.13: Three Months Pre and Post Event Average Price to Construct Groups

This table presents the results of the difference-in-differences estimation for the long leg (the highest performing quintile), short leg (the lowest performing quintile) and long-minus-short portfolio return. The period is between January 1980 and April 1997. The pilot is a dummy variable that is equal to one if portfolio i is formed on the treatment group, zero otherwise. During is a time dummy variable that is equal to one if month m is between February 1995 and April 1997, zero otherwise. I distinguish firms based on the average three months' daily closing price before and after the event starts. First I calculate three months' average daily price before the event starts, then I calculated the average daily stock price after the event. After that, I only retain the stock that stays at the same price level. If the average share price of the stock is between \$5 and \$10 then it will be in the treatment group; if the average share price of the stock is above \$10 then it will be in the control group. Equal-weighted portfolios are constructed based on the momentum variable. Momentum anomaly is constructed in the traditional way: portfolio formation period is between month $m-12$ and $m-2$, and I skip the most recent past return month $m-1$, and holding period return in month m is calculated from the equal-weighted average of stock returns in each quintile. All common stocks in the AMEX and NYSE are used and companies are sorted into quintiles based on formation period return. All coefficients are in percentage. Robust t-statistics are in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Long	Short	Long-Short	Long	Short	Long-Short
Pilot ×During	0.753	-1.360	2.112	0.753	-1.360	2.112*
	(0.53)	(-0.81)	(1.54)	(0.79)	(-1.19)	(1.85)
Pilot	-0.943	-0.105	-0.839	-0.943**	-0.105	-0.839
	(-1.32)	(-0.13)	(-1.30)	(-2.50)	(-0.20)	(-1.48)
During	-0.859	-0.515	-0.344	-	-	-
	(-0.92)	(-0.50)	(-0.41)			
Constant	2.475***	1.306***	1.169***	-2.269***	-5.595***	3.326***
	(5.46)	(3.11)	(3.69)	(13.59)	(-5.31)	(4.40)
Time Fixed Effect	NO	NO	NO	YES	YES	YES

Table 4.14: Shorten the Period

This table presents the shorter period of main results of the difference-in-differences estimation for the long leg (the highest performing quintile), short leg (the lowest performing quintile) and long-minus-short portfolio return. The period is between January 1990 and April 1997. The pilot is a dummy variable that is equal to one if portfolio i is formed on the treatment group, zero otherwise. During is a time dummy variable that is equal to one if month m is between February 1995 and April 1997, zero otherwise. I distinguish firms based on the daily closing price on January 31, 1995. If the stock has a share price between \$5 and \$10 then it will be in the treatment group; if the stock share price is above \$10 then the stock will be in the control group. Equal-weighted portfolios are constructed based on the momentum variable. Momentum anomaly is constructed in the traditional way: portfolio formation period is between month $m-12$ and $m-2$, and I skip the most recent past return month $m-1$, and holding period return in month m is calculated from the equal-weighted average of stock returns in each quintile. All common stocks in the AMEX are used and companies are sorted into quintiles based on formation period return. All coefficients are in percentage. Robust t-statistics are in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Long	Short	Long-Short	Long	Short	Long-Short
Pilot ×During	0.735	-1.707	2.442	0.753	-1.707	2.442*
	(0.45)	(-0.88)	(1.49)	(0.68)	(-1.34)	(1.83)
Pilot	-0.404	0.097	-0.500	-0.404	0.097	-0.500
	(-0.39)	(0.08)	(-0.48)	(-0.65)	(0.12)	(-0.59)
During	-0.858	-1.093	0.235	-	-	-
	(-0.82)	(-0.98)	(0.26)			
Constant	2.475***	1.597**	0.878*	2.212***	1.262***	0.950***
	(3.94)	(2.50)	(1.74)	(8.75)	(4.04)	(2.86)
Time Fixed Effect	NO	NO	NO	YES	YES	YES

