Essays on Empirical Market Microstructure

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Essays on Empirical Market Microstructure

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Chapter 1

Introduction

Liquidity is an elusive and multifaceted concept. Generally it is the ability of trading an asset quickly, at low cost and without causing significant movement in the market price. In practice, whenever an investor considers a potential investment in an asset, he would also consider the ability to sell it again and the cost to trade it in the future. No asset is perfectly liquid. Three sources of illiquidity are defined in the market microstructure literature:

(i) Exogenous transaction cost: This is the explicit cost that a buyer and/or seller pays every time a security is traded. It could be order-processing cost, brokerage fee, or transaction tax.

(ii) Inventory risk: Different from the ideal market model, not all investors are present in the market at all time. Supply and demand imbalance arises when investors cannot find the counter party at the time they need to trade. For example, an investor needs to sell a security quickly, but buyers may not be available at that moment. As a result, the seller may sell to a market maker who buys in anticipation of being able to lay off the position later. Then the market makers are exposed to the risk of holding a suboptimal inventory position and price moving against them. Inventory cost is the compensation for this risk.

(iii) Asymmetric information: Investors process different information sets in the market. Some investors are better informed than others. For example, the buyer of a stock may worry that a potential seller has private information that the company is losing money, and the seller may be afraid that the buyer has private information that the company is about to be taken over. If informed traders are correct, they gain a profit and who is on the other side of their trades losses. In addition to private information about the fundamentals of the security, some investors can also have private information about order flow. For instance, if a trading desk knows that a hedge fund needs to liquidate a large position which will depress prices, then the trading desk can sell early at relatively high prices and buy back later at lower prices. Asymmetric information cost represents the risk that the counter party of a trade can be superiorly informed about the fundamental value or order flow.

Liquidity is important to all market participants, stock exchanges and regulators. Investors demand liquidity because it allows them to implement their trading strategies at low cost. Stock exchanges endeavor to improve liquidity since it is one of the most important characteristics of a well-functioning market and a liquid market attracts more investors. Regulators also pay much attention to liquidity as it is an important factor for a stable market. This dissertation studies liquidity from two aspects. In Chapter 2 and 3, I look at liquidity and asset prices with a focus on liquidity leak events and downside liquidity respectively. In Chapter 4, I look at liquidity and institutional design where I examine the value of designated market makers.

1.1 Liquidity and asset prices

Liquidity asset pricing deviates from standard asset pricing by relaxing several unrealistic assumptions, for example the zero cost assumption, the assumption of price-taking behavior, the assumption that all investors are equally informed and that all investors are present in the market at all time. In this section I review the theories on how liquidity is priced and the empirical studies that test these theories. Then I discuss the contribution of my dissertation in this field.

It is well accepted that liquidity is an important feature and a desirable property for an asset. Other things being equal, investors would prefer assets which can be traded faster, at lower cost and with smaller price impact. However, is liquidity valuable enough to affect asset returns? Over a short period of time, higher levels of transaction costs must lower the return available to investors, and lower the price that investors are willing to pay for the asset. However, given a long enough time horizon, are these effects of liquidity still large enough to actually affect returns?

The answer from the traditional view in asset pricing would be “no”. For example, Constantinides (1986) shows theoretically that transaction costs can only have a second-order effect on the liquidity premium implied by the equilibrium asset returns in an inter-temporal portfolio selection model. A similar conclusion is drawn by Aiyagari and Gertler (1991), Heaton and Lucas (1996), and Vayanos and Vila (1999). These authors all argue that the transactions costs are just too small relative to the equilibrium risk premium to make any real difference.

The counter-argument is first brought forward by Amihud and Mendelson (1986), who proposed a single-period model with non-stochastic level of liquidity. In their setting, investors try to maximize the present value of expected cash flows and they have different expected holding periods. They proxy illiquidity by the bid-ask spread, so higher spreads result in lower overall returns for investors. While all investors prefer assets with low spreads, these assets are more valued by short-term investors who incur transaction costs most frequently. Long-term investors then choose for assets which bring them the greatest advantages, namely those that are most costly to trade. As a result only investors with long horizons will hold illiquid assets, and they will demand compensation for doing so. Therefore, their model suggests that in equilibrium assets with low liquidity (high bid-ask spread) will command a return premium.

Recently theorists argue that not only the absolute level of liquidity commands a return premium, but also the risk of systematic shocks to liquidity might lead to important liquidity risk premiums as well. Acharya and Pedersen (2005) derive a liquidity-adjusted capital asset pricing model where they view liquidity as a stochastic variable. In equilibrium, a stock's required return depends on the expected liquidity level as well as three dimensions of liquidity risks, i.e. commonality in liquidity, return sensitivity to market liquidity and liquidity sensitivity to market return. The first effect is that the return increases with the covariance between the asset's illiquidity and the market illiquidity. This is because investors want to be compensated for holding a security that becomes illiquid when the market becomes illiquid. The second effect is usually negative because investors are willing to accept a lower return on an asset which has a high return in times of low market liquidity. The third effect on required returns is also negative for most stocks. When the market declines, marginal utility of consumption is high and the ability to sell easily is especially valuable. Thus, an investor is willing to accept a discounted return on stocks with high liquidity level in the state of low market return.

Moreover, Watanabe and Watanabe (2008) model how liquidity betas and liquidity risk premium change over time. They propose a model that relates preference uncertainty to time variation in liquidity betas and liquidity risk premium. Specifically, the model implies that in the state of high (low) preference uncertainty, liquidity betas are high (low) and liquidity risk premium goes up (down).

Brunnermeier and Pedersen (2009) provide a model that links an asset's liquidity and traders' funding liquidity. They show that there can be multiple equilibria in the market. In one equilibrium, market is liquid and margin requirements are favorable for speculators, so speculators are in general liquidity suppliers in the market. In another equilibrium, market is illiquid with higher margin requirement, then speculators turn to be liquidity demanders instead of suppliers. A large market shock can lead to losses for speculators. When their capital is reduced to a certain level, the market will eventually switch to a low-liquidity/high-margin equilibrium.

There is a number of empirical literature that studies the existence of a liquidity effect. Here we only look at the empirical investigations that examine the relationship between liquidity and asset prices for stocks. The first study is initiated by Amihud and Mendelson (1986) where they test two major predictions derived from their model. First, average portfolio risk-adjusted returns increase with their bid-ask spread. Second, the slope of the return-spread relationship decreases with the spread. They use monthly stock returns over the period 1961-1980 and quoted bid-ask spread of the years 1960-1979 for NYSE stocks. Their findings provide supportive evidence for both predictions. Specifically, the difference in the monthly excess return between the two extreme spread groups is 0.857% when estimated by OLS and 0.681% when estimated by GLS. Many other empirical studies use different measures of liquidity and find significant relation between stocks returns and these measures of liquidity. For example, Brennan and Subrahmanyam (1996) uses Kyle (1985) λ as the measure of liquidity, estimated from intraday trade and quote data. Brennan, Chordia, and Subrahmanyam (1998) take the stock's dollar trading volume as a measure of liquidity. Amihud (2002) propose an illiquidity measure as the ratio of the absolute return to the trading volume. All of these studies find positive and significant effect of illiquidity on stock returns, after controlling for different kinds of other well-known firm characteristics and risk factors.

In addition, another line of empirical research tests whether liquidity risk is systematic and whether systematic liquidity risk is priced in the cross section of stock returns. For example, Chordia, Roll, and Subramanyam (2000) demonstrate that liquidity has a common systematic factor. They show that quoted spreads, quoted depth, and effective spreads co-move with market-wide and industry-wide liquidity. After control for well-known individual liquidity determinants, common influences remain significant and material. Pastor and Stambaugh (2003) provide evidence that asset prices reflect a premium for the sensitivity of stock returns to market-wide liquidity. From 1966 through 1999, the average return on stocks with high sensitivities to liquidity exceeds that for stocks with low sensitivities by 7.5% annually. Acharya and Pedersen (2005) test the cross-sectional predictions of their liquidity-adjusted CAPM model using NYSE and AMEX stocks over the period 1963 to 1999. Under the models restrictions, liquidity risk contributes on average about 1.1% annually to the difference in risk premium between stocks with high expected illiquidity and low expected illiquidity while the premium for liquidity level is 3.5%.

Over time, both liquidity level and the premium required per unit of liquidity level have declined as evidenced by Amihud (2002), Jones (2005), and Ben-Rephael, Kadan, and Wohl (2009). For example, Ben-Rephael, Kadan, and Wohl (2009) use NYSE common stocks over 1964 and 2007 and three measures of liquidity, i.e. Amihud's ILLIQ measure, annual dollar volume and annual turnover. Their results show that both the sensitivity of returns to liquidity and liquidity level premium have significantly declined over the past 40 years. Moreover, the profitability of trading strategies of buying illiquid stocks and selling liquid stocks has dramatically decreased.

Has the level premium decline made liquidity unimportant for asset pricing? Chapter 2 explores a new dimension of liquidity inspired by the disaster risk literature, e.g., Rietz (1988) and Barro (2006). Investors might care little about liquidity in normal market conditions, but high transaction cost might become a first order concern if the stock hits a 'disaster' liquidity state. An example is a self-fulfilling liquidity dry-up if all believe others will not show up for trade or, in other words, a negative manifestation of the liquidity externality (see, e.g., Pagano (1989)). Such dry-up is particularly painful if this state is so persistent that waiting a day will not restore liquidity. We refer to these events as liquidity leaks or liquileaks.

In order to test whether liquidity leaks are priced, we need a measure that recognizes (i) the frequency of hitting an illiquid state and (ii) the duration of that state. Liquileaks are expected to hurt only if both of these are substantial. That is, securities that hit illiquid states frequently but revert in a day or securities that stay for a prolonged period in an illiquid state but almost never hit these state are not painful for an investor. We operationalize this idea by estimating a Markov regime-switching model where the transition probability matrix identifies these two dimensions. The measure for a liquidity leak event is then defined as the (unconditional) probability that one finds the security in the illiquid regime for more than a week. This is essentially a ‘product’ of frequency and duration, which captures the idea that both need to be large for liquidity leaks to hurt. Our findings show that a trading strategy that is long in high liquileak stocks and short in low liquileak stocks yields a significant average annual excess return of approximately 3.36%. Conducting Fama-MacBeth regressions that control for other return determinants, we further find that one standard deviation increase in liquileak probability yields an additional required return of 1.33% annually. Moreover, the premium of liquileak probability has increased over time.

While liquidity level and risk are important to investors in general, they can be particularly important in a declining market. Chapter 3 differentiate market downside and upside explicitly. We examine the relationship between liquidity and stock returns, with a particular focus on the downside market. Investors value downside losses differently from upside gains since they are not only risk averse but also loss averse. Liquidity is especially important in a declining market. Investors could hit their capital constraints and are forced to liquidate. At this time stocks with low liquidity level and/or high liquidity risk in a downside market are particularly undesirable and investors would demand a higher return for holding them. We measure the downside illiquidity level and beta conditioning on the market return. Moreover, we present evidence for a positive cross-sectional relation between stock returns and the downside illiquidity level and beta. An increase of one standard deviation in the downside illiquidity level would increase yearly returns by approximately 1.8%. This effect is both statistically and economically significant. When the downside illiquidity level and beta are jointly included in the cross-sectional regression, only the downside illiquidity level has a significantly positive return premium.

1.2 Liquidity and institutional design

Liquidity and institutional design are closely related. The structure and design of trading mechanism has been subject to dynamic changes in the last few years. Fierce competition for order flows and IPOs urges stock exchanges to take various actions to enhance liquidity and attract investors. One noticeable phenomenon is the increasingly important role of market makers, even in today's electronic era. In this section I first present the classification of market making systems based on market makers' characteristics and trading mechanisms. Then I go through the theoretical and empirical research about market making. Finally I explain in which way my dissertation extends the existing literature.

Since the inception of stock markets, financial intermediaries has played a significant role in the stock market design. Recently, due to advances in communication and computing technology, the needs for human participation in tasks such as order submission or information dissemination have significantly reduced. Meanwhile, automated trading system has proliferated worldwide. However, market makers are continue to be widely used in one form or another as liquidity providers and market stabilizers. Most stock exchanges, while mainly organized as limit order markets, have market makers as part of their market design. Although the main purpose of market making is the same, the way that market makers are integrated to the trading system can differer significantly across exchanges. In general, we can identify three types of market makers based on trading systems and the characteristics of market makers:

(i) Dealers in a quote-driven market: In a quote-driven market, dealers arrange all the trades and supply most, if not all, of the liquidity in the market. Normally each security has multiple dealers, who are responsible to quote continuously two-sided markets. Since dealers are profit-motivated traders, they attract order flow primarily by quoting aggressively price, accepting large sizes, providing high-quality service, etc. (Harris (2003)). The most well-known example is the National Association of Securities Dealers Automated Quotation (NASDAQ) dealer.

(ii) Market makers with privileges in a order-driven market: One important feature of this system is the use of single market maker and its inherent advantage in terms of unique information over other traders on both the market orders and the limit order book. Stock markets that apply this market making system are NYSE and German Deutsche Börse.

(iii) Competitive market makers in a order-driven market: Market makers in this system have affirmative obligations of submitting continuous bid and ask orders by trading on their own account. They do not possess any monopolistic information and have to compete with investors for order flows. They are usually, in many cases only, hired by small and mid caps with inactive-traded stocks and are subsidized by direct payment from the listed firms. Such kind of market makers can be found in Euronext, where they are called Designated Market Makers.

There are many theoretical models that study the behavior of market makers. Glosten (1989) provides a model of a monopolist market maker, motivated by the specialist in NYSE. He extends the Glosten and Milgrom (1985) analysis to allow for both large and small trades, and for monopolistic as well as competitive market making. His key finding is that for some parameters the monopolistic market maker is willing to incur losses on the large trades favored by informed traders, while earning profits on small trades. The monopolist structure is therefore more robust, in the sense that the market may remain open even at times when trading is dominated by informed investors, and where a fully competitive market would shut down. Rock (1996) and Seppi (1997) extend the analysis by allowing for limit orders that compete with a single market maker. In Rock's model, risk neutral limit order traders have an advantage against risk-averse specialists, countered by an information advantage to the specialist. In the Seppi's model, limit order submitters incur a cost, so that competition from the limit order book is mitigated, allowing the specialist to have a degree of monopoly power. Seppi uses this framework to assess the effect of a change in the minimum price increment, which alters relative importance of market price and time priority rules, on market quality.

In the literature cited above, the emphasis is on the first two kinds of market makers in our classification. Among limited models that incorporate affirmative market making obligation of the third kind of market makers, Sabourin (2006) models price formation and order placement strategies in a centralized limit order market with designated non-monopolist market makers. She shows that the clearing frequency is higher in a limit order market with designated market makers. The best quotes in a limit order market with designated market makers are more attractive than in a pure limit order market when the best quotes are placed by investors. Moreover, the presence of market makers in limit order markets can result in more or less favorable expected best quotes depending on the asset volatility and the differences in valuation among traders. Bessembinder, Hao, and Lemmon (2007) identify two reasons that the affirmative obligation of market makers can improve welfare. The first relies on the insight that the informational component of the competitive bid-ask spread represents a transfer across traders, not a social cost to completing trades. Therefore, this trading cost dissuades efficient trading, while a restriction on spread encourages efficient trading. Secondly, a restriction on spread encourages traders to become informed, which speeds the rate at which market prices move toward true asset values in the wake of information events.

Empirically, a number of studies has been conducted to examine the behavior and impact of market makers in the first two categories. For example, Madhavan and Smidt (1993), Madhavan and Sofianos (1998), Madhavan and Panchapagesan (2000) study various issues related to the performance of NYSE specialists. Neal (1992), Mayhew (2002) and Anand and Weaver (2006) examine the value of a specialist in the options market. A number of other studies compare execution costs and depth on market maker and specialist (NYSE) systems (for example Grossman and Miller (1988), Bessembinder and Kaufman (1997), and Bessembinder (1999)). Nimalendran and Petrella (2003) compare the performance of a pure order driven market with a hybrid order driven market that consists of specialist and limit order book, and find that the hybrid system improves market quality of thinly-traded stocks.

Compared with the first two kinds of market makers, the third kind of market makers has not been intensively investigated since they are only introduced during recent market structure evolution. Venkataraman and Waisburd (2007) examine the benefits of designated dealers to a sample of low-liquidity firms that are traded twice a day in a call caution on the Paris Bourse. They find that firms with designated dealers exhibit better market quality, namely lower book imbalance, more frequent auction clearing, and less variability in returns and trading volume than firms without a dealer. They document that younger firms, smaller firms, and less volatile firms prefer a designated dealer. Moreover, they find evidence that there is an average cumulative abnormal return of nearly 5% around the announcement of dealer introduction. Anand, Tanggaard, and Weaver (2009) study the Stockholm Stock Exchange where firms have privilege to negotiate the level of liquidity provision with liquidity providers. They find that quoted spreads decline and quoted depths increases for stocks that arrange market making service. In addition, committed liquidity providers lead to a decline in both inter and intraday volatility, and an increase in trade size. Consistent with Venkataraman and Waisburd (2007), they also document significant abnormal returns. Finally, they examine the relationship between contract costs to the contractual improvement in market quality, firm specific characteristics and existing relationships with liquidity provision firms. Results suggest that all three groups of factors are priced in the contracts.

Chapter 4 of this dissertation studies the impact of 'designated market maker' on small-caps in Euronext Amsterdam Exchange. On October 29 2001, Euronext rolled out their Paris limit order market system to the Dutch equity market. Arguably the most significant change was the possibility for small-caps to hire a designated market maker. The so called 'designated market maker' studied in this dissertation belongs to the third category of the classification mentioned above. They commit to provide a liquidity supply at all time in the market. We conduct an event study and, contrary to previous work, focus on liquidity *risk* in addition to liquidity level, since the minimum liquidity supply insures liquidity demanders against extreme illiquidity events. In essence, a broker is paid to be a "supplier of last resort" to insure current shareholders against the idiosyncratic risk of having to trade when liquidity is low. It also mechanically reduces covariation with market return and market liquidity and therefore reduces systematic liquidity risk (see Acharya and Pedersen (2005)). The value is realized when the supply constraint binds, and shareholders realize a gain from trade that otherwise might have met too high transaction cost (in the absence of the minimum supply guarantee). This effect shows up in the data by more volume and higher DMM participation in these extreme market conditions.

The contribution to existing literature is two-fold: (i) an analysis of liquidity risk changes associated with DMM introductions and (ii) empirical identification of the channel that DMMs are "liquidity suppliers of last resort." Anand, Tanggaard, and Weaver (2009) is most related to our study. They find that DMM introduction in Sweden increases the liquidity level, produces a positive CAR, increases volume, and leads DMMs to trade more in the stocks that they contract for. Our findings are consistent with theirs. We contribute by exploring the "liquidity risk channel" which is closer to the *spirit* of a DMM contract, i.e., it guarantees a minimum for liquidity supply that is stochastic in nature. Liquidity risk changes around DMM introductions are analyzed and the liquidity insurance channel is explicitly tested by comparing DMM participation, DMM trading profit, and overall volume across days where the constraint binds and days where it does not.

1.3 Liquidity measures and data

One of the biggest challenge of empirical studies in market microstructure is how to measure liquidity (and to some extent, how to define liquidity). As mentioned before, liquidity is a concept that has many facets. Therefore, a single measure can hardly capture all of its aspects. Moreover, empirical investigations are also constrained by data availability. Basically liquidity measures can be classified based on the frequency of data.

Examples of liquidity measures calculated by high-frequency data are quoted spreads and effective spreads. The quoted bid-ask spread is the difference between the lowest ask price and the highest bid price for a security. For small orders, the quoted spread is a good indication of the execution cost for a trade. For large orders, however, it may not fully represent the cost. Effective spread is defined as twice the difference between the actual execution price and the market quote at the time of order entry. The effective spread better captures the cost of a round-trip order by including both price movement (dealers coming in to execute orders at a better price than previously quoted) and market impact (spread widening due to the size of the order itself.) The effective spread can be decomposed into two components using standard techniques. The adverse selection component captures the average loss of liquidity suppliers due to informationally-motivated market orders (suppliers are on the wrong side of the trade in these transactions). The realized spread component is the remaining part and therefore captures the gross profit to liquidity suppliers. These two components are identified through an estimate of the average information in a (signed) market order, which is revealed through post-trade midquotes. That is, if we wait long enough we find how much permanent price impact the market order has. In the implementation (as in Chapter 4 of this dissertation), we use 15 minutes to allow the market to settle on the permanent price impact of the order.

However, high-frequency data is only available recently and mainly in the U.S.. The first limitation is then the relatively short period of sample time. Second, the availability of high-frequency data in other stock markets is not as high as in the U.S.. Moreover, studies that examine the relationship between liquidity and expected stock returns usually use realized returns whose variance around the expected return is high. As a result, a long sample period is needed to increase the power of the tests. In order to solve these problems, researchers then go for low-frequency data, such as daily return and volume, and find substitute measures of liquidity. Here I discuss two often-used measures, which are also used in this dissertation.

The first one is proposed by Amihud (2002) and is used in many empirical studies (e.g. Acharya and Pedersen (2005), Kamara, Lou, and Sadka (2008), Watanabe and Watanabe (2008), etc.). Amihud *illiq* measure is defined by the average ratio of the daily absolute return to the (dollar) trading volume on that day. Specifically, for each stock i and day d, the Amihud illiquidity measure is given by:

$$illiq_d^i = \frac{|r_d^i|}{dvol_d^i}$$

where r_d^i is the daily return of stock i on day d. $dvol_d^i$ is the daily dollar volume of stock i on day d. In effect, this measure gives the percentage daily price change per dollar of daily volume, or the daily price impact of the order flow. Hasbrouck (2009) demonstrates that among many daily proxies of liquidity, the Amihud illiquidity measure is most strongly correlated with the TAQ-based price impact coefficient. In addition, we normally need a filtering procedure for this measure based on the purpose of the study. For example, in Chapter 2 of this dissertation we do not follow the existing filtering procedure since the focus of that chapter is on liquidity leaks, which are in general extreme situations.

The second measure is developed by Pastor and Stambaugh (2003) where they use a variant of a volume-linked price change as the liquidity measure. Specifically, they define liquidity for stock i in month t as the OLS estimate of $\gamma_{i,t}$ in a regression as follows:

$$r_{i,d+1,m} = \theta_{i,m} + \phi_{i,m} r_{i,d,m} + \gamma_{i,m} sign(r_{i,d,m}) v_{i,d,m} + \varepsilon_{i,d+1,m} \tag{1.1}$$

where $r_{i,d,t}$ is the excess return of stock i on day d in month t; $v_{i,d,t}$ is the dollar volume (in million dollars) of stock i on day d in month t. Two filters are imposed to compute this liquidity measure in each year: (1) A stock should have at least 100 observations in a year; and (2) A stock should have a share price between \$5 and \$1000 at the end of the previous year. The monthly liquidity measure, which is the coefficient $\gamma_{i,y}$, measures the expected price reversal for a given dollar volume. The idea is that a big buy order in an illiquid stock at day d will result in large volume and negative return. If it really was price impact, and not news, we should see an unusually large return the next day (correcting for any typical serial correlation with the ϕ term), as the price bounces back. Thus when a stock's liquidity is lower, $\gamma_{i,y}$ is expected to be negative and large in absolute magnitude. This is a return reversal measure, which captures order-flow induced temporary price fluctuations.

In Chapter 2 the liquileak identification requires a daily measure of liquidity and the natural

Pastor-Stambaugh alternative to the daily Amihud ILLIQ measure is[1] :

$$psilliq_{i,d} = -\left(\frac{r_{i,d+1,y} - \hat{\theta}_{i,y} - \hat{\phi}_{i,y} r_{i,d,y}}{sign(r_{i,d,y}) v_{i,d,y}}\right) \tag{1.2}$$

where $\hat{\theta}_{i,y}$ and $\hat{\phi}_{i,y}$ are obtained by estimating the model in equation (6.1) on a sample of daily observations for stock i in year y. This *psilliq* measure replaces the *illiq* measure in the "Appendix: Liquileaks" where all empirical analyses are redone.

In Chapter 2 and Chapter 3, daily and monthly data of stock prices, returns, volume, shares outstanding, and dividend are obtained from CRSP, with a sample period from December 31, 1962, through December 31, 2008. Following Chordia, Roll, and Subramanyam (2000) and Kamara, Lou, and Sadka (2008), we utilize only common stocks (CRSP share code 10 and 11) listed on NYSE/AMEX (CRSP exchange code 1 and 2). Moreover, we obtain the daily and monthly risk-free rate and the daily Fama and French three factors from Kenneth French at Dartmouth College. In addition, Chapter 2 also uses fundamental data from COMPUSTAT, including stockholder's equity, total assets, total long-term debt, net income, and book value per share. In the main text of Chapter 2 and Chapter 3, we use Amihud *illiq* measure as the measure of liquidity. Furthermore, we also consider the alternative measure of liquidity level, developed by Pastor and Stambaugh (2003), for robustness check in Chapter 2 .

Chapter 4 uses three datasets for the empirical analysis. First, we have an intraday dataset for 11 months before and after the introduction day which contains (i) the best bid and ask quote and (ii) the price and size of all transactions along with a label that indicates whether or not a DMM was involved in the transaction (only their own-account trades are considered) and, if so, on which side of the trade. Second, we have daily data for the same period that includes market capitalization for each stock. Third, we have a file that for all DMM stocks contains the initiation and termination date of a DMM service. In this chapter we use three liquidity measures: the effective spread and Amihud's *illiq* measure as ex-post measures of liquidity and quoted spread as an ex-ante measure of liquidity.

1.4 Dissertation outline

The remainder of this dissertation is organized as follows: In Chapter 2, we propose a measure of liquidity that captures the feature of liquidity leaks, and we examine its pricing in the cross-section of stock returns. Previous literature suggests that liquidity is time-varying and there are good reasons to believe that there exists an illiquid regime and a liquid regime. When a stock has a long life of the illiquid regime, we say it is stuck in a liquidity leak (or liquileak)

[1]A Pastor-Stambaugh *illiquidity* (instead of liquidity) measure is trivially defined as minus γ.

situation. Liquidity leaks thus have two dimensions, a low liquidity level and a long duration of illiquidity. Risk-averse investors should demand a high return to compensate for the losses they may incur in a liquidity leak. We propose to measure liquidity leaks by the liquileak probability, which is the probability that a stock remains in the illiquid regime for five consecutive trading days, estimated by the Markov regime switching model. We present evidence for a positive cross-sectional relation between stock returns and liquileak probability. This effect is both statistically and economically significant. An increase of one standard deviation in liquileak probability would increase yearly returns by approximately 1.33%. Moreover, the return premium of liquileak probability has increased over time.

Chapter 3 investigates the pricing of the downside liquidity. We argue that investors regard downside market differently from upside market, and stocks that have a high liquidity level and low liquidity risk in downside market are especially valuable to investors. In a declining market, investors are very likely hit their funding constraint and have to liquidate their stocks. Thus they prefer to hold stocks that can be executed at a low cost during the market downturns and would demand higher returns for stocks that have high downside liquidity. We define the downside illiquidity level and the downside liquidity beta (comovement of stock's illiquidity with market illiquidity) conditioning on the market average return. We find a significantly positive return premium for the downside illiquidity level and beta. An increase of one standard deviation in the downside illiquidity level would increase yearly returns by approximately 1.8%. Moreover, the statistical significance of the downside liquidity beta disappears in the presence of the downside illiquidity level, implying that it is the downside illiquidity level that has the major explanatory power for the cross-sectional returns.

In Chapter 4, we examine the effect of designated market maker on small-caps in Euronext Amsterdam market. Firms care about stock liquidity as it affects their cost of capital. Small-caps care most as their stock exhibits lowest liquidity level and highest liquidity risk. Euronext allows them to contract with designated market makers (DMMs) who then have to supply minimum liquidity unconditionally. In Amsterdam, 74 small-cap firms sign up on the introduction day. We find that this improves liquidity level and reduces liquidity risk, both in an absolute sense and relative to non-DMM stocks. Moreover, it creates value as (i) DMM stocks enjoy an average abnormal return of 3.5% around the announcement day and (ii) both liquidity level and risk changes explain the cross-sectional dispersion in abnormal returns. We further find that DMMs participate in more trades and their gross trading revenue turns to a loss on high quoted spread days, i.e. days when they are likely to be constrained by their contract.

Chapter 5 concludes the dissertation. I first summarize the most important findings of this dissertation. Then I present the policy implications for market participants, stock exchange and regulators.

Chapter 2

Liquileaks

This chapter is based on Menkveld and Wang (2010).

2.1 Introduction

A participation externality makes asset liquidity inherently unstable. If investors believe that others participate in the market, they 'pay' the participation cost and the market becomes liquid. If, however, they believe others do not participate, they choose not to do so either and the market becomes extremely illiquid (see, e.g., Pagano (1989)). If, in addition, some agents are subject to institutional constraints such as loss limits one would observe negative liquidity spirals (see, e.g., Gromb and Vayanos (2002), Morris and Shin (2004), Brunnermeier and Pedersen (2009)).[1] This chapter studies such liquidity leaks empirically, i.e., a prolonged state of illiquidity.

Most evidence on the pricing of liquidity is based on the equity market. In the cross-section of stocks, Amihud and Mendelson (1986) are the first to show that average liquidity (liquidity level) is priced.[2] More recently, time variation in liquidity (liquidity risk) has been shown to matter for returns to the extent that it correlates with a systematic factor (see Pastor and Stambaugh (2003) and Acharya and Pedersen (2005)). Amihud, Mendelson, and Pedersen (2005) provide an extensive review of the literature on asset pricing and liquidity.

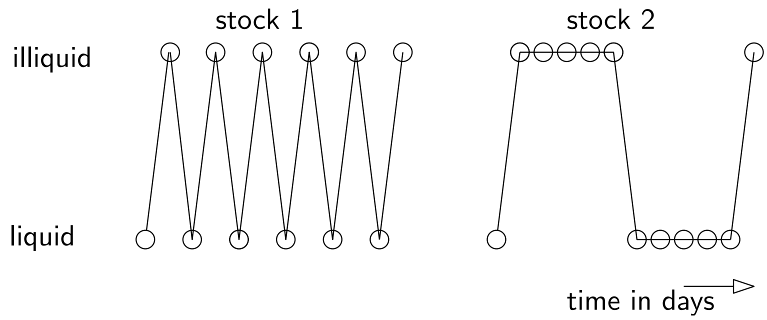
The magnitude of a liquidity premium in required returns for equities has declined over time. As for liquidity risk, Pastor and Stambaugh (2003) find that differential loadings on the market liquidity factor creates a cross-sectional difference in returns of 7.5% annually. Acharya and Pedersen (2005) use a more comprehensive model for returns that also includes liquidity level and a stock's liquidity covariation with market liquidity and market return. They find that among

[1] Carlin, Lobo, and Viswanathan (2007) model "episodic illiquidity" as a breakdown of a cooperation equilibrium when for one of the (strategic) players the stakes are so high that predation (noncooperation) becomes the dominant strategy.

[2] Liquidity level studies include Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), and Hasbrouck (2009).

the three *risk* factors, a stock's liquidity covariation with market return is the dominant one in explaining the aggregate liquidity risk premium in the cross-section of stocks. They further find that the *aggregate* liquidity risk premium is smaller than the liquidity level premium. Hasbrouck (2009) has recently reconfirmed these findings based on a longer dataset. The liquidity level in and of itself has gradually improved (see, e.g., Amihud (2002) and Jones (2005)). Moreover, the compensation per unit of illiquidity has declined (see Ben-Rephael, Kadan, and Wohl (2010)).

Has this level premium decline and the relatively small risk premium made liquidity unimportant for asset pricing? This chapter explores a new dimension of liquidity inspired by the disaster risk literature (see, e.g., Rietz (1988) and Barro (2006)). Investors might care little about liquidity in normal conditions, but high transaction cost might become a first order concern if the stock hits a 'disaster' liquidity state such as, for example, a self-fulfilling non-participation equilibrium. Such liquidity leak is particularly painful if the state is persistent so that waiting a day will not restore liquidity. We refer to these events as liquidity leaks or liquileaks. The graph below illustrates the key new feature as these stocks are similar in terms of level and risk, yet only stock 2 is a liquileak stock.



Ex ante, security-specific liquidity leak risk does not necessarily wash in the cross-section of stocks and might in fact command a substantial additional return. One potential reason is that stocks are not perfect substitutes if some investors' endowment/labor risk factor correlates with a security's idiosyncratic return.[3] Liquileaks make the cost of such transaction uncertain and if investors cannot borrow against future income this negatively affects their immediate consumption. Another potential reason is that inter-temporal risk-sharing among patient and impatient investors breaks down in the presence of liquidity "blackout" periods (see Longstaff (2009)).

To test whether liquidity leaks are priced requires a measure that recognizes (i) the frequency of hitting an illiquid state and (ii) the duration of that state. Liquileaks are expected to hurt only if both of these are substantial. That is, securities that hit illiquid states frequently only to revert back in a day or securities that stay for a prolonged period in an illiquid state but almost never hit this state do not necessarily hurt an investor. We operationalize this idea by estimating a Markov

[3]For example, if two investors switch jobs then they will want to also swap their positions in the two companies' stock. See Lo, Mamaysky, and Wang (2004) for a mathematical formalization of such non-traded risk.

regime-switching model where the transition probability matrix identifies these two dimensions. A liquidity leak is then naturally defined as the (unconditional) probability that one finds the security in the illiquid state and that it is stuck in that state for over a week, i.e., longer than the average trading horizon of an institutional investor (see, e.g., Keim and Madhavan (1995)). This probability is essentially the product of frequency and duration and therefore captures the notion that both are necessary conditions for pain.[4]

A regime-switching model is estimated by stock-year for a sample of common stocks listed on the New York Stock Exchange (NYSE) or the American Stock Exchange (AMEX) in the period from 1963 to 2008. The daily Amihud ILLIQ measure (Amihud (2002)) is modeled as drawn from either the liquid or the illiquid state distribution.[5] To make cross-sectional comparisons meaningful, the mean of the illiquid state distribution is bounded from below to the 80% quantile of *all* stock-day observations for the year of estimation. Estimates lead to the following observations. Perhaps most important is that the data select the two-regime model over the standard (single-regime) model in 97.10% of the stock-year samples. Estimates of this regime-switching model reveal that the average probability of the illiquid state is 0.21 and its average continuation probability is 0.45. The average liquileak (or disaster) probability is 0.06. Finally, the nature of liquileaks seems to be primarily idiosyncratic as the first principal component of an ex-post illiquid state estimate captures between 10% and 15% of its variation.[6]

The conjectured relationship between a stock's liquileak probability and its required return is tested in two conventional ways: portfolio sorts and Fama-MacBeth regressions. The portfolio sort analysis reveals that a trading strategy that is long in high liquileak stocks and short in low liquileak stocks yields a significant average annual excess return of 3.36%. To explore whether this positive return is only due to one of the two factors of the liquileak probability (i.e., frequency or duration) or just captures the (unconditional) average liquidity level, we double-sort and find that, still, the return differential across low and high liquileak stocks remains significantly positive. The Fama-MacBeth regressions enable us to also control for the standard Fama-French factors and other stock characteristics. Liquileak probability remains significantly positive. A one standard deviation increase in liquileak probability increases annual returns by 1.33%. These regressions are repeated for the two equal-length sub-periods (1964 through 1985 and 1986 through 2008) and the results indicate that the liquileak probability has become more important for returns over time whereas, consistent with earlier literature, liquidity level has

[4]The focus here is on security-specific regime switches, not switches in the aggregate state of the market. The latter was analyzed in Watanabe and Watanabe (2008) which lets securities' liquidity-betas *collectively* switch between low and high states.

