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The exposure to illiquidity of stocks – a study of the determinants with a focus on the 2007-2009 financial crisis*

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Abstract

This paper investigates the determinants of stocks' exposure to illiquidity in the US stock market. The periods that are examined are the financial crisis of 2007-2009 and the non-crisis period of 2005-2007. We find that the significant determinants of stocks' exposure to illiquidity in the non-crisis period are the historical and current illiquidity level of the stock, the goodwill to assets ratio of the underlying firm and, to some extent, the sector that the stock belongs to. However, in the crisis period, risk measures become more important. In fact, in addition to the current illiquidity level of the stock and, to some extent, the sector that the stock belongs to, the standard deviation of stock returns, leverage, interest coverage ratio and firm size become significant determinants. These findings are in line with our hypotheses that the flight to quality dynamics during the crisis cause stocks of risky firms to be more exposed to illiquidity, everything else equal. The results furthermore indicate that investors do not anticipate the flight to quality dynamics when trading stocks in the non-crisis periods, since none of the risk measures are significant in the non-crisis period.

Keywords: Illiquidity, Exposure to illiquidity, Financial crisis, Flight to quality, Flight to liquidity

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1. Introduction

In one of the earliest papers about illiquidity and asset pricing, Amihud and Mendelson (1986) find that the expected returns of stocks increase with their illiquidity level and thus investors seem to require compensation for bearing illiquidity costs. Since then, other studies have confirmed that illiquidity is a priced factor (Amihud et al., 2005). Sadka and Lou (2011) define illiquidity level as the average cost of trading a security. The higher the trading cost, the higher the illiquidity level. In line with that definition, Pastor and Stambaugh (2003) propose that a high level of liquidity is indicative of the ability to trade large quantities of stocks quickly, at low cost and without moving the price. Amihud et al. (2005) suggest that the illiquidity level of a security depends on exogenous transaction costs, inventory risk for market makers, agents' private information about stock fundamentals and order flow and lastly search frictions. A stock's exposure to illiquidity is dependent on how much the illiquidity premium in the market affects the return of the stock. The more illiquidity premium a stock gets, the more exposed the stock is to illiquidity. So far, the literature about the determinants of stocks' exposure to illiquidity is thin. Therefore, to contribute to the literature and research within this area, this paper will focus on the determinants of stocks' exposure to illiquidity in the period around the financial crisis of 2007-2009 in the US. This is an important topic since the stocks' exposure to illiquidity should affect the returns required by investors, meaning that it affects the cost of capital of firms and hence the allocation of the real resources in the economy (Amihud et al. 2005).

Underlying our hypotheses regarding the determinants of stocks' exposure to illiquidity lie the flight to quality and flight to liquidity dynamics. In a crisis, the flight to quality dynamics lead investors to sell off risky assets in exchange for safer ones, indicating that risky stocks from a fundamental perspective should also be more exposed to illiquidity compared to safer stocks. To identify fundamentally risky stocks, we rely on risk measures that investors use when examining the risk of a stock. In addition, we also include the stock's level of illiquidity, both the current and historical, as potential determinants of the stocks' exposure to illiquidity. An illiquid stock should be more exposed to illiquidity since it should get more illiquidity premium compared to a more liquid stock. However, this must not always be the case since investors might incorporate other factors than just the current illiquidity level. Furthermore, due to the flight to liquidity dynamics (Acharya and Pedersen, 2005; Amihud et al., 1990), one could expect the magnitude of effect from the stocks' illiquidity level on determining stocks' exposure to illiquidity to increase in times of crisis. Flight to liquidity means that illiquid stocks are sold off in exchange for more liquid ones during crisis. Moreover, as business risk varies across sectors (Smith and Markland, 1981), one has reason to believe that stocks' exposure to illiquidity will also vary between sectors.

In this paper, nine hypotheses are outlined. If investors do anticipate the flight to quality and flight to liquidity dynamics, variables that measure the risk and the illiquidity of stocks should be significant determinants in both the non-crisis and the crisis periods. However, we expect that the magnitude of effects will increase in the crisis period, since that is when the dynamics actually take place. The first hypothesis is that a higher leverage ratio of a firm increases the stock's exposure to illiquidity. Hypothesis number two is that stocks of bigger firms have lower exposure to illiquidity. Hypothesis number three is that the higher the ratio of goodwill to assets for a firm, the higher the stock's exposure to illiquidity. Hypothesis number four is that a high interest coverage ratio compared to a low one will decrease stocks' exposure to illiquidity. Hypothesis number five is that stocks' exposure to illiquidity will increase with their historical level of illiquidity. Hypothesis six is that a high current illiquidity level of the stocks will increase the stocks' exposure to illiquidity compared to a low current illiquidity level. Hypothesis seven is that the higher the standard deviation of stock returns, the higher the exposure to illiquidity. Hypothesis number eight is that sectors will affect stocks' exposure to illiquidity. Lastly, hypothesis nine is that the magnitude of the effects from leverage, sectors, firm size, goodwill to assets, interest coverage ratio, standard deviation of stock returns and the illiquidity level, both historical and current, on the stocks' exposure to illiquidity will increase in the crisis compared to the non-crisis period due to the fact that the flight to quality and liquidity dynamics kick in.

The findings in this paper suggest that the stocks' exposure to illiquidity increases on average during the crisis, which further stresses the importance to look at the determinants in the crisis period. In the non-crisis period, the significant determinants of stocks' exposure to illiquidity are their historical illiquidity level, their current level of illiquidity, the goodwill to assets of the firm and, to some extent, the sector that the stock belongs to. However, in the crisis period the significant determinants of stocks' exposure to illiquidity are the current illiquidity level of the stock, leverage, interest coverage ratio, firm size and the standard deviation of stock returns. Thus, stocks' historical illiquidity level and the goodwill to assets ratio become insignificant determinants of stocks' exposure to illiquidity during the crisis. Moreover, the sectors still have some significant effects on stocks' exposure to illiquidity.

Our results indicate that investors look more on firm specific risk measures compared to sectors when determining how risky firms are in the flight to quality dynamics since the sectors do not become significant determinants to a greater extent in the crisis compared to the non-crisis period but the firm specific risk measures do. Also, investors do not seem to incorporate the effects of the flight to quality dynamics in the non-crisis period when trading stocks since none of the risk measures are significant determinants in the non-crisis period. Lastly, the findings in this paper does not support the hypothesis that the magnitude of effect from the current illiquidity level of the stocks on the exposure to illiquidity increases in the crisis period, as one would expect given the flight to liquidity dynamics. Either, the flight to liquidity dynamics are already incorporated by investors in the non-crisis period and therefore, the magnitude of effect from the current illiquidity level of the stocks does not increase or the flight to liquidity dynamics are not strong enough to create a statistically significant increase.

2. Previous Literature

2.1 The pricing of illiquidity level

The starting point of illiquidity and asset pricing was set by Amihud and Mendelson (1986) who concluded that expected stock returns had an increasing relationship with the illiquidity of the stock. After Amihud and Mendelson, many studies have found similar results (Amihud et al. 2005). Amihud (2002) found that stocks' individual level of illiquidity as well as the market-wide illiquidity is priced. In addition, Amihud et al. (1990) study the changes in illiquidity and the effect on stock prices. Focusing on the 1987 crash, the results show that stocks which suffered most in terms of returns also experienced the most negative impact in liquidity. In addition, the stocks that performed the best in the recovery after the crisis also had a high recovery rate in liquidity level, suggesting that variations in liquidity affect stock prices.

2.2 Illiquidity measures

One of the main issues in the literature has been to find a satisfactory measure of illiquidity (Amihud et al., 2005). Amihud (2002) argues that illiquidity is not directly observable and furthermore has a number of aspects that can not be incorporated in a single measure. Proceeding from this statement, Ibbotson et al. (2013) conclude that an ultimate measure of illiquidity will most likely not exist. In one of the earliest papers about illiquidity and asset pricing, Amihud and Mendelson (1986) suggest that the bid-ask spread is a natural measure of illiquidity. From there, the literature has developed into several new measures. For instance, Pastor and Stambaugh (2003) measure illiquidity based on how returns reverse when there is high volume and thus try to capture the price impact effect of illiquidity. Another approach is to measure illiquidity through order flows and price changes as Brennen and Subrahmanyam (1996) have done. Kyle (1985) also uses the approach of market microstructure data based on order flow to discover the probability of information based trading, which generated the ratio later referred to as Kyle’s lambda (Glosten and Harris, 1988). A widely used end-of-day measure is the Amihud (2002) ILLIQ-measure. Even though microstructure ratios are considered as more crisp, Amihud (2002) notes that the relationship between the ILLIQ-measure (which is based on end-of-day data) and Kyle’s lambda (which is a microstructure ratio) is strong.