Table 4.15: Decile Portfolios
This table presents the main results of the difference-in-differences estimation for the long leg (the highest performing quintile), short leg (the lowest performing quintile) and long-minus-short portfolio return. The period is between January 1980 and April 1997. The pilot is a dummy variable that is equal to one if portfolio i is formed on the treatment group, zero otherwise. During is a time dummy variable that is equal to one if month m is between February 1995 and April 1997, zero otherwise. I distinguish firms based on the daily closing price on January 31, 1995. If the stock has a share price between \$5 and \$10 then it will be in the treatment group; if the stock share price is above \$10 then the stock will be in the control group. Equal-weighted portfolios are constructed based on the momentum variable. Momentum anomaly is constructed in the traditional way: portfolio formation period is between month $m-12$ and $m-2$, and I skip the most recent past return month $m-1$, and holding period return in month m is calculated from the equal-weighted average of stock returns in each decile. All common stocks in the AMEX are used and companies are sorted into quintiles based on formation period return. All coefficients are in percentage. Robust t-statistics are in the parenthesis. *, **, *** present the statistical significance at the 10, 5, and 1 per cent levels, respectively.

	Long	Short	Long-Short	Long	Short	Long-Short
Pilot ×During	1.060	-1.864	2.924	1.060	-1.864	2.924*
	(0.65)	(-0.74)	(1.40)	(0.83)	(-1.00)	(1.64)
Pilot	-1.206	-0.493	-0.713	-1.206	-0.493	-0.713
	(-1.45)	(-0.50)	(-0.78)	(-0.65)	(-0.71)	(-0.85)
During	-0.957	-0.837	-0.120	-	-	-
	(-0.78)	(-0.53)	(-0.10)			
Constant	2.763***	1.568**	1.195***	2.638***	1.459***	1.179***
	(5.09)	(3.19)	(2.65)	(10.84)	(4.52)	(3.11)
Time Fixed Effect	NO	NO	NO	YES	YES	YES

Chapter 5

Limitations and Conclusion

5.1 Limitations and Suggestions for Future Research

Even though this thesis tries to solve the most important problem in empirical research, the issue of endogeneity, there are still some limitations to each chapter.

One of the common limitations is using low-frequency liquidity proxies in each chapter due to the lack of accessibility to high-frequency data. Researchers have begun to use high-frequency data when they want to examine the effect of stock liquidity on asset pricing context. There are two advantages to using intraday data. First, it can capture the impact of the events that have been examined in this thesis. As we know, the effect of most of the policy changes continues for a short period then the market adjusts itself to these changes and eliminates their effect. Second, the high-frequency proxies can capture the true variation of stock liquidity. Quoted and effective spread are the stock liquidity proxies that most asset pricing or market microstructure studies are currently using and these proxies give a more accurate estimation of stock liquidity since they directly capture the difference between bid and ask price. On the other hand, there are also some disadvantages to using high-frequency data. First, the acquisition cost of this dataset is high, which many institutions cannot afford. Second, high-frequency data require a powerful computer if we need to use a long time horizon in our estimations.

In addition to common limitations, each empirical chapter has its own limitations. The first empirical chapter (Chapter 2) argues that illiquidity premium exists mainly during low sentiment periods. In that chapter, I only use the Amihud measure as a proxy for stock liquidity. Goyenko et al. (2009) show that the Amihud measure is the best proxy for stock liquidity to capture the price impact, compared with other low-frequency price impact proxies. Nevertheless, it would be useful to show that the positive relation between stock liquidity and investor sentiment index is consistent with other proxies of stock liquidity. Another limitation of that chapter is that there is an endogeneity issue. It is not easy to understand whether liquidity increases because investor sentiment is high or vice versa. Also, as we have seen in Figure 2.1, low investor sentiment periods mostly coincide with NBER recession periods. Therefore, it is not easy to distinguish the result from the effect of business cycle, as stated by Naes et al. (2011). One suggestion could be to use an exogenous shock to the sentiment index and estimate the effect of liquidity afterwards. Such an exogenous shock could, for example, be the surprise result of a political referendum such as Brexit. Moreover, the investor sentiment index is a market-wide index. In other words, it assumes that all sectors experience the same sentiment period at the same time but we know that it is not true in reality. For instance, the market might be in a high sentiment period overall but there might be an oil crisis that adversely affects oil industry stocks. In this case the stock liquidity of oil companies might be illiquid. Therefore, there is a problem in the overall estimation of stock liquidity.