[5]We have repeated all analysis based on the Pastor and Stambaugh (2003) reversal measure (instead of ILLIQ) and find very similar results. See "Appendix: Liquileaks".

[6]This low commonality does not necessarily contradict the funding-constraint models if liquidity-supply is not fully fungible across securities. In fact, Aragon and Strahan (2011) show that the 2008 Lehman bankruptcy disproportionately affected liquidity supply in stocks which were held by Lehman-connected hedge funds.

become less important.

As a robustness check, all analysis is repeated based on (model-free) nonparametric proxies for frequency and duration that are calculated directly from the raw data. Frequency is measured as the fraction of days that a stock is illiquid and duration is measured as the average number of days that a stock is in the illiquid state. Redoing the required return analysis based on these (noisy) proxies shows that our main finding that liquileak probability matters for required returns is robust.

Finally, the current chapter relates to a microstructure literature that studies the "resiliency" dimension of liquidity at the highest frequency. Demsetz (1968, p.41) first emphasized that "waiting costs are relatively important for trading in organized exchanges, and would seem to dominate the determination of spreads." Following up on this idea, Black (1971) and Kyle (1985) characterized as a liquid market one that has a high instant supply (low bid-ask spread and high depth) which replenishes quickly when consumed (high resiliency). Foucault, Kadan, and Kandel (2005) characterize the interaction of instant supply and resiliency in a dynamic equilibrium model where traders arrive sequentially, observe the liquidity supply in the limit order book, and decide to either post an order in the book (increase supply) or consume an order from the book (reduce supply). Empirically, Biais, Hillion, and Spatt (1995) label incoming limit orders on an ordinal scale from "large buy" (extreme consumption) to "new bid below" (extreme supply). Large (2007) characterizes resiliency by estimating the conditional arrival intensities for each of these order types.

The remainder of the chapter is organized as follows. Section 2.2 introduces the Markov regime switching model to identify liquidity leaks. Section 2.3 describes the data and presents descriptive statistics on the liquileak estimates. Section 2.4 tests the hypothesized relation between a stock's liquileak probability and its return. Section 2.5 analyzes what stock and firm characteristics might explain variation in liquileak probability. Section 2.6 contains a robustness analysis. Section 2.7 concludes.

2.2 Liquidity leak measurement

The nature of liquidity leaks is that a stock is in a normal liquidity state most of the days, but occasionally hits an illiquid state. A natural econometric model to capture such characterization is a Markov regime-switching model that potentially switches daily between these two states (cf. Rietz (1988)). Within each state, liquidity draws are assumed to follow a first order autoregressive process with a state-specific mean and variance; the autoregressive nature allows for some persistence in shocks which has been documented to exist by, for example, Acharya and Pedersen (2005). The model we propose therefore is:

$$illiq_d^i = \begin{cases} \mu_0^i + \phi^i illiq_{d-1}^i + \varepsilon_d^i, & \text{if } s_d^i = 0 \\ \mu_1^i + \phi^i illiq_{d-1}^i + \varepsilon_d^i, & \text{if } s_d^i = 1 \end{cases} \tag{2.1}$$

where d indexes days, i indexes stocks, $illiq$ is the illiquidity measure (e.g., the Amihud $illiq$ measure used in the main text or the Pastor-Stambaugh reversal measure used in the "Appendix: Liquileaks"), s is the (unobserved) liquidity regime, and ε is an independent normally distributed error term with mean zero and state-dependent variance σ_s^2.

The states are labeled such that the state zero ($s = 0$) is the normal liquidity state and state one ($s = 1$) is the illiquid state. The state itself follows a first order Markov chain with transition matrix $\{p_{jk}^i\}$ for stock i:

$$p_{jk}^i = Pr(s_d^i = j | s_{d-1}^i = k) \quad \forall j,k \in \{0,1\} \tag{2.2}$$

The probability of a liquileak event is defined as the unconditional probability to find a stock in the illiquid state and, if so, to have it 'trapped' in that state for more than a week. The Markovian nature of the model allows for straightforward calculation of such probability:

$$liquileak\_prob := Pr(s_d = 1) Pr(s_{d+1} = s_{d+2} = \cdots = s_{d+5} = 1 | s_d = 1) \tag{2.3}$$

where d is some random day in the sample. The first factor on the right-hand side is the unconditional probability to find the stock in the illiquid state:

$$Pr(s_d = 1) = \frac{1 - p_{00}^i}{2 - p_{00}^i - p_{11}^i} =: p_1^i \tag{2.4}$$

and the second factor is the probability to find it in such state for five consecutive days, conditional on starting off in the illiquid state:

$$Pr(s_{d+1} = s_{d+2} = \cdots = s_{d+5} = 1) = (p_{11}^i)^5 = \left(Pr(s_d^i = 1 | s_{d-1}^i = 1)\right)^5 \tag{2.5}$$

The liquileak probability is therefore:

$$liquileak\_prob = p_1^i (p_{11}^i)^5 = \frac{(1 - p_{00}^i)(p_{11}^i)^5}{2 - p_{00}^i - p_{11}^i} \tag{2.6}$$

The model is estimated by stock-year based on daily observations where all parameters are stock-specific. To make meaningful comparisons across stocks, the illiquid state's mean is constrained to be larger than the 80% quantile of all stock-day observations on $illiq$ in the year of estimation. The parameters are estimated with maximum likelihood where the likelihood function is calculated using the standard Hamilton filter (see Hamilton (1989)). The implementation details are included in the Appendix 2A.

2.3 Data, summary statistics, and liquileak estimates

Data. The data are standard and obtained from the Center for Research in Security Prices (CRSP) and Ken French's website. The sample period is 1963 through 2008. The CRSP data used are stock prices, returns, volume, shares outstanding, and dividend. Following standard practice, the universe of stocks consists of only common stocks (CRSP share code 10 and 11) listed on the NYSE or AMEX (CRSP exchange code 1 and 2). The data obtained from French's website are the risk-free rate and the three Fama-French factors.

The Amihud ILLIQ measure is used as the main liquidity measure (see Amihud (2002)). Compared with potentially better measures, such as the price impact of order flow or the bid-ask spread, the Amihud measure requires only daily data and thus enables us to study a much longer time period. Among the various daily measures, Hasbrouck (2009, p.1456-1459) finds that ILLIQ correlates highest with the price impact measure (which is to be preferred over spread when orders execute in multiple trades).[7] The ILLIQ measure is defined as:

$$illiq_d^i = \frac{|r_d^i|}{dvol_d^i} \tag{2.7}$$

where r is the transaction price return and $dvol$ is dollar volume. Admittedly, the daily ILLIQ measure is noisy but note that such noise is naturally captured by the 'error' terms ε_d^i in each of the two liquidity states (see equation (2.1)).

The empirical analysis consists of essentially two stages. First, the liquileak regime-switching model and the Fama-French betas are estimated by stock-year which yields a 'panel' of parameter estimates. Second, standard asset pricing analysis is done based on the cross-section of monthly returns where previous year stock characteristics (e.g., $liquileak\_prob$ and the Fama-French betas) are used as explanatory variables.

The data filters used to prepare for liquileak model estimation are careful to not discard days for which the ILLIQ measure cannot be calculated (due to zero volume) as such days might indicate extreme illiquidity which is the focus of our study. The following filters have been applied. First, zero volume days are treated as missing observation days rather than discarded in order to avoid a downward bias in the duration measure.[8] Second, for each stock ILLIQ values are winsorized at the 1% and the 99% quantile. Third, the stock-year parameter estimate

[7] Robustness of results is verified by redoing all analysis based on the Pastor and Stambaugh (2003) price reversal measure. This set of tables is included in the "Appendix: Liquileaks".

[8] Zero-volume days might also be evidence of extreme illiquidity. If instead of making them missing observations, one fills them with the highest observed illiquidity value, the chapter's main result is largely unaffected, see "Appendix: Liquileaks".

of *liquileak_prob*, which is the focus explanatory variable of required returns, is only retained when the stock-year has at least 150 *illiq* observations and the average stock price is between \$2 and \$1000.[9] The filter removes about 5% of all stock-years.

Summary statistics. Table 2.1 presents summary statistics on the variables used in the analysis. There are between 1123 and 2147 stocks for all years included in the (unbalanced) panel dataset. This universe of stocks exhibits substantial variation in size and trade characteristics both in the cross-section and through time. For example, the average market capitalization is \$2.41 billion with a cross-sectional (between) standard deviation of \$7.46 billion and a time (within) standard deviation of \$8.58 billion. Daily volume is \$10.53 million on average with a between standard deviation of \$28.88 million and a within standard deviation of \$40.67 million.

Table 2.1: Summary statistics

This table presents summary statistics for a variety of variables. The variable average by stock-year makes up a panel dataset so that between and within variation can be calculated. The sample consists of NYSE/AMEX stocks from December 31, 1962 through December 31, 2008. The included variables are: daily stock return based on end-of-day transaction price (*ret*), daily end-of-day transaction price (*prc*), daily dollar volume (*dvol*), market capitalization (*mcap*), Amihud's ILLIQ measure (*illiq*), mean-adjusted illiquidity level (*illiqma*), return over the last 100 days of the year (*r*100), return from the start of the year until the day that is 100 days before the end of the year (*r*100*yr*), standard deviation of daily return (*sdret*), dividend yield calculated as the sum of all dividends in the year divided by the end-of-year price (*divyld*). Variable units are included in parentheses.

	Mean	St.Dev.	St.Dev. Between[a]	St.Dev. Within[b]	Min	Max	Median
ret (bps)	6.22	20.66	8.18	18.98	-594.85	666.67	6.25
prc (\$)	29.16	24.53	17.93	16.75	2.03	899.36	24.40
dvol (\$ mln)	10.53	49.88	28.88	40.67	0.00	2418.54	0.54
mcap (\$ bln)	2.41	11.37	7.46	8.58	0.00	498.41	0.32
illiq (%/\$mln)	0.41	1.06	0.74	0.76	0.00	31.88	0.06
illiqma	1.00	1.77	1.38	1.10	0.00	26.86	0.31
*r*100	0.05	0.28	0.10	0.26	-0.99	15.44	0.03
*r*100*yr*	0.12	0.39	0.14	0.36	-0.94	12.15	0.07
sdret (%)	2.43	1.20	0.82	0.87	0.00	42.63	2.19
divyld (%)	3.76	19.30	8.43	17.36	0.00	1920.00	2.69
#*stocks*	1639.28	261.65	112.13	236.40	1123.00	2147.00	1668.00

[a]: Based on stock-specific averages, i.e., $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$.
[b]: Based on deviations from stock-specific averages, i.e., $x^*_{i,t} = x_{i,t} - \bar{x}_i$.

[9]The filter is less restrictive than Amihud (2002) in that the bar for inclusion is lowered from 200 observations to 150 observations. The reason is that the focus is on extreme illiquidity events which are more likely to exist for less actively traded stocks.

The Amihud ILLIQ measure (*illiq*) exhibits considerable variation both in the cross-section and through time. On average, its value is a 0.41% change per \$1 million volume. The between and within standard deviation are 0.74 and 0.76, respectively, which indicates that there is substantial variation both in the cross-section and, more importantly in view of liquileak risk, through time. A particularly promising feature of *illiq* is that it has a positive skew since the median (0.06) is substantially smaller than the mean (0.41); the dataset does appear to exhibit days of extreme illiquidity (although this might still be entirely driven by the cross-sectional dimension, not the time dimension).

Liquileak model estimates. Before presenting the liquileak model estimates by stock-year, we first test whether the data actually support such regime-switching model. Table 2.2 presents the results of a likelihood ratio test that tests the null of a single AR(1) process against the liquileak model that switches between two AR(1) processes (see equation (2.1)). The results show that for 97.10% of all stock-year samples (consisting of all days in that stock-year) the null is rejected. This result seems representative of all years in the sample as for every year more than 90% of the stock-year samples reject the null.

Table 2.3 presents various statistics on the 'panel' of liquileak model parameters that are estimated by stock-year. Panel A presents the means and variances which lead to a couple of observations. First, the average normal liquidity mean of *illiq* (μ_0) is 0.25 which is less than half the average illiquid state mean (μ_1) which is 0.59. More importantly, this distance is almost twice the liquid state standard deviations (σ_0) which indicates that there is meaningful separation between the two liquidity states. The illiquid state standard deviation (σ_1) is relatively high which indicates either erratic liquidity supply or large measurement errors which one might expect to be present in a turbulent state. Second, there is evidence of persistence within a regime as the AR(1) coefficient (φ) is 0.18 on average. Third, the transition probability estimates show that the average duration is roughly 9 days (=1/(1-p_{00})) for the normal liquidity state but only 2 days for the illiquid state. This implies that, for an 'average' stock, liquileaks are rare events as it requires a week spent in the illiquid state. Yet, there is considerable variation in the continuation probability (p_{11}), its standard deviation is 0.31, which implies that these events are more likely for at least some stock-years. Finally, liquileaks are indeed rare events for the average stock in the sample as the average probability is 0.06. But, as predicted, there is considerable variation across stock-years as the standard deviation is 0.12.

Figure 2.1 illustrates the regime-switching model estimates by plotting both the daily observations on *illiq* and, for these days, an 'ex-post' estimate of the likelihood of the (unobserved) illiquid state. This likelihood is the smoothed probability estimate, i.e., the best estimate conditional on all past, current, and *future* observations on *illiq*. The top graph represents a high liquileak stock; the bottom one presents a low liquileak stock. The period is 100 days in 1986, the median year in the sample. The high liquileak stock graph exhibits both features

Table 2.2: Likelihood ratio test on one regime vs. two regimes

The table examines whether liquidity level (as proxied by Amihud ILLIQ) is subject to regime switches or not. The null hypothesis of no-switching is an AR(1) model and the alternative is a two state Markov regime switching model where each state is represented by an AR(1) model (mean and mean-reversion parameters are state dependent, for details see Section 2.2, equations (2.1) and (2.2). A likelihood ratio test is conducted where the test statistic is defined as $LR = 2(\ln L_{2AR} - \ln L_{1AR})$. The critical value is based on the Davies (1987) p-value as suggested by Garcia and Perron (1996). The test is conducted by stock-year and the table summarizes the findings by presenting the average likelihood, the fraction of null rejections and its complement by year, by the two sub-periods, and for the full sample.

1963-1985				1986-2008			
year	likelihood ratio	% stocks p-value < 0.01	% stocks p-value ≥ 0.01	year	likelihood ratio	% stocks p-value < 0.01	% stocks p-value ≥ 0.01
1963	127.95	96.85	3.15	1986	190.66	97.08	2.92
1964	128.39	97.18	2.82	1987	207.96	97.48	2.52
1965	144.07	97.83	2.17	1988	188.17	96.58	3.42
1966	143.51	97.74	2.26	1989	189.67	95.99	4.01
1967	166.77	98.96	1.04	1990	191.41	96.05	3.95
1968	154.64	98.62	1.38	1991	191.69	96.24	3.76
1969	156.84	98.93	1.07	1992	176.04	95.30	4.70
1970	159.98	97.22	2.78	1993	179.16	95.95	4.05
1971	173.47	98.50	1.50	1994	173.60	96.31	3.69
1972	171.05	99.09	0.91	1995	179.46	96.22	3.78
1973	150.23	97.76	2.24	1996	177.27	95.47	4.53
1974	114.11	91.67	8.33	1997	181.62	96.11	3.89
1975	154.97	96.70	3.30	1998	194.60	96.59	3.41
1976	168.51	99.35	0.65	1999	164.84	95.86	4.14
1977	161.28	99.09	0.91	2000	160.95	94.85	5.15
1978	203.01	98.75	1.25	2001	170.74	95.22	4.78
1979	192.02	98.57	1.43	2002	175.75	95.63	4.37
1980	197.24	98.49	1.51	2003	190.86	95.30	4.70
1981	183.32	99.05	0.95	2004	172.60	94.21	5.79
1982	200.35	98.21	1.79	2005	168.29	94.33	5.67
1983	194.02	97.75	2.25	2006	180.68	95.00	5.00
1984	190.17	97.95	2.05	2007	195.97	94.98	5.02
1985	190.86	96.79	3.21	2008	262.03	94.28	5.72
1963-1985	167.67	98.01	1.99	1986-2008	184.30	95.83	4.17
1963-2008	174.62	97.10	2.90				
#stocks*#years		1605*23		#stocks*#years		1672*23	

of liquileaks: trading seems to hit an illiquid state relatively often and, once it does, it seems to be stuck in this state for multiple days. The low liquileak stock, on the other hand, does not hit the illiquid state often and, if so, reverts back to the liquid state within a day. The graphs also suggests that one needs to control for average *illiq* in the pricing analysis as it clearly is lower in the bottom graph.

Panel B of Table 2.3 presents statistics on the cross-sectional and time covariation in the panel of liquileak parameter estimates. This yields useful insights as to what drives variation in $liquileak\_prob$ before turning to its explanatory power for required returns in the next section. The within and between correlations lead to the following observations. First, the two factors that make up $liquileak\_prob$ (=$p_1 p_{11}^5$, see equation (2.6)) are far from perfectly correlated. The cross-sectional and time correlation between (i) the unconditional probability of hitting the illiquid state (p_1) and (ii) staying a week in the illiquid state (p_{11}^5) are 0.54 and 0.63, respectively.[10] The absence of (perfect) collinearity enables us to explore both these drivers of $liquileak\_prob$ as separate explanatory variables in our asset pricing regressions. Second, the between and within correlation of $liquileak\_prob$ with both these factors is of equal magnitude which indicates that variation in this focus explanatory variable is driven by both its factor components Third, the $liquileak\_prob$ correlation with any of the parameters that govern the autoregressive process within each state is relatively low. It is therefore unlikely that a significant effect of $liquileak\_prob$ in the asset pricing analysis is just a proxy for any of these characteristics of the *illiq* process (although the unconditional liquidity level will be controlled for in the Fama-MacBeth regressions).

Finally, liquileaks seem to be idiosyncratic in nature. Table 2.4 shows that the first principal component of the ex-post illiquid state estimate captures between 10% and 15% of its variation. This is true for both the filtered and the smoothed estimate as well as for both sub-periods separately. The first five principal components capture less than 25% of the variation.

2.4 Are liquileaks priced in the cross-section of stocks?

This section does a standard asset pricing analysis to study whether the risk of disaster liquidity, the probability of a liquileak, commands higher returns in the cross-section of stocks. The first part does portfolio sorts, both single- and double-sorts, to explore any such relationship. The second part does Fama-MacBeth regressions that allow for simultaneously bringing in a multiple of standard control variables.

[10]The positive correlation is not surprising as p_1 is a monotonically increasing function of p_{11} (see equation (2.4)). The focus here is on the size of this covariation.

Table 2.3: Liquileak model estimates

This table presents the parameter estimates of the Markov regime switching model that aims to characterize liquileak events, i.e., getting stuck in an illiquid disaster state for at least a week. The model is estimated by stock-year and the table provides statistics on the 'panel' of parameter estimates. The Markov regime switching model that is estimated for each stock-year ($\sim$250 observations) is:

$$illiq_t^i = \begin{cases} \mu_0^i + \phi^i illiq_{d-1}^i + \varepsilon_t^i, & \text{if } s_t^i = 0, \\ \mu_1^i + \phi^i illiq_{d-1}^i + \varepsilon_t^i, & \text{if } s_t^i = 1, \end{cases}$$

where i indexes stocks, d indexes days, $illiq_t^i$ is the observed Amihud ILLIQ measure, s_t^i is the unobserved liquidity state, and ε_t^i is an independent normally distributed error term with a state-dependent variance σ_s^2. The state transition matrix is defined by the following transition probabilities:

$$Pr(s_d^i = 0 | s_{d-1}^i = 0) = p_{00}^i$$
$$Pr(s_d^i = 1 | s_{d-1}^i = 1) = p_{11}^i$$

Liquileak probability is therefore obtained as:

$$liquileak\_prob = p_1^i (p_{11}^i)^5 = \frac{(1-p_{00}^i)(p_{11}^i)^5}{2 - p_{00}^i - p_{11}^i}$$

In the estimation the mean liquidity in the disaster liquidity state (μ_1) is constrained to be larger than the 80% quantile of *illiq* across all stock-days. This parameter is pooled across stocks to make cross-sectional analysis meaningful. Implementation details are included in the Appendix 2A. Panel A presents mean and variance statistics; Panel B presents within and between correlations.

Panel A: Mean and variance parameter estimates

	Mean	St.Dev.	St.Dev. Between[a]	St.Dev. Within[b]	Min	Max	Median
μ_0	0.25	0.39	0.28	0.28	-3.63	4.92	0.10
μ_1	0.59	0.41	0.21	0.36	0.07	1.68	0.52
σ_0	0.18	0.28	0.20	0.20	0.00	1.87	0.07
σ_1	1.41	2.36	1.65	1.69	0.00	20.29	0.47
ϕ	0.18	0.17	0.08	0.14	-0.93	1.00	0.12
p_{00}	0.89	0.08	0.04	0.07	0.00	1.00	0.90
p_{11}	0.45	0.31	0.13	0.28	0.00	1.00	0.42
p_1	0.21	0.15	0.07	0.14	0.00	1.00	0.17
p_{11}^5	0.15	0.26	0.11	0.23	0.00	1.00	0.01
liquileak_prob	0.06	0.12	0.05	0.11	0.00	1.00	0.00
#stocks	1639.28	261.65	112.13	236.40	1123.00	2147.00	1668.00

[a]: Based on the time means, i.e., $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$.
[b]: Based on the deviations from time means i.e. $x_{i,t}^* = x_{i,t} - \bar{x}_i$.

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Panel B: Between and within correlation parameter estimates										
		μ_1	σ_0	σ_1	ϕ	p_{00}	p_{11}	p_1	p_{11}^5	$liquileak\_prob$
μ_0	ρ(between)	0.37*	0.99*	0.93*	0.19*	-0.27*	0.19*	0.33*	0.04	0.10*
	ρ(within)	0.39*	0.95*	0.79*	-0.01*	-0.01*	-0.04*	-0.05*	-0.04*	-0.06*
μ_1	ρ(between)		0.36*	0.26*	0.13*	-0.02	0.02	0.06*	-0.02	0.02
	ρ(within)		0.39*	0.29*	0.18*	-0.04*	0.15*	0.16*	0.13*	0.14*
σ_0	ρ(between)			0.94*	0.18*	-0.29*	0.20*	0.34*	0.04	0.10*
	ρ(within)			0.81*	0.02*	-0.03*	-0.02*	-0.02*	-0.02*	-0.02*
σ_1	ρ(between)				0.12*	-0.29*	0.17*	0.31*	0.01	0.07*
	ρ(within)				-0.05*	-0.02*	-0.04*	-0.05*	-0.07*	-0.06*
ϕ	ρ(between)					0.17*	0.77*	0.62*	0.79*	0.81*
	ρ(within)					0.07*	0.66*	0.68*	0.72*	0.77*
p_{00}	ρ(between)						0.10*	-0.52*	0.33*	0.12*
	ρ(within)						0.11*	-0.44*	0.24*	0.05*
p_{11}	ρ(between)							0.68*	0.86*	0.77*
	ρ(within)							0.64*	0.81*	0.64*
p_1	ρ(between)								0.54*	0.74*
	ρ(within)								0.63*	0.82*
p_{11}^5	ρ(between)									0.89*
	ρ(within)									0.85*
#stocks*#years: 1639*46										

[a]: Based on stock-specific averages, i.e., $\bar{x}_i = \frac{1}{Y}\sum_{y=1}^{Y} x_{i,y}$.

[b]: Based on deviations from stock-specific averages, i.e., $x_{i,y}^{*} = x_{i,y} - \bar{x}_i$.

*: Significant at a 95% level.

Figure 2.1: ILLIQ and the probability of the illiquid state

This figure depicts daily observations on the Amihud ILLIQ measure and an 'ex-post' probability estimate of the illiquid state for a high and a low liquileak stock (PERMNO 60695 and PERMNO 44740, respectively). The data period is last 100 days of 1986, the median year in the sample. The probability estimate is 'ex-post' in the sense that it is the smoothed probability estimate of the state given the regime-switching model parameter estimates and all observations in the sample, i.e., it is based on a forward and a backward recursion.

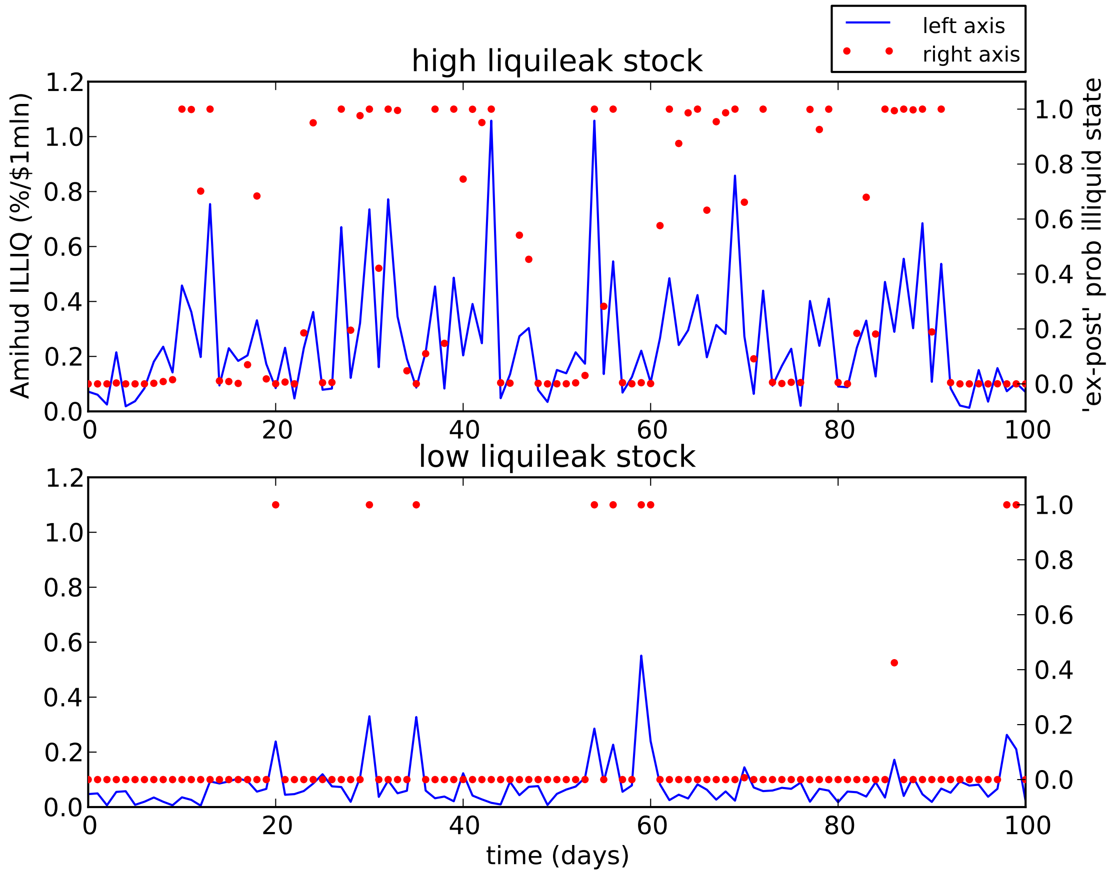

Table 2.4: Commonality in the liquidity state across stocks

This table assesses commonality in the liquidity state across stocks. It does so through a principal component analysis of the 'ex-post' probability of the illiquid state. In Panel A this probability is obtained as the filtered estimate of the illiquid state based on the estimates of a regime-switching model. The filtered estimate is obtained through a forward recursion and therefore is an estimate conditional on the stock's history of observations on ILLIQ. Panel B is obtained the same way except that it is also based on a backward recursion and therefore takes the stock's past, current, *and* future observations on ILLIQ into account when calculating the probability estimate. The percentage of variance explained by the largest five eigenvalues is presented for the full data sample, the first sub-period, and the second sub-period.

Panel A: Filtered probability of the illiquid state

	All years	1963-1985	1986-2008
1	12.01	12.86	11.23
2	3.93	3.92	3.95
3	2.37	2.32	2.42
4	1.81	1.84	1.78
5	1.53	1.54	1.52
sum	21.66	22.48	20.90

Panel B: Smoothed probability of the illiquid state

	All years	1963-1985	1986-2008
1	13.04	13.96	12.20
2	4.22	4.21	4.23
3	2.53	2.48	2.58
4	1.91	1.95	1.88
5	1.61	1.62	1.61
sum	23.32	24.23	22.50
#stocks*#years	1639*46	1605*23	1672*23

Portfolio sorts. The comparative advantage of portfolio sorts over regressions is that they produce easy-to-interpret returns on a straightforward and feasible investment strategy. The idea is simple. If $liquileak\_prob$ is priced, then a zero-investment portfolio that is long high $liquileak\_prob$ stocks and short low $liquileak\_prob$ stocks should earn a positive return.

Table 2.5 shows that a single-sort portfolio strategy produces a monthly excess return of 0.28% which is 3.36% annually. Each month, stocks are sorted into five quintiles based on their previous year $liquileak\_prob$. These portfolios are rebalanced monthly and they are equal weighted[11]. The table presents average monthly excess returns (relative to the risk-free rate) for each portfolio. This return is 0.62% for the low liquileak portfolio and 0.91% for the high liquileak portfolio. The return differential across these portfolios is 0.28% and significant as tested using robust standard errors. The result seems to be particularly strong in the second sub-period as the differential is larger (0.35%) and remains statistically significant. It is worth noting that this return differential appears to be driven by the highest rather than the lowest liquileak portfolio as intermediate portfolios have returns that are similar in magnitude to the low liquileak return.

Table 2.5: Excess returns single-sorted portfolios

This table presents excess returns for portfolios of stocks that are sorted on their previous year liquileak probability ($liquileak\_prob$). These portfolios are rebalanced monthly and are equal weighted. The excess return ($ret - r_f(\%)$) is the time-series mean of monthly portfolio returns. The t-stat are based on Newey-West (1987) robust standard errors. The "5-1" row pertains to the return differential across the lowest (1) and the highest (5) liquileak probability portfolio. The results are presented for the full data sample, the first sub-period, and the second sub-period.

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (lowest $liquileak\_prob$)	0.62	2.68**	0.68	1.93*	0.57	1.86*
2	0.61	2.49**	0.67	1.83*	0.56	1.69*
3	0.64	2.49**	0.69	1.77*	0.60	1.75*
4	0.70	2.46**	0.77	1.76*	0.63	1.73*
5 (highest $liquileak\_prob$)	0.91	2.86**	0.90	1.90*	0.92	2.16**
differential ('5-1')	0.28	2.36**	0.21	1.33	0.35	1.98**
#stocks*#months	1639*540		1605*264		1672*276	

**: Significant at a 95% level.
* : Significant at a 90% level.

Portfolio double-sorts enables one to control for one variable when analyzing excess returns. The standard double-sort strategy first sorts stocks into five portfolios based on the control variable and then, within each quintile, stocks are further sorted on $liquileak\_prob$. For each of these five by five portfolios the average return is calculated and a $liquileak\_prob$ quintile return

[11] If one uses value-weighting instead, the results are largely unchanged, see "Appendix: Liquileaks".

is now obtained as the average return for this *liquileak_prob* quintile across the five control variable portfolios.

Table 2.6 shows that it really is liquileak risk that drives excess returns beyond either one of its component factors or average liquidity. This chapter's basic premise is that it takes both a non-negligible probability of hitting the illiquid state *and* a substantial probability of being stuck in that state. A double-sort portfolio strategy is useful to verify its validity: liquileak probability should continue to produce excess returns after controlling for each of these factors separately, i.e., p_1 and p_{11}^5, respectively. Panel A shows that the monthly return differential across the extreme liquileak portfolios is somewhat lower (not surprisingly), 0.13%, but continues to be positive and significant after controlling for the illiquid state probability (p_1). Panel B shows a similar result when controlling for the likelihood of being stuck in the illiquid state for more than a week when started off in such state (p_{11}^5); in this case, the differential is 0.19% and significant. Both these results, again, are particularly strong in the second sub-period. These findings show that both the probability of hitting the illiquid state and being stuck there seem to matter for required returns.

Panel C controls for the average (unconditional) liquidity level and continues to find a positive return differential associated with liquileak risk. The monthly return differential across the low and the high liquileak portfolio is a significant 0.33%. This is the same order of magnitude as the single-sort differential (0.31%). The result is particularly strong for the second sub-period (0.81% and significant) but not present in the first sub-period (-0.12% and insignificant). This contrast across these two sub-periods is stronger than what was found in the single-sort analysis. This is a first indication that perhaps the first sub-period's increased return was driven by liquidity level, whereas in the second sub-period it really is a liquileak risk effect. We will revisit these time trends in the regression analysis. Overall, this double-sort analysis shows that liquileaks do appear to matter over and above the average liquidity level.