2.3 The sources of illiquidity

Amihud et al. (2005) explain that the sources of illiquidity that give rise to illiquidity costs are exogenous transaction costs, demand pressure and inventory risk, private information about fundamentals and order flow and search frictions. Exogenous transaction costs are illiquidity costs related to the transaction of the security. Brokerage fees, transaction taxes and order-processing costs are examples of exogenous transaction costs. Moreover, one needs to bear in mind that investors incur these costs both when the security is bought and when the security is sold and that these costs could vary between the two occasions. Hence, if higher illiquidity costs are expected in the future by the investors, these costs will be taken into account at the time of the initial transaction. Furthermore, demand pressure and inventory risk borne by market makers give rise to illiquidity costs. If not all agents are present in the market at the same time, market makers step in to either buy/sell the security when there is high demand pressure to facilitate the liquidity needs in the market. The market maker then holds/sells the security until it can be sold/bought back later on. Naturally, the market maker is exposed to price changes of the security while it is in his/her inventory and thus the market maker will require compensation from the seller/buyer for bearing this risk.

Furthermore, Amihud et al. (2005) argue that another concern for investors is that the counterparty they are trading with possesses private information. For instance, if the counterparty has private information about the fundamentals of a stock, that counterparty will be more willing to sell if deterioration in the fundamentals of the stock is likely to occur, which would impose a cost on the buyer. Also, if the counterparty has private information about the future order flow of the security, he can buy/sell in anticipation of these buying or selling pressures.

2.4 Commonality in Liquidity

Chordia, Roll and Subrahmanyam (2000) show that stocks' individual liquidity is to a large extent dependent on market-wide liquidity factors and thus unexpected changes in liquidity for a security is highly dependent on unexpected changes in market-wide liquidity. In addition, Hameed et al. (2010) show that the level of commonality for stock's liquidity in the stock market is dependent on the contemporaneous market returns. In crisis periods where market returns are negative, there is a significant drop in the liquidity level and the commonality in liquidity increases to a great extent. Not only does liquidity commonality increase in periods of negative market returns, but also illiquidity contagion arises where illiquidity in one industry tends to spill over to other industries. Cifuentes et al. (2005) show that the reason for increases in commonality in liquidity during crisis periods could be triggered by the mark-to-market valuation by financial institutions. When a financial institution is forced to sell securities, the market values of these securities are depressed. If other financial institutions also hold these securities they might be forced to sell too due to the depreciating market prices, which in turn triggers even higher illiquidity in the market.

3. Hypotheses

To answer our research question about determinants of stocks' exposure to illiquidity for firms in the US market during a crisis and a non-crisis period, we develop a set of hypotheses with support from the area of behavioural finance.

3.1 Flight to quality dynamics

Firstly, it is necessary to explain the dynamics underlying our hypotheses where the main component will be the flight to quality phenomena. The area of flight to quality have been studied previously in relation to macroeconomic events and flight between the stock and bond market (Chordia, Sarkar, and Subrahmanyam, 2002). In essence, flight to quality is when investors reallocate from risky to less risky assets during periods of turbulence and uncertainty in the financial market. Caballero and Krishnamurthy (2008) note that the turbulence and uncertainty are not only affecting investors' views of payoffs of risky assets, but it also leads to investors "questioning their worldview". According to Caballero and Krishnamurthy (2008), agents react to negative liquidity shocks and uncertainty by selling off risky assets and reallocating into safer ones, which provides the intuition behind the flight to quality phenomena.

Secondly, behavioural finance predicts that investors would reallocate into less risky investments when they have experienced losses previously. Loss aversion is a concept introduced by Kahneman and Tversky (1979) where people are more sensitive to losses than gains of the same magnitude. Further research by Thaler and Johnson (1990) have found that loss aversion among people is not constant. Instead it changes depending on the outcomes of the persons' previous gambles. If the risk-taking person experiences a negative outcome in his/her previous gamble, the loss aversion increases and the risk-taking person will hence like to assume less risk in the next gamble or require a higher compensation for taking risk. Barberis (2011) puts loss aversion in the context of the financial crisis of 2007-2009 and proposes that as prices began to fall, investors' loss aversion increased. Consequently, the prices of risky assets fell even further leading to a negative spiral for risky assets during the crisis. Hence, in line with the flight to quality dynamics, stocks that investors perceive as risky should experience more sell offs during a financial crisis compared to when there is no crisis. In a bull market, on the other hand, one would expect loss aversion to be low since asset prices keep appreciating and therefore investors are willing to accept more risk.

To conclude, when investors reallocate from risky assets, such as risky stocks, to assets considered as safer, such as bonds and safer stocks, the illiquidity level of stocks that are perceived as risky by investors should rise. Therefore, risky stocks should be more exposed to illiquidity compared to safer stocks. Furthermore, if investors to some extent anticipate the effects from the sell-offs in non-crisis periods, risky stocks should also be more exposed to illiquidity in non-crisis periods. Naturally, this line of reasoning poses the question if one can find any relationship between a stock's exposure to illiquidity and risk measures. Furthermore, since there is less flight to quality dynamics during normal and good market conditions compared to bear markets, risky firms should experience relatively less sell offs during good times compared to bad. It is therefore also interesting to examine if the significant determinants, if any, will change across non-crisis and crisis periods in terms of the magnitude of effect and significance. To find out if risk measures of firms can determine the exposure to illiquidity of stocks, eight hypotheses are formulated and tested. To test if the determinants change across the non-crisis and crisis period, these eight hypotheses are tested for data during a financial crisis and for data in a non-crisis period.

3.2 Risk measures

To measure risk, we rely partly on accounting ratios used by investors to gauge risks that are related to the firm. First, we use leverage from the solvency category of accounting measures as defined in White, Sondhi and Fried (2003). The more leveraged a firms is, the more risky its equity will be everything else equal (Ramadan, 2012). Secondly, the size of the firm conveys relevant information about the risk of the firm as proposed by Ben-Zion and Shalit (1975). A bigger firm size, everything else equal, should imply that the firm is safer compared to a smaller firm size. Thirdly, the interest coverage ratio conveys information about the firm's ability to cover its debt commitments (White, Sondhi and Fried, 2003). Since firms with low interest coverage ratios are more likely to declare bankruptcy, the interest coverage ratio could be seen as a proxy for bankruptcy risk. Furthermore, the standard deviation of stock returns is included as a risk measure of the stocks. A high standard deviation of stock returns should imply a more risky stock compared to a low standard deviation, everything else equal.

3.3 Goodwill

We include goodwill over assets as a proxy for value uncertainty of the company. Ambiguity aversion (Barberis and Thaler, 2003) gives one reason to believe that investors should be concerned with this uncertainty. Put simply, ambiguity aversion is the observation that people prefer situations with certainty over situations with uncertainty. In addition, Heath and Tverksy (1991) propose that ambiguity aversion varies between situations depending on the level of confidence experienced by the risk-taking person. Barberis (2011) puts ambiguity aversion in the context of the financial crisis in a similar manner as with loss aversion. The author argues that when the market begins to decline after a bull market period, the average investor will find strong evidence that he/she is less competent than he/she previously thought in predicting the uncertain situations due to the losses in investments. Therefore ambiguity aversion increases and investors become less willing to participate in situations with ambiguity, which lowers the prices of securities with higher levels of ambiguity.

We argue that the goodwill over assets ratio conveys information about value uncertainty of a firm since the value-estimation of goodwill is based on estimations of expectations and beliefs about the future, such as future cash flows and other unidentifiable factors such as market imperfections and discount rates (FAS statement 141 and 142). Not only is the present value model in itself sensitive to changes in input parameters, but also behavioural finance gives us reason to believe that these estimates of future cash flows and discount rates will be wrong. Barberis and Thaler (2003) present a set of belief biases, such as overconfidence and optimism, that influence people when forming expectations about the future. One has reason to believe that the belief biases should be present both when the acquired company is valued as well as for the annual impairment tests. In addition, the company itself performs the annual impairment tests, which give rise to principal-agent issues (Beatty and Weber, 2005). To conclude, we argue that the reported value of goodwill is uncertain and that investors should become increasingly averse to this since they are more sensitive to ambiguity in times of crisis. A high goodwill to assets ratio would hence indicate that there is uncertainty over a larger amount of the assets and vice versa. Hence, when ambiguity aversion increases in times of crisis, investors should sell off firms with more goodwill to assets, everything else equal.

3.4 Flight to liquidity dynamics and sectors

Besides the flight to quality dynamics, flight to liquidity dynamics also occur during times of crisis (Acharya and Pedersen, 2005; Amihud et al., 1990). In these dynamics, investors sell off illiquid assets in exchange for more liquid assets. With the same line of reasoning as with the flight to quality dynamics, the stocks that are sold off in the flight to liquidity dynamics should be more exposed to illiquidity. Therefore, the historical and the current illiquidity level of the stocks will be included in the regression as potential explanatory variables of stocks' exposure to illiquidity. The reason for including both a historical and a current illiquidity level is that we believe that investors might be looking at not only the current illiquidity level, but also the illiquidity level historically when evaluating how illiquid a stock is in the flight to liquidity dynamics. Furthermore, it is natural to believe that the illiquidity level of the stock per se should be significant in explaining the stocks' exposure to illiquidity, since an illiquid stock should receive more illiquidity premium compared to a more liquid stock.