In the second empirical chapter (Chapter 3), I show that change in stock liquidity causes change in idiosyncratic volatility, using several proxies for stock liquidity and an exogenous event decimalisation. The results in the chapter confirm the positive relation between stock illiquidity and idiosyncratic volatility, as well as the impact of decimalisation on stock liquidity. In that chapter, I only examine the effect from the liquidity side since decimalisation is a valid instrument with which to estimate stock liquidity. But there might be two-way causality between idiosyncratic volatility and stock liquidity. To examine two-way causality we need an exogenous variation for idiosyncratic volatility, which is not easy to find. There is no such event or valid instrument with which to estimate idiosyncratic volatility. This is important, since prior literature shows that idiosyncratic volatility eliminates the power of stock liquidity on the estimation of the effect of these two factors on the expected return. Thus, one might try to find a valid instrument for idiosyncratic volatility and examine the two-way causality. Moreover, an exogenous event decimalisation occurred at the same time for all companies listed on NYSE and AMEX, so that I cannot adopt the traditional difference-in-differences methodologies due to lack of treatment and control groups. I follow prior literature and adopt another way of difference-in-differences estimation but it is different from the traditional way. Exploiting event better with the traditional difference-in-differences approach might give us clearer evidence. Thus, further research should focus on finding a natural experiment to analyse the link between these two factors. Decimalisation has been used as an exogenous variation to estimate stock liquidity, and I conclude my results based on this event. One should bear in mind that the results I obtain are limited to this specific regulation change. Another regulation change or other event might give different results. As further research, one might investigate this relation in an international context.

The last empirical chapter (Chapter 4) investigates the impact of stock liquidity on momentum anomaly. Contrary to limits to arbitrage theory, I find that liquid stocks earn more momentum profits. I exploit this relation using another exogenous change in the US exchange market, specifically in AMEX. One of the limitations of this chapter is that constructing the treatment and control group means making a strong assumption. Since there is a threshold to distinguishing the treatment group and the control group, I use the last trading day to construct my groups, and I do not change my treatment and control groups during the analysis. The assumption that I make is that even though companies pass the threshold I do not change their group. Another limitation in the fourth chapter is the number of observations. Since there is a certain threshold, it would be better to employ regression discontinuity design but as shown in the Appendix, I do not have enough observations to implement regression discontinuity methodology. Moreover, I employ the traditional way of constructing momentum anomaly, cumulative return from $m-12$ to $m-2$, but there are other momentum anomaly constructions that are widely used, such as cumulative return from $m-6$ to $m-2$ or using a holding period longer than one month. As future research, one might employ different versions of momentum anomaly to ensure the results are consistent with all versions. To generalise the results of this analysis, one might find another natural experiment with which to examine the relationship again. Since this peculiar event imposes a lower tick size for companies in a certain price range, there may be some characteristics that inflate the overall result (the conclusion to Chapter 4 states that liquid firms earn around 3 per cent more momentum profit compared with illiquid firms). One of the main characteristics is size. As Banz (1981) shows, there is a small size anomaly that needs to be taken care of to present clear evidence. Nevertheless, my robustness analyses show that my results do not depend entirely on this effect but may be inflated by it.

5.2 Conclusion

The aim of this thesis is to examine the impact of stock liquidity on various concepts of financial markets by exploiting causal econometrics methodologies such as instrumental variables and the difference-in-differences approaches. One of the main problems in the empirical literature is how to eliminate the problem of endogeneity. It is a vital issue, since endogeneity can cause a violation of the assumption of unbiasedness and leads to inconsistent estimation. Many corporate finance studies use a natural experiment to adopt the traditional difference-in-differences methodology or regression discontinuity or find a valid instrument and employ an instrumental variable approach. But, these methodologies are not commonly used in the context of asset pricing. One of the reasons for this is that it is difficult to find a suitable natural experiment or valid instrument with which to estimate stock liquidity. I use various tick size changes in the US exchange markets in this thesis as a source of exogenous variation to understand the role of stock liquidity.