Fama-MacBeth regressions. The portfolio analysis is complemented with standard Fama-MacBeth regressions in order to control for multiple well-known determinants of expected returns (see Fama and MacBeth (1973)). The approach consists of two steps. First, The Fama-French factor loadings are estimated for each stock-year by running the regression:

$$r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y} \tag{2.8}$$

where i indexes stocks, d indexes days, y indexes years, MKT is the excess market return (relative to the risk-free rate), SMB is the Fama-French size factor, and HML is the Fama-French book-to-market factor.

Second, for each month we perform the following cross-sectional regression:

$$r_{i,m,y} = \gamma_m + \lambda_m' \beta_{i,y-1} + \delta_m' Z_{i,y-1} + \varepsilon_{i,m,y} \tag{2.9}$$

Table 2.6: Excess returns double-sorted portfolios

This table presents excess returns for portfolios of stocks that are sorted on their previous year liquileak probability ($liquileak\_prob$) after first sorting on a control variable which is either the previous year unconditional probability of the illiquid regime (p_1) in Panel A, the previous year continuation probability of the disaster regime (p_{11}^5) in Panel B, or the average illiquidity level in Panel C. Following standard practice, stocks are first sorted on their control variable and then, within each quintile, stocks are sorted on the variable of interest. Once these 5×5 portfolios are established, the return for each $liquileak\_prob$ quintile is calculated as the average return for this $liquileak\_prob$ quintile across the five control variable portfolios. These portfolios are rebalanced monthly and are equal weighted. The excess return ($ret - r_f(\%)$) is the time-series mean of monthly portfolio returns. The t-stat are based on Newey-West (1987) robust standard errors. The "5-1" row pertains to the return differential across the lowest (1) and the highest (5) liquileak probability portfolio. The results are presented for the full data sample, the first sub-period, and the second sub-period.

Panel A: Controlling for disaster state probability (p_1)

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (lowest $liquileak\_prob$)	0.66	4.44**	0.68	3.46**	0.63	2.85**
2	0.46	2.89**	0.41	1.92*	0.51	2.17**
3	0.51	3.10**	0.40	1.79*	0.61	2.60**
4	0.61	3.53**	0.56	2.35**	0.66	2.64**
5 (highest $liquileak\_prob$)	0.79	4.22**	0.71	2.73**	0.87	3.24**
differential ('5-1')	0.13	1.70*	0.03	0.24	0.24	2.55**

Panel B: Controlling for disaster state continuation probability (p_{11}^5)

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (lowest $liquileak\_prob$)	0.52	3.48**	0.47	2.37**	0.56	2.55**
2	0.55	3.60**	0.52	2.50**	0.58	2.59**
3	0.63	3.92**	0.58	2.62**	0.68	2.93**
4	0.62	3.57**	0.56	2.38**	0.68	2.67**
5 (highest $liquileak\_prob$)	0.70	3.63**	0.63	2.37**	0.77	2.76**
differential ('5-1')	0.19	2.35**	0.16	1.29	0.21	2.18**

Panel C: Controlling for average liquidity ($illiq$)

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (lowest $liquileak\_prob$)	0.48	3.28**	0.66	3.40**	0.29	1.31
2	0.53	3.31**	0.58	2.61**	0.48	2.07**
3	0.57	3.41**	0.53	2.36**	0.61	2.46**
4	0.66	3.81**	0.53	2.28**	0.79	3.09**
5 (highest $liquileak\_prob$)	0.81	4.48**	0.54	2.25**	1.10	4.02**
differential ('5-1')	0.33	3.06**	-0.12	-0.78	0.81	5.37**
#stocks*#months	1639*540		1605*264		1672*276	

**: Significant at a 95% level.

* : Significant at a 90% level.

where m indexes months, r is a stock's excess return (relative to the risk-free rate), β is the vector of factor loadings, λ is the vector of associated risk premiums, Z is a vector of further stock-specific characteristics such as, for example, liquileak probability ($liquileak\_prob$). The parameter estimates for δ and λ are obtained as (time) averages of the coefficients obtained in each month's cross-sectional regression.

Table 2.7 presents the Fama-MacBeth results which show that liquileaks do command a significant premium. A one standard deviation change in the liquileak probability (0.12, see Table 2.3) yields a significant additional annual return of 100%*12*0.12*0.00746=1.07%. To put it in perspective, a one standard deviation change in the average liquidity level (1.77, see Table 2.1) commands a premium of 3.40%. It further appears that both factors of $liquileak\_prob$, the unconditional probability of hitting the illiquid regime (p_1) and its duration (p_{11}^5), matter as they are significantly positive when included individually (models (2) and (3)) and remain so (although p_{11}^5 significance is marginal) when included jointly. To find significance at all when both are included (given their strong correlation, 0.54, see Table 2.3) is surprising and support the liquileak logic that both matter for required returns.

Splitting the sample in two sub-periods and repeating the Fama-MacBeth regressions shows that the liquileak premium has increased. In the first subsample, 1964 through 1985, $liquileak\_prob$ and its two separate factors (p_1 and p_{11}^5) carry the right sign but are not significant. The second sub-period, 1986 through 2008, appears to carry the overall result as the signs are correct, the coefficients are larger, and, most importantly, this time they are all significant (even when the two factors are included jointly in model (4)). Moreover, the three formal tests on equality of coefficients on $liquileak\_prob$, p_1, and p_{11}^5 across the two sub-periods all reject the null hypothesis. Not only has the premium *per unit* of liquileak probability increased, the premium differentials across stock-years have increased as well. A one *first-period* standard deviation (0.13) increase commands an additional (first-period) annual return of 0.46%; a one *second-period* standard deviation (0.12) increase commands an additional return of 1.69%.

The subsample analysis further reveals that the liquidity level premium has decreased. The average liquidity level significantly explains returns in both sub-periods. The second-period coefficient is significantly lower than the first-period coefficient (the null of equal coefficients is rejected, see Table 2.7). This confirms the diminishing per-unit liquidity premium first documented in Ben-Rephael, Kadan, and Wohl (2010). The liquidity premium differentials across stock-years have also grown as a first-period standard deviation (1.23) increase in illiquidity commands an additional annual return of 3.39% whereas a second-period standard deviation (2.15) increase commands an additional return of 2.43%. It seems that, over time, the liquileak premium has grown to become similar in magnitude as the liquidity level premium; a one second-period standard deviation increase implies an annual premium of 1.69% and 2.43%, respectively.

Table 2.7: Fama-MacBeth regressions of stock returns on liquileak probability and standard control variables

This table presents the results of a Fama-MacBeth regression analysis on whether the probability of liquileaks (*liquileaks_prob*) is priced in the cross-section of returns. First, the Fama-French factor loadings are estimated for each stock-year by running the following regression: $r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y}$ where i indexes stocks, d indexes days, y indexes years, MKT is the excess market return (relative to the risk-free rate), SMB is the Fama-French size factor, and HML is the Fama-French book-to-market factor. Second, for each month the following cross-sectional regression is performed: $r_{i,m,y} = \gamma_m + \lambda_m' \beta_{i,y-1} + \delta_m' Z_{i,y-1} + \varepsilon_{i,m,y}$ where m indexes months, r is a stock's excess return (relative to the risk-free rate), β is the vector of factor loadings, λ is the vector of associated risk premiums, Z is a vector of further stock-specific characteristics which includes liquileak probability (*liquileak_prob*), the (unconditional) probability that a stock hits the illiquid regime (p_1), the probability that it is stuck in this regime for five consecutive days (p_{11}^5), and the mean-adjusted illiquidity level (*illiqma*). The parameter estimates for δ and λ are obtained as (time) averages of the coefficients obtained in each month's cross-sectional regression. t-statistics are in parentheses. All coefficients have been multiplied by 1000.

	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
liquileak_prob	7.46**				2.95				11.77**			
	(3.92)				(1.27)				(3.97)			
p_1		6.13**		4.19**		2.26		1.99		9.82**		6.30**
		(4.94)		(2.83)		(1.58)		(1.11)		(4.96)		(2.70)
p_{11}^5			3.31**	1.95*			1.03	0.39			5.49**	3.44**
			(3.96)	(1.94)			(0.97)	(0.30)			(4.31)	(2.30)
illiqma	1.60**	1.57**	1.61**	1.59**	2.30**	2.28**	2.31**	2.29**	0.94**	0.89**	0.95**	0.92**
	(9.01)	(8.80)	(9.05)	(8.83)	(7.48)	(7.39)	(7.49)	(7.33)	(5.27)	(5.03)	(5.34)	(5.16)
β_{MKT}	5.35**	5.62**	5.28**	5.47**	3.76	3.83	3.80	3.90	6.86**	7.34**	6.71**	6.97**
	(2.91)	(3.05)	(2.87)	(2.97)	(1.52)	(1.55)	(1.54)	(1.57)	(2.53)	(2.69)	(2.47)	(2.56)
β_{SMB}	-1.56	-1.75	-1.49	-1.67	0.60	0.52	0.62	0.58	-3.62*	-3.92**	-3.52*	-3.83**
	(-1.32)	(-1.48)	(-1.26)	(-1.42)	(0.42)	(0.37)	(0.44)	(0.41)	(-1.93)	(-2.09)	(-1.88)	(-2.04)
β_{HML}	-0.61	-0.65	-0.61	-0.64	0.50	0.52	0.47	0.45	-1.66	-1.76	-1.64	-1.69
	(-0.50)	(-0.54)	(-0.51)	(-0.54)	(0.31)	(0.32)	(0.29)	(0.27)	(-0.94)	(-1.00)	(-0.93)	(-0.96)
intercept	1.17	0.38	1.07	0.51	0.69	0.41	0.63	0.29	1.63	0.35	1.49	0.73
	(1.10)	(0.36)	(1.01)	(0.50)	(0.44)	(0.26)	(0.39)	(0.19)	(1.15)	(0.25)	(1.05)	(0.52)
#stocks*#months	1639*540				1605*264				1672*276			

p-value of test $H_0(\ \delta(liquileak\_prob, 1964\text{-}1985) = \delta(liquileak\_prob, 1986\text{-}2008)\ )$ is 0.02^{**}

p-value of test $H_0(\ \delta(p_1, 1964\text{-}1985) = \delta(p_1, 1986\text{-}2008)\ )$ is 0.00^{**}

p-value of test $H_0(\ \delta(p_{11}^5, 1964\text{-}1985) = \delta(p_{11}^5, 1986\text{-}2008)\ )$ is 0.01^{**}

p-value of test $H_0(\ \delta(illiqma, 1964\text{-}1985) = \delta(illiqma, 1986\text{-}2008)\ )$ is 0.00^{**}

**: Significant at a 95% level.
* : Significant at a 90% level.

Table 2.8: Fama-MacBeth regressions on liquileak probability and extended set of control variables

This table presents the results of a Fama-MacBeth regression analysis on whether the probability of liquileaks (*liquileaks_prob*) is priced in the cross-section of returns. First, the Fama-French factor loadings are estimated for each stock-year by running the following regression: $r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y}$ where i indexes stocks, d indexes days, y indexes years, MKT is the excess market return (relative to the risk-free rate), SMB is the Fama-French size factor, and HML is the Fama-French book-to-market factor. Second, for each month the following cross-sectional regression is performed: $r_{i,m,y} = \gamma_m + \lambda_m' \beta_{i,y-1} + \delta_m' Z_{i,y-1} + \varepsilon_{i,m,y}$ where m indexes months, r is a stock's excess return (relative to the risk-free rate), β is the vector of factor loadings, λ is the vector of associated risk premiums, Z is a vector of further stock-specific characteristics which includes liquileak probability (*liquileak_prob*), the (unconditional) probability that a stock hits the illiquid regime (p_1), the probability that it is stuck in this regime for five consecutive days (p_{11}^5), the mean-adjusted illiquidity level (*illiqma*), the return during the last 100 days of each year ($r100$), the return from the start of the year until 100 days before its end ($r100yr$), the standard deviation of daily returns (*sdret*), the logarithm of the market capitalization (*lnsize*), and the dividend yield (*divyld*). The parameter estimates for δ and λ are obtained as (time) averages of the coefficients obtained in each month's cross-sectional regression. t-statistics are in parentheses. All coefficients have been multiplied by 1000.

	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
liquileak_prob	9.25**				4.80**				13.52**			
	(4.58)				(2.09)				(4.14)			
p_1		5.63**		2.10		2.14		-0.27		8.97**		4.36*
		(4.41)		(1.38)		(1.50)		(-0.15)		(4.32)		(1.78)
p_{11}^5			4.29**	3.75**			2.41**	2.59**			6.09**	4.86**
			(5.28)	(3.89)			(2.40)	(2.07)			(4.84)	(3.33)
illiqma	1.30**	1.27**	1.30**	1.30**	1.88**	1.85**	1.88**	1.88**	0.74**	0.72**	0.75**	0.75**
	(7.48)	(7.33)	(7.51)	(7.46)	(6.15)	(6.06)	(6.15)	(6.11)	(4.46)	(4.31)	(4.50)	(4.48)
$r100$	3.17*	3.15*	3.26*	3.16*	5.76**	5.92**	5.77**	5.80**	0.70	0.49	0.86	0.63
	(1.72)	(1.71)	(1.77)	(1.71)	(2.15)	(2.22)	(2.16)	(2.17)	(0.27)	(0.19)	(0.34)	(0.25)
$r100yr$	1.29	1.19	1.22	1.14	4.44**	4.43**	4.37**	4.31**	-1.73	-1.90	-1.79	-1.88
	(1.11)	(1.03)	(1.06)	(0.99)	(2.76)	(2.76)	(2.72)	(2.68)	(-1.06)	(-1.17)	(-1.09)	(-1.15)
lnsize	-2.05**	-1.96**	-2.10**	-2.05**	-2.63**	-2.62**	-2.66**	-2.69**	-1.50**	-1.32**	-1.56**	-1.44**
	(-7.49)	(-7.12)	(-7.63)	(-7.47)	(-7.25)	(-7.20)	(-7.32)	(-7.41)	(-3.69)	(-3.25)	(-3.81)	(-3.54)
sdret	-4.62**	-4.47**	-4.68**	-4.68**	-7.20**	-7.06**	-7.25**	-7.25**	-2.15**	-1.98**	-2.22**	-2.22**
	(-7.94)	(-7.63)	(-8.05)	(-8.07)	(-8.33)	(-8.11)	(-8.38)	(-8.41)	(-2.85)	(-2.62)	(-2.95)	(-2.96)
divyld	0.06	0.07	0.06	0.06	0.13	0.14	0.13	0.12	-0.00	0.00	-0.00	-0.00
	(1.08)	(1.19)	(1.09)	(1.05)	(1.16)	(1.23)	(1.15)	(1.10)	(-0.10)	(0.04)	(-0.03)	(-0.03)

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	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
β_{MKT}	9.16**	9.13**	9.27**	9.18**	9.32**	9.30**	9.38**	9.31**	9.01**	8.97**	9.16**	9.05**
	(4.97)	(4.96)	(5.03)	(4.98)	(3.70)	(3.70)	(3.73)	(3.70)	(3.36)	(3.34)	(3.41)	(3.37)
β_{SMB}	-2.32**	-2.30**	-2.40**	-2.34**	0.13	0.13	0.09	0.11	-4.67**	-4.62**	-4.77**	-4.68**
	(-2.02)	(-2.00)	(-2.08)	(-2.04)	(0.10)	(0.10)	(0.07)	(0.08)	(-2.52)	(-2.50)	(-2.58)	(-2.53)
β_{HML}	-2.33**	-2.34**	-2.34**	-2.35**	-1.86	-1.87	-1.87	-1.89	-2.78*	-2.78*	-2.79*	-2.78*
	(-2.06)	(-2.07)	(-2.07)	(-2.08)	(-1.21)	(-1.22)	(-1.21)	(-1.23)	(-1.68)	(-1.68)	(-1.68)	(-1.68)
intercept	18.46**	18.71**	16.86**	18.14**	23.22**	23.37**	22.68**	23.57**	13.91**	14.25**	11.30**	12.94**
	(7.78)	(7.90)	(7.08)	(7.78)	(6.83)	(6.88)	(6.69)	(7.10)	(4.22)	(4.33)	(3.41)	(3.98)
#stocks*#months	1639*540				1605*264				1672*276			

p-value of test $H_0(\ \delta(liquileak\_prob, 1964\text{-}1985) = \delta(liquileak\_prob, 1986\text{-}2008)\ )$ is 0.03^{**}

p-value of test $H_0(\ \delta(p_1, 1964\text{-}1985) = \delta(p_1, 1986\text{-}2008)\ )$ is 0.01^{**}

p-value of test $H_0(\ \delta(p^5_{11}, 1964\text{-}1985) = \delta(p^5_{11}, 1986\text{-}2008)\ )$ is 0.02^{**}

p-value of test $H_0(\ \delta(illiqma, 1964\text{-}1985) = \delta(illiqma, 1986\text{-}2008)\ )$ is 0.00^{**}

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 2.8 redoes the Fama-MacBeth regressions with an extended set of stock-specific control variables suggested by Amihud (2002). These additional variables do not weaken the results of the standard model as presented in Table 2.7. If anything, they make them stronger. Liquileak probability now commands an annual return of 100%*12*0.12*0.00925=1.33% which is higher than the 1.07% obtained for the standard Fama-MacBeth regressions. And, $liquileak\_prob$ now also turns significant for the first sub-period, which seems to be driven by the duration part as it is p^5_{11} that turns significant, not p_1. The coefficients in the second sub-period are generally larger than what was found for the standard regressions.

The table further shows that some additional variables appear to matter for required returns. There is a momentum effect as the previous year return (either over the last 100 days of the year ($r100$) or from the start of the year until its end ($r100yr$)) carries a significantly positive coefficient in the first sub-period. There is a size effect as market capitalization ($lnsize$) carries a significantly negative sign throughout the sample. The stock's volatility matters as more volatility implies a lower future return. These findings are all consistent with what has been documented in Amihud (2002).[12] The only variable that does not appear to matter is dividend yield ($divyld$).

Overall, the portfolio sorting analysis and the Fama-MacBeth regressions show consistent evidence that the liquidity leak probability commands a premium in the cross-section of returns. This premium is economically and statistically significant. Both factors that make up the liquidity leak probability, p^5_{11} and p_1, seem to contribute to the premium. Moreover, the liquidity leak probability becomes more relevant in explaining cross-sectional returns over time whereas the importance of liquidity level declines.

2.5 Which are the high-liquileak stocks?

Table 2.9 regresses liquileak probability on various standard trade and accounting variables in order to characterize stocks that are prone to liquileaks. These regressions are based on a panel dataset of variables that are calculated by stock-year. The overall OLS panel regression reveals that high liquileak stocks seem to be highly volatile, small-cap stocks that exhibit high daily volume variability. If only cross-sectional variability is used (based on the time averages of all variables), these explanatory variables remain significant, but also two accounting variables turn significant: return-on-assets and growth-rate-of-assets, i.e., highly profitable fast-growing companies are more prone to liquileaks. If only time variability is used (based on a variable's deviation from its time average), volume variability is no longer significant, but asset growth

[12] A recent explanation for the somewhat puzzling volatility effect is in Fu (2008) which finds that it is driven by non-synchronicity (lagged volatility, future return) and the time-varying (GARCH) nature of volatility. If this is properly controlled for, the relation turns positive; conditional idiosyncratic volatility positively correlates with expected returns.

and leverage do become significant, i.e., in years that a company exhibits fast growth and high leverage, liquileaks are more likely.

Table 2.9: Which are the high-liquileak firms?

This table regresses stock-year liquileak probability (*liquileak_prob*) estimates on firm characteristics. The panel dataset regressions include a:
(i) full-sample variation regression (i.e., a simple OLS regression),
(ii) a between-regression that based only on cross-sectional variation (i.e., the variables are averaged across years and the result enters an OLS regression across stocks),
(iii) and a within-regression on only the time series variation (i.e., all variables are demeaned by subtracting off the stock-specific mean and the result enters an OLS regression).
Some explanatory variables are pure trade variables: end-of-day transaction price (*prc*), volume in shares (*svol*), standard deviation of daily share volume (*sdsvol*), standard deviation of daily return (*sdret*), market capitalization (*mcap*). Some explanatory variables are pure book values: book to market value (*btm*), return on assets (*roa*), growth rate of assets (*growth_asset*). And, finally, one is calculated based on both trade and book values: financial leverage calculated by the ratio of long-term debt to stockholder's equity (*leverage*).

	OLS	between-OLS	within-OLS
prc	0.01	0.08	-0.07
	(0.37)	(1.43)	(-1.60)
svol	-4.17	-7.65	-1.91
	(-0.87)	(-0.57)	(-0.39)
sdsvol	17.11**	40.63**	10.30
	(3.01)	(2.34)	(1.59)
sdret	40.81**	33.45**	55.14**
	(46.36)	(18.25)	(36.14)
mcap	-1.17**	-1.76**	-1.90**
	(-4.95)	(-3.62)	(-4.48)
btm	0.02	-2.28**	0.40
	(0.06)	(-5.65)	(1.64)
roa	0.60	31.77**	4.13
	(0.07)	(2.56)	(0.34)
growth_asset	0.06	0.11	0.52**
	(0.94)	(0.60)	(3.72)
leverage	0.03	-0.06	0.06**
	(1.08)	(-1.25)	(2.03)
intercept	-38.68**	-24.89**	
#stocks*#years	1639*46		

**: Significant at a 95% level.
* : Significant at a 90% level.

2.6 Robustness checks

This section contains four robustness checks on the pricing of liquidity leaks. First, the liquileak probability is replaced by a (model-free) proxy that is calculated directly from the raw data.

Second, the financial crisis period, 2007-2008, was removed from the second sub-period to verify whether the increased liquileak premium was due to the crisis. Third, the full sample Fama-MacBeth regressions are re-done where liquileaks are defined as the security being stuck in the illiquid state for three, ten, and fifteen days. Fourth, all analysis is redone without the month of January as there is evidence that the pricing of liquidity is entirely a 'January effect'.

Model-free raw data proxies for $liquileak\_prob$**.** All results thus far are based on parameter estimates from a Markov regime switching model. These results therefore require one to believe that the model is a reasonable approximation to the data-generating process. Ideally, one wants to see the results hold up in a nonparametric approach so as to avoid the criticism that all is driven by the modeling choice. This is the aim of the first robustness analysis.

The liquileak probability, $liquileak\_prob$, is the product of two factors which both have a natural analogue measure in the raw data. This probability is essentially the product of the unconditional probability of hitting the illiquid state (p_1) and the probability of being stuck in it for five consecutive days (p_{11}^5) (see equation (2.3)). We propose the following two raw data proxies for these factors. The probability to find a stock in the illiquid state is proxied for by the frequency with which a stock exhibits an Amihud ILLIQ value that is above the 80% quantile across all stock-day observations on ILLIQ for that year ($freq\_illiq$). The duration factor is proxied for by the average time a stock spends in this state ($duration\_illiq$). The product of these two factors is then taken as the raw data proxy for liquileak probability ($freq\_illiq \times duration\_illiq$).

Table 2.10 presents summary statistics on the raw data proxies. Panel A finds that the frequency of the illiquid regime ($freq\_illiq$) is 0.22 on average.[13] The measure's cross-sectional variation is substantial, 0.20, and of the magnitude as its variation through time, 0.23. The duration of the illiquid state is 2.37 days on average with a cross-sectional variation of 3.43 and an even larger time variation of 6.69. These statistics show that a threshold of five days might make liquileaks a 'negligible' event for the average stock, but certainly not for some stocks in some years. Not surprisingly, the liquileak proxy, being the product of these two proxies, also shows substantial variation in the cross-section as well as through time. This is promising for a variable that is tested as a 'right-hand side' variable.

Panel B presents the correlations (i) among the raw data proxies and (ii) between these proxies and the model-based parameter estimates. It leads to the following observations. First, the raw data proxies for the two factors of liquileak probability ($freq\_illiq$ and $duration\_illiq$) are highly correlated both in the cross-section (ρ(between)=0.93) and in the time dimension (ρ(within)=0.82). These proxies therefore cannot discriminate well between the two characteristics that make a liquileak event. Second, both proxies are significantly positively correlated with the model-based parameters that they proxy for. They correlate better in cross-section (0.20

[13] It is not exactly 0.20 because the average frequency is the average of frequencies that are themselves calculated by stock-year. The 80% percentile is based on all stock-day values for the year.

Table 2.10: Raw data proxies for liquileak probability

This table presents summary statistics on a raw data based proxy for the probability of a liquidity leak event, i.e., finding the stock in the illiquid state where it is stuck for five consecutive days. This event probability in the regime-switching model is the product of two factors: the (conditional) probability of finding the stock in an illiquid state and the duration of that state when starting off in it. We propose a raw data proxy for both factors. The probability to find a stock in the illiquid state is proxied for by the frequency with which a stock exhibits an Amihud ILLIQ value that is above the 80% quantile across all stock-day observations on ILLIQ for that year (*freq_illiq*). The duration is proxied for by the average time a stock spends in this state (*duration_illiq*). The product of these two factors is then the raw proxy for the liquileak probability ($freq\_illiq \times duration\_illiq$). Panel A presents summary statistics of *freq_illiq*, *duration_illiq*, and $freq\_illiq \times duration\_illiq$. Panel B presents the between and within correlation among them as well as with the model-based equivalents (p_1,p_{11}^5, and *liquileak_prob*) and *illiq*.

Panel A: Mean and variance raw data proxies for liquileak probability

	Mean	St.Dev.	St.Dev. Between[a]	St.Dev. Within[b]	Min	Max	Median
freq_illiq	0.22	0.30	0.20	0.23	0.00	1.00	0.03
duration_illiq	2.37	7.52	3.43	6.69	0.00	231.00	1.00
$freq\_illiq \times duration\_illiq$	1.68	7.41	3.30	6.64	0.00	230.02	0.03
#stocks	1639.28	261.65	112.13	236.40	1123.00	2147.00	1668.00

Panel B: Between and within correlation raw data proxies for liquileak probability

		duration_illiq	$freq\_illiq \times duration\_illiq$	p_1	p_{11}^5	*liquileak_prob*	*illiq*
freq_illiq	ρ(between)	0.93*	0.91*	0.20*	0.08*	0.10*	0.24*
	ρ(within)	0.82*	0.82*	0.03*	0.01*	0.02*	0.10*
duration_illiq	ρ(between)		0.95*	0.23*	0.10*	0.13*	0.30*
	ρ(within)		0.93*	0.04*	0.02*	0.03*	0.11*
$freq\_illiq \times duration\_illiq$	ρ(between)			0.18*	0.09*	0.11*	0.25*
	ρ(within)			0.03*	0.01*	0.02*	0.10*
p_1	ρ(between)				0.54*	0.74*	0.41*
	ρ(within)				0.63*	0.82*	0.19*
p_{11}^5	ρ(between)					0.89*	0.10*
	ρ(within)					0.85*	0.08*
liquileak_prob	ρ(between)						0.17*
	ρ(within)						0.13*

#stocks*#years: 1639*46

[a]: Based on the time means i.e. $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$.
[b]: Based on the deviations from time means i.e. $x_{i,t}^* = x_{i,t} - \bar{x}_i$.
*: Significant at a 95% level.

and 0.10) than they do through time (0.03 and 0.02) although all are significant. Not surprisingly, the same pattern exists for $freq\_illiq \times duration\_illiq$ which proxies for $liquileak\_prob$ (ρ(between)=0.11 and ρ(within)=0.02). The higher between-correlation is encouraging as the Fama-MacBeth approach identifies return premiums off of the cross-section. Third, the correlations between the proxies and the average liquidity level ($illiq$) are similar in magnitude as those for model-based parameter estimates. This alleviates the concern that the raw data proxies might not capture as much of the disaster event nature of liquileaks but might just be another (noisy) proxy for the average liquidity level.

Table 2.11 redoes the standard Fama-MacBeth analysis of Table 2.7 based on the raw data proxy for $liquileak\_prob$ and continues to find that liquileaks are priced. The coefficient of this proxy ($freq\_illiq \times duration\_illiq$) is significantly positive and a one standard deviation change in this proxy commands an annual premium of 100%*12*7.41*0.00040=3.56%. The component factors are both significantly positive when included individually in the regression, but only duration remains weakly significant when entered jointly. This is not surprising given that both factors are highly collinear in the cross-section. The two sub samples both show that the liquileak proxy is significantly positive in both sub-periods with alternating significance on both of its component factors.

Table 2.12 uses the extended set of control variables in the Fama-MacBeth regressions (cf. Table 2.8) and also finds that liquileaks continue to be priced when using the raw data proxy, both in the full sample and in the two sub samples. Its two component factors both carry a positive coefficient when included individually or jointly, but they are not consistently significant. The findings are very similar to those discussed for the standard Fama-MacBeth regressions based on the raw data proxies (i.e., the results presented in Table 2.11).

2007-2008 financial crisis. Table 2.14 in the "Appendix: Liquileaks" redoes the Fama-McBeth analysis of Table 2.7 and 2.8 after removing the financial crisis years 2007-2008 from the second subperiod (1986-2008). The coefficient on $liquileak\_prob$ is slightly higher, 12.07 vs. 11.77 (and 14.63 vs. 13.52 with extended controls), and we therefore conclude that the increase in the second subperiod relative to the first subperiod was not due to the financial crisis.

Duration liquileaks. Liquileaks are defined as the security being stuck in the illiquid state for more than five days (see equation (2.3)). Tables 2.15 through 2.17 redo the full sample Fama-MacBeth regressions but now define liquileaks based on three, ten, and fifteen days respectively. The results show that liquileaks continue to be priced for all durations. The per-unit premium increases monotonically with duration.

Table 2.11: Fama-MacBeth regressions of stock returns on raw data proxies for liquileak probability and standard control variables

This table presents the results of a Fama-MacBeth regression analysis on whether the probability of liquileaks (*liquileaks_prob*) is priced in the cross-section of returns. It replicates Table 2.7 with the only difference that the model-based liquileak probability is replaced by proxies for it based on the raw data. First, the Fama-French factor loadings are estimated for each stock-year by running the following regression: $r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y}$ where i indexes stocks, d indexes days, y indexes years, MKT is the excess market return (relative to the risk-free rate), SMB is the Fama-French size factor, and HML is the Fama-French book-to-market factor. Second, for each month the following cross-sectional regression is performed: $r_{i,m,y} = \gamma_m + \lambda_m' \beta_{i,y-1} + \delta_m' Z_{i,y-1} + \varepsilon_{i,m,y}$ where m indexes months, r is a stock's excess return (relative to the risk-free rate), β is the vector of factor loadings, λ is the vector of associated risk premiums, Z is a vector of further stock-specific characteristics which includes the frequency with which a stock is more illiquid than the 80% quantile of all stocks' Amihud's ILLIQ measure in that year ($freq\_illiq$), the average duration that a stock of this event ($duration\_illiq$), the product of these two variables ($freq\_illiq \times duration\_illiq$), and the mean-adjusted illiquidity level ($illiqma$). The parameter estimates for δ and λ are obtained as (time) averages of the coefficients obtained in each month's cross-sectional regression. t-statistics are in parentheses. All coefficients have been multiplied by 1000.

	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$freq\_illiq \times duration\_illiq$	0.40**				0.57**				0.24**			
	(3.82)				(3.12)				(2.22)			
$freq\_illiq$		2.33**		0.81		4.28**		3.70**		0.47		-1.96
		(3.30)		(0.75)		(3.45)		(2.18)		(0.68)		(-1.48)
$duration\_illiq$			0.27**	0.23*			0.40**	0.08			0.14	0.37**
			(2.98)	(1.66)			(2.58)	(0.36)			(1.50)	(2.18)
$illiqma$	1.83**	1.81**	1.90**	1.81**	2.57**	2.51**	2.70**	2.52**	1.13**	1.13**	1.13**	1.13**
	(7.09)	(7.20)	(7.49)	(7.10)	(5.43)	(5.50)	(5.86)	(5.41)	(5.16)	(5.19)	(5.18)	(5.19)
β_{MKT}	4.73**	4.78**	4.74**	4.77**	4.38*	4.46*	4.39*	4.44*	5.07*	5.08*	5.08*	5.09*
	(2.56)	(2.59)	(2.57)	(2.58)	(1.80)	(1.83)	(1.80)	(1.82)	(1.83)	(1.83)	(1.83)	(1.84)
β_{SMB}	-0.93	-0.98	-0.98	-0.99	-0.16	-0.29	-0.25	-0.30	-1.67	-1.64	-1.66	-1.65
	(-0.79)	(-0.83)	(-0.83)	(-0.84)	(-0.11)	(-0.20)	(-0.18)	(-0.21)	(-0.90)	(-0.88)	(-0.90)	(-0.89)
β_{HML}	-0.52	-0.54	-0.53	-0.53	0.51	0.48	0.49	0.49	-1.50	-1.51	-1.50	-1.52
	(-0.43)	(-0.45)	(-0.44)	(-0.45)	(0.32)	(0.30)	(0.30)	(0.31)	(-0.85)	(-0.86)	(-0.85)	(-0.86)
$intercept$	1.33	1.19	1.20	1.15	0.61	0.26	0.36	0.25	2.03	2.09	2.01	2.02
	(1.26)	(1.12)	(1.13)	(1.09)	(0.37)	(0.16)	(0.22)	(0.15)	(1.47)	(1.50)	(1.45)	(1.45)
#stocks*#months	1639*540				1605*264				1672*276			

p-value of test $H_0(\ \delta(freq\_illiq \times duration\_illiq, 1964\text{-}1985) = \delta(freq\_illiq \times duration\_illiq, 1986\text{-}2008)\ )$ is 0.12

p-value of test $H_0(\ \delta(freq\_illiq, 1964\text{-}1985) = \delta(freq\_illiq, 1986\text{-}2008)\ )$ is 0.01**

p-value of test $H_0(\ \delta(duration\_illiq, 1964\text{-}1985) = \delta(duration\_illiq, 1986\text{-}2008)\ )$ is 0.15

p-value of test $H_0(\ \delta(illiqma, 1964\text{-}1985) = \delta(illiqma, 1986\text{-}2008)\ )$ is 0.00**

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 2.12: Fama-MacBeth regressions of stock returns on raw data proxies for liquileak probability and extended set of control variables

This table presents the results of a Fama-MacBeth regression analysis on whether the probability of liquileaks (*liquileaks_prob*) is priced in the cross-section of returns. It replicates Table 2.8 with the only difference that the model-based liquileak probability is replaced by proxies for it based on the raw data. First, the Fama-French factor loadings are estimated for each stock-year by running the following regression: $r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y}$ where i indexes stocks, d indexes days, y indexes years, MKT is the excess market return (relative to the risk-free rate), SMB is the Fama-French size factor, and HML is the Fama-French book-to-market factor. Second, for each month the following cross-sectional regression is performed: $r_{i,m,y} = \gamma_m + \lambda_m' \beta_{i,y-1} + \delta_m' Z_{i,y-1} + \varepsilon_{i,m,y}$ where m indexes months, r is a stock's excess return (relative to the risk-free rate), β is the vector of factor loadings, λ is the vector of associated risk premiums, Z is a vector of further stock-specific characteristics which includes the frequency with which a stock is more illiquid than the 80% quantile of all stocks' Amihud's ILLIQ measure in that year (*freq_illiq*), the average duration that a stock of this event (*duration_illiq*), the product of these two variables ($freq\_illiq \times duration\_illiq$), the mean-adjusted illiquidity level (*illiqma*), the return during the last 100 days of each year ($r100$), the return from the start of the year until 100 days before its end ($r100yr$), the standard deviation of daily returns (*sdret*), the logarithm of the market capitalization (*lnsize*), and the dividend yield (*divyld*). The parameter estimates for δ and λ are obtained as (time) averages of the coefficients obtained in each month's cross-sectional regression. t-statistics are in parentheses. All coefficients have been multiplied by 1000.