Lastly, when examining the risk of stocks, one has to take into account the difference in risk across sectors. Smith and Markland (1981) find that there are significant differences in average business risk across most sectors. According to the flight to quality reasoning, investors will prefer firms with less risk in times of crisis. Since risk varies between sectors, one therefore has reason to believe that sectors will play a role in determining stocks' exposure to illiquidity.

3.5 Hypotheses summary

Hypothesis 1: Leverage is a significant determinant of a stock's exposure to illiquidity. The more leveraged a firm is, the more exposed its stocks should be to illiquidity.

Hypothesis 2: Firm size is a significant determinant of a stock's exposure to illiquidity. The bigger a firm is, the less exposed its stocks should be to illiquidity.

Hypothesis 3: The proportion of goodwill to total assets of the firm is a significant determinant of the stock's exposure to illiquidity. The more goodwill to total assets a firm has, the more exposed its stocks should be to illiquidity.

Hypothesis 4: The interest coverage ratio is a significant determinant of a stock's exposure to illiquidity. The higher interest coverage ratio a firm has, the less exposed its stocks should be to illiquidity.

Hypothesis 5: The historical illiquidity level of the stock is a significant determinant of the stock's exposure to illiquidity. A higher level of historical illiquidity will contribute to a higher exposure to illiquidity.

Hypothesis 6: The current illiquidity level of the stock is a significant determinant of the stock's exposure to illiquidity. A higher level of current illiquidity will contribute to a higher exposure to illiquidity.

Hypothesis 7: The standard deviation of the stock returns should be a significant determinant of stocks' exposure to illiquidity. A higher standard deviation should, everything else equal, lead to a higher exposure to illiquidity due to the flight to quality dynamics.

Hypothesis 8: The sector in which the firm is active in is a significant determinant of a stock's exposure to illiquidity.

Hypothesis 9: If any of the potential determinants of stocks' exposure to illiquidity are significant in the non-crisis period, the magnitude of effects from these potential determinants should increase during the crisis due to the flight to quality and flight to liquidity dynamics as well as the increased ambiguity aversion among investors.

4. Data and Method

4.1 Data

To get data representative for US stocks, the firms included in NYSE and AMEX that were registered and traded as of January 2014 are included in the sample. The data is gathered through Compustat, CRSP and Bloomberg. While data regarding the returns and trading volumes of the stocks are collected on a daily basis, the data from the financial reports such as interest coverage and goodwill to assets ratios are collected on a quarterly basis. The reader should be aware of the fact that the data suffers from survivorship bias, since the firms that are delisted due to for example bankruptcy during the crisis and non-crisis periods were not registered and traded in January 2014 and are therefore not included in the data.

4.2 Estimating exposure to illiquidity

4.2.1 Measures of illiquidity

The illiquidity measure used in this study is the ILLIQSQRT-measure as proposed by Hasbrouck (2005). ILLIQSQRT builds on ILLIQ, which was invented by Amihud (2002). The intuition behind ILLIQ is based on the notion of illiquidity as a price-impact measure since it captures how much the stock price moves per volume traded in terms of USD. Thus, a high (low) value of ILLIQ indicates an illiquid (liquid) stock. ILLIQ has been widely used in the literature and is known to be a good candidate when it comes to trade-offs between accuracy and simplicity as mentioned by Amihud et al. (2005) and Acharya and Pedersen (2005). Hasbrouck (2005) decided to take the square-root of the measure to control for outliers in the distribution of ILLIQ, generating ILLIQSQRT.

ILLIQSQRT is defined as:

$$ILLIQSQRT_{i,t} = \frac{1}{D_{i,t}} \sqrt{\sum_{i=1}^{D_{i,t}} \frac{|r_{i,t,d}|}{DOLVOL_{i,t,d}} * 10^6}$$

where $DOLVOL_{i,t,d}$ is the volume traded in terms of USD of stock i in period t on day d. $DOLVOL_{i,t,d}$ is calculated using the close price of stock i in period t on day d multiplied by the total volume traded during that day. $|r_{i,t,d}|$ is the absolute return of stock i in period t on day d. $D_{i,t}$ denotes the number of trading days in period t for security i.

4.2.2 Forming portfolios

Since the stocks' exposure to illiquidity is not directly observable, it must be estimated. In order to do this, portfolios are created according to the framework introduced by Fama and French (1993). In addition, a portfolio based on the stocks' illiquidity level is formed and included in the model. The extended model is shown in regression 1).

Regression 1):

$$r_{i,t} = r_{f_t} + \beta_i^{Market} * MRP_t + \beta_i^{HML} * HML_t + \beta_i^{SMB} * SMB_t + \beta_i^{IML} * IML_t + \varepsilon_{i,t}$$

where $r_{i,t}$ is the return for security i on day t, r_{f_t} is the prevailing risk-free rate (derived from the US 10Y bond yields) on day t, MRP_t is the daily market excess return calculated as the difference between the market return (the return of the S&P 500 index) and the risk-free rate on day t, HML_t is the difference in return between the high book-to-market portfolios and the low book-to-market portfolios on day t, SMB_t is the difference in return between the small market capitalization portfolios and the high market capitalization portfolios on day t and IML_t is the difference in return between the illiquid portfolios and the liquid portfolios on day t, which also is a measure for the market illiquidity premium (Amihud, Hameed, Kang and Zhang, 2013). Regression 1) is conducted in both the crisis and non-crisis period to estimate the stocks' exposure to illiquidity, β_i^{IML}, in each period. Furthermore, the data used in regression 1) has a panel structure.

4.2.3 Fama and French portfolios

In order to form the high book-to-market portfolios, low book-to-market portfolios, small market capitalization portfolios and high market capitalization portfolios, one first has to divide the firms in the sample into two groups, big and small firms. Big firms have market capitalizations that are higher than the median market capitalization of the firms in the sample while small firms have market capitalizations lower than the median. The next step is to divide the stocks into groups of high book-to-market, medium book-to-market and low book-to-market among the big and small firms respectively. High book-to-market firms are the ones with book-to-market-ratios that are above the percentile 70-value of the firms within the big- and small firm groups respectively. Low book-to-market firms are the ones with book-to-market-ratios below the percentile 30-value of the firms within the big and small firm groups respectively. Finally, the medium book-to-market firms are the ones with book-to-market-ratios that are above the percentile 30-value but below the percentile 70-value within the big and small firm groups respectively. By intersecting firm size and book-to-market-ratios, Fama and French (1993) created six portfolios denoted B/H, B/M, B/L, S/H, S/M and S/L, where B denotes big group firm, S denotes small group firm, H denotes a firm with high book-to-market, M denotes a firm with medium book-to-market and L denotes a firm with low book-to-market.

4.2.4 Creation of SMB and HML

When the six portfolios are constructed, one creates SMB by taking the difference between the simple average of the returns of the three small-stock portfolios (S/L, S/M and S/H) and the simple average of the returns of the three big-stock portfolios (B/L, B/M and B/H). HML is constructed using four of the six portfolios. It is the difference between the simple average of the returns of the two high-book-to-market portfolios (S/H and B/H) and the simple average of the returns of the two low book-to-market portfolios (S/L and B/L). The portfolios are formed once in the beginning of each year and then used to calculate SMB and HML on a daily basis.

4.2.5 Creating IML

To create the portfolios consisting of liquid and illiquid stocks the method introduced by Amihud, Hameed, Kang and Zhang (2013) is used. They refer to the approach used by Fama and French (1993) to form liquid-stock and illiquid-stock portfolios. Stocks are sorted at the beginning of each month into three portfolios based on their standard deviation of their daily returns during the three preceding months, where the cut-off points are percentile 30-value and percentile 70-value. Each of these volatility-based portfolios are in turn sorted into five portfolios based on their average ILLIQSQRT-measure calculated over the three preceding months. In total there are fifteen portfolios created. However, one only needs to use six of them to calculate IML. IML is the difference between the simple average of the returns of the most illiquid portfolio within each of the three standard deviation-based portfolios and the simple average of the returns of the most liquid portfolio within each of the three standard deviation-based portfolios. As mentioned before, the IML-return is a measure of the market illiquidity premium.