Chapter 2 answers the question of whether the illiquidity premium is different in different investor sentiment scenarios high or low. Univariate and Fama-MacBeth cross-sectional analyses show that the Amihud (2002) measure of stock illiquidity is priced in the low sentiment period and illiquidity premium is higher compared to the high sentiment period. The Fama-MacBeth cross-sectional analysis shows that one standard deviation increase in the logarithm of Amihud measure is associated with a monthly return of 0.39 per cent, which is similar to the univariate analysis. This result is economically and statistically significant after employing several robustness analyses such as controlling for financial and utility firms, including idiosyncratic volatility as a control variable, controlling for seasonality, and controlling for size effect. The result is consistent with prior literature that the expected stock return is higher for illiquid stocks since during the low sentiment period overall stocks become illiquid.

Chapter 3 answers the question of whether changes in liquidity affect idiosyncratic volatility of stocks. This is an important question since both these variables are considered determinants of the quality of the stock market. The contemporaneous effect is examined by adopting an instrumental variable approach to eliminate the potential problem of reverse causality. Using the exogenous event of decimalisation that occurred in the US equity markets at the beginning of 2001 as an instrumental variable, I show that increases in illiquidity lead to higher idiosyncratic volatility. Graphical and univariate analyses confirm earlier studies that show that idiosyncratic volatility and illiquidity are positively correlated and the first-stage regression confirms that the reduction in the tick size in the three major US equity markets that occurred as a result of decimalisation improved liquidity. Results are consistent with various other stock liquidity proxies and using several other robustness analyses.

Chapter 4 answers the question of whether liquid stocks earn higher momentum profits compared with illiquid stocks. Limits to arbitrage theory suggest that when the market is liquid there should be less momentum anomaly profit since the market is considered more efficient during a liquid period. However, I show that liquid stocks earn more profit compared to illiquid stocks. I have examined this question by exploring the implementation of different tick sizes for different price ranges in the AMEX. The programme provides a plausibly exogenous variation to disentangle the endogeneity issue and answer the question by clearly exploiting the difference-in-differences framework. The long-minus-short portfolio of the treatment companies experiences a 3 per cent higher return than the control group per month, where the treatment group comprises the companies whose tick sizes declined. The results are robust to the use of value-weighted portfolio returns, the use of benchmark-adjusted return, the use of different control groups, and the use of a shorter sample period. One of the explanations for this could be related to the illiquidity premium literature (Amihud, 2002). Illiquid stock brings higher expected returns in the following month. So, the short leg of illiquid stock will be associated with higher expected returns in subsequent months compared to liquid firms, which lowers the long-minus-short portfolio return.

Appendix A

Appendix

Construction of Market-to-Book Ratio is as follows:

- Book Value of Equity= ((Stockholders' Equity + Balance Sheet Deferred Taxes + Investment Tax Credit) - Book Value of Preferred Stock) Stockholders' Equity is reported by Compustat (SEQ) or Moody's
- If SEQ is not available, use the book value of common equity (CEQ) + Book Value of Preferred Stock
- If CEQ is not available, stockholders' equity is defined as the book value of asset (AT) minus total liabilities (LT)
- Balance Sheet Deferred Taxes is reported by Compustat (TXDB)
- Investment Tax Credit is reported by Compustat (ITCB)
- In terms of Book Value of Preferred Stock, we use redemption value (PSTKRV) or liquidation value (PSTKL) or par value (PSTK) in that order.

The book value of a stock i is obtained at the end of the fiscal year t and market value of a stock is obtained at the end of the calendar year t. Market-to-book ratio of a stock i in year t is matched with a monthly return of stock i from July of year $t+1$ to June of year $t+2$.

Appendix B

Appendix

Table B.1: Distribution of the number of Companies in Each Price Range
This table reports the number of firms in the treatment, control groups separately in the different price range for the AMEX on 31st of January, 1995.

Treatment Group		Control Group		Additional Information	
Price Range	# of Firms	Price Range	# of Firms	Price Range	#of Firms
\$5-\$5.99	33	\$10-\$19.99	122	\$10-\$10.99	17
\$6-\$6.99	34	\$20-\$29.99	33	\$11-\$11.99	13
\$7-\$7.99	36	\$30-\$39.99	20	\$12-\$12.99	12
\$8-\$8.99	25	\$40-\$49.99	9	\$13-\$13.99	16
\$9-\$9.99	20	\$50 above	9	\$14-\$14.99	11

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