	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$freq\_illiq \times duration\_illiq$	0.42**				0.59**				0.27**			
	(3.86)				(3.00)				(2.52)			
$freq\_illiq$		2.72**		1.71		4.46**		3.59**		1.06		-0.08
		(3.80)		(1.58)		(3.46)		(2.06)		(1.61)		(-0.06)
$duration\_illiq$			0.29**	0.16			0.42**	0.16			0.16*	0.17
			(3.07)	(1.15)			(2.51)	(0.67)			(1.81)	(1.03)
$illiqma$	1.93**	1.94**	2.01**	1.93**	2.96**	2.99**	3.12**	2.97**	0.94**	0.94**	0.94**	0.94**
	(6.91)	(7.20)	(7.33)	(7.01)	(5.70)	(6.01)	(6.17)	(5.80)	(4.45)	(4.44)	(4.46)	(4.44)
$r100$	3.34**	3.25*	3.26*	3.24*	4.61*	4.44*	4.42*	4.38*	2.13	2.12	2.16	2.14
	(1.97)	(1.92)	(1.92)	(1.91)	(1.83)	(1.76)	(1.75)	(1.74)	(0.94)	(0.93)	(0.95)	(0.94)
$r100yr$	0.69	0.67	0.62	0.66	2.96**	2.92**	2.82*	2.90**	-1.48	-1.48	-1.48	-1.48
	(0.69)	(0.67)	(0.62)	(0.66)	(2.03)	(2.00)	(1.93)	(1.99)	(-1.09)	(-1.08)	(-1.08)	(-1.08)
$lnsize$	-2.19**	-2.09**	-2.14**	-2.08**	-2.96**	-2.75**	-2.86**	-2.73**	-1.46**	-1.46**	-1.46**	-1.45**
	(-8.82)	(-8.45)	(-8.67)	(-8.41)	(-8.22)	(-7.69)	(-8.02)	(-7.65)	(-4.31)	(-4.30)	(-4.30)	(-4.29)
$sdret$	-5.30**	-5.27**	-5.30**	-5.27**	-8.39**	-8.34**	-8.40**	-8.35**	-2.35**	-2.33**	-2.34**	-2.33**
	(-9.71)	(-9.68)	(-9.70)	(-9.66)	(-10.53)	(-10.51)	(-10.52)	(-10.49)	(-3.33)	(-3.31)	(-3.32)	(-3.30)
$divyld$	0.13**	0.13**	0.13**	0.13**	0.28**	0.28**	0.28**	0.28**	-0.01	-0.01	-0.01	-0.01
	(2.45)	(2.49)	(2.43)	(2.47)	(2.62)	(2.66)	(2.60)	(2.64)	(-0.38)	(-0.38)	(-0.39)	(-0.39)

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	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
β_{MKT}	9.15**	9.17**	9.20**	9.19**	10.70**	10.74**	10.79**	10.77**	7.67**	7.67**	7.67**	7.67**
	(5.00)	(5.01)	(5.02)	(5.02)	(4.35)	(4.37)	(4.38)	(4.38)	(2.84)	(2.84)	(2.84)	(2.84)
β_{SMB}	-2.04*	-2.04*	-2.03*	-2.03*	-0.55	-0.55	-0.54	-0.54	-3.46*	-3.46*	-3.46*	-3.46*
	(-1.77)	(-1.76)	(-1.76)	(-1.76)	(-0.41)	(-0.41)	(-0.40)	(-0.40)	(-1.86)	(-1.86)	(-1.86)	(-1.86)
β_{HML}	-2.53**	-2.53**	-2.52**	-2.52**	-2.32	-2.34	-2.32	-2.31	-2.72*	-2.71*	-2.72*	-2.71*
	(-2.26)	(-2.27)	(-2.26)	(-2.26)	(-1.54)	(-1.55)	(-1.54)	(-1.53)	(-1.66)	(-1.65)	(-1.66)	(-1.65)
intercept	20.05**	19.63**	19.23**	19.14**	26.09**	25.29**	24.45**	24.35**	14.27**	14.21**	14.24**	14.15**
	(8.82)	(8.67)	(8.46)	(8.43)	(7.70)	(7.51)	(7.22)	(7.21)	(4.74)	(4.72)	(4.71)	(4.68)
#stocks*#months	1639*540				1605*264				1672*276			

p-value of test $H_0(\ \delta(freq\_illiq \times duration\_illiq, 1964\text{-}1985) = \delta(freq\_illiq \times duration\_illiq, 1986\text{-}2008)\ )$ is 0.15

p-value of test $H_0(\ \delta(freq\_illiq, 1964\text{-}1985) = \delta(freq\_illiq, 1986\text{-}2008)\ )$ is 0.02^{**}

p-value of test $H_0(\ \delta(duration\_illiq, 1964\text{-}1985) = \delta(duration\_illiq, 1986\text{-}2008)\ )$ is 0.17

p-value of test $H_0(\ \delta(illiqma, 1964\text{-}1985) = \delta(illiqma, 1986\text{-}2008)\ )$ is 0.00^{**}

**: Significant at a 95% level.

* : Significant at a 90% level.

January effect. A fourth robustness analysis removes the months of January to show that liquileak pricing is not just a 'January effect'. Keim (1983) and Eleswarapu and Reinganum (1993) find that the bid-ask spread does no longer increase the expected return in the cross-section once the month of January is excluded. A straightforward robustness check is therefore to remove the January months and redo both the model-based and the raw data proxy analysis using the extended set of control variables.

Panel A of Table 2.13 shows that *liquileak_prob* continues to carry a significantly positive sign in the cross-section of returns. There is some evidence of a January effect as its coefficient, 0.00676, is lower than the coefficient of the full sample analysis, 0.00925 (see Table 2.8). The two component factors of *liquileak_prob* (p_1 and p_{11}^5) continue to be significant when included individually, but are now also significant when included jointly.

The raw data proxy analysis presented in Panel B also finds that liquileaks continue to be priced. Its proxy $freq\_illiq \times duration\_illiq$ carries a significantly positive sign and its coefficient, 0.43, is of the same magnitude as the coefficient in the full sample analysis, 0.42 (cf. Table 2.12). The two factors that make up this proxy are significantly positive when included individually, but not when included jointly (due to high collinearity).

2.7 Conclusion

This study proposes a new liquidity measure that formalizes the risk of finding the security in a market from which all liquidity has leaked for a considerable amount of time. Whereas normal market liquidity might not be a concern to investors, such liquileak event might be painful. The probability of such event was estimated using a Markov regime-switching model where the security's trading state alternates between a liquid and an (extremely) illiquid state. Standard asset pricing analysis based on both portfolio sorts and Fama-MacBeth regressions on all AMEX and NYSE common stocks from 1963 to 2008 shows that liquileaks do command additional returns. The regression results show that a one standard deviation increase in the liquileak probability commands an additional annual return of 1.33%. A nonparametric robustness analysis confirms that liquileak events are priced.

To find that liquileak risk matters in equity markets that generally have wide participation implies that this might be an even more important issue for non-equities. Also, post-crisis regulatory efforts might consider liquileak risk in capital adequacy requirements. The recent financial crisis has shown that normal market liquidity might not be there when it is needed most.

Table 2.13: Fama-MacBeth regressions, excluding January effects

This table presents the results of a Fama-MacBeth regression analysis on whether the probability of liquileaks ($liquileaks\_prob$) is priced in the cross-section of returns. It replicates Table 2.8 and 2.12 with the only difference that the month of January is excluded from the sample. First, the Fama-French factor loadings are estimated for each stock-year by running the following regression: $r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y}$ where i indexes stocks, d indexes days, y indexes years, MKT is the excess market return (relative to the risk-free rate), SMB is the Fama-French size factor, and HML is the Fama-French book-to-market factor. Second, for each month the following cross-sectional regression is performed: $r_{i,m,y} = \gamma_m + \lambda_m' \beta_{i,y-1} + \delta_m' Z_{i,y-1} + \varepsilon_{i,m,y}$ where m indexes months, r is a stock's excess return (relative to the risk-free rate), β is the vector of factor loadings, λ is the vector of associated risk premiums, Z is a vector of further stock-specific characteristics which includes the model-based liquileak probability ($liquileak\_prob$), the model-based (unconditional) probability that a stock hits the illiquid regime (p_1), the model-based probability that it is stuck in this regime for five consecutive days (p_{11}^5), the frequency with which a stock is more illiquid than the 80% quantile of all stocks' Amihud's ILLIQ measure in that year ($freq\_illiq$), the average duration that a stock of this event ($duration\_illiq$), the product of these two variables ($freq\_illiq \times duration\_illiq$), the mean-adjusted illiquidity level ($illiqma$), the return during the last 100 days of each year ($r100$), the return from the start of the year until 100 days before its end ($r100yr$), the standard deviation of daily returns ($sdret$), the logarithm of the market capitalization ($lnsize$), and the dividend yield ($divyld$). The parameter estimates for δ and λ are obtained as (time) averages of the coefficients obtained in each month's cross-sectional regression. t-statistics are in parentheses. All coefficients have been multiplied by 1000.

Panel A: liquileak_prob

	(1)	(2)	(3)	(4)
$liquileak\_prob$	6.76**			
	(3.29)			
p_1		5.49**		3.22**
		(4.13)		(2.04)
p_{11}^5			3.31**	2.36**
			(4.01)	(2.42)
$illiqma$	0.95**	0.93**	0.96**	0.95**
	(5.71)	(5.59)	(5.73)	(5.66)
$r100$	7.93**	7.83**	7.98**	7.85**
	(4.73)	(4.66)	(4.76)	(4.66)
$r100yr$	2.07*	1.93*	2.01*	1.92
	(1.77)	(1.65)	(1.72)	(1.64)
$lnsize$	-1.85**	-1.75**	-1.89**	-1.82**
	(-6.68)	(-6.31)	(-6.80)	(-6.59)
$sdret$	-4.56**	-4.49**	-4.62**	-4.61**
	(-7.73)	(-7.56)	(-7.82)	(-7.83)
$divyld$	-0.00	0.00	-0.00	-0.00
	(-0.03)	(0.04)	(-0.02)	(-0.02)
β_{MKT}	7.16**	7.26**	7.14**	7.20**
	(3.79)	(3.84)	(3.78)	(3.81)
β_{SMB}	-3.25**	-3.32**	-3.22**	-3.28**
	(-2.75)	(-2.81)	(-2.73)	(-2.78)
β_{HML}	-2.93**	-2.93**	-2.94**	-2.95**
	(-2.56)	(-2.56)	(-2.56)	(-2.57)
$intercept$	18.67**	17.15**	18.87**	18.00**
	(7.69)	(7.08)	(7.79)	(7.59)

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Panel B: raw data proxy for liquileak probability: $freq\_illiq \times duration\_illiq$				
	(1)	(2)	(3)	(4)
$freq\_illiq \times duration\_illiq$	0.43**			
	(3.98)			
$freq\_illiq$		2.50**		1.32
		(3.71)		(1.19)
$duration\_illiq$			0.29**	0.20
			(3.14)	(1.34)
$illiqma$	1.46**	1.51**	1.56**	1.50**
	(5.39)	(5.76)	(5.84)	(5.56)
$r100$	7.80**	7.72**	7.73**	7.70**
	(5.08)	(5.04)	(5.04)	(5.02)
$r100yr$	1.60	1.59	1.55	1.58
	(1.59)	(1.58)	(1.54)	(1.57)
$lnsize$	-1.91**	-1.82**	-1.86**	-1.80**
	(-7.67)	(-7.36)	(-7.53)	(-7.32)
$sdret$	-5.35**	-5.32**	-5.35**	-5.32**
	(-9.72)	(-9.69)	(-9.71)	(-9.67)
$divyld$	0.07	0.08	0.07	0.07
	(1.35)	(1.40)	(1.34)	(1.38)
β_{MKT}	7.18**	7.21**	7.21**	7.21**
	(3.83)	(3.85)	(3.84)	(3.85)
β_{SMB}	-2.86**	-2.85**	-2.86**	-2.85**
	(-2.42)	(-2.41)	(-2.42)	(-2.41)
β_{HML}	-3.05**	-3.05**	-3.05**	-3.04**
	(-2.67)	(-2.67)	(-2.67)	(-2.67)
$intercept$	19.65**	18.93**	19.22**	18.82**
	(8.37)	(8.09)	(8.24)	(8.05)
#stocks*#months	1639*495			

**: Significant at a 95% level.

*: Significant at a 90% level.

Appendix 2A: Implementation details on likelihood optimization using the Hamilton filter

A number of empirical research suggests that the time series behavior of economic and financial variables may exhibit different patterns over time. Therefore, instead of using one model for the conditional mean of a variable, it is natural to employ several models to capture different patterns. The idea of liquidity leaks is that a stock is in a normal liquidity state most of time, but occasionally hits an illiquid state. These features can be readily accommodated by a Markov regime-switching model.

A Markov regime-switching model is constructed by combining two or more dynamic models via a Markovian switching mechanism. It involves multiple structures that can characterize different time series behaviors in different states. By permitting switching between these states, this model is able to represent more complex dynamic patterns. A novel feature of the Markov switching model is that the switching mechanism is controlled by an unobservable state variable that follows a first-order Markov chain process. In particular, the probability of a change in state depends on the past only through the value of the most recent state. As such, a structure may prevail for a random period of time, and it will be replaced by another structure when a switching takes place. This is in sharp contrast with the random switching model of Quandt (1972) in which the events of switching are independent over time. The Markov switching model is therefore suitable for describing correlated data that exhibit distinct dynamic patterns during different time periods.

The estimation of a Markov regime-switching model with no autoregressive coefficient dates back to the analysis of Baum, Petrie, Soules, and Weiss (1970). Later, Poritz (1982), Juang and Rabiner (1985), and Rabiner (1989) incorporate autoregressive elements and describe such processes as “hidden Markov models”. The estimation procedure described below follows the approach of Hamilton (1989) and Hamilton (1994).

Let y_t be the observation series that is drawn from the regime switching model described in Section 2.2. Let $\Omega_t = \{y_t, y_{t-1}, \cdots, y_0\}$ denote the set of observations up to time t and let $\theta = (p, q, \mu_0, \mu_1, \rho, \sigma_0, \sigma_1)'$ be the parameter vector. The transition probabilities p_{00} and p_{11} are constrained to be between 0 and 1 and are therefore parameterized as:

$$p_{00} = \frac{\exp(p)}{1+\exp(p)} \tag{2.10}$$

$$p_{11} = \frac{\exp(q)}{1+\exp(q)} \tag{2.11}$$

The autocorrelation parameter ϕ is constrained to be between -1 and 1 (to ensure stationarity) and is therefore parameterized as:

$$\phi = \frac{\exp(\rho) - 1}{\exp(\rho) + 1} \tag{2.12}$$

The parameter estimates are obtained through maximum likelihood where the likelihood is calculated with the Hamilton filter as described in the remainder of the appendix. First, the likelihood is written as a product of conditional probabilities which are evaluated iteratively, i.e., the likelihood is:

$$\log f(y_0, y_1, \cdots, y_T | y_0; \theta) = \sum_{t=0}^{T} \log f(y_t | \Omega_{t-1}; \theta) \tag{2.13}$$

In the iteration, given the probability of state s_t, the conditional density of y_{t+1} is calculated as well as the probability of s_{t+1} (where the probability for the initial state s_0 is set to the unconditional probability (cf. equation (2.3)). So, let $Pr(s_t = 0|\Omega_t) = \pi_0$ and $Pr(s_t = 1|\Omega_t) = \pi_1$. The transition probabilities are:

$$\begin{aligned}
Pr(s_{t+1} = 0, s_t = 0|\Omega_t) &= Pr(s_{t+1} = 0|s_t = 0; \Omega_t) \cdot Pr(s_t = 0|\Omega_t) = p_{00}\pi_0 && (2.14)\\
Pr(s_{t+1} = 1, s_t = 0|\Omega_t) &= Pr(s_{t+1} = 1|s_t = 0; \Omega_t) \cdot Pr(s_t = 0|\Omega_t) = p_{01}\pi_0 && (2.15)\\
Pr(s_{t+1} = 0, s_t = 1|\Omega_t) &= Pr(s_{t+1} = 0|s_t = 1; \Omega_t) \cdot Pr(s_t = 1|\Omega_t) = p_{10}\pi_1 && (2.16)\\
Pr(s_{t+1} = 1, s_t = 1|\Omega_t) &= Pr(s_{t+1} = 1|s_t = 1; \Omega_t) \cdot Pr(s_t = 1|\Omega_t) = p_{11}\pi_1 && (2.17)
\end{aligned}$$

For each of these transitions the distribution of y_{t+1} is:

$$\begin{aligned}
f(y_{t+1}|s_{t+1} = 0; s_t = 0; \Omega_t; \theta) &= \frac{1}{\sqrt{2\pi\sigma_0}} exp\left(\frac{-[(y_{t+1} - \mu_0) - \phi(y_t - \mu_0)]^2}{2\sigma_0^2}\right) && (2.18)\\
f(y_{t+1}|s_{t+1} = 1; s_t = 0; \Omega_t; \theta) &= \frac{1}{\sqrt{2\pi\sigma_1}} exp\left(\frac{-[(y_{t+1} - \mu_1) - \phi(y_t - \mu_0)]^2}{2\sigma_1^2}\right) && (2.19)\\
f(y_{t+1}|s_{t+1} = 0; s_t = 1; \Omega_t; \theta) &= \frac{1}{\sqrt{2\pi\sigma_0}} exp\left(\frac{-[(y_{t+1} - \mu_0) - \phi(y_t - \mu_1)]^2}{2\sigma_0^2}\right) && (2.20)\\
f(y_{t+1}|s_{t+1} = 1; s_t = 1; \Omega_t; \theta) &= \frac{1}{\sqrt{2\pi\sigma_1}} exp\left(\frac{-[(y_{t+1} - \mu_1) - \phi(y_t - \mu_1)]^2}{2\sigma_1^2}\right) && (2.21)
\end{aligned}$$

The density therefore is:

$$\begin{aligned}
f(y_{t+1}|\Omega_t; \theta) &= \sum_{j=0}^{1}\sum_{i=0}^{1} f(y_{t+1}, s_{t+1} = j, s_t = i|\Omega_t; \theta) && (2.22)\\
&= \sum_{j=0}^{1}\sum_{i=0}^{1} f(y_{t+1}|s_{t+1} = j; s_t = i; \Omega_t; \theta) \cdot Pr(s_{t+1} = j, s_t = i|\Omega_t; \theta) && (2.23)\\
&= (2.18) \times (2.14) + (2.19) \times (2.15) + (2.20) \times (2.16) + (2.21) \times (2.17) && (2.24)
\end{aligned}$$

If observation y_{t+1} is then added to the conditioning set, the state probabilities are updated with Bayes' rule:

$$\begin{aligned}
Pr(s_{t+1}=0,s_t=0|\Omega_{t+1}) &= Pr(s_{t+1}=0,s_t=0|y_{t+1};\Omega_t) && (2.25)\\
&= \frac{f(y_{t+1},s_{t+1}=0,s_t=0|\Omega_t;\theta)}{f(y_{t+1}|\Omega_t;\theta)} && (2.26)\\
&= \frac{f(y_{t+1}|s_{t+1}=0;s_t=0;\Omega_t;\theta)\cdot Pr(s_{t+1}=0,s_t=0|\Omega_t;\theta)}{f(y_{t+1}|\Omega_t;\theta)} && (2.27)\\
&= ((2.18)\times(2.14))\,/\,(2.24) && (2.28)
\end{aligned}$$

Similarly,

$$\begin{aligned}
Pr(s_{t+1}=1,s_t=0|\Omega_{t+1}) &= ((2.19)\times(2.15))\,/\,((2.24)) && (2.29)\\
Pr(s_{t+1}=0,s_t=1|\Omega_{t+1}) &= ((2.20)\times(2.16))\,/\,((2.24)) && (2.30)\\
Pr(s_{t+1}=1,s_t=1|\Omega_{t+1}) &= ((2.21)\times(2.17))\,/\,((2.24)) && (2.31)
\end{aligned}$$

Finally, the state probability for the next period is obtained as:

$$\begin{aligned}
Pr(s_{t+1}=0|\Omega_{t+1}) &= Pr(s_{t+1}=0,s_t=0|\Omega_{t+1})+Pr(s_{t+1}=0,s_t=1|\Omega_{t+1}) && (2.32)\\
&= (2.28)+(2.30) && (2.33)\\
Pr(s_{t+1}=1|\Omega_{t+1}) &= Pr(s_{t+1}=1,s_t=0|\Omega_{t+1})+Pr(s_{t+1}=1,s_t=1|\Omega_{t+1}) && (2.34)\\
&= (2.29)+(2.31) && (2.35)
\end{aligned}$$

Chapter 3

Downside Liquidity

This chapter is based on Wang (2011).

3.1 Introduction

In the market microstructure literature, we usually refer liquidity as the ability to buy or sell an asset, at low cost, without affecting the asset's price. Whether investors demand higher returns for less liquid stocks has been a focus for a substantial body of research. Meanwhile, a series of market crisis, for example, the crash of 1987, the 1997 Asian financial crisis, the dot-com bubble of 2000, and more recently the credit crisis of 2008, has drawn much attention of market participants and regulators on liquidity in the downside market. In this chapter, we investigate liquidity level and risk explicitly conditioning on the market return and examine whether the downside illiquidity level and beta are priced differently in the cross section of stock returns.

There are a number of theoretical and empirical papers that examine the pricing of liquidity. One line of literature focuses on the relationship between liquidity level and stock returns. For example, Amihud and Mendelson (1986) propose a single-period model with non-stochastic liquidity and suggest that assets with low liquidity level will command a positive return premium. Lo, Mamaysky, and Wang (2004) also investigate how fixed transaction costs affect asset prices and trading volume. In their continuous-time equilibrium model, they show that in the presence of fixed transaction costs, agents choose to trade only infrequently. This reduces agents' asset demand and in equilibrium leads to a significant illiquidity discount in asset prices. Empirically, Amihud (2002) first proposes to use the ratio of absolute returns to trading volume (ILLIQ measure) as a measure of illiquidity and finds that the positive return-illiquidity relationship exists both across stocks and over time. The other line of literature studies the systematic component of liquidity as a source of priced risk. For example, Chordia, Roll, and Subramanyam (2000) demonstrate that liquidity has a common systematic factor. Pastor and Stambaugh (2003) regard market liquidity as a state variable and propose a liquidity beta as return sensitivity to market liquidity. They find a substantial annual return difference of 7.5% across low and high liquidity beta stocks. Acharya and Pedersen (2005) derive a liquidity-adjusted capital asset pricing model. In addition to the level of liquidity and the 'Pastor- Stambaugh' return sensitivity to market liquidity, they show that commonality in liquidity with the market liquidity and liquidity sensitivity to market returns should also matter for required returns. Empirically they find that the aggregate liquidity risk premium is approximately 1.1% annually.

While liquidity level and risk are important to investors in general, they can be particularly important during a crisis period. Brunnermeier and Pedersen (2008) provide a model that links an asset's liquidity with traders' funding liquidity. They show that there can be multiple equilibria in the market. In one equilibrium, market is liquid and margin requirements are favorable for speculators, so speculators are in general liquidity suppliers in the market. In another equilibrium, market is illiquid with higher margin requirement, then speculators turn to be liquidity demanders instead of suppliers. A large market shock can lead to losses for speculators. When their capital is reduced to a certain level, the market will eventually switch to a low-liquidity/high-margin equilibrium. Vayanos (2004) presents a dynamic equilibrium model of a multi-asset market with stochastic volatility and transaction costs. His key assumption is that investors are fund managers, subject to withdrawals when fund performance falls below a threshold. This model reveals a link between asset liquidity premium and the extent of uncertainty (represented by the volatility of asset payoffs). During volatile times, the probability that performance falls below an exogenous threshold increases, and withdrawals become more likely. This reduces the managers' willingness to hold illiquid assets, and raises the liquidity premium. Empirically, Hameed, Kang, and Viswanathan (2007) provide evidence that market condition affects the time variation in liquidity. They find that negative market returns reduce liquidity more than positive market returns. Moreover, the impact of negative market returns on liquidity is stronger when financial intermediaries are more likely to face funding constraints. Next, they find the commonality in spreads increases during market declines. They also document the industry spill-over effect in liquidity and show that the cost of providing liquidity is highest in the declining market.

Economists have recognized that investors regard downside losses differently from upside gains. It is well accepted that investors are not only risk averse but also loss averse, and they place more weight on losses relative to gains in their utility function. In a declining market, investors are especially unwilling to hold assets that co-move with the market since these assets tend to have very low payoffs when the wealth of investors is low. Therefore, investors who are averse to downside losses require higher expected returns for holding stocks with high downside risk. Recent market microstructure literature suggests that market conditions also have effects on investors trading behavior. In a declining market, liquidity often dries up suddenly either because financial intermediaries withdraw from providing liquidity or market participants engage in panic selling. In a normal market state, market makers provide liquidity by absorbing temporary liquidity shocks. When stock market is declining, the value of their portfolio is shrinking. Then it is very likely that market makers hit their capital constraints and are forced to liquidate. The usual liquidity suppliers then turn to become liquidity demanders. Moreover, when investors are in need of capital, they are more willing to hold liquid assets in a down market so that they can easily sell those assets and meet the capital requirement. Therefore, market decline could reduce the aggregate collateral of the market making sector which may lead to higher commonality in liquidity.

In this chapter, we differentiate market downside and upside explicitly. We set the average market return as a cutoff level and define a market is in a downside (upside) if its return is lower (higher) than this cutoff level. Amihud ILLIQ measure is used as our daily illiquidity measure. The downside (upside) illiquidity level is defined as the average of daily ILLIQ measure in a downside (upside) market. The downside and upside liquidity beta is the comovement of stock's illiquidity level with the market illiquidity level conditioning on the market return. The mean value of the downside illiquidity level is 0.33, which is about 3% higher than the mean of the upside illiquidity level. There are considerable variations in the downside and upside illiquidity level, both in the cross-section and over time. Although the summary statistics of the downside and upside liquidity beta are similar, their between correlation is 0.59 implying that these two variables are far from perfectly correlated.

We use two approaches to investigate the relation between the downside liquidity and stock returns in the cross-section. One is the portfolio sorting approach, which produces easy-to-interpret returns on a feasible investment strategy. We sort individual stocks into five quintiles based on the their downside (and upside) illiquidity level and downside (and upside) liquidity beta, and find that stocks with high downside illiquidity level and beta have higher returns than stocks with low downside illiquidity level and beta. For example, a trading strategy that is long in stocks with high downside illiquidity level and short in stocks with low downside illiquidity level yield an average monthly excess return of approximately 0.94%. The return difference between the two extreme downside liquidity beta quintiles is 0.74% per month. To differentiate the effects of downside and upside illiquidity level and beta, we further conduct a double-sorting analysis. After control for the upside illiquidity level we still find that the return spread of portfolios sorted by the downside illiquidity level is significantly positive. Also, the increasing pattern of return from the low downside liquidity beta to high downside liquidity beta remains after first sort on the upside liquidity beta. The other approach applied is the Fama-MacBeth regression, which allows us to regress cross-sectional excess returns directly on the downside illiquidity level and beta and enable us to control for other well-known return determinants. The regression is conducted on the firm level. We find evidence that the downside illiquidity level and beta have a significantly positive effect on stock returns in the cross-section. For example, an increase of one standard deviation in the downside illiquidity level would increase monthly returns by 0.15%. It is approximately 1.8% on an annual basis, which also indicates economical significance. The downside liquidity beta also has a significantly positive effect on stock returns. However, when the downside illiquidity level, the upside illiquidity level, the downside and upside liquidity beta are included jointly in the cross-sectional regression, only the downside illiquidity level still has a significantly positive coefficient on returns. In the robustness check, we find that the results are robust to the January effect.

The remainder of the chapter is organized as follows. Section 3.2 describes the data and presents the descriptive statistics of the downside illiquidity level and beta. In section 3.3, we examine the cross-sectional relation between the downside illiquidity level and beta and stock returns. Section 3.4 presents the robustness check, where we repeat the analysis but control for the January effect. Section 3.5 concludes.

3.2 Data and the downside liquidity level and beta

Data. The data consists of two parts. First, daily and monthly data of stock prices, returns, volume, shares outstanding, and dividend are obtained from CRSP, with a sample period from December 31, 1962, through December 31, 2008. Following Chordia, Roll, and Subramanyam (2000) and Kamara, Lou, and Sadka (2008), we utilize only common stocks (CRSP share code 10 and 11) listed on NYSE/AMEX (CRSP exchange code 1 and 2). Second, we obtain the daily and monthly risk-free rate and the daily Fama and French three factors from Kenneth French at Dartmouth College.

Summary statistics. Table 3.1 presents overall, between, and within summary statistics for NYSE/AMEX firms over the sample period from 1963 through 2008. In addition to return (*ret*), price (*prc*), dollar volume (*dvol*), and market capitalization (*mcap*), there are several additional variables used in the analysis: $r100$ is the return during the last 100 days of each year; $r100yr$ is the return between the beginning of the year and the 100 days before its end; *sdret* is the standard deviation of the daily return; *divyld* is the dividend yield calculated as the sum of the dividends during one year divided by the end-of-year price. There are between 1123 and 2147 stocks in our sample. The average daily stock return is 6.90 basis point. It has a minimum value of -594.47 basis point indicating that there are considerable downturns in the stock market. The daily closing price has a range from $2.02 to $906.50 and a mean value of $29.08. There is substantial variation in volume and size both in the cross-section and through time. For example, daily volume is 7.50 million on average with a between standard deviation of 14.29 million and a within standard deviation of 19.98 million. The average market capitalization is 1.69 billion with a cross-sectional (between) standard deviation of 3.47 billion and a time (within) standard deviation of 3.60 billion.

Table 3.1: Summary statistics of general variables

This table presents overall, between, and within summary statistics for NYSE/AMEX firms over the sample period from December 31, 1962 through December 31, 2008. The included variables are: daily stock returns (*ret*), daily closing price (*prc*), daily dollar volume (*dvol*), market capitalization (*mcap*), the return during the last 100 days of each year ($r100$), the return between the beginning of the year and the 100 days before its end ($r100yr$), the standard deviation of the daily return (*sdret*), the dividend yield calculated as the sum of the dividends during one year divided by the end-of-year price (*divyld*). *#stocks* denotes the number of stocks. Variable units are included in parentheses.

	Mean	St.Dev.	St.Dev. Between[a]	St.Dev. Within[b]	Min	Max	Median
ret (bps)	6.90	22.42	8.69	20.67	-594.47	859.66	6.58
prc ($)	29.08	24.20	17.66	16.55	2.02	906.50	24.43
dvol ($ mln)	7.50	24.57	14.29	19.98	0.01	1193.43	0.56
mcap ($ bln)	1.69	5.00	3.47	3.60	0.00	131.03	0.32
$r100$	0.05	0.28	0.10	0.26	-0.99	15.44	0.03
$r100yr$	0.12	0.39	0.14	0.36	-0.94	12.15	0.07
sdret (%)	2.42	1.18	0.81	0.86	0.00	42.63	2.18
divyld	2.67	6.51	2.53	6.00	0.00	296.56	1.76
#stocks	1638.76	262.59	113.62	236.74	1123.00	2147.00	1650.00

[a]: Based on the time means i.e. $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$.

[b]: Based on the deviations from time means i.e. $x^*_{i,t} = x_{i,t} - \bar{x}_i$.