4.2.6 Definition of crisis and non-crisis period

One logical definition of the financial crisis period for the purpose of this paper is introduced by Itzhak, Francesco and Rabih (2010). They argue that the crisis period starts in the third quarter of 2007 with the Quant Meltdown and ends in the first quarter of 2009 with the trough of the stock market. Given this definition the number of trading days during the financial crisis period is 441. This means that there should be 441 observations per firm that are used in regression 1) during the crisis. However some firms have a lower amount of observations because they are listed on the exchanges during this period and hence miss data for some parts of the period. Since the goal of regression 1) is to estimate the stocks' exposure to illiquidity for each stock, there has to be observations enough to get trustworthy results in the regression. Due to this fact, firms with less than 200 observations during the period of interest are dropped. While some people might still argue that 441 observations are not good enough to give trustworthy estimations of stocks' exposure to illiquidity, this is the total amount of data available during the crisis period. Furthermore, the stocks' exposure to illiquidity changes over time. From that perspective, it could be motivated to not have a too long estimation period.

Since the β_i^{IML} obtained from regression 1) is partly dependent of the length of the estimation-window, one would like to use the same length on the estimation-windows in both periods. The reason for this is that we want β_i^{IML} to be comparable, otherwise it is not meaningful to compare their determinants. As stated previously, the stocks' exposure to illiquidity change over time, especially between crisis and non-crisis periods (Pastor and Stambaugh, 2003). Therefore, one also needs to take this fact into account, otherwise the determinants might change in significance or sign between the non-crisis and crisis period solely due to the fact that β_i^{IML} changes over time and not because of factors caused by the crisis. One way to mitigate this problem is to use a period very close to the crisis as the estimation window for the non-crisis period. By doing so, most of the changes in β_i^{IML} for each firm should be caused by the crisis and not factors that change stocks' exposure to illiquidity in the long run. Therefore the estimation-window for the non-crisis period is as long as the crisis-period and ends right before the crisis, starting in the fourth quarter of 2005 and ending in the second quarter of 2007. The number of trading days during the non-crisis period is 438. Also in the non-crisis period, firms with less than 200 observations are dropped.

4.3 Determinants of stocks' exposure to illiquidity

4.3.1 Definitions

Standard deviation of the stock returns

The standard deviation is simply defined as the yearly standard deviation of the stock returns measured during the period of interest. For example, the standard deviation of the return for a stock during the crisis is used in the crisis period.

Goodwill to assets

An absolute measure of goodwill is meaningless for the purpose of this paper since it is natural for big firms to carry more goodwill on their balance sheets compared to small firms. Instead, the ratio goodwill to assets is used to indicate how much of the total assets that consist of goodwill.

$$\text{Goodwill to assets} = \frac{\boldsymbol{Goodwill}}{\boldsymbol{Total\ assets}}$$

Leverage

The definition of leverage used in this research is the total liabilities divided by the total assets:

$$\text{Leverage} = \frac{\boldsymbol{Total\ liabilities}}{\boldsymbol{Total\ assets}}$$

Interest coverage ratio

In order to calculate the interest coverage ratio, the earnings before interest income and expense is divided with the interest expense.

$$\text{Interest coverage ratio} = \frac{\boldsymbol{Earnings\ before\ interest\ income\ and\ interest\ expense}}{\boldsymbol{Interest\ expense}}$$

Firm size

To measure firm size, the total asset of the firm is used. One other thinkable measure is the market capitalization of the firm. However the market capitalization of a firm is to a great extent dependent on the capital structure of the firm, everything else equal. The more leveraged the firm is, the less market capitalization the firm should have (Berk and DeMarzo, 2013), since it is less financed by equity and more by debt. To get a measure independent of the capital structure, the total assets of the firm is used. Due to the great variation of the firm sizes in terms of total assets, the natural logarithms of the values are used.

$$\text{Firm size} = ln(total\ assets)$$

Historical illiquidity

The historical illiquidity level of a stock is calculated during the period preceding the period of interest, based on the ILLIQSQRT-measure.

$$\text{Historical illiquidity}_{i,t} = \frac{\sum \boldsymbol{ILLIQSQRTi,t-1},d}{\boldsymbol{D_{i,t-1}}}$$

where i denotes the specific stock, t is the time period where t = 1 denotes the period right before the non-crisis period with the same time-length as the crisis and non-crisis periods, t = 2 denotes the non-crisis period and t=3 denotes the crisis period, d is the day and $D_{i,t-1}$ is the total number of trading days for stock i during period t-1.

Current illiquidity

The current illiquidity level of a stock is calculated during the period of interest, based on the ILLIQSQRT-measure.

$$\text{Current illiquidity}_{i,t} = \frac{\sum \boldsymbol{ILLIQSQRTi,t,d}}{\boldsymbol{D_{i,t}}}$$

where i denotes the specific stock, t is the time period where t = 1 denotes the period right before the non-crisis period with the same time-length as the crisis and non-crisis periods, t = 2 denotes the non-crisis period and t=3 denotes the crisis period, d is the day and $D_{i,t}$ is the total number of trading days for stock i during period t.

Sectors

When determining which sector the firm is active in, the Global Industry Classification Standard is used. In table 1) in the Appendix, the sectors with their corresponding codes are listed.

4.3.2 Regression

When regression 1) has been conducted for each firm in both the crisis and non-crisis period, the estimated exposure to illiquidity for each stock obtained from regression 1) will be the dependent variable in regression 2), which is a multiple linear regression. The independent variables in regression 2) are the variables mentioned in the hypotheses. Hence, the explanatory variables in regression 2) are the historical and current illiquidity level of the stock, leverage, goodwill to assets, interest coverage ratio, firm size, standard deviation, and sector.

Regression 2):

$$\beta_{i,t}^{IML} = \propto_{i,t} + \beta_{i,t}^{Standard\ deviation} * Standard\ deviation_{i,t} + \beta_{i,t}^{\ln(size)} * \ln(size)_{i,t} +$$

$$+\beta_{i,t}^{Leverage} * Leverage_{i,t} + \beta_{i,t}^{Goodwill\ to\ assets} * Goodwill\ to\ assets_{i,t} +$$

$$+\beta_{i,t}^{Historical\ illiquidity} * Illiquidity_{i,t-1} + \beta_{i,t}^{Current\ illiquidity} * Illiquidity_{i,t} +$$

$$+\beta_{i,t}^{Interest\ coverage\ ratio} * Interest\ coverage\ ratio_{i,t} + \beta_{i,t}^{Sectors} * Sector\ dummies_{i,t} + \varepsilon_{i,t}$$

where t=1 is the period before the non-crisis period, t=2 is the non-crisis period and t=3 is the crisis period. $\beta_{i,t}^{IML}$ is the stocks' exposure to illiquidity obtained from regression 1) for security i during period t, $Standard\ deviation_{i,t}$ is the standard deviation of the return for security i in period t, $Leverage_{i,t}$ is the average leverage during period t for firm i, $ln(size)_{i,t}$ is the average natural logarithm of size during period t for firm i, $Interest\ coverage\ ratio_{i,t}$ is the average interest coverage ratio during period t for firm i, $Goodwill\ to\ asset_{i,t}$ is the average goodwill to assets for firm i in period t, $Illiquditiy_{i,t-1}$ is the average illiquidity level for stock i during period t-1, $Illiquidity_{i,t}$ is the average illiquidity level of stock i during period t and $Sector\ dummies_{i,t}$ is a dummy for the sector in which firm i is active in period t. The data used to conduct this regression has a cross-sectional structure. Since the periods of interest are the defined non-crisis and crisis periods, the regression will be conducted for t=2 and t=3. When interpreting the results of regression 2), one has to bear in mind that the dependent variable, $\beta_{i,t}^{IML}$, used in the regression is estimated through regression 1). As a consequence, the results of regression 2) can be distorted due to the fact that the dependent variable is estimated and carries some uncertainty. The regression is performed with robust standard errors to control for heteroscedasticity. Since the research regarding the determinants of stocks' exposure to illiquidity is thin, one should also note that there is a risk that regression 2) is endogenous. The reason for this is simply that the lack of research within this area makes it difficult to know if any important explanatory variables, that could cause an omitted variable bias, are omitted from the regression. However, we have included the explanatory variables that we have intuition for.

4.3.3 Dropping observations with missing values

Before the formation of the different portfolios described in section 4.2.4 and 4.2.5, observations without data needed to calculate market capitalization, book-to-market-ratios and standard deviation of stock returns have been dropped. The reason for this is simply to be able to form the portfolios without any impact from the observations with missing values. When it comes to regression 2) the observations with missing values for the explanatory variables are dropped since they would otherwise distort the results in the regression.

4.3.4 Winsorising

After plotting histograms of the explanatory variables in regression 2), one can conclude that all of the variables have a distribution reminding of a normal distribution. However, the interest coverage ratio has relatively more outliers compared to the other explanatory variables. The reason for that is due to the fact that there are some firms with very low leverage and hence low interest expense. Therefore, the interest coverage ratios for these firms are very high if the earnings before interest income and expense is positive and not close to zero and very low if negative and not close to zero. In order to handle these outliers, we have used the method called winsorising. In other words, we have replaced the values exceeding the percentile 95-value with the percentile 95-value and the values that fall below the percentile 5-value with the percentile 5-value. For the other variables with a normal distribution and only one or two extreme outliers, the extreme outliers have been dropped manually. Extreme outliers are defined as the values that are more than three interquartile ranges greater than the third quartile or smaller than the first quartile respectively.