Illiquidity and downside illiquidity. We use the Amihud (2002) measure as our daily illiquidity measure. Compared with other measures of illiquidity, such as the bid-ask spread or the price impact, the Amihud measure only requires daily data and thus enable us study a much long time period. Moreover, Hasbrouck (2006) and Korajczyk and Sadka (2008) have shown that the Amihud measure is highly correlated with many other measures of illiquidity, suggesting that it is a reliable measure of illiquidity. Specifically, for each stock i and day d, the Amihud illiquidity measure is defined as:

$$illiq_d^i = \frac{|r_d^i|}{dvol_d^i}$$

where r_d^i is the daily return of stock i on day d. $dvol_d^i$ is the daily dollar volume of stock i on day d. We follow the filtering procedure of Chordia, Roll, and Subramanyam (2000), and Kamara, Lou, and Sadka (2008). In specific, first, $illiq_d^i$ is defined only for positive values of $dvol_d^i$, and non-missing non-zero values of r_d^i. Second, for a daily observation to be included in the sample, the stock's price at the end of the previous trading day has to be at least $2. Third, firm-days outliers with $illiq_d^i$ in the lowest and highest 1% percentiles of the sample are discarded after applying the first two filters. Finally, a stock is retained in a given year only if it has at least 200 valid observations

The downside illiquidity level ($illiq^-$) and upside illiquidity level ($illiq^+$) are defined as follows:

$$illiq^- = \frac{1}{N}\sum_{d=1}^{N}(illiq|r_m < \mu_m)$$
$$illiq^+ = \frac{1}{N}\sum_{d=1}^{N}(illiq|r_m > \mu_m)$$

where r_m is the market's excess return, and μ_m is the average market excess return. In addition, the downside liquidity beta (β_{cc}^-) and upside liquidity beta (β_{cc}^+) are defined as follows:

$$\beta_{cc}^- = \frac{cov(c_i, c_m|r_m < \mu_m)}{var(c_m|r_m < \mu_m)}$$
$$\beta_{cc}^+ = \frac{cov(c_i, c_m|r_m > \mu_m)}{var(c_m|r_m > \mu_m)}$$

Panel A of Table 3.2 presents overall, between, and within summary statistics for the yearly estimates of illiquidity level, downside illiquidity level and beta. The mean value of downside illiquidity level is 0.33, which is about 3% higher than the mean value of the upside illiquidity level. It implies that on average the downside market is more illiquid than the upside market. Moreover, there are considerable variations in downside and upside illiquidity level, both in the cross-section and over time. There is no difference in the mean value of the downside liquidity beta and upside liquidity beta. The average value of Amihud's ILLIQ measure (*illiq*) is a 0.34% change per $1 million volume. The between and within standard deviation are 0.69 and 0.50, respectively, which indicates that there is substantial variation both in the cross- section and through time.

Panel B of Table 3.2 presents the between, and within correlation of the estimated downside and upside illiquidity level and beta. The between and within correlation between $illiq^-$ and $illiq^+$ are 0.99 and 0.96 respectively, both significant at 95% level. Although the summary statistics of β_{cc}^- and β_{cc}^+ are similar, their between correlation is 0.59, significant at a 95% level implying that these two variables are not same. As expected, $illiq^-$, $illiq^+$, β_{cc}^- and β_{cc}^+ all have significantly positive correlation with the Amihud ILLIQ measure.

3.3 The pricing of the downside illiquidity level and beta

In this section we investigate whether the downside illiquidity level and beta are priced in the cross-section. We first implement portfolio sorting approach to examine the relationship between the downside liquidity and stock average returns. Then we move on to Fama-MacBeth regressions which enable us regress cross-sectional returns directly on the downside liquidity and meanwhile control for other firm characteristics and risk factors.

Table 3.2: Downside and upside illiquidity level and beta

This table presents summary statistics for the yearly estimates of the downside and upside illiquidity level and beta conditioning on movements of the market excess return. The daily ILLIQ measure is defined as

$$illiq_d^i = \frac{|r_d^i|}{dvol_d^i}$$

where i indexes stocks, d indexes days, r is the transaction price return and $dvol$ is dollar volume. The downside illiquidity level ($illiq^-$) and upside illiquidity level ($illiq^+$) are defined as follows:

$$illiq^- = \frac{1}{N}\sum_{d=1}^{N}(illiq|r_m < \mu_m)$$
$$illiq^+ = \frac{1}{N}\sum_{d=1}^{N}(illiq|r_m > \mu_m)$$

where r_m is the market's excess return, and μ_m is the average market excess return. In addition, the downside liquidity beta (β_{cc}^-) and upside liquidity beta (β_{cc}^+) are defined as follows:

$$\beta_{cc}^- = \frac{cov(c_i, c_m|r_m < \mu_m)}{var(c_m|r_m < \mu_m)}$$
$$\beta_{cc}^+ = \frac{cov(c_i, c_m|r_m > \mu_m)}{var(c_m|r_m > \mu_m)}$$

Panel A presents mean and variance statistics; Panel B presents within and between correlation.

Panel A: Mean and variance

	Mean	St.Dev.	St.Dev. Between[a]	St.Dev. Within[b]	Min	Max	Median
$illiq^-$(%/mln)	0.33	0.65	0.51	0.41	0.00	5.93	0.06
$illiq^+$(%/mln)	0.32	0.63	0.49	0.40	0.00	6.43	0.06
β_{cc}^+	0.39	1.56	0.99	1.21	-41.89	75.32	0.03
β_{cc}^-	0.39	1.59	1.00	1.23	-32.17	78.39	0.03
$illiq$ (%/mln)	0.34	0.69	0.50	0.47	0.00	5.08	0.06

Panel B: Between and within correlation

		$illiq^+$	β_{cc}^-	β_{cc}^+	$illiq$
$illiq^-$	ρ(between)	0.99*	0.58*	0.60*	0.99*
	ρ(within)	0.96*	0.30*	0.33*	0.96*
$illiq^+$	ρ(between)		0.60*	0.60*	0.99*
	ρ(within)		0.32*	0.31*	0.96*
β_{cc}^-	ρ(between)			0.80*	0.59*
	ρ(within)			0.59*	0.30*
β_{cc}^+	ρ(between)				0.60*
	ρ(within)				0.31*

[a]: Based on the time means i.e. $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$.

[b]: Based on the deviations from time means i.e. $x_{i,t}^* = x_{i,t} - \bar{x}_i$.

*: Significant at a 95% level.

Portfolio sorting analysis Compared to the regression approach, portfolio sorting is interesting since it produces easy-to-interpret returns on a feasible investment strategy. For example, if individual stocks with high downside illiquidity level have higher returns than stocks with low downside illiquidity level, then a zero-investment portfolio that is long in high $illiq^-$ stocks and short in low $illiq^-$ stocks should earn a positive return.

First, the single-sorting portfolio analysis is conducted. Panel A of Table 3.3 presents the excess returns of portfolios that are sorted based on previous year downside illiquidity level $illiq^-$. These portfolios are rebalanced monthly and are equal weighted. For each portfolio, the average monthly excess returns (relative to the risk-free rate) and robust Newey-West (1987) t-statistics are presented, and the analysis is done for the full data sample, the first sub-period and the second sub-period respectively. The returns are generally higher for portfolios with higher values of the downside illiquidity level $illiq^-$. The average monthly excess return is 1.35% for the portfolio with highest $illiq^-$, whereas the portfolio with lowest $illiq^-$ has 0.41% return. The average monthly excess return for a zero-investment portfolio is 0.94% (about 11.28% per year), which is both economically and statistically significant. For both sub-periods, the return difference across $illiq^-$ quintiles is significantly positive. However, for the first 264 months (from year 1964 to 1985) the return spread is 1.37% per month, which is more than twice as big as that of the second sub-period. In Panel B stocks are sorted by the pervious year upside illiquidity level $illiq^+$. We find that over the full data sample, the return difference across the two extreme $illiq^+$ portfolios is 0.93%, which is 0.01% lower than the return difference of the $illiq^-$ portfolios. The trend is similar that a higher return difference is found in the first sub-period.

Panel C and Panel D of Table 3.3 present the excess return of portfolios that are sorted based on previous year downside liquidity beta β_{cc}^- and upside liquidity beta β_{cc}^+ respectively. The excess return increases monotonically within the β_{cc}^- quintiles. The difference in excess returns between the two extreme β_{cc}^- quintiles is 0.74% per month (approximately 8.88% per year). The same analysis is also conducted for two sub-periods. For the period from year 1964 to 1985, the return difference across β_{cc}^- quintiles is 1.06%, statistically and economically significant. The second sub-period still shows significantly positive return difference, but the magnitude of the return difference is much smaller than that in the first sub-period. Moreover, the monthly return of the zero-investment strategy in β_{cc}^- portfolios is approximately 0.2% smaller than that of $illiq^-$ portfolios. Last, stocks are sorted by β_{cc}^+ in Panel D. The two extreme β_{cc}^+ portfolios have the smallest monthly return of 0.64% for the full sample period, although it is still statistically significant. Similarly, the positive return spreads are mainly resulted from the first sub-period.

In the next step, we apply the double-sorting portfolio analysis which allows us to check the robustness of the $illiq^-$ and β_{cc}^- effects controlling for $illiq^+$ and β_{cc}^+ respectively. As we have shown in Table 3.3, both the downside and upside illiquidity level have a positive premium

Table 3.3: Excess returns single-sorted portfolios

This table presents the excess returns of single-sorted portfolios. In each month stocks are sorted into five quintiles based on their previous year downside illiquidity level $illiq^{-}$ in Panel A, upside illiquidity level $illiq^{+}$ in Panel B, downside liquidity beta β_{cc}^{-} in Panel C, and upside liquidity beta β_{cc}^{+} in Panel D. These portfolios are rebalanced monthly and are equally weighted. The column labeled "$ret - r_f(\%)$" is the time-series means of the monthly portfolio returns in percentage. The column labeled "t-stat" is the robust Newey-West (1987) t-statistics. "1" ("5") represents the low (high) value. The row "5-1" refers to the difference in monthly returns between portfolio 5 and portfolio 1. The results are presented for the full data sample, the first sub-period, and the second sub-period.

Panel A: stocks sorted by $illiq^{-}$

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (Low)	0.41	1.84	0.31	0.95	0.51	1.66
2	0.54	2.14*	0.52	1.37	0.55	1.67
3	0.63	2.32*	0.70	1.70	0.56	1.58
4	0.80	2.79*	0.99	2.28*	0.61	1.64
5 (High)	1.35	4.56*	1.68	3.54*	1.04	2.90*
5 – 1	0.94	5.60*	1.37	5.25*	0.52	2.58*

Panel B: stocks sorted by $illiq^{+}$

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (Low)	0.42	1.85	0.30	0.92	0.53	1.70
2	0.53	2.12*	0.51	1.34	0.55	1.68
3	0.62	2.28*	0.72	1.74	0.53	1.48
4	0.81	2.87*	0.99	2.30*	0.65	1.74
5 (High)	1.34	4.54*	1.69	3.56*	1.01	2.85*
5 – 1	0.93	5.54*	1.39	5.29*	0.49	2.43*

Panel C: stocks sorted by β_{cc}^{-}

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (Low)	0.50	2.26*	0.45	1.39	0.55	1.81
2	0.51	2.16*	0.47	1.31	0.55	1.76
3	0.64	2.38*	0.72	1.78	0.55	1.58
4	0.79	2.75*	0.97	2.20*	0.62	1.67
5 (High)	1.24	3.99*	1.51	3.03*	0.99	2.62*
5 – 1	0.74	4.82*	1.06	4.04*	0.43	2.74*

Panel D: stocks sorted by β_{cc}^{+}

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (Low)	0.55	2.46*	0.50	1.55	0.60	1.94
2	0.53	2.27*	0.51	1.46	0.55	1.77
3	0.64	2.41*	0.70	1.72	0.58	1.70
4	0.76	2.64*	0.91	2.04*	0.62	1.68
5 (High)	1.19	3.80*	1.50	3.00*	0.90	2.36*
5 – 1	0.64	4.32*	1.00	3.93*	0.30	1.99*

*: Significant at a 95% level.

Table 3.4: Excess returns double-sorted portfolios

This table presents the excess returns of double-sorted portfolios. In Panel A, stocks are sorted into five quintiles based on their upside illiquidity level $illiq^{+}$ in the previous year. Then within each quintile, stocks are sorted again based on their downside illiquidity level $illiq^{-}$ in the previous year. In Panel B, stocks are sorted into five quintiles based on their upside liquidity beta β_{cc}^{+} in the previous year. Then within each quintile, stocks are sorted again based on their downside liquidity beta β_{cc}^{-} in the previous year. These portfolios are rebalanced monthly and are equally weighted. The column labeled "$ret - r_f(\%)$" is the time-series means of the monthly portfolio returns in percentage. The column labeled "t-stat" is the robust Newey-West (1987) t-statistics. "1" ("5") represents the low (high) value. The row "5-1" refers to the difference in monthly returns between portfolio 5 and portfolio 1. The results are presented for the full data sample, the first sub-period, and the second sub-period.

Panel A: $illiq^{-}$ sorts controlling for $illiq^{+}$

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (Low)	0.43	2.86*	0.32	1.43	0.53	2.67*
2	0.53	3.14*	0.54	2.12*	0.52	2.33*
3	0.60	3.40*	0.71	2.58*	0.50	2.21*
4	0.70	3.75*	0.94	3.26*	0.47	1.96*
5 (High)	1.05	5.31*	1.42	4.28*	0.69	3.16*
$5-1$	0.62	4.84*	1.10	5.29*	0.16	1.07

Panel B: β_{cc}^{-} sorts controlling for β_{cc}^{+}

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (Low)	0.45	3.10*	0.43	1.97*	0.47	2.42*
2	0.52	3.33*	0.51	2.12*	0.54	2.63*
3	0.62	3.51*	0.72	2.65*	0.53	2.30*
4	0.74	3.89*	0.96	3.21*	0.53	2.23*
5 (High)	0.97	4.64*	1.32	3.80*	0.63	2.68*
$5-1$	0.51	4.22*	0.89	4.21*	0.16	1.26

*: Significant at a 95% level.

when they are sorted separately with stock returns. The same is found for the downside and upside liquidity betas. The single-sorting portfolio analysis above do not shed light on the differential effects of the downside and upside illiquidity level or the differential effects of the downside and upside liquidity betas. To explore this, we then follow the approach suggested by Ang, Chen, and Xing (2006). In Panel A of Table 3.4, we first sort stocks into five quintiles based on their $illiq^{+}$ in the previous year. Then, within each quintile, we sort stocks into five quintiles based on their previous year $illiq^{-}$. These portfolios are rebalanced monthly and are equal weighted. After forming the 5×5 $illiq^{+}$ and $illiq^{-}$ portfolios, we average the return of each $illiq^{-}$ quintile over the five $illiq^{+}$ portfolios. In this way these $illiq^{-}$ quintiles control for differences in $illiq^{+}$. Over the entire sample period, controlling for $illiq^{+}$ reduces the magnitude of the return difference from 0.94% in Table 3.3 to 0.62% per month. However, we still observe the increasing pattern of returns from the low $illiq^{-}$ portfolio to the high $illiq^{+}$ portfolio and the $5-1$ difference in average returns is significantly positive for the full data sample. Unlike the results of the single sorting analysis, the return difference in the second sub-period is no longer significant. Panel B of Table 3.4 present the excess return of double-sorted portfolios of the downside liquidity beta β_{cc}^{-} controlled for β_{cc}^{+}. The excess return increases monotonically within the β_{cc}^{-} quintiles. The difference in excess returns between the two extreme β_{cc}^{-} quintiles is positive and significant at 95% level for all months, and for the first sub-period. The return spread for the full sample is 0.51% per month, 0.23% smaller than that of the single sorting analysis.

Fama-MacBeth regressions The portfolio-sorting analysis suggests that both downside illiquidity level and beta have a positive relation with average stock returns. However, it does not account for other well-known determinants of expected returns and therefore could possibly introduce biases in the inference. To address this issue, we next examine the relation between the downside illiquidity level and beta and stock returns by cross-sectional Fama-MacBeth regressions. The asset-pricing model is of the form:

$$E(r^{i}) = \gamma + \lambda' \beta^{i} + \delta' Z_{i} \tag{3.1}$$

where $E(r^{i})$ denotes the expected return of stock i. β^{i} is a vector of factor loadings of stock i relative to several different risk factors. λ is a vector of risk premiums. Z^{i} is a set of firm characteristics of stock i and δ is a vector of characteristic premiums. The coefficients of Equation (3.1) are estimated for each month, $m = 1, 2, \ldots, M$, in the cross-sectional regression:

$$r_{i,m,y} = \gamma_{m} + \lambda_{m}' \beta_{i,y-1} + \delta_{m}' Z_{i,y-1} + \varepsilon_{i,m,y} \tag{3.2}$$

where $r_{i,m,y}$ denotes the monthly excess return (relative to the risk-free rate) of stock i in month m of year y. $\beta_{i,y-1}$ is a vector of K factor loadings of stock i in year $y-1$. λ_{m} is a vector of risk premiums in month m. δ_m is a vector of premiums of firm characteristics. $Z_{i,y-1}$ is a vector of L firm characteristics of stock i in year $y-1$. Among them, the variables of interest are the downside illiquidity level ($illiq^-$), the upside illiquidity level ($illiq^+$), the downside liquidity beta (β^-_{cc}), and the upside liquidity beta (β^+_{cc}).

Since factor loadings are unobservable, they are pre-estimated through a time-series regression:

$$r_{i,d,y} = a_{i,y} + \beta^{MKT}_{i,y} MKT_{d,y} + \beta^{SMB}_{i,y} SMB_{d,y} + \beta^{HML}_{i,y} HML_{d,y} + \varepsilon_{i,d,y} \tag{3.3}$$

This is the commonly used Fama-French three-factor model, where $r_{i,d,y}$ is the daily return of stock i on day d in year y. $MKT_{d,y}$ is the daily excess market return in year y. $SMB_{d,y}$ and $HML_{d,y}$ are the daily excess return of small caps over big caps and of value stocks over growth stocks in year y.

The final estimate, $\hat{\delta}$ and its variance are given by:

$$\hat{\delta} = \frac{1}{M}\sum_{m=1}^{M}\hat{\delta}_m \tag{3.4}$$

$$Var(\hat{\delta}) = \frac{1}{M(M-1)}\sum_{m=1}^{M}(\hat{\delta}_m - \hat{\delta})^2 \tag{3.5}$$

where M is the total number of months in the sample. Similarly, $\hat{\lambda}$ and its variance are given by:

$$\hat{\lambda} = \frac{1}{M}\sum_{m=1}^{M}\hat{\lambda}_m \tag{3.6}$$

$$Var(\hat{\lambda}) = \frac{1}{M(M-1)}\sum_{m=1}^{M}(\hat{\lambda}_m - \hat{\lambda})^2 \tag{3.7}$$

Table 3.5 presents the results of Fama-MacBeth two-step regressions. In the first step, factor loadings are estimated for each stock each year via OLS regression (3.3). Then in the second step, we apply the cross-sectional regression (3.2) in each month via OLS. All models are estimated over the entire sample period. Thus, we calculate the average of the 540 estimated coefficients, and also present t-statistics against the null hypothesis that the average is zero. Model (1) examines the pricing of the downside illiquidity level after control for the Fama-French three risk factors. The coefficient of $illiq^-$ is 2.31, significant at a 95% level. It implies that an increase of one standard deviation in $illiq^-$ (0.65; see Table 3.2) would increase monthly returns by $2.31 \times 10^{-3} \times 0.65 = 0.15\%$. It is approximately 1.8% on an annual basis. As we can see, the downside illiquidity level is priced both statistically and economically significant. Model (2) includes the upside illiquidity level $illiq^+$ instead of $illiq^-$ in the regression. The coefficient of $illiq^+$ is also significantly positive, implying that the upside illiquidity level has a positive effect on cross-sectional returns. An increase of one standard deviation in $illiq^+$

Table 3.5: Fama-MacBeth regressions of stock returns on downside and upside illiquidity level and beta with standard control variables

This table presents the results of Fama-MacBeth regressions on downside and upside illiquidity level and beta over the full data sample. First, the Fama-French factor loadings are estimated for each stock-year by running the following regression: $r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y}$ where i indexes stocks, d indexes days, y indexes year, MKT is the excess market return (relative to the risk-free rate), SMB is the Fama-French size factor and HML is the Fama-French book-to-market factor. Second, for each month the following cross-sectional regression is performed: $r_{i,m,y} = \gamma_m + \lambda_m' \beta_{i,y} + \delta_m' Z_{i,y-1} + \varepsilon_{i,m,y}$, where m indexes months, r is a stock's excess return (relative to the risk-free rate), β is the vector of factor loadings, λ is the vector of associated risk premiums, Z is a vector of further stock-specific characteristics which includes the downside illiquidity level ($illiq^-$), the upside illiquidity level ($illiq^+$), the downside liquidity beta(β_{cc}^-), the upside liquidity beta(β_{cc}^+). The parameter estimates for δ and λ are obtained as (time) averages of the coefficients obtained in each month's cross-sectional regression. t-statistics are in parentheses. All coefficients have been multiplied by 1000.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$illiq^-$	2.31*		2.44*				2.86*
	(8.09)		(3.00)				(2.89)
$illiq^+$		2.23*	-0.12				-0.48
		(7.95)	(-0.17)				(-0.56)
β_{cc}^-				0.73*		0.51*	-0.08
				(6.66)		(5.31)	(-0.82)
β_{cc}^+					0.68*	0.33*	-0.17
					(6.56)	(3.83)	(-1.80)
β_{MKT}	6.02*	6.00*	6.02*	5.09*	5.07*	5.18*	6.13*
	(3.43)	(3.42)	(3.43)	(2.95)	(2.94)	(2.99)	(3.48)
β_{SMB}	-0.64	-0.62	-0.65	-0.06	-0.01	-0.13	-0.63
	(-0.53)	(-0.52)	(-0.54)	(-0.05)	(-0.01)	(-0.11)	(-0.53)
β_{HML}	-0.80	-0.79	-0.80	-0.61	-0.60	-0.63	-0.82
	(-0.68)	(-0.67)	(-0.68)	(-0.51)	(-0.51)	(-0.53)	(-0.69)
$intercept$	0.66	0.71	0.65	1.97*	2.00*	1.84	0.50
	(0.67)	(0.72)	(0.66)	(2.02)	(2.06)	(1.89)	(0.50)

*: Significant at a 95% level.

(2.23; see Table 3.2) would increase monthly returns by $2.23 \times 10^{-3} \times 0.63 = 0.14\%$, implying a smaller economic effect than the downside illiquidity level. In Model (3) both of the downside and upside illiquidity level are included. The coefficient of the downside illiquidity level $illiq^{-}$ is slightly bigger than that in Model (1) and remains statistically significant. On the contrary, the upside illiquidity level $illiq^{+}$ turns out to be insignificant. It implies that when both $illiq^{-}$ and $illiq^{+}$ are included in the regression, it is $illiq^{-}$ that takes the major effect on the stock returns. Next, we investigate the pricing of the commonality in liquidity that is conditioning on the market return. Model (4) includes the downside liquidity beta β_{cc}^{-}. It has a significantly positive coefficient with value 0.73, indicating that one standard deviation increase in β_{cc}^{-} would yield a monthly return of 0.12%. Although the effect of β_{cc}^{-} on stock returns is statistically significant, its economic significance is smaller than that of the downside illiquidity level. Model (5) investigates the pricing of the upside liquidity beta separately. β_{cc}^{+} is positively associated with stock returns. However the magnitude of its economic influence on stock returns is the smallest compared to other three variables. When the downside and upside liquidity beta are included together in Model (6), both variables have significantly positive coefficients, indicating independent explanatory power for β_{cc}^{-} and β_{cc}^{+} in the cross-sectional returns. Moreover, the coefficients of both the downside and upside liquidity beta when included jointly are smaller than when included separately. Model (7) tests the effects of all four variables on stock returns jointly. As we can see, the downside illiquidity level is the only one that remains significantly positive. This evidence implies that eventually it is the downside illiquidity level that has the most important explanatory power for stock returns among others.

In Table 3.6 we add other well-known firm characteristics in the cross-sectional regressions. $r100$ and $r100yr$ are two variables that measure past stock returns. *lnsize* is the logarithm of market capitalization, which measures the size of a firm. *sdret* reflects the total risk of a stock. And *divyld* is the dividend yield. The results of these control variables are consistent with theories and previous studies. Small firms have a higher premium. Stocks with higher volatility have lower require returns, which is consistent with the tax trading option theory of Constantinides and Scholes (1980). Dividend yield has a significantly positive coefficient. The variables of interest, $illiq^{-}$, $illiq^{+}$, β_{cc}^{-}, and β_{cc}^{+} have similar results as the previous table. When include separately in Model (1), (2), (4), and (5), each variable is positively associated with the cross-sectional returns. When $illiq^{-}$ and $illiq^{+}$ are both included in the cross-sectional regression, the coefficient of $illiq^{-}$ remains highly significant and its magnitude even becomes bigger. On the other hand, the statistical significant of $illiq^{+}$ disappears in the presence of $illiq^{-}$. The downside and upside liquidity beta both have significantly positive effect on stock returns when included jointly. In the presence of $illiq^{-}$, the other three variables, the upside illiquidity level, the downside and upside liquidity beta all turn to be insignificant, indicating the overruled explanatory power of the downside illiquidity level.

Table 3.6: Fama-MacBeth regressions of stock returns on downside and upside illiquidity level and beta with extended set of control variables

This table presents the results of Fama-MacBeth regressions on downside and upside illiquidity level and beta over the full data sample. First, the Fama-French factor loadings are estimated for each stock-year by running the following regression: $r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y}$ where i indexes stocks, d indexes days, y indexes years, MKT is the excess market return (relative to the risk-free rate), SMB is the Fama-French size factor, and HML is the Fama-French book-to-market factor. Second, for each month the following cross-sectional regression is performed: $r_{i,m,y} = \gamma_m + \lambda_m' \beta_{i,y-1} + \delta_m' Z_{i,y-1} + \varepsilon_{i,m,y}$ where m indexes months, r is a stock's excess return (relative to the risk-free rate), β is the vector of factor loadings, λ is the vector of associated risk premiums, Z is a vector of further stock-specific characteristics which includes the downside illiquidity level ($illiq^-$), the upside illiquidity level ($illiq^+$), the downside liquidity beta(β_{cc}^-), the upside liquidity beta(β_{cc}^+, the return during the last 100 days of each year ($r100$), the return from the start of the year until 100 days before its end ($r100yr$), the standard deviation of daily returns ($sdret$), the logarithm of the market capitalization ($lnsize$), and the dividend yield ($divyld$). The parameter estimates for δ and λ are obtained as (time) averages of the coefficients obtained in each month's cross-sectional regression. t-statistics are in parentheses. All coefficients have been multiplied by 1000.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$illiq^-$	2.08*		2.30*				2.63*
	(8.35)		(2.82)				(2.65)
$illiq^+$		2.01*	-0.19				-0.43
		(8.30)	(-0.26)				(-0.48)
β_{cc}^-				0.72*		0.46*	-0.05
				(8.28)		(5.11)	(-0.45)
β_{cc}^+					0.69*	0.37*	-0.02
					(8.18)	(4.35)	(-0.22)
$r100$	1.51	1.58	1.54	1.71	1.66	1.71	1.72
	(0.94)	(0.98)	(0.96)	(1.07)	(1.03)	(1.07)	(1.07)
$r100yr$	0.11	0.05	0.09	0.06	0.09	0.13	0.16
	(0.13)	(0.06)	(0.10)	(0.06)	(0.10)	(0.14)	(0.17)
$lnsize$	-2.19*	-2.22*	-2.18*	-2.80*	-2.82*	-2.75*	-2.15*
	(-9.30)	(-9.40)	(-9.21)	(-11.56)	(-11.51)	(-11.38)	(-9.05)
$sdret$	-4.46*	-4.43*	-4.45*	-3.93*	-3.93*	-4.03*	-4.44*
	(-9.96)	(-9.89)	(-9.92)	(-8.89)	(-8.87)	(-9.06)	(-9.83)
$divyld$	0.16*	0.16*	0.16*	0.16*	0.15*	0.16*	0.16*
	(2.90)	(2.92)	(2.92)	(2.93)	(2.82)	(2.93)	(2.94)
β_{MKT}	10.52*	10.51*	10.52*	10.07*	10.08*	10.16*	10.54*
	(5.94)	(5.94)	(5.94)	(5.70)	(5.71)	(5.74)	(5.94)
β_{SMB}	-1.57	-1.59	-1.57	-1.98	-2.00	-1.95	-1.54
	(-1.40)	(-1.42)	(-1.39)	(-1.78)	(-1.79)	(-1.76)	(-1.38)
β_{HML}	-2.57*	-2.57*	-2.58*	-2.48*	-2.48*	-2.52*	-2.60*
	(-2.36)	(-2.35)	(-2.36)	(-2.27)	(-2.27)	(-2.30)	(-2.37)
$intercept$	2.03	2.00	2.03	1.64	1.67	1.76	1.98
	(1.68)	(1.65)	(1.68)	(1.35)	(1.38)	(1.45)	(1.63)

*: Significant at a 95% level.

Overall, the portfolio sorting analysis and Fama-MacBeth cross-sectional regressions show consistent evidence that the downside liquidity is positively priced in the cross-section. The premium of the downside illiquidity level and beta is economically and statistically significant after control for the upside illiquidity level and beta. However, when the downside illiquidity level and beta are included jointly in the cross-sectional regression, only the downside illiquidity level has significantly positive return premium.

3.4 Robustness check

This section explores the robustness test that investigates whether the well-known January effect has any impact on our findings. Previous studies show that excluding January makes the effects of size and big-ask spread insignificant (for example, Keim (1983); Eleswarapu and Reinganum (1993)). To explore whether the return premium we found is related to the January effect, we conduct the Fama-MacBeth cross-sectional regressions over the entire sample period excluding January.

Table 3.7 presents the results of Fama-MacBeth regressions after control for the January effect. Excluding January, there are in total a number of 495 monthly estimates in the second step of the Fama-MacBeth regression. As before, in univariate regressions the coefficient on $illiq^{-}$, $illiq^{+}$, β_{cc}^{-}, and β_{cc}^{+} are significantly positive after control for the Fama-French three factors and other firm characteristics. The joint test implies that the downside illiquidity level has the most important explanatory power for cross-sectional returns.

3.5 Conclusion

There are a number of theoretical and empirical papers that study the relationship between liquidity level and stuck returns (e.g. Amihud and Mendelson (1986), Amihud (2002)), and also liquidity risk and stock returns (e.g. Pastor and Stambaugh (2003) and Acharya and Pedersen (2005)). In this chapter, we argue that investors behave differently in a declining market and a rising market. In general, investors are not only risk averse but also loss averse, meaning that they care more about downside losses than upside gains. Market return endogenously affects both liquidity level and liquidity risk, and liquidity level and risk should be particularly important in the downside market. Therefore, we differentiate the downside and upside liquidity explicitly and examine the relation between the downside liquidity and stock returns.

Using NYSE/AMEX common stock data between 1963 to 2008, we measure the downside illiquidity level as the average of Amihud's ILLIQ measure when market return is below its average. The downside liquidity beta is defined as the comovement of stock's illiquidity with market illiquidity conditioning on the market return. We investigate the pricing of the down-

Table 3.7: Fama-MacBeth regressions, excluding January effects

This table presents the results of Fama-MacBeth regressions on downside and upside illiquidity level and beta over the full data sample. It replicates Table 3.6 with the only difference that the month of January is excluded from the sample. First, the Fama-French factor loadings are estimated for each stock-year by running the following regression: $r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y}$ where i indexes stocks, d indexes days, y indexes years, MKT is the excess market return (relative to the risk-free rate), SMB is the Fama-French size factor, and HML is the Fama-French book-to-market factor. Second, for each month the following cross-sectional regression is performed: $r_{i,m,y} = \gamma_m + \lambda_m' \beta_{i,y-1} + \delta_m' Z_{i,y-1} + \varepsilon_{i,m,y}$ where m indexes months, r is a stock's excess return (relative to the risk-free rate), β is the vector of factor loadings, λ is the vector of associated risk premiums, Z is a vector of further stock-specific characteristics which includes the downside illiquidity level ($illiq^-$), the upside illiquidity level ($illiq^+$), the downside liquidity beta(β_{cc}^-), the upside liquidity beta(β_{cc}^+, the return during the last 100 days of each year ($r100$), the return from the start of the year until 100 days before its end ($r100yr$), the standard deviation of daily returns ($sdret$), the logarithm of the market capitalization ($lnsize$), and the dividend yield ($divyld$). The parameter estimates for δ and λ are obtained as (time) averages of the coefficients obtained in each month's cross-sectional regression. t-statistics are in parentheses. All coefficients have been multiplied by 1000.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$illiq^-$	1.70*		2.01*				2.27*
	(6.73)		(2.33)				(2.15)
$illiq^+$		1.63*	-0.28				-0.41
		(6.69)	(-0.35)				(-0.44)
β_{cc}^-				0.54*		0.35*	-0.04
				(6.57)		(3.76)	(-0.38)
β_{cc}^+					0.55*	0.30*	-0.02
					(6.90)	(3.48)	(-0.16)
$r100$	6.69*	6.76*	6.75*	6.88*	6.80*	6.86*	6.87*
	(5.00)	(5.05)	(5.04)	(5.11)	(5.04)	(5.09)	(5.09)
$r100yr$	1.01	0.96	0.97	0.98	0.99	1.03	1.04
	(1.13)	(1.08)	(1.09)	(1.09)	(1.10)	(1.15)	(1.15)
$lnsize$	-1.79*	-1.81*	-1.77*	-2.29*	-2.29*	-2.24*	-1.75*
	(-7.61)	(-7.70)	(-7.52)	(-9.70)	(-9.64)	(-9.54)	(-7.38)
$sdret$	-4.74*	-4.71*	-4.73*	-4.27*	-4.30*	-4.37*	-4.71*
	(-10.67)	(-10.62)	(-10.61)	(-9.70)	(-9.70)	(-9.84)	(-10.48)
$divyld$	0.12*	0.12*	0.12*	0.12*	0.11*	0.12*	0.12*
	(2.06)	(2.08)	(2.07)	(2.09)	(2.00)	(2.08)	(2.08)
β_{MKT}	8.89*	8.88*	8.88*	8.52*	8.53*	8.59*	8.89*
	(4.88)	(4.87)	(4.87)	(4.67)	(4.68)	(4.71)	(4.87)
β_{SMB}	-2.55*	-2.57*	-2.55*	-2.89*	-2.90*	-2.87*	-2.52*
	(-2.22)	(-2.24)	(-2.22)	(-2.55)	(-2.55)	(-2.52)	(-2.20)
β_{HML}	-3.30*	-3.29*	-3.30*	-3.22*	-3.23*	-3.25*	-3.32*
	(-2.97)	(-2.97)	(-2.97)	(-2.90)	(-2.91)	(-2.93)	(-2.99)
$intercept$	3.68*	3.66*	3.67*	3.33*	3.38*	3.45*	3.63*
	(2.99)	(2.97)	(2.98)	(2.70)	(2.74)	(2.79)	(2.94)

*: Significant at a 95% level.

side liquidity using portfolio sorting analysis and Fama-MacBeth regressions. We find reliable evidence that the downside illiquidity level has a positive effect on cross-sectional returns. The premium of the downside illiquidity level is both statistically and economically significant. The downside liquidity beta is also positively associated with stock returns when it is included separately in the cross-sectional regressions. However, in the joint regression only the downside illiquidity level has significantly positive return premiums, implying that the downside illiquidity level has the most important explanatory power for stock returns among others. Our results are also robust to the January effect.