5. Results

5.1 Inputs in regression 1)

In graph 1) – graph 3) in the Appendix, the returns over time for the IML-, SMB- and HML-portfolios are shown.

5.2 Results for regression 2)

5.2.1 Stocks' exposure to illiquidity in the crisis and non-crisis period

Graph 4) and graph 5) in the Appendix display the distributions of β_i^{IML} for both the crisis and non-crisis period, which will be the dependent variable in regression 2). Furthermore, a variable denoted as Betadifference is defined in order to perform a two-sided t-test to find out whether the stocks' exposure to illiquidity risk are greater, smaller or unchanged in the crisis period compared to the non-crisis period. Betadifference is defined as following:

$$Betadifference_i = \beta_{i,2}^{IML} - \beta_{i,1}^{IML}$$

where 2 denotes the crisis period, 1 denotes the non-crisis period and i denotes each firm in the sample.

Table 2)

Variable	Observations	Mean	Std. Error	Std. Dev.	95% Confidence interval	
Betadifference	1364	0.0623	0.0064	0.2361	0.0497	0.0748
t = 9.7382						

The results reported in table 2) show that Betadifference is positive and significantly different from zero at 5%-level. In other words, the stocks are on average more exposed to illiquidity during the crisis compared to the non-crisis period.

5.2.2 Results regression 2)

Table 3)

Variables	Non-crisis period Exposure to illiquidity		Crisis period Exposure to illiquidity	
Standard deviation	-0.033	(-0.64)	0.103***	(2.77)
Historical illiquidity level	0.0675***	(4.03)	0.014	(0.53)
Current illiquidity level	0.0486*	(1.71)	0.0536***	(3.19)
ln(size)	-0.00241	(-0.96)	-0.00898**	(-2.37)
Leverage	0.0252	(0.94)	0.120***	(3.73)
Interest coverage ratio	-0.000147	(-0.92)	-0.00134***	(-4.83)
Goodwill to assets	-0.0672**	(-2.57)	0.00492	(0.13)
Sectors:				
Consumer Staples	0	(.)	0	(.)
Health Care	-0.000724	(-0.04)	0.0371	(1.33)
Financials	-0.0366***	(-2.90)	-0.0419	(-1.50)
Information Technology	0.0278	(1.39)	0.045	(1.49)
Telecommunication Services	0.0113	(0.55)	0.0431	(1.42)
Utilities	-0.0776***	(-2.82)	-0.0268	(-0.88)
Energy	-0.254***	(-14.84)	0.0152	(0.54)
Materials	-0.00777	(-0.46)	-0.0434	(-1.49)
Industrials	0.0111	(0.86)	-0.0421*	(-1.66)
Consumer Discretionary	0.0149	(1.14)	0.0699**	(2.51)
_cons	0.0664**	(2.24)	0.0281	(0.64)
t statistics in parentheses	N	1193	N	1339
* p<0.1, ** p<0.05, *** p<0.01	R-squared	0.3673	R-squared	0.2884

Table 3) shows the results of regression 2). Regarding the non-crisis period, the significant determinants of stocks' exposure to illiquidity are the illiquidity level of the stocks, both the current and the historical levels, and the goodwill to assets ratio. Furthermore, the Utilities, Financials and Energy sectors affect the stocks' exposure to illiquidity in a significantly different way compared to the base-case sector Consumer Staples.

When it comes to the crisis period the standard deviation of stock returns, firm size, the stocks' current illiquidity level, leverage and interest coverage ratio are significant determinants of the stock's exposure to illiquidity. Furthermore, the sectors Industrials and

Consumer Discretionary affect the stock's exposure to illiquidity in a significantly different way compared to the base-case sector Consumer Staples.

5.2.3 Magnitude of effect

Table 4)

Variable	Non-crisis period		Crisis period	
	Coefficient	95% confidence interval	Coefficient	95% confidence interval
Current illiquidity	0.0486	-0.0071167 : 0.1043167	0.0536	0.020613 : 0.086586

In table 4), the 95% confidence intervals for the estimated betas for the only variable that is significant in both periods, the current illiquidity level, are shown for both periods. By comparing the 95% confidence interval for the estimated betas, one can draw the conclusion that the magnitude of effect from the current illiquidity level on the stocks' exposure to illiquidity does not increase significantly in the crisis compared to the non-crisis period.

Table 5)

Variables	Non-crisis period		
	Coefficient	Standard deviation	One standard deviation effect
Current illiquidity	0.0486	0.391	0.0190
Historical illiquidity	0.0675	0.664	0.0448
Goodwill to assets	-0.0672	0.139	-0.0093

Table 6)

Variables	Crisis period		
	Coefficient	Standard deviation	One standard deviation effect
Current illiquidity	0.054	0.576	0.0309
ln(size)	-0.009	2.142	-0.0192
Leverage	0.120	0.210	0.0252
Standard deviation of stock returns	0.103	0.183	0.0188
Interest coverage ratio	-0.001	21.267	-0.0285

In tables 5) and 6), some descriptive statistics for the significant variables in each period except for the sector dummies are shown. The beta-coefficients for each of the variables obtained from regression 2) are listed as well as the cross-sectional standard deviation for each variable in both the crisis and non-crisis period. In the column called one standard deviation effect, the beta-coefficients of the variables have been multiplied with the corresponding cross-sectional standard deviation of the variables in each period respectively. In the crisis period, the current illiquidity variable has the greatest one standard deviation effect. In the non-crisis period, the historical illiquidity variable has the greatest one standard deviation effect.

6. Discussion

6.1 Standard deviation of stock returns

The results indicate that the standard deviation of stock returns is not a significant determinant of stocks' exposure to illiquidity during the non-crisis period. However, it becomes a significant determinant during the crisis period. Holding all other variables constant, a stock with a high standard deviation of returns should be more exposed to illiquidity compared to a stock with a low standard deviation of returns according to the results. This is in line with the flight to quality dynamics, since stocks with a higher standard deviation of stock returns should be perceived as more risky by the investors and therefore sold off to a greater extent compared to stocks with lower standard deviation of returns, everything else equal.

6.2 Goodwill

In the non-crisis period the goodwill to assets ratio is a significant determinant of stocks' exposure to illiquidity, suggesting that a higher goodwill to assets ratio leads to a lower exposure to illiquidity everything else equal. In contrast to our hypothesis regarding goodwill, the coefficient before goodwill to asset in regression 2) is not significant in the crisis period. Even though there is no significance during the crisis period, the change in significance and sign of the coefficient from the non-crisis to the crisis period is consistent with the theory about ambiguity aversion. The reason for this is that the ambiguity aversion would predict that firms with high goodwill to assets will be more exposed to illiquidity due to the sell-off. These dynamics might be causing the beta-coefficient for goodwill to assets in regression 2) to go from being negative and significant to positive and insignificant. However, since there is no statistical significance in the crisis period, no stronger conclusions can be drawn.

6.3 Leverage

In line with hypothesis 1), leverage is a significant determinant of stocks' exposure to illiquidity in the crisis period. The more leveraged a firm is, the more exposed its stocks will be to illiquidity. However, in the non-crisis period, leverage is not a significant determinant of stocks' exposure to illiquidity. The shift in significance going from the non-crisis period to the crisis period supports the fact that the flight to quality dynamics take place, causing leverage to become a significant determinant during the crisis.

6.4 Interest coverage ratio

The beta-coefficient for interest coverage ratio in regression 2) is negative but not significant in the non-crisis period. In the crisis period on the other hand, the beta-coefficient becomes significant with a negative sign. This means that a firm with a high interest coverage ratio contributes to a low exposure to illiquidity for its stocks, everything else equal. The finding is in line with hypothesis 4), suggesting that the flight to quality dynamics during the crisis period cause interest coverage ratio as a firm risk measure to become significant in determining stocks' exposure to illiquidity.

6.5 Firm size

The results suggest that the size of a firm's assets is a significant determinant of the corresponding stocks' exposure to illiquidity in the crisis period but not in the non-crisis period. The higher the value of the firm's assets, the lower the stock's exposure to illiquidity will be during the crisis period holding all other factors constant. The results are in line with hypothesis 2) and support the fact that the flight to quality dynamics during the crisis period cause firm size to become a significant determinant of stocks' exposure to illiquidity.

6.6 Illiquidity level

The results show that the current illiquidity level significantly increases the stocks' exposure to illiquidity both in the crisis and the non-crisis period. In other words, the results indicate that the more illiquid a stock is during the period of interest, the more exposed its stocks are to illiquidity. These results are not surprising since the actual level of illiquidity should give an indication about the stocks exposure to illiquidity. However, in contrast to hypothesis nine, the magnitude of effect from the current illiquidity level on stocks' exposure to illiquidity does not increase significantly in the crisis compared to the non-crisis period. This could be interpreted in two ways. Either, investors are rational to some extent and incorporate the fact that there will be a flight to liquidity procedure during a future crisis when valuing the stocks. Therefore, the magnitude of effect does not increase during the crisis. The other way to interpret this result is that the flight to liquidity dynamics was not strong enough in the crisis period to increase the magnitude of effect.

While the stocks' historical illiquidity level is a significant determinant of the stocks' exposure to illiquidity in the non-crisis period, it becomes insignificant in the crisis period. This might seem contradictory to the flight to liquidity dynamics at first. However, referring to table 7) in the Appendix, the results show that the illiquidity level significantly changes between the crisis and non-crisis period. Since the average illiquidity level for each firm is more stable across the period prior to the non-crisis period and the non-crisis period compared to across the non-crisis and the crisis period, it is not surprising that the historical illiquidity level is a poorer determinant in the crisis compared to the non-crisis period. One should note that the non-crisis period used in this paper is considered as a bull market period, a market condition when the liquidity of stocks is normally high (Pastor and Stambaugh, 2003). Furthermore, illiquidity increases on average during crisis. Therefore, it would be interesting to conduct this study with another period as the non-crisis period which is less bullish than the non-crisis period used in this paper, to see if the results for the stocks' historical illiquidity level will change in the crisis period.

To sum up, the results suggest that the current illiquidity level of the stocks is a significant determinant of the stocks' exposure to illiquidity in both periods but the historical illiquidity level of the stocks is only significant in the non-crisis period.

6.7 Sectors

The results regarding the sectors must be interpreted in relation to the base-case sector Consumer Staples. In the crisis period, two sectors affect stock's exposure to illiquidity significantly different at the 10%-level compared to Consumer Staples. The stocks belonging to the Consumer Discretionary sector are more exposed to illiquidity compared to the stocks in the Consumer Staples sector, everything else equal. The stocks belonging to the Industrials sector are on the other hand significantly less exposed to illiquidity compared to stocks belonging to the Consumer Staples sector.

In the non-crisis period, neither of the Consumer Discretionary or the Industrials sectors are affecting stocks' exposure to illiquidity in a significantly different way compared to the base-case. However, the Financials, Utilities and Energy sectors are affecting the stock's exposure to illiquidity in a significantly different way. The results suggest that the stocks belonging to these sectors are less exposed to illiquidity compared to the firms belonging to the Consumer Staples sector, everything else equal. To conclude, the results support the fact that the stocks' exposure to illiquidity varies across some sectors, everything else equal. Also, the sectors that affect stocks' exposure to illiquidity in a significantly different way compared to Consumer Staples varies across the periods. However, the effect from sectors on stocks' exposure to illiquidity is not as extensive as we expected, especially not in the crisis period as one would believe given the flight to quality dynamics. These results therefore indicate that investors do focus more on firm specific risk measures when determining whether a stock is risky or not and less on which sector the stocks belong to. The preceding statement of course builds upon the assumption that the flight to quality dynamics are causing the changes in significance for the risk measures. While we can not be sure that this assumption is true, the results in the paper during the crisis period are consistent with the flight to quality dynamics.

6.8 Do investors anticipate the flight to quality dynamics in advance?

The results in this paper indicates to some extent that investors are irrational from the perspective that they do not take into account the effects of flight to quality dynamics in advance when purchasing stocks in non-crisis times. The reason for this statement is that neither of the standard deviation of stock returns, leverage, firm size or interest coverage ratio are significant in the non-crisis period. However, they become significant in the crisis period, when the flight to quality dynamics take place. If investors would take the flight to quality effects into account also in the non-crisis period, standard deviation of stock returns, leverage, firm size and interest coverage ratio should be significant determinants even in the non-crisis period. This theory builds upon the assumption that the flight to quality dynamics are causing the changes in significance for the risk measures.

7. Robustness

To verify the validity of the results in this paper, the same tests are performed with a different illiquidity measure. This is especially meaningful in the illiquidity area since different measures build upon different aspects of illiquidity. The illiquidity measure used for the robustness test in this paper is TURNOVER as used by Ibbotson et al. (2013). Ibbotson et al. (2013) find that liquidity as measured by TURNOVER is a significant indicator of return dynamics in the US market. While the ILLIQSQRT-measure measures the price-impact per traded volume in terms of USD, TURNOVER is completely free from the volume-price relationship. Hence, TURNOVER takes a fundamentally different approach in measuring illiquidity, which motivates the use of TURNOVER as a robustness measure against ILLIQSQRT. TURNOVER is measured as the dollar volume traded over the tradable market capitalization during the trading day. A high value of TURNOVER indicates a liquid stock whereas a low value of TURNOVER indicates an illiquid stock.

Turnover is defined as:

$$Turnover_{i,t} = \frac{1}{D_{i,t}} \sum_{i=1}^{D_{i,t}} \frac{DOLVOL_{i,t,d}}{DTMV_{i,t,d}}$$

where $DTMV_{i,t,d}$ is the total tradable market capitalization denoted in dollar of stock i at day d in period t and $DOLVOL_{i,t,d}$ is the volume traded in terms of USD of stock i in period t on day d. The same regressions are conducted for the non-crisis and crisis periods but with TURNOVER instead of ILLIQSQRT as the illiquidity measure. The careful reader notes that the illiquid portfolio in regression 1) is now represented by stocks with a *low* value of TURNOVER instead of a *high* value for ILLIQSQRT. In other words, IML now become the portfolio of stocks with *low* TURNOVER (illiquid stocks) minus the portfolio of stocks with *high* TURNOVER (liquid stocks).

Table 8)

Variables	Non-crisis period Exposure to illiquidity		Crisis period Exposure to illiquidity	
Standard deviation	-0.185	(-1.48)	0.0696***	(3.16)
Historical illiquidity level	-0.248***	(-3.49)	-0.354	(-0.37)
Current illiquidity level	-0.382***	(-6.63)	-0.423***	(-5.43)
ln(size)	-0.0195	(-1.38)	-0.0123**	(-2.21)
Leverage	0.154	(1.29)	0.252***	(5.23)
Interest coverage ratio	-0.000685	(-1.22)	-0.00110**	(-2.45)
Goodwill to assets	-0.150**	(-2.20)	0.157***	(2.97)
Sectors:				
Consumer Staples	0	(.)	0	(.)
Health Care	0.127	(1.00)	0.0492	(1.64)
Financials	-0.0864***	(-2.70)	0.0834	(1.28)
Information Technology	0.0918*	(1.87)	0.0546	(0.69)
Telecommunication Services	0.122	(0.87)	0.022	(0.49)
Utilities	-0.252**	(-2.45)	0.016	(0.38)
Energy	-.082***	(-17.93)	-0.371***	(-11.53)
Materials	-0.0955	(-1.54)	-0.338	(-0.69)
Industrials	0.00848	(0.25)	-0.0198	(-0.71)
Consumer Discretionary	0.155	(1.34)	0.100***	(3.26)
_cons	0.423***	(5.66)	0.0899	(1.51)
t statistics in parentheses	N	1193	N	1339
* p<0.1, ** p<0.05, *** p<0.01	R-squared	0.33559	R-squared	0.3933

In line with the table 3) for regression 2) using the ILLIQSQRT-measure, the significant determinants in the non-crisis period are the historical illiquidity level, the current illiquidity level and the goodwill to assets according to table 8). Note that the beta-coefficients for the illiquidity levels are negative for TURNOVER since a higher TURNOVER denotes a more liquid stock everything else equal. Therefore, the higher the TURNOVER, the less exposed the stock should be to illiquidity. On the other hand, a higher ILLIQSQRT-measure indicates a more illiquid stock. Therefore, it is consistent that the beta-coefficients for the illiquidity levels measured using TURNOVER is negative while the beta-coefficients for the illiquidity levels measured with ILLIQSQRT are positive. Furthermore, when it comes to the sectors, the signs of the significant sectors are consistent with the results using the ILLIQSQRT-measure. However, when using the TURNOVER measure, the Information Technology sector is also significant.

In the crisis period, the signs of the beta-coefficients for the significant variables are in line with the signs obtained using the ILLIQSQRT-measure. However, as opposed to the results using the ILLIQSQRT-measure, the goodwill to assets ratio becomes significant in the crisis period when using the TURNOVER-measure. Furthermore, the Energy sector affects stocks' exposure to illiquidity in a significantly different way compared to the Consumer Staples sector while the Industrials sector is not significant.

Overall, the results using the two different measures are consistent with one another. Even though there are some differences in significance, the signs of the estimated beta-coefficients for the variables are consistent. The differences in significance could potentially be explained by the fact that the dependent variable in regression 2) is estimated in regression 1), which provides some uncertainties to the results of regression 2).