Chapter 4

How Do Designated Market Makers Create Value for Small-Caps?

This chapter is based on Menkveld and Wang (2009).

4.1 Introduction

The May 6, 2010 flash crash has re-ignited the debate on affirmative obligations for market makers to effectively create a minimum liquidity guarantee. On this day, liquidity dried up quickly when a single investor aggressively demanded liquidity to sell the E-Mini S&P 500 futures contract. As a result, all major U.S. equity indices dropped by 5-6% in a matter of minutes (see SEC (2010)). A key contributing factor was that some high-frequency traders — the new market makers — quickly withdrew from the market. Triggered by the crash, a committee of academics and industry professionals recommended that the SEC reconsiders market maker obligations (see Born, Brennan, Engle, Ketchum, O'Hara, Philips, Ruder, and Stiglitz (2011, recommendation 9)). The value of such obligations is the subject of this chapter.

A liquidity guarantee is potentially most valuable to small-cap stocks. Cross-sectionally, small-caps exhibit lowest liquidity levels and highest liquidity risk, which both raise their cost of capital substantially. Amihud and Mendelson (1986) link liquidity levels to asset prices and estimate that stocks with the highest bid-ask spread could gain 50% in value if, all else equal, spread is reduced to the level of the lowest spread stocks. In addition, Acharya and Pedersen (2005) find that these low liquidity stocks also suffer high liquidity risk.[1] Both studies show that these illiquid stocks typically belong to small-cap firms. Pastor and Stambaugh (2003) study

[1]On page 391, they state "In other words, a stock which is illiquid in absolute terms, also tends to have a lot of commonality in liquidity with the market, a lot of return sensitivity to market liquidity, and a lot of liquidity sensitivity to market returns. This result is interesting on its own since it is consistent with the notion of flight to liquidity."

size directly and confirm that liquidity risk is highest for small-caps and is compensated for through an additional required return of 3.7% annually.

Some exchanges have responded by facilitating a contract whereby small-cap firms hire designated market makers (DMMs) to guarantee a minimum supply of liquidity in their stock. A firm typically pays a broker a lump-sum fee for a commitment to *always* provide a bid and ask quote with (i) a price differential (weakly) smaller than the contracted maximum spread and (ii) a depth (weakly) larger than the contracted minimum depth.[2] Recent empirical studies find that this type of DMM raises a stock's liquidity level (see Nimalendran and Petrella (2003)) and produces abnormal returns of roughly five percent around the introduction (see Venkataraman and Waisburd (2007) and Anand, Tanggaard, and Weaver (2009)).

We conduct an event study and, contrary to previous work, focus on liquidity *risk* as the minimum liquidity supply insures liquidity demanders against extreme illiquidity events. In essence, a broker is paid to be a 'supplier of last resort' to insure current shareholders against the idiosyncratic risk of having to trade when liquidity is low. It also mechanically reduces covariation with market return and market liquidity and therefore reduces systematic liquidity risk (see Acharya and Pedersen (2005)). The value is realized if, at times of low endogenous liquidity, the supply constraint binds and shareholders realize a gain from trade that otherwise might have met too high transaction cost (in the absence of the minimum supply guarantee). This effect should show up in the data by more volume and higher DMM participation in these extreme market conditions.

We study the exogenous event of a Euronext roll-out of their Paris limit order market system to Amsterdam on October 29, 2001. Arguably the most significant change was the possibility for small-caps to hire a DMM as, otherwise, the system replaced an already well-functioning limit order system. We find that 74 out of 101 eligible firms enter DMM contracts. An important advantage of this exogenous all-stock migration is that the analysis does not suffer from an endogenous timing bias that haunts any study based on sequential introductions (e.g., the existing DMM studies based on French and Swedish stocks). If at some point brokers privately learn that future liquidity supply will be less costly for a particular firm they will aggressively pitch to be a DMM. This is consistent with the observed pattern of an abnormal return around the introduction as well as an ex-post liquidity improvement. Admittedly, there is still a potential endogenous selection bias across DMM and nonDMM stocks for which we control with a standard Heckman procedure. We find no empirical support for such bias as the inverse Mills ratio is not significant in our cross-sectional regressions.[3]

[2] An alternative model is to require that a designated market maker maintain price continuity as has been the case for the NYSE specialist. Weill (2007) illustrates why such requirement does not lead to a Pareto efficient outcome.

[3] Furthermore, the institutional setting is such that most brokers are members of financial conglomerates that pitch a DMM sponsorship to cross-sell other financial products. ABN-AMRO, for example, announced that all their existing corporate finance clients receive DMM sponsorship for free. This is consistent with the lack of

The novel DMM contracts fit into a large literature on designated market makers with affirmative obligations. Most studies focus on the NYSE specialist who was subject to the Price Continuity Rule—an obligation to participate in order to smooth price discovery. Panayides (2007) shows that this rule is costly to her at times when the constraint binds. In return, she enjoyed trading privileges such as a last-mover advantage when supplying liquidity as she could condition on the incoming market order (see, e.g., Rock (1990)). These arrangements prompted studies on whether a specialist system can compete with a pure limit order book (see, e.g., Parlour and Seppi (2003) and Glosten (1994)). Back and Baruch (2007) show that if technology (e.g., algorithms) allows informed traders to split their orders at low cost and pool them with small uninformed orders, the last-mover advantage loses its value. Further examples of trading privileges are: reduced trading fees, private access to the content of the limit order book, or a pro rata share of the order flow (see Saar (2009) for a review). It seems that any such privilege effectively taxes other market participants and therefore might distort agents' incentives. The advantage of the Euronext DMM system is that the issuer pays for liquidity support and therefore internalizes this cost in her overall financing strategy.[4]

Our empirical strategy consists of essentially two analyses. First, liquidity level, liquidity risk, and cumulate abnormal returns (CARs) are studied surrounding DMM introductions. Second, a proprietary dataset on DMM own-account trading enables us to verify whether a DMM loses money on a binding supply constraint.

Liquidity level, liquidity risk, and CARs are studied in three steps. First, we document how liquidity level and liquidity risk change with the introduction of a DMM where liquidity risk measures are taken from Acharya and Pedersen (2005). A difference-in-difference approach (i.e., post- minus pre-event and DMM minus non-DMM stocks) measures a 'DMM treatment' effect. Second, a valuation effect is studied through cumulative abnormal returns around the announcement and the effective date. Finally, cross-sectional regressions relate CARs to liquidity level and liquidity risk changes: Are abnormal returns higher for stocks that exhibit stronger level improvement, larger risk reduction, or both? We essentially find that both are significant explanatory variables for the cross-sectional dispersion in positive abnormal returns associated with DMM stocks. These returns are economically significant as they are 3.5% on average and, if multiplied by market capitalization, amount to an aggregate value creation of approximately 1 billion euro.

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support for endogenous selection in the Heckman procedure.

[4]A more extreme example of unnatural taxation is cross-subsidization where a specialist is forced to quote loss-making inactive securities and is compensated through valuable trading privileges in actively traded securities (see Cao, Choe, and Hatheway (1997)). Recently, the NYSE has relabeled specialists as 'designated market makers' and removed their informational advantage. They continue to require them to 'maintain an orderly market' for which they are compensated by the exchange through rebates on executed limit orders, see NYSE-Euronext press release, October 24, 2008 and *Traders Magazine*, "2008 Review: NYSE Fights Back with Designated Market Makers," December 2008.

The second set of empirical analyses aims at identifying the conjectured channel for value creation, i.e., investors benefit from a DMM as 'supplier of last resort'. A proprietary transaction dataset identifies for each side of a trade (buy or sell) whether there was a DMM or not. We do three analyses after all post-event trading days are sorted according to whether the minimum supply constraint was likely bind or not. First, the DMM participation rate in trades is compared across these two types of days to verify whether they participate more on binding-constraint days. Second, the same comparison is done for DMM gross trading revenues to verify whether the conjectured increased participation is costly to them. Finally, we verify whether their service was 'consumed' in that it generated more volume. This is done by comparing binding-constraint post-event days with similar pre-event days. We find empirical support in all three analyses.

The contribution to existing literature is three-fold: (i) an analysis of liquidity *risk* changes associated with DMM introductions, (ii) an analysis on how their arrival relates to the two basic components of price changes, i.e., (efficient) price innovations and pricing errors, and (iii) empirical identification of the channel that DMMs are 'liquidity suppliers of last resort'. Anand, Tanggaard, and Weaver (2009) is most related to our study. They find that DMM introduction in Sweden increases the liquidity level, produces a positive CAR, increases volume, and leads DMMs to trade more in the stocks that they contract for. Our findings are consistent with theirs. We contribute by exploring the 'liquidity risk channel' which is closer to the *spirit* of a DMM contract, i.e., it guarantees a minimum for liquidity supply that is stochastic in nature. Liquidity risk changes around DMM introductions are analyzed and the liquidity insurance channel is explicitly tested for by comparing DMM participation, DMM trading profit, and overall volume across days where the constraint binds and days where it does not.

In analyzing how DMMs create social value, Bessembinder, Hao, and Lemmon (2007) propose an alternative channel by which DMMs could create value.[5] This explanation relies on improved price discovery as the liquidity guarantee creates incentives for investors to become informed. Such improved price discovery, in turn, generates superior information for management decisions (see, e.g., Holmstrom and Tirole (1993) and Subrahmanyam and Titman (1999)). We consider this explanation less likely in our sample as (i) the adverse selection component is substantially smaller than the realized spread component, (ii) spread does not increase significantly with the addition of a DMM, and (iii) the size of price innovations is reduced for DMM stocks[6]. We do find that DMMs reduce pricing errors which is some evidence of improved price discovery.

The remainder of the chapter is organized as follows. Section 4.2 discusses the institutional

[5] They also discuss a non-informational channel that is not as explicit as our conjecture of 'supplier of last resort' but also relies on the externality associated with investors participating in a market.

[6] This in contrast to Perotti and Rindi (2009) who find that the introduction of a designated market maker in the Italian stock market is associated with improved price discovery. In their case, however, DMMs are obliged to write at least two 'analyst reports' per year and organize roadshows where the company meets investors. No such obligations exist for Euronext DMMs.

background of DMM introduction in the Dutch market. Section 4.3 discusses how DMMs could create value as liquidity suppliers of last resort. Section 4.4 presents the data, discusses the methodology, and reviews the results. Section 4.5 concludes.

4.2 Institutional background

In 2000, the exchanges in Paris, Amsterdam, and Brussels merged and the new exchange, Euronext, decided to structure all markets according to the Paris Bourse trading model: an electronic limit order book market. Orders are transmitted from 10:00 a.m. through 5:00 p.m. to a transparent limit order book that is observable to all market participants. Market orders (or marketable limit orders) are executed automatically against the book according to strict price-time priority. Trading takes place continuously for the more actively traded securities. Less active stocks trade only twice a day via call auctions at 10:30 a.m. and 4:30 p.m. with no trading in between the auctions.[7] We refer to Biais, Hillion, and Spatt (1995) for a detailed description of the Euronext trading model.

In 1992, the Paris Bourse introduced designated market makers—officially termed "liquidity providers"—to address poor liquidity supply by public limit orders for inactively traded stocks. The exchange, however, did not mandate stocks to trade with a DMM, nor was it involved in the process of selecting a broker who provides a DMM service. Both decisions were taken by the listed firm. The exchange only facilitated the process by providing firms with a list of DMM brokers. It did require a DMM to sign its standard contract and guarantee a minimum liquidity supply set by the exchange ("General Terms"). That is, the DMM commits to always have a bid and ask quote in the market with a price differential (weakly) smaller than the exchange-mandated maximum spread and a depth (weakly) larger than the exchange-mandated minimum depth. The issuer, however, was free to negotiate tighter liquidity supply with the DMM. Once the contract was in place, the exchange monitored the DMMs and could terminate the service if a DMM did not meet her commitment.

In this model the DMM is compensated for the cost of the minimum supply constraint in essentially three ways. First, the issuer pays the DMM an annual lump sum amount specified in a private contract between the issuer and the brokerage firm (and therefore unknown to us). Second, a designated market maker relationship gives the broker a foot in the door to cross-sell other financial services to the firm, such as a seasoned offering, banking services, insurance, etc.[8] This might be seen as a 'soft' payment by the firm as these brokers now might not need

[7]Call auctions are used to trade less active stocks in several world markets, including Euronext, Athens, Madrid, Milan, Vienna, etc. In addition, the call auction is commonly used by many exchanges to open and close trading in securities.

[8]This compensation is particularly important for the Dutch market as brokers who offer a DMM service are members of financial conglomerates. Examples of cross-selling are: ING is DMM for Unit4Agresso and has

to give aggressive price discounts when pitching their products to management. Third, the exchange supports DMM activity by waiving all fees on quotes and trades by DMMs. It also markets the DMM as primary facilitator for upstairs transactions. We emphasize that, unlike the NYSE specialist, a DMM does not have any ex-post quote privilege in the sense that she cannot condition her quotes on the arriving order flow and cherry-pick (uninformed) market orders.

Venkataraman and Waisburd (2007) studies the early years (1992-1998) of designated market makers in the Paris Bourse system for a sample of stocks that trade twice a day in a call auction. They identify 75 firms that at some time in their sample hire a DMM and use the 206 firms that do not hire a DMM as a control group. They document that stocks that add a DMM trade more frequently and exhibit lower order book imbalances ex-post. They further find that younger firms, smaller firms, and firms with less volatile stock returns are more likely to hire a DMM. Finally, they report an average cumulative abnormal return of nearly five percent around the introduction day.

On Monday, October 29, 2001, Euronext introduced the Paris Bourse system with its DMM option for small-caps in the Dutch equity market in order to harmonize trading systems within the Euronext group. The new system replaced a similar well-functioning electronic limit order book. The new DMM feature had raised a lot of local regulatory interest ahead of the introduction. The Dutch regulator did not approve early proposals as they did not offer sufficient guarantees against illegal insider trading.[9] Euronext eventually addressed these concerns by agreeing to report all DMM transactions to the local regulator.[10] Another feature unique to the Amsterdam market is that Euronext introduced the DMM option only for a subset of small-cap stocks. It excluded all Euronext 100 index stocks and stocks that generated less than 2,500 transactions per annum. It further set the minimum liquidity supply in the "General Terms" of the contract to a maximum spread of 4% and a minimum depth of €10,000 for the majority of stocks.[11] Excerpts from a sample contract regarding a DMM's obligation and her remuneration are included in the Appendix 4A.

In addition to the DMM option as its most salient change, the new system brought two other changes worthy of discussion. First, the old system did have a designated market maker (the 'hoekman') for all stocks who, by all practical means, did not have any material duty nor any

organized a stock option scheme for management; ABN-AMRO is DMM for Fugro and Imtech and has organized a share buy-back for them; SNS is DMM for DBA and has created a prospectus for them ahead of their merger with Flex; SNS and FORTIS are DMM for Stern Group and have organized three recent seasoned equity offerings for them. The brokers admit that they might have had this business without acting as DMM, but a DMM relationship allows them to make a bid when the firm shows interest in these products.

[9]See interview with Chief Operating Officer Euronext, G. Möller, in *Financieel Dagblad*, "Euronext: 'Werk in Uitvoering'," October 6, 2001.

[10]See manuscript of Chief Operating Officer Euronext, G. Möller, published in *Financieel Dagblad*, "Euronext kiest Wel voor Transparantie Handel Eigen Aandelen'," October 12, 2001.

[11]These were the conditions for the most important small-cap index (Next150) to which most of our stocks belong. For other small-cap stocks, the maximum spread is 5% and the minimum depth is €5000.

trading privileges. She was effectively hired by the exchange and paid a fixed commission (and did not pay any fees on orders or trades) for ensuring that the market keeps a continuous bid-ask quote (no minimum supply constraint). In our event study, any change in liquidity level is therefore unlikely to be caused by a waiver on DMM fees as the old system also featured a DMM who did not pay any fee. Second, stocks with less than 5,000 trades per year had to move from the old continuous market to a twice a day electronic auction. The only way to stay in the continuous market for these firms was to hire a DMM. If ignored, this effect might lead to a selection bias if characteristics of these firms correlate with the error term in the difference-in-difference regression analysis. We control for such potential bias in a Heckman procedure where we find only weak support for such concern as the auction-threat dummy carries a positive but insignificant sign in the DMM-or-not Probit regression (see Table 4.6).

On the Monday in the week ahead of the introduction day, Euronext published the list of the 74 firms that signed up with brokers for a DMM service.[12] Interestingly, Dutch small-caps contracted with more than one DMM—3.13 on average out of a dozen brokerage firms that offer the service[13]—whereas the majority of French firms hired only one. We see two reasons for the apparently aggressive pitch by Dutch brokers. First, an important institutional feature of the Dutch brokerage market is that most brokers are part of large financial conglomerates, so that a DMM relationship created many opportunities for cross-selling other products. Second, the average Dutch DMM stock was potentially more interesting than its French counterpart as it belonged to a 12 times larger firm (in terms of market cap) and generated 63 times more volume.[14]

4.3 The value of a supplier of last resort: a discussion

> *A maximum spread commitment of 4% with an associated minimum depth of €10,000 seems to be meaningless, but for these small-cap stocks, it does hurt sometimes. As designated market maker you lose money for sure when the market is very volatile.*
> —Willem Meijer, SNS Securities[15]

To motivate our empirical strategy, this section discusses how a DMM might create value for small-cap firms in her role as supplier of last resort. The quote of Willem Meijer, who heads one of the most active local DMM brokers, illustrates how it is natural to consider two liquidity

[12]For a report on the Euronext DMM announcement on Monday October 22, 2001, see, "Animateur en Fonds Bekend Amsterdam," *Het Financieele Dagblad*, October 23, 2001.

[13]The active brokers are ABN-AMRO, AEK, AOT, Brom, Dexia, Deutsche Bank, Fortis (previously known as MeesPierson), ING, Kempen &Co, Rabobank, SNS Securities, Van Lanschot, Van der Wielen. From *Financieel Dagblad*, "Animateurs betalen Leergeld," September 17, 2002

[14]Based on comparing our Table 4.1 with Table 1 in Venkataraman and Waisburd (2007).

[15]See *Financieel Dagblad*, "Animateurs Betalen veel Leergeld," September 17, 2002.

regimes: a normal regime where the minimum supply constraint does not bind and an adverse liquidity regime where it does bind. It is at these times of a binding constraint that the DMM effectively becomes the 'last man standing' and she suffers a net trading loss if her supply is consumed.

DMMs and the cost of capital. The cap on transaction cost produced by the DMM contract is valuable for liquidity demanders as it mechanically improves the average liquidity level and it reduces liquidity risk. This is best illustrated by the liquidity-CAPM model proposed by Acharya and Pedersen (2005). It is essentially an application of the CAPM model to returns *net* of transaction cost. Formally, it yields:

$$E(r_t^i - c_t^i) = E(r_t^f) + \lambda\beta_i^{net}, \tag{4.1}$$

where

$$\begin{aligned}
\beta_i^{net} &= \frac{cov(r_t^i - c_t^i, r_t^m - c_t^m)}{var(r_t^m - c_t^m)}, \qquad (4.2)\\
&= \frac{cov(r_t^i, r_t^m)}{var(r_t^m - c_t^m)} + \frac{cov(c_t^i, c_t^m)}{var(r_t^m - c_t^m)} - \frac{cov(r_t^i, c_t^m)}{var(r_t^m - c_t^m)} - \frac{cov(c_t^i, r_t^m)}{var(r_t^m - c_t^m)},\\
&= \beta_i^{rr} + \beta_i^{cc} + \beta_i^{rc} + \beta_i^{cr}.
\end{aligned}$$

We rewrite the model and find for required *gross* returns:

$$E(r_t^i) = E(r_t^f) + E(c_t^i) + \lambda(\beta_i^{rr} + \beta_i^{cc} + \beta_i^{rc} + \beta_i^{cr}) \tag{4.3}$$

It is now immediate that if we cap the transaction cost c_t^i it mechanically reduces the expected transaction cost and its covariation with market transaction cost and market return (β_i^{cc} and β_i^{cr}, respectively). As they both feed into a stock's required return, the cap thus reduces the cost of capital along both the level and risk dimension.

Cost of capital reduction vs. cash outflow. Ultimately, DMMs only create value if the cash outflow from the firm to compensate for a DMM's trading loss offsets the reduction in its cost of capital. Clearly, in a rational world a DMM arrangement must create nonnegative value given that both sides to the DMM contract enter voluntarily. Ex-ante, however, it is not obvious that the arrangement produces positive shareholder value particularly if the bargaining power resides with the brokerage firms. We nevertheless believe that this is unlikely in our case as multiple brokers offer a DMM service which is good for the bargaining power on the side of the firm.

But, at a more fundamental level, how can a DMM contract create social value if it means that a DMM is effectively pushed into suboptimal trading positions at times of a binding liquidity constraint? One potential source of value creation is that a DMM contract serves as a coordination device to overcome the externality associated with trading (cf. Pagano (1989)). That is, the liquidity guarantee attracts more investors to a stock where each new arrival reduces the trading cost of existing investors (as they are more likely to find a counter-party to a trade when they demand liquidity). Another source of value creation arises when markets are incomplete with respect to hedging investors' idiosyncratic liquidity shocks. The DMM contract then becomes an insurance policy for current shareholders as the DMM fee insures against high transaction costs at the time that the trading need arises. For both sources of value creation we should see that volume increases at times when the liquidity constraint binds relative to the benchmark of no DMM.[16] For the second source of value creation, the reason for a volume increase is that shareholders might not realize a gain from trade if it is less than the transaction cost, whereas they might if DMMs cap such transaction cost. We will test this volume prediction in the data.

4.4 Empirical results

This section presents our empirical results. We first describe our dataset and present some summary statistics. We then conduct the first set of empirical analyses that aim (i) to identify the liquidity level and liquidity risk change associated with a DMM introduction, (ii) to measure abnormal returns in the event period which contains the announcement date and the effective date, and (iii) to cross-sectionally relate the abnormal return to the liquidity level and the liquidity risk change in order to establish a direct link between value creation and liquidity effects. In a second set of analyses we search for evidence in support of a DMM as a supplier of last resort. We study whether (i) DMMs participate in more trades and (ii) generate less trading revenue on days that their contract is likely to bind. We further test whether (iii) their minimum supply on these days is indeed consumed as evidenced by increased volume on these days.

4.4.1 Data and summary statistics

Data

We use four datasets for our empirical analysis. First, we have an intraday dataset for 11 months before and after the introduction day which contains (i) the best bid and ask quote and (ii) the price and size of all transactions along with a label that indicates whether or not a DMM was involved in the transaction (only their own-account trades are considered) and, if so, on which side of the trade. Second, we have daily data for the same period that includes market capitalization for each stock. Third, we have a file that for all DMM stocks contains the initiation

[16]We will operationalize this in our empirical analysis by comparing volume on days in the post-event period when the constraint is likely to bind with similar days in the pre-event period.

and termination date of a DMM service. Unfortunately, we do not have access to the contracts themselves and we therefore do not know whether the issuer and broker have contracted on a tighter minimum supply than the Euronext mandated 4% maximum spread and €10,000 minimum depth. Finally, we use the Compustat Global database for Tobin's q calculations.

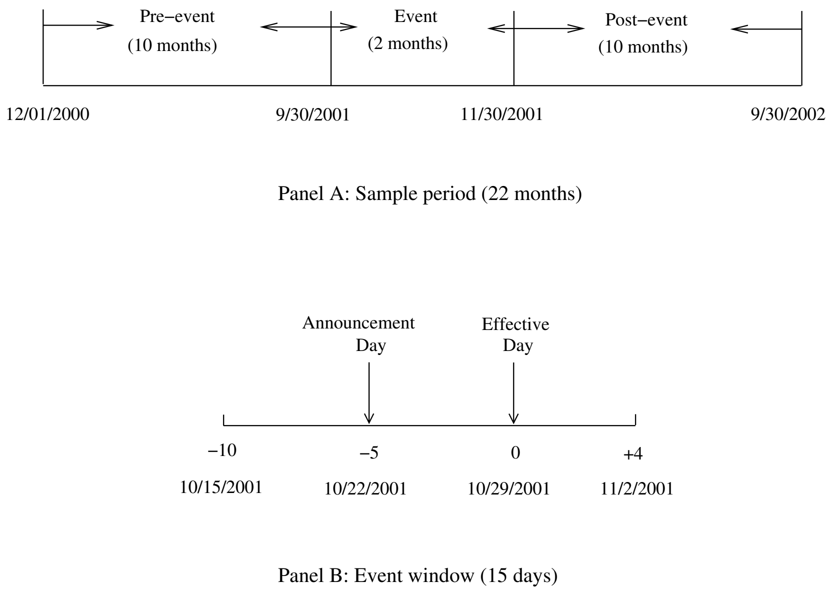


Figure 4.1: Time line event study

This figure depicts the time line of our event study. Panel A depicts the sample period which consists of 22 months: a 10 month pre-event period, a two month event period, and a 10 month post-event period. Panel B depicts the three week event window used for the cumulative abnormal return (CAR) analysis. It includes the announcement day at the start of week two and the effective day at the start of week three.

All our analysis is essentially an event study on 74 small-caps that sign up for DMMs at the introduction day and 27 small-caps that do not and thus serve as benchmark firms. Figure 4.1 depicts the time line: a ten month pre-event period, a two month event period, and a ten month post-event period. The effective date was Monday, October 29, 2001, and Euronext published the list of the 74 stocks on the Monday in the week before. As nonDMM benchmark stocks, we select all stocks that are eligible for DMM service but that do not sign up a broker on the introduction day or any time in the post-event period. We reiterate that not all listed firms are eligible as, for example, all Euronext 100 index stocks are not allowed to hire a DMM. We add the complete list of all DMM and nonDMM stocks in the Appendix 4B.

Before presenting any summary statistics, let us review the definitions of the three standard liquidity measures that we use in our study. We propose the effective spread and Amihud's *ILLIQ* measure as ex-post measures of liquidity and quoted spread as an ex-ante measure of liquidity. An important advantage of the ex-post measures is that they account for actual consumption of liquidity and therefore are a better measure for the transaction cost as it was really paid by the 'representative' investor.

Effective spread. We define the daily effective spread as the share-weighted average of

$$espread_{it} = 2q_{it}(p_{it} - m_{it})/m_{it}, \tag{4.4}$$

where i indexes stocks, t indexes transactions, q_{it} is an indicator variable that equals +1 for market buy orders and -1 for market sell orders, p_{it} is the transaction price, and m_{it} is the midquote prevailing at the time of the transaction. Trades are trivially signed in electronic limit order markets as transaction prices at or above (below) the prevailing ask (bid) quotes indicate market buys (sells). We also decompose the effective spread into two components using standard techniques. The adverse selection component captures the average loss of liquidity suppliers due to informationally-motivated market orders (suppliers are on the wrong side of the trade in these transactions). The realized spread component is the remaining part and therefore captures the gross profit to liquidity suppliers. These two components are identified through an estimate of the average information in a (signed) market order, which is revealed through post-trade midquotes. That is, if we wait long enough we find how much permanent price impact the market order had. In the implementation we use 15 minutes to allow the market to settle on the permanent price impact of the order. Formally, the two components are defined as:

$$rspread_{it} = 2q_{it}(p_{it} - m_{it+15min})/m_{it} \text{ and} \tag{4.5}$$

$$adv\_selection_{it} = 2q_{it}(m_{it+15min} - m_{it})/m_{it}. \tag{4.6}$$

Amihud's *ILLIQ* measure. We also calculate the illiquidity measure as proposed by Amihud (2002), which is based on daily data:

$$ILLIQ_{it} = \frac{|r_{it}|}{volume_{it}} \tag{4.7}$$

where r_{it} is the midquote return from day $t-1$ to day t and $volume_{it}$ is the volume (in euro) on day t.

Quoted spread. We define the quoted spread as a time-weighted daily average of

$$qspread_{it} = (ask_{it} - bid_{it})/m_{it}, \tag{4.8}$$

where t indexes time in the trading day.

We then winsorize all variables in the sample by setting values larger the 99% quantile to the 99% quantile and values smaller than the 1% quantile to the 1% quantile.

Table 4.1 presents summary statistics based on our panel dataset which consists of 22 trading

Table 4.1: Summary statistics panel dataset

This table presents overall, between, and within summary statistics based on 74*22 stock-month observations for stocks that hire a designated market maker (DMM) (Panel A) and 27*22 stock-month observations for stocks that do not (Panel B). The sample period runs from 12/01/00 through 9/30/02. The dataset includes monthly averages of: share-weighted effective spread (*espread*), time-weighted quoted spread (*qspread*), share-weighted realized spread based on the average 15 minute price impact of a trade (*rspread*), share-weighted adverse selection component of the spread - again based on the 15 minute price impact (*adv_selection*), Amihud's ILLIQ measure (*ILLIQ*), standard deviation of daily midquote return (*volatility*), daily volume in shares (*volume*), daily closing price (*price*), daily number of trades (*nr_trades*), first order autocorrelation of the daily midquote return (*ret_autocorr*), market capitalization (*mktcap*) and the number of registered designated market makers (*nr_DMMs*). We winsorize all data using the 1% and 99% quantile. We include the units of each variable in parentheses.

	Mean	Pre-Mean	St.Dev. Between[a]	St.Dev. Within[b]	St.Dev.	Min	Max	Median
Panel A: 74 DMM stocks								
espread(%)	1.17	1.24	0.81	0.69	0.42	0.12	5.87	0.95
qspread(%)	1.40	1.63	1.14	0.94	0.64	0.14	7.71	1.02
rspread(%)	0.89	1.00	0.83	0.68	0.48	0.06	7.04	0.61
adv_selection(%)	0.28	0.24	0.44	0.24	0.38	-3.18	4.53	0.26
ILLIQ (%/mln)	2.50	2.33	9.80	4.68	8.61	0.00	181.33	0.14
volatility(%)	1.99	2.13	1.23	0.90	0.83	0.11	8.43	1.70
volume(1000 shares)	37.79	35.52	66.50	59.65	29.40	0.52	780.12	13.44
price(€)	19.56	21.48	13.45	12.47	5.06	0.38	72.83	16.42
nr_trades	74.20	88.06	111.33	100.50	47.90	1.95	1017.34	31.67
ret_autocorr	-0.04	-0.05	0.23	0.08	0.22	-0.74	0.65	-0.04
mktcap(€ bln)	0.49	0.49	0.70	0.70	0.00	0.02	5.25	0.34
nr_DMMs	3.13	0.00	1.44	1.33	0.56	1.00	8.00	3.00
Panel B: 27 nonDMM stocks								
espread(%)	2.41	1.76	2.26	1.64	1.55	0.18	17.00	1.92
qspread(%)	2.95	2.55	2.59	1.93	1.73	0.22	19.16	2.43
rspread(%)	1.79	1.21	1.91	1.13	1.54	0.06	15.47	1.16
adv_selection(%)	0.62	0.55	1.49	0.97	1.14	-6.10	13.80	0.46
ILLIQ (%/mln)	7.89	5.04	38.49	14.84	35.51	0.00	478.93	0.52
volatility(%)	3.46	3.50	2.67	1.82	1.96	0.17	18.44	3.00
volume(1000 shares)	52.95	50.30	76.04	63.28	42.15	0.00	670.32	17.52
price(€)	13.94	17.23	25.79	23.01	11.64	0.06	194.34	3.21
nr_trades	76.94	97.64	124.96	110.12	59.06	0.05	983.43	25.91
ret_autocorr	-0.12	-0.10	0.25	0.10	0.23	-0.83	0.55	-0.13
mktcap(€ bln)	2.14	2.14	7.30	7.30	0.00	0.00	38.64	0.07
nr_DMMs	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

[a]: Based on the time means i.e. $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$.

[b]: Based on the deviations from time means i.e. $x^*_{i,t} = x_{i,t} - \bar{x}_i$.

months for 74 DMM stocks (Panel A) and 27 nonDMM stocks (Panel B).[17] The statistics lead to a couple of observations. First, we find that DMM stocks in spite of belonging to small-cap firms are still sizable stocks in terms of trade activity and firm size. The average firm has a market capitalization of €490 million and its stock has an average of 74.20 trades per day. Second, the average quoted spread is 1.40% and exhibits a monthly within[18] variation of 0.94% which is an early indication that liquidity risk might indeed be important. These statistics suggest that spreads are well within the Euronext mandated 4% spread most of the time, but we know from interactions with brokers and from plotting quoted spread histograms stock by stock that many firms appear to contract on tighter spreads.[19] Third, the average effective spread is 1.17% and is therefore smaller than the quoted spread which is undoubtedly the result of the typical intraday trading pattern where the bulk of trading happens at the start and the end of the day.[20] The spread decomposition shows that more than three quarters of the effective spread is gross profit to liquidity suppliers with the remaining part compensating for losses against informed market orders. Fourth, the average number of DMMs a firm hires is 3.13 with considerable cross-sectional dispersion as the between (see footnote 18) standard deviation is 1.44. Fifth, if we compare trade statistics across Panel A and B we find that the pre-event mean is the same order of magnitude for DMM and nonDMM stocks. For example, we find that the average effective spread is 1.24% vs. 1.76% for DMM and nonDMM stocks, respectively, the average daily volume is 35,520 vs. 50,300 shares per day, and market capitalization is €490,000 vs. €2,140,000.

Table 4.2 presents overall, between, and within correlations for our liquidity proxies along with volume and volatility for both DMM stocks and nonDMM stocks. We find that the three proxies are significantly correlated both across stocks and in the time dimension which is not surprising given that they are proxies for the same object. We also find significant evidence that liquidity is negatively correlated with volatility and positively correlated with volume in both the cross-section and the time dimension which is reassuring.

[17] We use the monthly frequency as our point of departure as some series are only naturally defined at a monthly frequency, e.g., *ILLIQ* or volatility of daily midquote returns.

[18] The within variation is defined in panel data analysis as the sample variation after all time series are demeaned using an individual-specific mean. The between variation, on the other hand, is the variation in individual-specific means (see Table 4.2 for the mathematical definitions).