8. Summary and conclusion

This paper examines the determinants of stocks' exposure to illiquidity. This is an important topic since the stocks' exposure to illiquidity should affect the returns required by investors, meaning that it affects the cost of capital of firms and hence the allocation of the real resources in the economy (Amihud et al. 2005). There is evidence supporting the fact that flight to quality and flight to liquidity dynamics take place during crisis, where investors both reallocate from risky assets to less risky assets (Caballero and Krishnamurthy, 2008) and from illiquid to more liquid assets (Acharya and Pedersen, 2005; Amihud et al., 1990). Given these dynamics, one has reason to believe that firm-specific risk measures as well as the illiquidity level of the stocks should be significant determinants of stocks' exposure to illiquidity.

The findings in this paper suggest that, in the non-crisis period, the significant determinants of stocks' exposure to illiquidity are their historical illiquidity level, their current level of illiquidity, goodwill to assets and, to some extent, the sector that the stock belongs to. The results suggest that the higher the stocks' historical and current illiquidity level, the higher the stocks' exposure to illiquidity. On the other hand, an increase in the goodwill to assets ratio for the firm decreases the stock's exposure to illiquidity, everything else equal. The sectors that affect the stocks' exposure to illiquidity differently compared to the base-case sector Consumer Staples are the Financials, Utilities and Energy sectors.

In the crisis period, the significant determinants of stocks' exposure to illiquidity change. Compared to the non-crisis period, the stocks' historical illiquidity level as well as the goodwill to assets ratio become insignificant and instead stocks' leverage, interest coverage ratio, firm size and the standard deviation of stock returns becomes significant determinants of stocks' exposure to illiquidity. Furthermore, the stocks' current illiquidity level is still a significant determinant. These findings are in line with the flight to quality dynamics where investors would sell off fundamentally risky firms, thus making the stocks of risky firms more exposed to illiquidity. When it comes to the sectors, the Industrials and Consumer Discretionary sectors affects the stocks' exposure to illiquidity in a significantly different way compared to the Consumer Staples sector. As the flight to quality dynamics would predict, stocks' exposure to illiquidity increases with their leverage and standard deviation of returns while a higher interest coverage ratio and a larger firm size will decrease stocks' exposure to illiquidity, everything else equal.

Since the risk measures become significant determinants of the stocks' exposure to illiquidity during the crisis period, but not in the non-crisis period, our results suggest that investors do not fully incorporate the effects of the flight to quality dynamics on stocks' exposure to illiquidity in the non-crisis period. If they would, we argue that the risk measures would have been significant, to some extent, also in the non-crisis period. Furthermore, an interesting finding is that our results do not show that the magnitude of effect from the current illiquidity level of the stock on the stocks' exposure to illiquidity increases during the crisis compared to the non-crisis period, suggesting that the flight to liquidity dynamic is either not strong enough to provide a significant increase of the magnitude of effect or that investors incorporate the effects of the flight to liquidity dynamics already in the non-crisis period. Lastly, since the sectors do not become significant in determining stocks' exposure to illiquidity to a greater extent in the crisis period, one could argue that investors look more at firm specific risk measures during flight to quality dynamics compared to sectors.

Given the importance of using an adequate measure for illiquidity, the validity of our results are tested and confirmed with another illiquidity measure. While the findings from this paper shed light on the determinants of stocks' exposure to illiquidity during the financial crisis of 2007-2009 and the years 2005-2007 preceding the crisis in the US stock market, the generality of our findings ends with this specific time period. Therefore, an interesting area for further research would be to perform the same tests for several crisis periods to extend the generality. Also, to extend the set of potential determinants of stocks' exposure to illiquidity is a definitive area for further research.

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10. Appendix

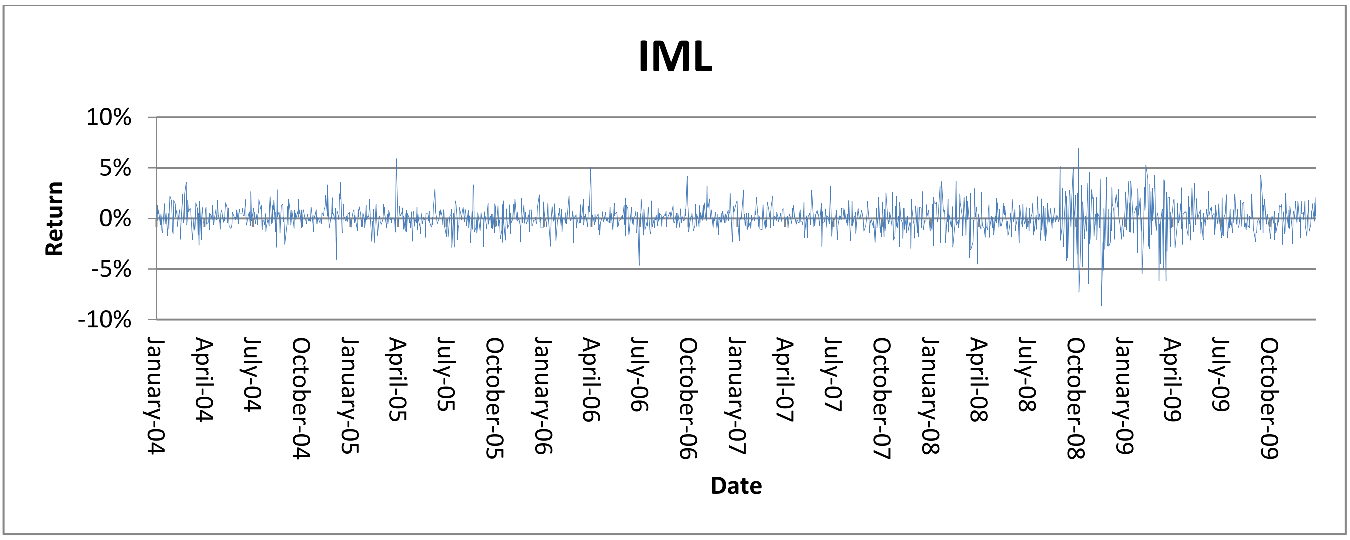
Table 1)

Code	Sector
10	Energy
15	Materials
20	Industrials (capital goods, Commercial & Professional Services, Transportation)
25	Consumer Discretionary (Automobiles & Components, Consumer Durables & Apparel, Hotels Restaurants & Leisure, Media, Retailing)
30	Consumer Staples (Food & Staples Retailing, Food, Beverage & Tobacco, Household & Personal Products)
35	Health Care (Health Care Equipment & Services, Pharmaceuticals & Biotechnology)
40	Financials (Banks, Diversified Financials, Insurance, Real Estate)
45	Information Technology (Software & Services, Technology Hardware & Equipment, Semiconductors & Semiconductor Equipment)
50	Telecommunication Services
55	Utilities

Notes. Table 1) shows the sectors with their corresponding codes according to the Global Industry Classification Standard.

Graph 1)

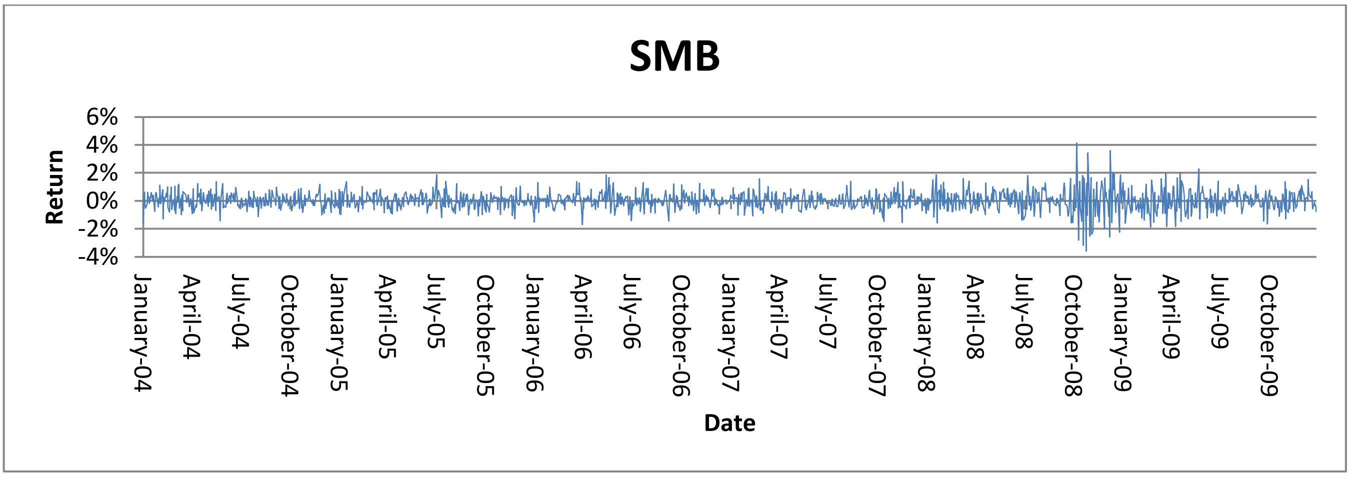
The IML-return over time



Notes. The figure presents the time series returns for the IML portfolio in regression 1) from the 5th of January 2004 to 31th of December 2009. Stocks are sorted at the beginning of each month into three portfolios based on their standard deviation of their daily returns during the three preceding months, where the cut-off points are the percentile 30-value and the percentile 70-value. Each of these standard deviation-based portfolios are in turn sorted into five portfolios based on their average ILLIQSQRT-measure calculated over the three preceding months. In total there are fifteen portfolios created. IML is the difference between the simple average of the returns of the most illiquid portfolio within each of the three standard deviation-based portfolios and the simple average of the returns of the most liquid portfolio within each of the three standard deviation-based portfolios.