[19] If we consider contractual spread maximums to be on a grid with a 0.5% step size, we find ,e.g., 26 firms with a 4% cutoff, 15 firms with a 1.5% cutoff, 11 firms with a 3% cutoff, and 11 firms with a 2% cutoff. We do not want to hang our hats on these numbers as, admittedly, we only observe realizations and the probability of the event that a spread is lower than $x\%$ throughout the sample is likely to be positive even if the true maximum spread is $y\% > x\%$. We therefore treat these numbers only as indicative evidence.

[20] The trading externality makes that this concentration of trading within the day reduces the effective spread which is not reflected in the *time*-weighted quoted spread.

Table 4.2: Overall, between, and within correlation liquidity proxies

This table presents the overall, between, and within correlation for share-weighted effective spread, time-weighted quoted spread, Amihud's *ILLIQ* measure, volatility of midquote return, and daily volume in shares. The correlations are based on our monthly panel dataset and span the full sample period (12/01/00-9/30/02). Panel A presents the correlations for the 74 DMM stocks and Panel B presents them for the 27 nonDMM stocks.

Panel A: 74 DMM stocks					
		qspread	*ILLIQ*	*volatility*	*volume*
espread	ρ(overall)	0.87**	0.44**	0.42**	-0.29**
	ρ(between)[a]	0.95**	0.80**	0.45**	-0.36**
	ρ(within)[b]	0.68**	0.26**	0.41**	-0.05**
qspread	ρ(overall)		0.46**	0.44**	-0.31**
	ρ(between)		0.85**	0.42**	-0.40**
	ρ(within)		0.26**	0.47**	-0.05**
ILLIQ	ρ(overall)			0.13**	-0.13**
	ρ(between)			0.31**	-0.29**
	ρ(within)			0.04	-0.01
volatility	ρ(overall)				0.31**
	ρ(between)				0.37**
	ρ(within)				0.24**
Panel B: 27 nonDMM stocks					
		qspread	*ILLIQ*	*volatility*	*volume*
espread	ρ(overall)	0.92**	0.24**	0.46**	-0.26**
	ρ(between)	0.97**	0.37*	0.77**	-0.44**
	ρ(within)	0.85**	0.14**	0.17**	-0.01
qspread	ρ(overall)		0.28**	0.48**	-0.31**
	ρ(between)		0.48**	0.71**	-0.49**
	ρ(within)		0.15**	0.26**	-0.02
ILLIQ	ρ(overall)			0.08*	-0.12**
	ρ(between)			0.27	-0.34*
	ρ(within)			-0.04	-0.02
volatility	ρ(overall)				0.04
	ρ(between)				-0.14
	ρ(within)				0.30**

[a]: Based on the time means i.e. $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$.

[b]: Based on the deviations from time means i.e. $x^*_{i,t} = x_{i,t} - \bar{x}_i$.

**: Significant at a 95% level.

* : Significant at a 90% level.

4.4.2 Liquidity level change, liquidity risk change, and cumulative abnormal return

Liquidity level change. We study whether the DMM contract causes a stock's liquidity level to improve in what is essentially a difference-in-difference approach. We use our 20*101 stock-month panel dataset to estimate various perturbations of the following model (with slight abuse of notation to minimize notational burden):

$$y_{it} = \alpha_i + \beta_1 post_t * DMM_i + \beta_2 post_t + \beta_3' control\_vars_{it} + \gamma_t + \varepsilon_{it} \tag{4.9}$$

where i indexes stocks and t indexes months, y_{it} is the liquidity proxy of interest, α_i is a fixed effect, $post_t$ is a dummy for the post-event period, DMM_i is a dummy for DMM stocks, $control\_vars_{it}$ is a vector of control variables including price, volume, and volatility, γ_t is a time effect, and ε_{it} is the error term. Standard errors are calculated following Thompson (2011) to account for any (remaining) correlation in residuals. In this specification, the β_1 coefficient captures the difference-in-difference effect. That is, it estimates how the average y_{it} changes for DMM stocks in the post-event period relative to how it changes for nonDMM stocks. It is therefore this coefficient and its associated t-value that tests, for example, whether the DMM stock effective spread change more than the nonDMM stock effective spread.

Table 4.3 finds that the average liquidity level improves for DMM stocks in the post-event period relative to nonDMM stocks, but only finds significance for quoted and effective spread, not for the *ILLIQ* measure. In model (1) that does not yet add the control variables we find that the difference-in-difference for effective spread is a significant -1.50%. This means that the effective spread declines by 1.50% for DMM stocks relative to the change in effective spread for nonDMM stocks. DMM stocks' effective spread declines by 0.13% (i.e., 1.37%-1.50%) comparing the pre- and post-event period. This substantially smaller difference effect relative to the difference-in-difference effect is caused by a substantial increase in effective spread in nonDMM benchmark stocks. Such increase most likely reflects a general decline in (small-cap) liquidity in the aftermath of the September 11 attacks, which should be controlled for (this is the strength of the difference-in-difference approach). These effective spread results are robust to adding price, volume, and volatility as control variables (model (2)). The effective spread decomposition into realized spread and adverse selection shows that the spread decrease appears to be due to a reduction in gross profits to liquidity suppliers and not a reduction in adverse selection. That is, in model (2) the realized spread for DMM stocks declines significantly relative to nonDMM stocks by 1.53% and the adverse selection component does not change significantly. The quoted spread results are similar. The *ILLIQ* measure analysis also shows qualitatively similar results, but here we do not find any statistical significance. We believe that it is primarily due to its noisy character as for low volume days the ratio explodes and

Table 4.3: Designated market makers and post-event change in liquidity level and nonliquidity variables

This table regresses liquidity variables on a set of dummies and standard control variables. The dummies allow for a difference-in-difference test (post-event minus pre-event, DMM minus nonDMM) to verify whether a DMM introduction changes the liquidity level. We use the following liquidity variables in the test: effective spread, quoted spread, Amihud's *ILLIQ* measure, realized spread, and the adverse selection component of the spread (where the latter two are based on the average 15-minute price impact of a trade). We also perform a difference-in-difference test for the following nonliquidity variables: volume, volatility, and daily return autocorrelation. We use our 101*20 stock-month panel dataset to estimate the following model:

$$y_{it} = \alpha_i + \beta_1 post_t * DMM_i + \beta_2 post_t + \beta_3' control\_vars_{it} + \gamma_t + \varepsilon_{it}$$

where i indexes stocks and t indexes months, α_i is a fixed effect, $post_t$ is a dummy for the post-event period, DMM_i is a dummy for DMM stocks, $control\_vars_{it}$ is a vector of control variables including price, volume, and volatility, γ_t is a time effect, and ε_{it} is the error term. The liquidity variable regressions are done with and without the standard control variables (model 1 and model 2, respectively). We do not use any control variables for the nonliquidity variables. We add t-values in parentheses, where the standard errors are corrected for both firm and time clustering.

	Liquidity variables										Nonliquidity variables		
	espread		*qspread*		*ILLIQ*		*rspread*		*adv_selection*		*volume*	*volatility*	*ret_autocorr*
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(1)	(1)
post ∗ DMM	-1.50**	-1.48**	-1.28**	-1.23**	-4.88	-5.10	-1.51**	-1.53**	0.01	0.05	5.64	0.02	0.07**
	(-3.50)	(-3.69)	(-2.91)	(-3.09)	(-0.84)	(-0.83)	(-3.63)	(-3.71)	(0.02)	(0.17)	(0.94)	(0.11)	(3.42)
post	1.37**	1.37**	0.81**	0.80**	5.18	5.21	1.28**	1.33**	0.09	0.04	-0.77	-0.32	-0.05**
	(3.35)	(3.70)	(1.99)	(2.21)	(0.96)	(0.90)	(3.18)	(3.33)	(0.32)	(0.16)	(-0.15)	(-1.64)	(-3.31)
price		-0.01		-0.01*		0.01		0.01		-0.02**			
		(-1.17)		(-1.87)		(0.21)		(0.95)		(-3.81)			
volume		-0.00**		-0.00**		0.01		-0.00		-0.00**			
		(-2.62)		(-3.51)		(1.00)		(-0.27)		(-2.38)			
volatility		0.15**		0.24**		-0.67		0.03		0.12**			
		(8.99)		(5.29)		(-1.51)		(0.95)		(6.08)			
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	2,005	2,005	2,020	2,020	1,897	1,897	2,005	2,005	2,005	2,005	2,020	2,020	2,020

**: Significant at a 95% level.
*: Significant at a 90% level.

these observations start to dominate the regressions.[21] We exclude the *ILLIQ* measure from any remaining analysis given its poor statistical performance.[22]

Table 4.3 further finds that volume and volatility appear unaffected by the introduction of a DMM, yet the quality of price discovery seems to improve. That is, we do not find any significant effect for volume and volatility in the model (1) estimates. We do find, however, that the return autocorrelation becomes significantly less negative for DMM stocks relative to nonDMM stocks. The difference-in-difference estimate is +0.07 for DMM stocks, which compares to a pre-event mean of -0.05 (see Table 4.1).

Table 4.4 further studies price discovery through the estimation of a state space model (cf. Menkveld, Koopman, and Lucas (2007)). Such approach decomposes price changes into 'efficient' price innovations and pricing errors.[23] The standard deviation of each component is then related to DMM introduction. In the post-event period, pricing errors are a significant 100%*1.60/(0.96+1.15)=76% lower for DMM stocks relative to the untreated benchmark stocks. This indicates that price discovery has improved. More surprising is the finding that the size of efficient price innovations has shrunk by a significant 100%*0.69/(2.94-0.17)=25% for DMM stocks relative to the benchmark stocks. One possible explanation is that incentives to collect and trade on information are reduced for these stocks if one agent, the DMM, is naturally incentivized to collect all information she can — the marginal benefit of additional information collection is then reduced.[24]

Liquidity risk change. We measure liquidity risk through the Acharya and Pedersen (2005) liquidity risk betas as summarized in equation (4.1). To enable direct econometric tests

[21]Table 4.1 shows that even after a 1% winsorization on both sides, the maximum value of *ILLIQ* is 181.33 relative to an average value of 2.50.

[22]We added a more-than-one-DMM dummy to capture a potential additional effect from multiple DMMs; we generally find that this variable is not significant (for further discussion we refer to Section 4.4.4).

[23]Note that the decomposition assumes that both components are uncorrelated. This assumption is not innocuous as it is at odds with a canonical microstructure model that has both components be positively correlated (see discussion Menkveld, Koopman, and Lucas (2007, section 4.3)). Empirical identification requires (intraday) trade data which is not accessible to us for the full sample. We believe the zero-correlation assumption is still useful for exploratory analysis.

[24]The argument is in the spirit of Pasquariello and Vega (2007, p.1984) who observe that, in the presence of a public signal (the DMM quotes in our case), the "belief update about v stemming from S_p makes speculators' private information less valuable." In their model v is the unobserved fundamental value and S_p is the public signal.

Table 4.4: Designated market makers and post-event change in price discovery

This table presents the change in price discovery after the introduction of DMMs. We use three measures of price discovery in the test which are estimated from the following state space model:

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t} \\ m_{i,t} &= m_{i,t-1} + w_{i,t} \\ s_{i,t} &= \phi_i s_{i,t-1} + \varepsilon_{i,t} \end{aligned}$$

where $p_{i,t}$ is the observed price of stock i on day t and it is modeled as the sum of two unobservable components. The first component $m_{i,t}$ is the 'fundamental' or 'efficient' price , which follows a martingale process. The second component $s_{i,t}$ is a transitory deviation from the efficient price, the 'pricing error'. The state-space model is estimated stock by stock and for pre- and post-event periods separately with maximum likelihood using Kalman filter. We use the daily midquote, adjusted for splits, new issues and dividends, as the observed price $p_{i,t}$. The estimation is implemented in Ox using standard optimization techniques. Three measures for price discovery are $\sigma(w)$, $\sigma(\varepsilon)$ and $\frac{\sigma(\varepsilon)}{\sqrt{1-\phi^2}}$. To examine how DMMs affect price discovery, we apply the following cross-sectional regression:

$$y_i = \alpha + \beta_1 post_i * DMM_i + \beta_2 post_i + \varepsilon_i$$

where i indexes stocks, *post* is a dummy for the post-event period, and *DMM* is a dummy for DMM stocks. We add t-values in parentheses.

	$\sigma(w)$	$\sigma(\varepsilon)$	$\frac{\sigma(\varepsilon)}{\sqrt{1-\phi^2}}$
$post * DMM$	-0.69*	-1.31**	-1.60**
	(-1.72)	(-5.20)	(-4.99)
post	-0.17	0.96**	1.15**
	(-0.44)	(3.97)	(3.73)
intercept	2.94**	0.75**	0.96**
	(16.72)	(6.75)	(6.74)
#Observations	202	202	202

**: Significant at a 95% level.
* : Significant at a 90% level.

on beta changes, we estimate the following panel data model based on daily data:

$$r_{it} = \sum_{k \in \{pre,post\}} \alpha^{rr}_{ik} + \tilde{\beta}^{rr}_{ik} k_t * r^m_t + \varepsilon^{rr}_{it} \quad (4.10)$$

$$r_{it} = \sum_{k \in \{pre,post\}} \alpha^{rc}_{ik} - \tilde{\beta}^{rc}_{ik} k_t * c^m_t + \varepsilon^{rc}_{it} \quad (4.11)$$

$$c_{it} = \sum_{k \in \{pre,post\}} \alpha^{cr}_{ik} - \tilde{\beta}^{cr}_{ik} k_t * r^m_t + \varepsilon^{cr}_{it} \quad (4.12)$$

$$c_{it} = \sum_{k \in \{pre,post\}} \alpha^{cc}_{ik} + \tilde{\beta}^{cc}_{ik} k_t * c^m_t + \varepsilon^{cc}_{it} \quad (4.13)$$

where i indexes stocks, t indexes days, k indexes pre- and post-event periods, k_t is a dummy that equals one if day t falls into the k period, zero otherwise, r_{it} is the daily midquote return that is adjusted for stock-splits and includes dividends, c_{it} is the (effective or quoted) half-spread divided by 20 trading days (to be consistent with Acharya and Pedersen (2005)), r^m_t is the Amsterdam AEX index return, c^m_t is the market-cap weighted (effective or quoted) half spread of the AEX index stocks. Finally, we use tildes to emphasize that these are regression betas rather than the covariance expressions of the basic Acharya and Pedersen (AP) model (see equation (4.1)). In reporting our results, we scale the regression betas with the appropriate covariance ratio to arrive at the AP betas.[25] Note that we add a minus sign in front of β^{rc} and β^{cr} to make the signs of these betas consistent with the AP model (see equation (4.2)).

Table 4.5 finds strong support that β^{cc} liquidity risk is reduced for DMM stocks relative to nonDMM stocks and weak support for a reduction in β^{rc} and β^{cr} liquidity risk. The table reports the results for both the effective and the quoted spread measure. It leads to a couple of observations. First, we find, consistent with Acharya and Pedersen (2005), that the market beta (β^{rr}) is an order of magnitude larger than the liquidity betas (β^{cc},β^{rc},β^{cr}). In their basic liquidity-CAPM model, the risk premia are assumed to be constant across all sources of risk as evident from a single risk premium λ in equation (4.3)). In this case, liquidity risks would be dominated by market risk. If, however, the risk premiums associated with the liquidity risks are higher than the market risk premium (as Acharya and Pedersen (2005) find in their calibration) then liquidity risks start to matter for required returns as well. Second, again consistent with Acharya and Pedersen (2005), we find that all betas represent risk as almost all their estimates are positive. Third and most important, we find for DMM stocks relative to nonDMM stocks (last set of columns) that all three liquidity betas (β^{cc}, β^{cc}, and β^{rc}) decrease in the post-event period. These are all changes that reduce the liquidity risk and are therefore potential channels for liquidity to generate value. However, we only find statistical significance for a reduction in the β^{cc} liquidity risk for both the quoted and the effective spread measure, i.e., a security's transaction

[25]Stock by stock we multiply the regression beta with $(var(r_{it})/var(r^m_t - c^m_t))$ for equation (4.10) and (4.11) and $(var(c_{it})/var(r^m_t - c^m_t))$ for equation (4.12) and (4.13).

Table 4.5: Designated market makers and post-event change in liquidity risk

This table uses panel data regressions to perform a difference-in-difference (post-event minus pre-event, DMM minus nonDMM) test on Acharya and Pedersen (2005) liquidity risk betas associated with the introduction of a DMM. We use a 101*415 stock-day panel dataset to estimate the following model specification:

$$r_{it} = \sum_{k \in \{pre,post\}} \alpha_{ik}^{rr} + \tilde{\beta}_{ik}^{rr} k_t * r_t^m + \varepsilon_{it}^{rr} \quad (4.14)$$

$$r_{it} = \sum_{k \in \{pre,post\}} \alpha_{ik}^{rc} - \tilde{\beta}_{ik}^{rc} k_t * c_t^m + \varepsilon_{it}^{rc} \quad (4.15)$$

$$c_{it} = \sum_{k \in \{pre,post\}} \alpha_{ik}^{cr} - \tilde{\beta}_{ik}^{cr} k_t * r_t^m + \varepsilon_{it}^{cr} \quad (4.16)$$

$$c_{it} = \sum_{k \in \{pre,post\}} \alpha_{ik}^{cc} + \tilde{\beta}_{ik}^{cc} k_t * c_t^m + \varepsilon_{it}^{cc} \quad (4.17)$$

where i indexes stocks, t indexes days, k indexes pre- and post-event periods, k_t is a dummy that equals one if day t falls into the k period, zero otherwise, r_{it} is the daily midquote return that is adjusted for splits, new issues and dividends, c_{it} is the (effective or quoted) half-spread divided by 20 trading days (to be consistent with Acharya and Pedersen (2005)), r_t^m is the Amsterdam AEX index return, c_t^m is the market-cap weighted (effective or quoted) half spread of the AEX index stocks. We test for pre- vs. post-event beta changes for DMM and nonDMM stocks and the difference between them based on cross-sectional averages. Panel A uses the effective half spread as a liquidity measure (c_{it} and c_t^m); Panel B uses the quoted half spread as a liquidity measure. In reporting our results, we scale the regression betas and their corresponding standard errors with the appropriate covariance ratio. We calculate this ratio for pre-event and post-event period separately, and it equals $(var(r_{it})/var(r_t^m - c_t^m))$ for equation (4.14) and (4.15) and $(var(c_{it})/var(r_t^m - c_t^m))$ for equation (4.16) and (4.17). We add t-values in parentheses, where the standard errors are corrected for both firm and time clustering.

	DMM stocks				nonDMM stocks				DMM stocks - nonDMM stocks		
	β^{rr} $(\times 10^{-2})$	β^{cc} $(\times 10^{-4})$	β^{rc} $(\times 10^{-4})$	β^{cr} $(\times 10^{-4})$	β^{rr} $(\times 10^{-2})$	β^{cc} $(\times 10^{-4})$	β^{rc} $(\times 10^{-4})$	β^{cr} $(\times 10^{-4})$	β^{cc} $(\times 10^{-4})$	β^{rc} $(\times 10^{-4})$	β^{cr} $(\times 10^{-4})$
Panel A: Effective spread as the liquidity measure											
pre-event	42.77**	0.03**	0.09	-6.05**	69.76**	0.02**	-1.23**	5.93**	0.01**	1.31**	-11.98**
	(37.59)	(5.92)	(0.43)	(-2.23)	(101.18)	(5.46)	(-10.07)	(3.46)	(2.19)	(5.57)	(-3.73)
post-event	27.03**	0.01**	0.56**	3.32	39.31**	0.03**	0.36**	22.28**	-0.02**	0.21**	-18.96**
	(31.40)	(15.10)	(19.28)	(1.61)	(75.65)	(64.16)	(20.22)	(16.91)	(-21.69)	(6.07)	(-7.77)
post-event − pre-event	-15.74**	-0.02**	0.48**	9.37**	-30.45**	0.01**	1.58**	16.35**	-0.03**	-1.11**	-6.98*
	(-11.03)	(-3.66)	(2.34)	(2.75)	(-35.28)	(4.28)	(12.86)	(7.57)	(-5.35)	(-4.64)	(-1.73)
#Observations	39,926										
Panel B: Quoted spread as the liquidity measure											
pre-event	42.78**	0.02**	0.33**	0.47	69.76**	0.04**	0.13**	8.72**	-0.02**	0.19**	-8.25**
	(37.59)	(28.56)	(6.87)	(0.27)	(101.18)	(93.29)	(4.60)	(8.39)	(-23.65)	(3.49)	(-4.10)
post-event	27.03**	0.01**	0.64**	3.56**	39.30**	0.04**	0.41**	21.61**	-0.02**	0.23**	-18.05**
	(31.40)	(28.41)	(18.49)	(2.75)	(75.65)	(121.63)	(19.83)	(27.16)	(-39.21)	(5.59)	(-11.85)
post-event − pre-event	-15.74**	-0.01**	0.31**	3.09	-30.46**	-0.00**	0.28**	12.89**	-0.00**	0.03	-9.79**
	(-11.03)	(-6.49)	(5.34)	(1.43)	(-35.28)	(-3.20)	(7.90)	(9.84)	(-3.90)	(0.47)	(-3.88)
#Observations	41,092										

**: Significant at a 95% level.
*: Significant at a 90% level.

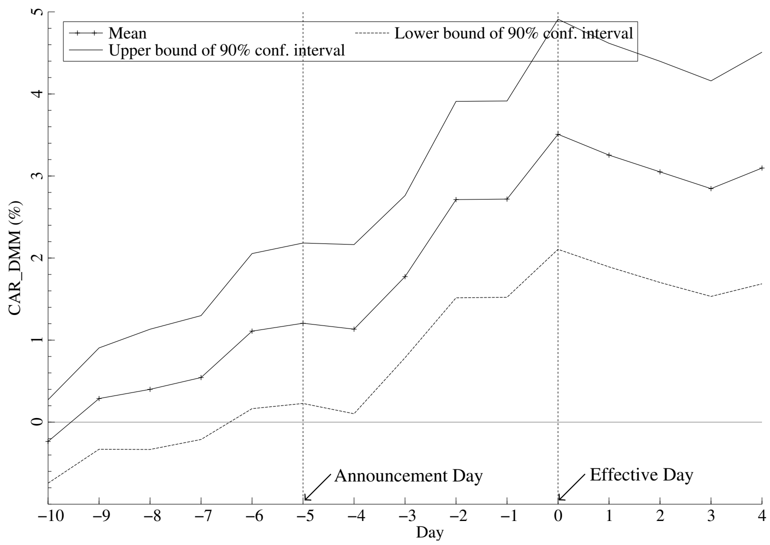
cost covaries less with market transaction cost after hiring a designated market maker. This reduction naturally arises with an upper bound on the spread as covariation with market liquidity is 'hampered'. The β_{rc} liquidity measure is only significantly reduced for the effective spread measure and the β_{cr} is significantly reduced for the quoted spread measure and only significantly reduced for the effective spread measured at the 90% confidence level.

Cumulative abnormal returns. Figure 4.2 shows that DMM stocks on average generate a significant cumulative abnormal return (CAR) in the three week window around the announcement and effective day (see also the timeline of Figure 4.1). We estimate CARs based on daily midquote returns and post-event market beta estimates.[26] Panel A shows that DMM stocks generate a significant CAR over this period of 3.5%. Most of this CAR is a strong run-up in prices in the week after Euronext publishes (t=-5) the list with all DMM stocks. We also find a 1.0% CAR in the week before the announcement which suggests that some of the information might have leaked to the market in the days before the announcement. We find another 0.5% on the effective day (t=0) and no significant changes afterwards. Panel B plots the CAR for nonDMM stocks which is insignificant throughout the entire period. Overall, the evidence suggests that the act of hiring a DMM appears to create value for the firm's shareholders.

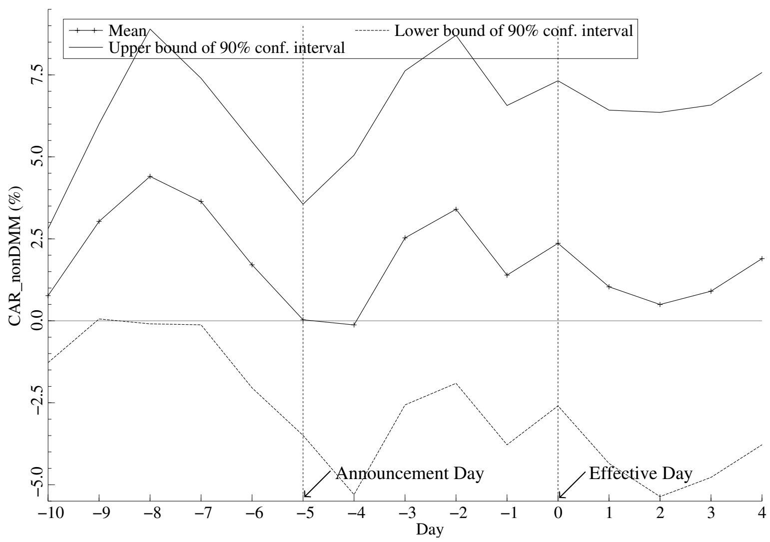
Cross-sectional regression of CARs on liquidity level and liquidity risk changes. If the liquidity changes that come with a DMM introduction are the cause of the DMM CARs, one expects the CARs to be largest for those stocks that show the largest improvement in liquidity level or the strongest reduction in liquidity risk. In the remainder of this subsection, we run a cross-sectional regression to verify whether one can indeed relate value creation to liquidity improvement. In the process, we worry about alternative explanations for the DMM stocks to generate CARs based on endogenous selection. We use an Heckman approach to control for such explanation in the cross-sectional regression.

We propose two alternative explanations for the abnormal returns based on endogenous selection of DMM stocks. First, the significant positive abnormal return for DMM stocks is really the result of a signaling game, where the good type firms take on the cost of hiring a DMM to signal their type to investors. For bad type firms this cost is prohibitively high. We consider this explanation unlikely as, in addition to a positive abnormal return for DMM stocks, it predicts a negative abnormal return for nonDMM stocks, which we do not find in the data. Second, a more plausible explanation that also captures the liquidity improvement is that DMM brokerage firms have private knowledge on future liquidity conditions of the small-cap firms

[26] We estimate the market model using post-event data to avoid an ex-post selection bias (cf. Amihud, Mendelson, and Lauterbach (1997, p.373)). If brokers select stocks with an exceptionally good pre-event performance relative to the market, then the pre-event beta estimator (and thus the CAR estimator around the event) correlates with DMM selection and thus biases the DMM CAR analysis. It is for this reason that we prefer a post-event beta estimator, where the post-event period (starting 11/30/01) is far removed from the event window we use to calculate CARs (ending 11/2/01) (see Figure 4.1).



Panel A: Cumulative abnormal return of DMM stocks



Panel B: Cumulative abnormal return of nonDMM stocks

Figure 4.2: Cumulative abnormal returns in the event period

This figure depicts the average cumulative abnormal return (CAR) with a 90% confidence interval over the three week event window that includes the announcement day as day -5 and the effective day as day 0 (see Figure 1 for the time line). We estimate CARs based on daily midquote returns. We use post-event beta estimates to avoid a potential ex-post selection bias (cf. Amihud, Mendelson, and Lauterbach (1997, p.373). Panel A reports the CAR for DMM stocks; Panel B for nonDMM stocks. The confidence intervals are based on robust standard errors which account for stock-specific autocorrelation and heteroskedasticity.

and only pitch aggressively to those firms with good liquidity prospects.[27] This explains both the post-event liquidity changes and their association with abnormal returns.

We recognize a potential endogenous selection in the cross-sectional regression through a Heckman procedure (see Heckman (1979)). That is, we first use a Probit model to estimate which observable factors drive the decision for a firm to hire a DMM. We then use a transformation of the likelihood of the (observed) firm's decision to hire a DMM given its observable characteristics, i.e., the inverse Mills ratio. A high ratio for stock i indicates that hiring a DMM was very unlikely given its characteristics. A selection bias now occurs if the *unobservables* that drive the hiring decision (i.e., the draw of the residual in the Probit selection equation) correlate with the regressors and with the error term in the cross-sectional regression of abnormal returns. In the Heckman procedure we control for such bias through the inclusion of the inverse Mills ratio in the cross-sectional regression. If, for example, consistent with the second alternative explanation, our results are only driven by private information on the side of brokerage firms on future liquidity conditions, the inverse Mills ratio is collinear with the liquidity change and this should make both variables insignificant in the cross-sectional regression.

We propose the following Probit model for a firm's decision on whether or not to hire a DMM (where all explanatory variables are based on the pre-event period):

$$\begin{aligned} Pr[DMM_i = 1] = \; & \Phi(\alpha_1 + \alpha_2 volatility_i + \alpha_3 volume_i + \alpha_4 price_i + \\ & \alpha_5 nr\_shares\_outstanding_i + \alpha_6 auction\_threat_i + \\ & \alpha_7 tobins\_q_i + \alpha_8 forecasted\_spread_i), \end{aligned} \tag{4.18}$$

where i indexes stocks, DMM_i is a dummy that equals one if firm i hires designated market makers and zero otherwise, $volatility_i$ is the average daily midquote return volatility, $volume_i$ is the average daily trading volume in shares, $price_i$ is the average daily closing price, $nr\_shares\_outstanding_i$ is the number of shares outstanding, $auction\_threat$ is a dummy that switches to one if the stock's trading frequency in the pre-event period is less than 5,000 transactions per year, $tobins\_q$ is Tobin's q measure, and $forecasted\_spread$ is a forecast of the post-event spread based on an AR(p) model fitted to pre-event observations (p is determined on a stock by stock basis using the AIC criterion). All these variables might affect the likelihood of DMM introduction and therefore need to enter the Heckman first stage Probit. In particular, the reason for the auction threat variable is that, in the new system, a stock with such low trading frequency has to move to a twice-a-day auction, unless the firm decides to hire a DMM.

Table 4.6 finds that DMM introduction is less likely for large firms and for firms for which the spread is forecasted to be high. The size result is consistent with Venkataraman and Waisburd (2007). We do not find any significance for volatility, volume, stock price, the auction

[27] For instance, they might know that (new) management will improve communication which allows liquidity suppliers to save on monitoring cost.

Table 4.6: Probit analysis of DMM-or-nonDMM in the cross-section of small-cap stocks

The table presents the estimates of a cross-sectional Probit model where the DMM-or-nonDMM dependent variable is explained by several pre-event firm and trade characteristics. The model specification is:

$$\begin{aligned} Pr[DMM_i = 1] &= \Phi(\alpha_1 + \alpha_2 volatility_i + \alpha_3 volume_i + \alpha_4 price_i + \alpha_5 nr\_shares\_outstanding_i \\ &\quad + \alpha_6 auction\_threat_i + \alpha_7 tobins\_q_i + \alpha_8 forecasted\_spread_i) \end{aligned}$$

where i indexes stocks, DMM_i is a dummy that equals one if firm i hires designated market makers and zero otherwise, $volatility_i$ is the average daily midquote return volatility, $volume_i$ is the average daily trading volume in shares, $price_i$ is the average daily closing price, $nr\_shares\_outstanding_i$ is the number of shares outstanding, $auction\_threat$ is a dummy that switches to one if the stock's trading frequency in the pre-event period is less than 5,000 transactions per year, $tobins\_q$ is the ratio of the market value to the book value of the firm's assets ($tobins\_q$ is not available for 3 nonDMM stocks in our database), and $forecasted\_spread$ is the forecasted spread calculated as follows: first, a time series $AR(p)$ model is estimated for each stock based on all observations of the quoted spread in the pre-event period, where the order p is determined individually based on the Akaike information criterion (AIC) (the average value of p equals to 1.3); next, the prediction of the spread in the post-event period is calculated based on the estimated AR coefficients; $forecasted\_spread$ is the average value of the predicted spread. The Probit regression is based on 98 stocks (74 DMM stocks and 24 nonDMM stocks). We use maximum likelihood to estimate the model parameters.

	Coefficient	t-stat
volatility	-0.27	-1.40
volume	-0.00	-0.83
price	-0.02	-1.46
nr_shares_outstanding	-12.17	-3.62**
auction_threat	0.72	1.37
tobins_q	0.02	0.43
forecasted_spread	-0.57	-2.44**
intercept	3.38	4.82**
#Observations		98

**: Significant at a 95% level.
* : Significant at a 90% level.

threat dummy, or Tobin's q.

Table 4.7 finds that both the liquidity level change and the liquidity risk change explain the abnormal return in the cross-section and it also shows that these findings are robust to a potential selection bias. For the ex-post liquidity measure, the effective spread, we find that its largest component, the realized spread, has strongest explanatory power in the univariate cross-sectional regressions.[28] Stocks with larger realized spread reductions experience higher abnormal returns. We also find that changes in liquidity risk significantly explain abnormal returns in the cross-section, i.e., stocks with larger risk reductions experience higher abnormal returns. The regression only includes β_{cc} liquidity risk as it was most significantly affected by DMM introduction — "Appendix: How Do Designated Market Makers Create Value for Small-Caps?" has all three liquidity betas as explanatory variables and finds no additional explanatory power for the other two. Model (3) includes both realized spread change and liquidity risk change in a multivariate regression and shows that both are important in explaining the cross-section of CARs.[29] We find these results to be robust as they do not change when we include the inverse Mills ratio to control for a potential selection bias. For the ex-ante liquidity measure, the quoted spread, we also find a significance for liquidity level change, but this time no significance for liquidity risk change.

4.4.3 Binding vs. nonbinding liquidity regimes

In this second set of empirical analyses, we search for evidence in support of value creation through DMMs as liquidity suppliers of last resort whose services are consumed at times of low 'endogenous' liquidity. First, we show that on days where the liquidity constraint is likely to bind, we find that DMMs participate in more trades and do so involuntarily as their trading revenue turns to a loss. Second, we show that their supply is appreciated by liquidity demanders as volume is higher on these days relative to comparable days in the pre-event period.