Graph 2)

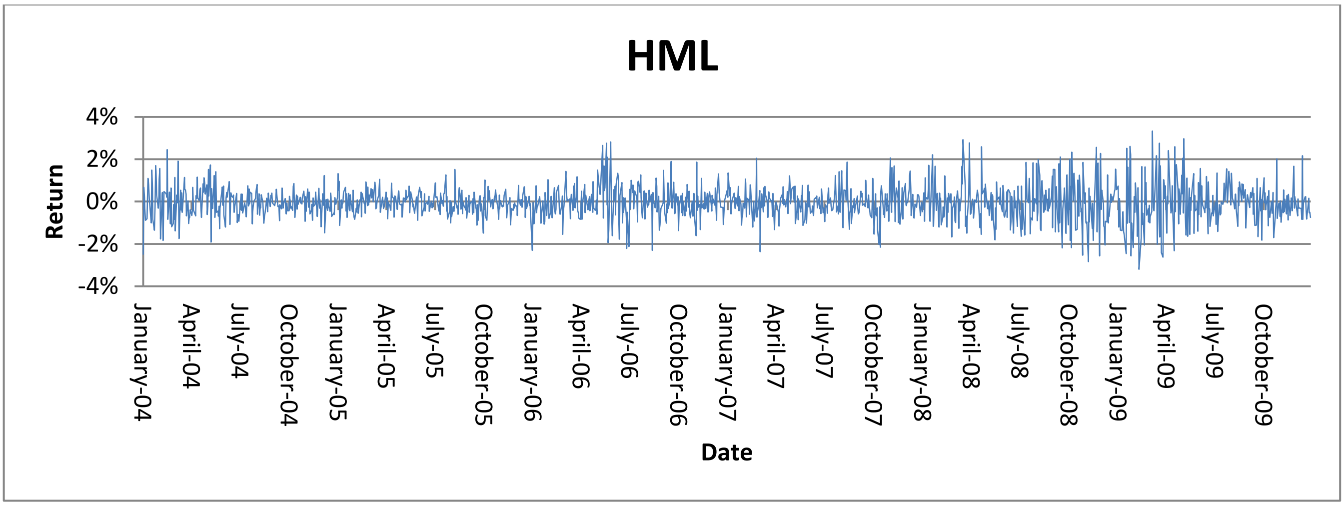
The SMB-return over time



Notes. The figure presents the time series returns for the SMB portfolio in regression 1) from the 5th of January 2004 to 31th of December 2009. SMB is created by taking the difference between the simple average of the daily returns of the three small-stock portfolios (S/L, S/M and S/H) and the simple average of the daily returns of the three big-stock portfolios (B/L, B/M and B/H). The SMB portfolios are formed on the first trading day of each year.

Graph 3)

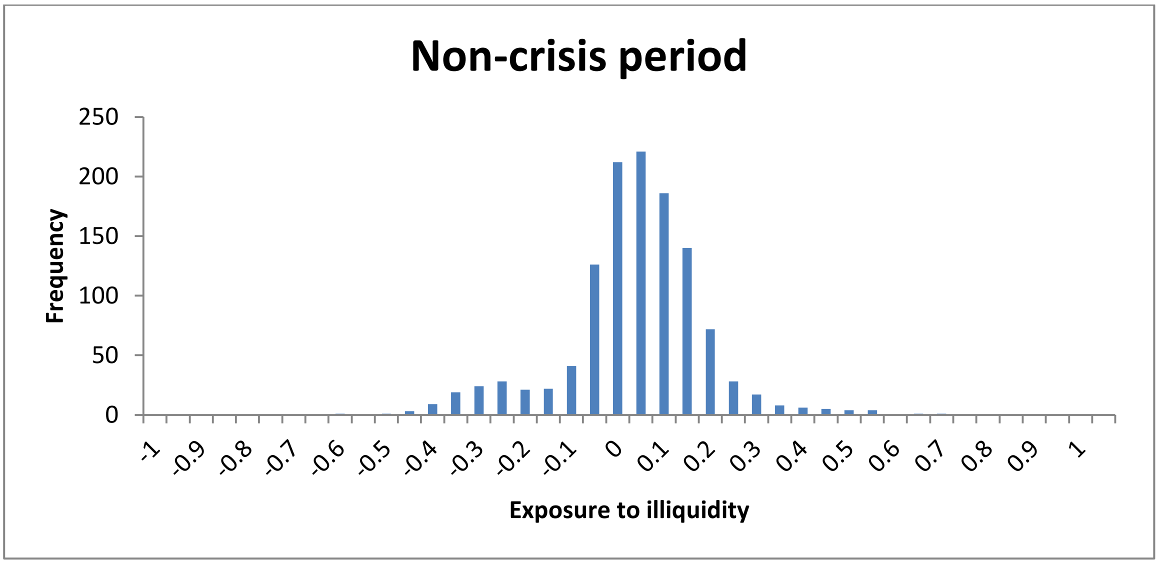
The HML-return over time



Notes. The figure presents the time series returns for the HML portfolio in regression 1) from the 5th of January 2004 to 31th of December 2009. HML is the difference between the simple average of the daily returns of the two high-book-to-market portfolios (S/H and B/H) and the simple average of the daily returns of the two low book-to-market portfolios (S/L and B/L). The HML portfolios are formed on the first trading day of each year.

Graph 4)

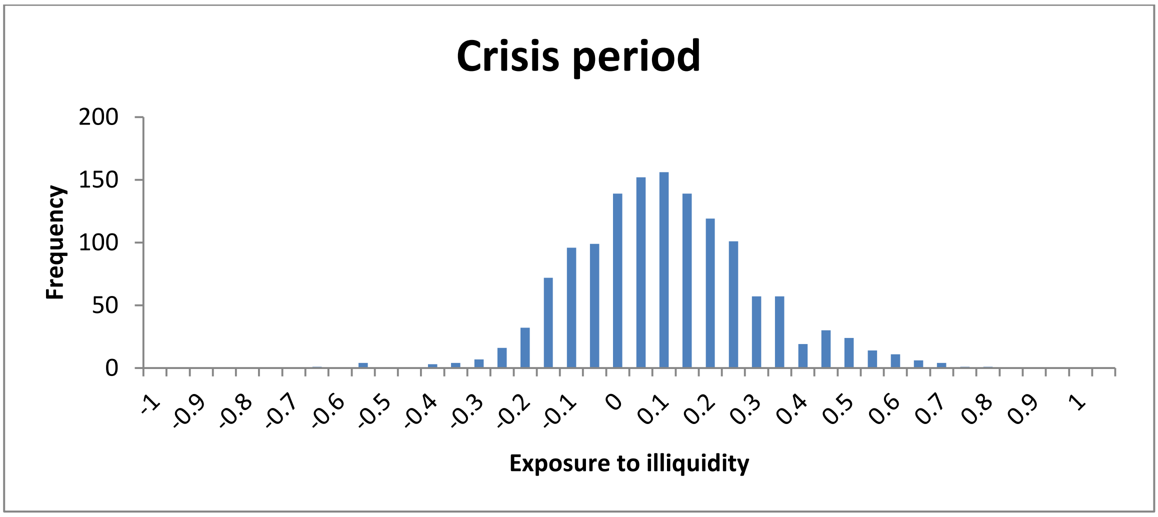
The distribution of stocks' exposure to illiquidity in the non-crisis period



Notes. Graph 4) shows a histogram for the stocks' exposure to illiquidity in the non-crisis period.

Graph 5)

The distribution of stocks' exposure to illiquidity in the crisis period



Notes. Graph 5) shows a histogram for stocks' exposure to illiquidity in the crisis period.

Table 7)

	Crisis period					
Variable	Observations	Mean	Std. Error	Std. Dev.	95% Confidence interval	
Current illiquidity – Historical illiquidity	1364	.0706	.0084	.3137	.0540	.0873
t = 8.3172						

Notes. Table 7) shows that the average illiquidity level significantly increases in the crisis period compared to the non-crisis period, which will be discussed further in the discussion section.