DMM liquidity supply on days where constraints are likely to bind. We do not observe the minimum liquidity supply that the issuer and the broker contract on and we therefore cannot identify times when broker's constraint binds. Instead, we propose the following. We take all post-event trading days for DMM stocks and sort them stock by stock based on quoted spread (which is what we know the contracts are based on). For each stock, we calculate the q and the

[28] We do not find the adverse selection component of the spread to be significant in the univariate regressions, which is not surprising as it does not change significantly with the addition of a DMM (see Table 4.3). This also makes alternative explanations for abnormal returns based on information asymmetry changes less likely (see, e.g., Easley and O'Hara (2004) and Chan, Menkveld, and Yang (2008))

[29] We are aware that we potentially suffer from an ex-post selection bias as brokers select firms with exceptionally strong ex-ante performance as discussed in footnote 26. In this case, however, the analysis requires estimation of pre-event liquidity betas to establish the *change* in betas. We are, however, somewhat less concerned about a conditioning on exceptional performance relative to nonstandard liquidity factors as opposed to the salient standard CAPM market factor.

Table 4.7: Determinants of cross-sectional dispersion in cumulative abnormal returns

This table regresses the three week cumulative abnormal return (CAR) around the DMM introduction date (see Figure 2) on changes in liquidity level, changes in liquidity risk, and the inverse Mills ratio (*IMR*) where the *IMR* is a Heckman control for a potential endogenous selection bias. The liquidity level and liquidity risk changes are simply the post- minus pre-event value of proxies for these variables (see also Table 4.3 and 4.5) where we follow Acharya and Pedersen (2005) to calculate liquidity risk. Although their model proposes various liquidity risk factors, we only include the covariation of a stock's liquidity with market liquidity (β^{cc}) in this regression as it was most significantly affected by the introduction of DMMs. The *IMR* is based on the Probit model estimate of Table 4.6. Panel A is based on the effective spread as liquidity measure; Panel B is based on the quoted spread. We include t-values in parentheses.

Panel A: Effective spread as the liquidity measure				
	(1)	(2)	(3)	(4)
$\Delta rspread^a$	-2.80 **		-2.12 **	-2.30 **
	(-3.43)		(-2.38)	(-2.27)
$\Delta adv\_selection^a$	0.62		1.18	1.10
	(0.55)		(1.00)	(0.91)
$\Delta\beta^{cc}(\times 10^4)$		-74.71**	-53.61*	-53.58*
		(-2.77)	(-1.85)	(-1.84)
IMR				3.02
				(0.37)
intercept	2.76 **	1.65	2.10 *	0.97
	(2.60)	(1.50)	(1.88)	(0.30)
R^2	0.12	0.07	0.15	0.15
#Observations	101	101	101	98
Panel B: Quoted spread as the liquidity measure				
	(1)	(2)	(3)	(4)
$\Delta qspread$	-2.02 **		-2.46 **	-2.32 **
	(-2.40)		(-2.61)	(-2.31)
$\Delta\beta^{cc}(\times 10^4)$		-2.13	57.12	54.47
		(-0.04)	(1.09)	(1.03)
IMR				-3.24
				(-0.42)
intercept	2.06 *	2.32 **	2.25 **	3.51
	(1.91)	(2.04)	(2.04)	(1.10)
R^2	0.05	0.00	0.07	0.07
#Observations	101	101	101	98

**: Significant at a 95% level.
* : Significant at a 90% level.
[a] : We prefer to use the two components of effective spread rather effective spread itself in order to trace down which component drives CARs. If, however, we include effective spread instead, we find its coefficient to be significantly negative in all models.

(1-q) quantile and label days with a spread larger than the (1-q) quantile as 'high spread days' where the constraint is likely to bind and days with a spread lower than the q quantile as 'low spread days' where it almost surely does not bind. In the implementation we use q equal to 0.10, 0.33, and 0.50. We prefer this approach to a more subjective armchair econometrics approach that studies quoted spread histograms and takes a guess at a cutoff level to label trading days. We nevertheless also followed this alternative approach and find that results are unchanged.

We interpret high quoted spread days as days when the 'endogenous' liquidity supply is low and these days therefore benefit from a DMM liquidity guarantee. In an intermediate empirical analysis that is available upon request, we characterize these days by comparing trade statistics across low and high spread days. We find that high spread days exhibit higher volatility, weakly lower volume, less trades, and contemporaneous and lagged negative stock and market returns. We indeed associate all these characteristics with low endogenous liquidity supply.

We calculate DMM participation rate, DMM gross trading revenue per share, and realized spread as a proxy for aggregate gross trading revenue per share for both the high and the low spread days. We then use a panel data model to test for differences across the two types of days. We use the following definitions. DMM participation rate is the ratio of the number of transactions with a DMM on one side of the trade and the total number of transactions. Inspired by Sofianos (1995), we calculate DMM gross trading revenue per share (GTR) by aggregating revenue across all DMM buys and sells in the day and marking-to-market her start of day and end of day inventory:

$$GTR_{it} = (S_{it} - B_{it} + p_{it}I_{it} - p_{i,t-1}I_{i,t-1})/nr\_shares\_transacted_{it}, \tag{4.19}$$

where i indexes stocks and t indexes days, p_{it} is the end of day midquote, I_{it} is the end of day DMM inventory in shares, S_{it} (B_{it}) is the total euro value of all sells (buys), and $nr\_shares\_transacted_{it}$ is the sum of trade size in shares of all transactions where a DMM is on one side of the trade. We do not observe DMM inventory directly and we therefore proxy for it with the sum over signed DMM volume in shares.[30]

We realize that high quoted spread days might, in addition to being costly to DMMs if their constraint binds, also enable DMMs (and others) to earn off of a wide bid-ask spread through round-trip trades. To analyze these two sources of daily DMM gross trading revenues (GTRs), we decompose them into a round-trip-trading-revenue component (RTR) and an inventory-repricing component (ITR) (see also Comerton-Forde, Hendershott, Jones, Seasholes, and Moul-

[30]We implicitly assume that the inventory level is zero at the start of the sample. We are not too worried about this assumption as we ultimately test for *differences* in GTR levels across the two types of trading days, not for the levels themselves. We check robustness by starting with different inventory levels and find that our main results are not affected.

ton (2010)). The first inventory-neutral component is defined as:

$$RTR_{it} = min(s_{it}, b_{it})(\overline{p}^s_{it} - \overline{p}^b_{it}), \tag{4.20}$$

where i indexes stocks and t indexes days, s_{it} (b_{it}) is the number of shares the DMM sells (buys), and $\overline{p}^s_{it}$ ($\overline{p}^s_{it}$) is the average price at which the DMM sells (buys) that day. The ITR component captures gross profits associated with DMM inventory and is defined as:

$$ITR_{it} = (p_{it} - \overline{p}^b_{it})(b_{it} - s_{it})^+ + (\overline{p}^s_{it} - p_{it})(s_{it} - b_{it})^+ + I_{i,t-1}(p_{it} - p_{i,t-1}), \tag{4.21}$$

where $(x)^+$ equals x if x is positive, zero otherwise. This term essentially captures the revenue associated with repricing inventory positions. The first two terms pick up the revenue for the inventory that was built in the course of the trading day (and turns negative if DMMs have to 'lean against the wind'). The last term picks up the result based on the start of day inventory position. By construction, we have:

$$GTR_{it} = RTR_{it} + ITR_{it} \tag{4.22}$$

for each day in the sample.

We estimate the following panel data model:

$$y_{it} = \alpha_i + \beta_{low} low\_qspread_{it} + \beta_{high} high\_qspread_{it} + \varepsilon_{it}, \tag{4.23}$$

where i indexes stocks and t indexes days, y_{it} is DMM participation rate, DMM gross trading revenue and its decomposition, or realized spread, $low\_qspread_{it}$ is a dummy that is one for the days that are labeled 'low spread days', zero otherwise, $high\_qspread_{it}$ is defined analogously.

Table 4.8 compares high to low quoted spread days and finds that DMMs participate in more trades, they build up larger excess inventory positions, and their gross trading revenue per share turns to a loss on high spread days, which indicates that they operate under a binding constraint. Not surprisingly, we find the strongest results when we zoom in on the tails, i.e., when we use q=0.10 (Panel A). For this quantile, we find that DMM trade participation in the high spread regime is 0.32, which is a significant 0.13 higher than their participation in the low spread regime. Excess inventory — the absolute deviation from average inventory — grows significantly during high spread days whereas there is no such effect for low spread days. They earn -€1.10 per share (GTR) in the high spread regime which is significantly lower than the €0.95 per share in the low spread regime. We decompose the (GTR) into its two components and find that the losses are due to adverse price movements on inventory as ITR is -€1.12 in in the high spread regime, which is significantly lower than €0.94 in the low spread regime. It seems that the DMM contract forces them to 'lean against the wind', i.e., they are long when the price falls and short when the price rises.[31] Panels B and C show that these results are generally robust to changing the quantile from 0.10 to 0.33 or 0.50, respectively.

Table 4.8 further shows that DMM *round-trip* trade revenues are higher on high quoted spread days, which is evidence of higher speculative profits on these days. It seems that DMMs do earn the larger spread (net of adverse selection) on their round-trip trades. For the 0.10 quantile reported in Panel A, we find that RTR is €0.02 per share on high quoted spread days, which is a significant €0.01 higher than the RTR on low quoted spread days. The realized spread, which represents the aggregate gross profits across all liquidity suppliers, also increases significantly from 0.32% on low spread days to 0.56% on high spread days. It seems that both the DMM round-trip trade revenue and the aggregate liquidity supplier revenue roughly double on high quoted spread days. These results illustrate that the only cause for DMM losses on high quoted spread days is that they suffer adverse price movements on their inventory positions. They are forced to lean against the wind as suppliers of last resort.

Volume change for binding constraint days. Finally, we study whether the forced liquidity supply on high spread days actually leads to more consumption by liquidity demanders. That is, does it actually allow current shareholders to realize a gain from trade that would otherwise be dominated by too high transaction cost or, does it attract new shareholders to the stock? Either way, we should see a volume increase if the DMM liquidity guarantee leads to increased consumption. We propose the following test. We use the previously used post-event high spread quantile q to label trading days in the pre-event period. We then compare volume differentials across pre- and post-event 'high spread days' in what is a difference-in-difference panel data approach similar to what we did in the tests on liquidity level change (see equation (4.9)).

Table 4.9 finds significant volume increases on high quoted spread days for DMM stocks relative to volume decreases for nonDMM stocks for two of the three quantile levels. The difference-in-difference estimates are also economically significant as for the $q = 0.10$ quantile analysis, for example, we find a volume increase of 14,670 shares per day, which compares to a pre-event DMM stock mean of 35,520 shares.[32]

4.4.4 Additional analysis

This section summarizes the results of some additional analysis which is available in the "Appendix: How Do Designated Market Makers Create Value for Small-Caps?".

[31] In the "Appendix: How Do Designated Market Makers Create Value for Small-Caps?" we show that DMM passive buys exceed their passive sales on days with price downturns and vice versa for days with price upturns. This indicates that DMMs trade against price swings (and supply liquidity) as their standing quotes in the book get consumed.

[32] We also find an overall volume increase in the difference-in-difference analysis of Table 4.3. It amounts to 5640 shares per day which is a substantial increase given the pre-event DMM stock mean of 35,520 shares per day (see Table 4.1). We do not find it to be statistically significant probably due to the less precise nature of the search, i.e., it also includes days where the DMMs are most likely not on a binding constraint.

Table 4.8: Post-event DMM activity and gross trade revenue in high and low quoted spread regimes

This table presents an analysis on whether DMMs are suppliers of last resort in the sense that they are forced to supply the minimum liquidity that they committed to at times of low "endogenous" supply. Empirically, we should find that they participate in more trades, suffer lower trading revenues, and have larger excess inventory positions on days that their constraint is likely to bind. For each stock, we calculate the q and the (1-q) quantile of the daily (time-weighted) quoted spread in the post-event period. We then label days with a spread larger than the (1-q) quantile as "high spread days" where the constraint is likely to bind and days with a spread lower than q as "low spread days" where it almost surely does not bind. We compare the DMM trade participation rate, DMM gross trading revenue (GTR), and DMM excess inventory changes across the two types of days. We define DMM participation rate as the ratio of the number of transactions with a DMM on one side of the trade and the total number of transactions. We calculate GTR by summing over all trade revenues in the day and marking-to-market DMM inventory any time the midquote changes (cf. Sofianos (1995)). We also decompose GTR into its two components: inventory-related trading revenue (ITR) and round-trip trading revenue (RTR) (cf. Comerton-Forde, Hendershott, Jones, Seasholes, and Moulton (2008)). We further calculate aggregate gross trading revenue across *all* liquidity suppliers using realized spread based on the average 15-minute price impact of a trade. We scale GTR, ITR, and RTR by the number of shares traded to make them comparable to the realized spread. The DMM excess inventory changes, $\Delta(|DMM\_excess\_inv|)$, is calculated as changes in the absolute value of the deviation from the stock average inventory position. We use the following panel data regression to test for differences across liquidity regimes:

$$y_{it} = \alpha_i + \beta_{low} low\_qspread_{it} + \beta_{high} high\_qspread_{it} + \varepsilon_{it}$$

where low_spread_{it} is a dummy for the low spread days and $high\_spread_{it}$ is a dummy for the high spread days. We add t-values in parentheses, where the standard errors are corrected for both firm and time clustering.

	Low quoted spread regime (1)	High quoted spread regime (2)	Difference (2)-(1)	#Observations
Panel A: q=0.10 quantile to identify liquidity regimes				
DMM_particip_rate	0.19	0.32	0.13 **	3,479
	(23.18)	(33.30)	(7.69)	
DMM_GTR_pershare	0.95	-1.10	-2.04 **	2,628
	(1.90)	(-2.27)	(-2.17)	
DMM_ITR_pershare	0.94	-1.12	-2.05 **	2,628
	(1.88)	(-2.31)	(-2.18)	
DMM_RTR_pershare	0.01	0.02	0.01 **	2,638
	(6.16)	(23.84)	(5.87)	
rspread	0.32	0.56	0.24 **	2,324
	(20.35)	(28.41)	(6.90)	
$\Delta(\|DMM\_excess\_inv\|)$	-0.17	0.38	0.55 **	3,515
	(-1.45)	(2.80)	(2.21)	

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	Low quoted spread regime (1)	High quoted spread regime (2)	Difference (2)-(1)	#Observations
Panel B: q=0.33 quantile to identify liquidity regimes				
$DMM\_particip\_rate$	0.21	0.31	0.10 **	11,193
	(32.09)	(45.02)	(7.66)	
$DMM\_GTR\_pershare$	0.27	-1.15	-1.42 **	8,855
	(0.87)	(-3.81)	(-2.60)	
$DMM\_ITR\_pershare$	0.26	-1.17	-1.43 **	8,855
	(0.83)	(-3.88)	(-2.61)	
$DMM\_RTR\_pershare$	0.01	0.02	0.01 **	8,900
	(16.62)	(29.91)	(6.14)	
$rspread$	0.34	0.49	0.15 **	7,557
	(30.37)	(37.47)	(6.55)	
$\Delta(\lvert DMM\_excess\_inv \rvert)$	0.01	0.13	0.13	11,279
	(0.10)	(2.04)	(1.08)	
Panel C: q=0.50 quantile to identify liquidity regimes				
$DMM\_particip\_rate$	0.22	0.30	0.08 **	16,712
	(46.21)	(59.13)	(8.23)	
$DMM\_GTR\_pershare$	-0.15	-1.32	-1.17 **	13,360
	(-0.63)	(-5.45)	(-3.02)	
$DMM\_ITR\_pershare$	-0.17	-1.34	-1.18 **	13,360
	(-0.69)	(-5.53)	(-3.03)	
$DMM\_RTR\_pershare$	0.01	0.02	0.01 **	13,444
	(26.19)	(37.61)	(5.51)	
$rspread$	0.35	0.46	0.11 **	11,364
	(39.00)	(43.35)	(6.31)	
$\Delta(\lvert DMM\_excess\_inv \rvert)$	-0.04	0.05	0.09	16,809
	(-0.74)	(0.92)	(0.82)	

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 4.9: Pre- and post-event volume in high quoted spread regime

This table studies whether DMM additions raise liquidity consumption in high quoted spread regimes. It uses a difference-in-difference (post- minus pre-event, DMM minus nonDMM) approach to volume on high quoted spread days. We use the post-event quantiles (consistent with Table 4.8) for the daily (time-weighted) quoted spread to label both the pre- and post-event trading days. We estimate the following panel data model:

$$y_{it} = \alpha_i + \beta_{post\_DMM} post\_DMM_{it} + \beta_{post\_nonDMM} post\_nonDMM_{it} + \beta_{DMM} DMM_i + \varepsilon_{it}$$

where $post\_DMM_{it}$ is a dummy that equals one if stock i is a DMM stock and day t is in post-event period and zero otherwise. $post\_nonDMM_{it}$ is defined analogously. DMM_i is a dummy that equals one if stock i is a DMM in the post-event period, zero otherwise. We add t-values in parentheses, where the standard errors are corrected for both firm and time clustering.

	Pre-event high quoted spread regime[a] (1)	Post-event high quoted spread regime[b] (2)	Difference (2)-(1)
Panel A: q=0.10 quantile to identify liquidity regimes			
DMM stocks	43.81**	48.70**	4.89
	(7.20)	(8.07)	(1.31)
NonDMM stocks	42.10**	32.32**	-9.78*
	(16.44)	(3.91)	(-1.67)
DMM stocks - NonDMM stocks	1.71	16.38	14.67**
	(0.20)	(1.19)	(2.28)
#Observations	7,728		
Panel B: q=0.33 quantile to identify liquidity regimes			
DMM stocks	41.87**	46.96**	5.09*
	(5.54)	(6.32)	(1.94)
NonDMM stocks	41.83**	33.81**	-8.02
	(13.89)	(3.26)	(-1.08)
DMM stocks - NonDMM stocks	0.03	13.14	13.11
	(0.00)	(0.74)	(1.72)*
#Observations	17,556		
Panel C: q=0.50 quantile to identify liquidity regimes			
DMM stocks	42.54**	48.39**	5.85**
	(8.33)	(9.69)	(2.23)
NonDMM stocks	43.03**	34.96**	-8.06
	(21.48)	(4.95)	(-1.58)
DMM stocks - NonDMM stocks	-0.48	13.43	13.91**
	(-0.07)	(1.13)	(2.52)
#Observations	23,837		

[a]: The pre-event volume of DMM stocks is calculated as $\frac{1}{74}\sum_{i=1}^{74}\alpha_i + \beta_{DMM}$. For nonDMM stocks, it is $\frac{1}{27}\sum_{i=75}^{101}\alpha_i$.

[b]: The post-event volume of DMM stocks is calculated as $\frac{1}{74}\sum_{i=1}^{74}\alpha_i + \beta_{DMM} + \beta_{post\_DMM}$. For nonDMM stocks it is $\frac{1}{27}\sum_{i=75}^{101}\alpha_i + \beta_{post\_nonDMM}$

**: Significant at a 95% level.

* : Significant at a 90% level.

Multiple DMMs. All analysis in this chapter was carried out conditioning on whether or not designated market makers are present. A perhaps more natural conditioning variable is the actual number of DMMs that enter. We have redone all major analyses with a multiple DMMs dummy as additional conditioning/explanatory variable but did not find it to be significant. It is for this reason that this chapter is focused on the binary variable: DMMs-or-not.

We believe the main reason for finding little additional information in the actual number of DMMs is in the nature of some of the DMM sponsorships. As discussed in Section 4.2, some brokers offered it for free in order to cross-subsidize other services. The value to the issuer of these DMMs was low as from informal discussions with both Euronext officials and issuing firms, we understood there typically was one broker that the issuer actively contracted with to obtain a substantially tighter maximum spread than what Euronext required. The additional free DMM offerings could straddle their quotes outside those of the 'lead' broker and avoid the cost of a binding constraint. In this case, it is as if there is only a single DMM operating which explains our results.

Industry-matched analysis. In addition to the unconditional comparison of DMM stocks and benchmark stocks in the main text, we group stocks into industries and do a comparison through industry pairs. In spite of the very small sample of only 7 industries, we continue to find that quoted and effective spread are significantly reduced upon DMM introduction. The liquidity risk analysis continues to show a significant reduction in β_{cc} liquidity risk for the quoted spread analysis. These findings show that the liquidity level and risk reduction that accompany DMM introduction are robust results.

September 2011. The terrorist attack on September 11, 2001, had a profound and immediate effect on financial markets world-wide. As this event is particularly close to the DMM introduction day (September, 30, 2011), we have redone all major analyses after removing this month from the sample. We generally find similar results except for that liquidity risk beta (β_{cc}) becomes a stronger explanatory factor in the cross-sectional CAR regression and the quoted spread becomes a weaker explanatory factor. The results therefore tilt in favor of a liquidity risk as opposed to a liquidity level explanation for abnormal returns.

4.5 Conclusion

We analyze a 22 month window around the event of a Euronext system roll-out to the Amsterdam market where small-caps get the opportunity to hire a designated market maker who guarantees a minimum liquidity supply in their stock. We find that 74 firms sign up for the service and 27 firms do not. In an event study analysis, we document the following results:

(i) DMM stocks generate a significant cumulative abnormal return of 3.5% in a three week window that includes the announcement and the effective day. We find that most of it occurs in the week after Euronext publishes the list of DMM stocks. In aggregate, this amounts to a value creation of about €1 billion.[33]

(ii) Based on what is essentially a difference-in-difference approach (post-event minus pre-event differenced across DMM and nonDMM stocks), we find that the effective spread declines significantly. The spread reduction appears to be driven by a realized spread decline (i.e., gross profit to liquidity suppliers), not by a decline in the adverse selection component of the spread. We further find that the effective spread covaries significantly less with market effective spread (i.e., β^{cc} in Acharya and Pedersen (2005)). We therefore argue that DMMs improve liquidity level and reduce liquidity risk. We report similar results for the quoted spread measure of liquidity.

(iii) We find that (i) the realized spread change and (ii) the effective spread market covariation change are both significant in explaining the abnormal returns cross-sectionally. In the regressions, we use a Heckman procedure to control for a potential selection bias.

(iv) We further find that DMMs are significantly more active on days when the (time-weighted) quoted spread is high relative to days of low quoted spreads. For example, we find that they participate in 32% of the trades in the highest decile days relative to a 19% participation in the lowest decile days. We also find that their gross trading revenue is significantly reduced on these days and actually turns into a trading loss.

(v) We find that for these highest decile quoted spread days, volume is significantly higher in the post-event period relative to similar days in the pre-event period. We interpret this as evidence that investors value the liquidity supply guarantee as they appear to consume it.

(vi) Finally, we find that DMMs reduce daily pricing errors.

It seems that these designated market maker contracts reduce the liquidity friction for small-caps and therefore reduce their cost of capital. If these firms are indeed an engine for economic growth, regulators should consider allowing for these type of contracts. We do want to emphasize though that any such regulatory effort should include a protection against the increased risk of insider trading.[34]

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[33] 74 stocks * 3.5% * €0.49 billion market cap (see Table 4.1).

[34] We reiterate that the Dutch regulator AFM only allows for a DMM contract if the broker agrees to report all her trading in that particular stock to the AFM.

Appendix 4A: An Example Euronext DMM Contract

Below are excerpts from a designated market maker contract that Euronext has made available to the authors. The name of the DMM has been changed to XXX to hide her identity. Numerical content is replaced with YYY.

The DMM obligation is stated as:

> XXX will act as a permanent Liquidity Provider, which implies that it will maintain a spread of firm bid and offer prices during the fifteen (15) minutes preceding the market opening and then throughout the Trading Day.
>
> XXX shall during Trading Days give Quotes and act as a counter-party for buyers and sellers of the Shares, whereby XXX shall maintain a maximum spread of firm bid and offer prices of YYY% for at least YYY shares (minimal amount Euro YYY).

The fee part of the contract says:

> The fee to be paid by the Company to XXX for the liquidity services provided amounts to YYY Euro per year with a fee holiday for the first year. The fee shall be payable in advance on the date of commencement of this Agreement and furthermore on or before the first Trading Day of each following year.

Appendix 4B: List of DMM and nonDMM stocks

We consider all stocks that were eligible for entering a contract with a designated market maker (DMM) on the day that Euronext rolls out the system from Paris to Amsterdam. We study 74 firms that hire a DMM on the introduction day (10/29/01) and we use the 27 stocks that do not hire a DMM in the post-event (11/30/01-9/30/02) period as benchmark nonDMM stocks.

Panel A: DMM stocks, N=74

AalbertsIndustries	FornixBiosciences	Ordina
AccellGroup	FoxKidsEurope	PetroplusInternational
Airspray	Fugro	Pinkroccade
Ajax	GammaHolding	RodamcoAsia
Amstelland	Grontmij	ScalaBusiness
Arcadis	Haslemere	Schuttersveld
ASMInternational	Heijmans	SligroBeheer
BalastNedam	ICTAutomatisering	SmitInternational
BESemiconductor	Imtech	SNT
BeterBed	KasAssociatie	Stork
BlueFoxEnterprise	KLM	TelegraafHolding
BoskalisWestminster	KoninklijkeBamGroep	TenCate
BrunelInternational	KoninklijkeWessanen	TwentscheKabel
Copaco	Laurus	Unit4Agresso
Corio	MacintoshRetailGroup	UnitedServiceGroup
CrownvanGelder	Magnus	vanLanschot
Crucell	McGregorFashion	VastnedOff\IND
CSM	Nedap	VastnedRetail
CTAC	NedconGroep	VendexKbb
DelftInstr	Nedloyd	VHSOnroerendGoed
DimVastgoed	NewSkiesSatellites	VolkerWesselStevin
DrakaHolding	NieuwSteenInvestments	Vopak
Econosto	Nutreco	Wegener
EurocommercialProperties	OCE	Wereldhave
ExactHolding	OPGGroep	

Panel B: nonDMM stocks, N=27

A.O.T	HalTrust	Ranstad
AABHold	Heineken	RoodTesthouse
AntonovPLC	Hitt	SimacTechniek
Athlon	IspatInternationa	SopheonPLC
Baan	ManagementShare	TieHolding
CapGemini	Newconomy	TulipComputers
CardioControl	OpenTV	UnileverPref
DeutscheBK	PharmingGRP	VanderMoolen
EVCInt	RaboCapFndTrust	ViaNetWorks

Chapter 5

Conclusion

Chapter 2, 3 and 4 in this dissertation analyze several aspects of two major equity markets in the world, U.S. NYSE/AMEX market and Dutch Euronext market . Chapter 2 explores a new dimension of liquidity, namely the liquidity leak event. It is a tail event that securities are trapped in a persistent illiquid state. Liquileak probability is proposed to measure this tail event and test whether liquidity leaks are priced in the cross-section of stock returns. Chapter 3 examines the relationship between liquidity and returns with a particular focus on the downside market. The downside illiquidity level and beta are defined conditioning on the market return and we investigate whether downside liquidity is priced differently in the cross-sectional returns. Chapter 4 studies how the introduction of designated market makers affects small-caps. In particular, what are the effects of a designated market maker on firms' liquidity level, liquidity risks and cumulative abnormal returns? The second part of Chapter 4 aims to answer what is the channel for the value creation of designated market makers. The empirical analysis verify whether a DMM loses money on a binding supply constraint. Since each chapter already contain a conclusion that summarizes the corresponding findings, in the current chapter I first highlight the most relevant results, and then provide the policy implications of the findings.

5.1 Summary of the main findings

5.1.1 Liquileaks

Chapter 2 uses NYSE/AMEX common stock data between 1963 to 2008. We measure liquidity leaks by the liquileak probability estimated from the Markov regime switching model. The liquileak probability is the interaction of the persistence of the illiquid regime and the frequency of the illiquid regime. The former is measured by the probability that a stock remains in the illiquid regime for five subsequent days given it is in the illiquid regime on previous day, and the latter is measured by the unconditional probability that a stock is in the illiquid regime.

The conjectured relationship between a stock's liquileak probability and its required return is tested in two conventional ways: portfolio sorts and Fama-MacBeth regressions. The portfolio sort analysis reveals that a trading strategy that is long in high liquileak stocks and short in low liquileak stocks yields a significant average annual excess return of 3.36%. To explore whether this positive return is only due to one of the two factors of the liquileak probability (i.e., frequency or duration) or just captures the (unconditional) average liquidity level, we double-sort and find that, still, the return differential across low and high liquileak stocks remains significantly positive. The Fama-MacBeth regressions enable us to also control for the standard Fama-French factors and other stock characteristics. Liquileak probability remains significantly positive. A one standard deviation increase in liquileak probability increases annual returns by 1.33%. These regressions are repeated for the two equal-length sub-periods (1964 through 1985 and 1986 through 2008) and the results indicate that the liquileak probability has become more important for returns over time whereas, consistent with earlier literature, liquidity level has become less important.

In the robustness check, we propose an alternative measure of liquidity leaks, which is calculated directly from raw data without any model specification. We proxy the persistence of the illiquid regime by the average duration that a stock is in the illiquid regime and the frequency of the illiquid regime by the percentage of the days that a stock is in the illiquid regime over total number of trading days. Correspondingly, the interaction of these two variables is the measure of liquidity leaks. Again, we find consistent evidence that this measure of liquidity leaks also has a significantly positive relation with stock returns. In addition, our results are robust to the January effect.

5.1.2 Downside liquidity

Chapter 3 investigates liquidity in a downside market. We set the average market return as a cutoff level and define a market is in a downside (upside) if its return is lower (higher) than this cutoff level. Amihud ILLIQ measure is used as our daily illiquidity measure. The downside (upside) illiquidity level is defined as the average of daily ILLIQ measure in a downside (upside) market. The downside and upside liquidity beta is the comovement of stock's illiquidity level with the market illiquidity level conditioning on the market return. The mean value of the downside illiquidity level is 0.33, which is about 3% higher than the mean of the upside illiquidity level. There are considerable variations in the downside and upside illiquidity level, both in the cross-section and over time. Although the summary statistics of the downside and upside liquidity beta are similar, their between correlation is 0.59 implying that these two variables are far from perfectly correlated.

We use two approaches to investigate the relation between the downside liquidity and stock returns in the cross-section. One is the portfolio sorting approach, which produces easy-to-interpret returns on a feasible investment strategy. We sort individual stocks into five quintiles based on the their downside (and upside) illiquidity level and downside (and upside) liquidity beta, and find that stocks with high downside illiquidity level and beta have higher returns than stocks with low downside illiquidity level and beta. For example, a trading strategy that is long in stocks with high downside illiquidity level and short in stocks with low downside illiquidity level yield an average monthly excess return of approximately 0.94%. The return difference between the two extreme downside liquidity beta quintiles is 0.74% per month. To differentiate the effects of downside and upside illiquidity level and beta, we further conduct a double-sorting analysis. After control for the upside illiquidity level we still find that the return spread of portfolios sorted by the downside illiquidity level is significantly positive. Also, the increasing pattern of return from the low downside liquidity beta to high downside liquidity beta remains after first sort on the upside liquidity beta. The other approach is the Fama-MacBeth regression, which allows us to regress cross-sectional excess returns directly on the downside illiquidity level and beta and enable us to control for other well-known return determinants. The regression is conducted on the firm level. We find evidence that the downside illiquidity level and beta have a significantly positive effect on stock returns in the cross-section. For example, an increase of one standard deviation in the downside illiquidity level would increase monthly returns by 0.15%. It is approximately 1.8% on an annual basis, which also indicates economical significance. The downside liquidity beta also has a significantly positive effect on stock returns. However, when the downside illiquidity level, the upside illiquidity level, the downside and upside liquidity beta are included jointly in the cross-sectional regression, only the downside illiquidity level still has a significantly positive coefficient on returns. In the robustness check, we find that our results are robust to the January effect.

5.1.3 Designated market makers

Chapter 4 studies an exogenous event on October 29 2001 when Euronext rolled out their Paris limit order market to Amsterdam. They provided small-cap firms an option to contract with designated market makers, who commit to affirmative obligations of supplying liquidity without informational advantage. An important advantage of this exogenous all-stock migration is that the analysis does not suffer from an endogenous timing bias that haunts any study based on sequential introductions. The dataset contains one file that includes the initiation and termination date of all DMM contracts during that period. We find that 74 out of 101 eligible firms enter DMM contracts. In addition the intraday dataset contains the best bid and ask quote and trades of all transactions. We benefit from the unique feature of the data that there is a label indicating whether or not a DMM was involved in the transaction (only their own-account trades are considered) and, if so, on which side of the trade. This allows us to go deep into the trading activities of DMMs and enable us to examine whether DMMs are acting as “supplier of last resort".

In Chapter 4 we analyze 11 months before and after the introduction of designated market makers and find that DMM stocks generate a significant cumulative abnormal return of 3.5% in a three week window that includes the announcement and the effective day. Most of it occurs in the week after Euronext publishes the list of DMM stocks. In aggregate, this amounts to a value creation of about €1 billion. Based on what is essentially a difference-in-difference approach (post-event minus pre-event differenced across DMM and nonDMM stocks), we find that the effective spread declines significantly and the effective spread covaries significantly less with market effective spread (i.e. β^{cc} in Acharya and Pedersen (2005)). We therefore argue that DMMs improve liquidity level and reduce liquidity risk. Moreover, both the liquidity level change and the liquidity risk change are significant explanatory variables for the positive abnormal returns associated with DMM stocks. We further find that DMMs participate in more trades and incur a trading loss on high quoted-spread days, i.e., days when their constraint is likely to bind.

5.2 Implications of the findings

Financial markets have experienced several "liquidity crises" over the last decade. For example, the dry up of liquidity accelerated the collapse of the Long Term Capital Management. The hedge fund could find no one to trade with when it needed liquidity most. This phenomenon has become the first concern of market participants and regulators and has drawn a lot of attention on liquidity in financial market.

It is widely recognized now that investors prefer liquid stocks and demand higher returns from less liquid stocks. The evidence presented in this dissertation conveys the idea that market returns endogenously affect liquidity and liquidity is especially crucial for investors during market downturns. When market goes down, the aggregate value of securities decreases substantially and results in a large decline in the collateral value of a trader (e.g. a dealer, hedge fund, or investment bank). These financial intermediaries who are liquidity suppliers under the normal market condition turns into liquidity demanders in a declining market. They are forced to liquidate their positions and the provision of liquidity in the market decreases sharply. The "fire sale" actions in turn push down asset prices, and thus, make the liquidity problem further deteriorate. Chapter 3 investigates liquidity explicitly conditioning on the market return. We set the average market return as a cutoff level. The downside (upside) illiquidity level is the average of daily ILLIQ measure when market return is lower (higher) than the cutoff level. Analogously, the downside and upside liquidity beta is the comovement of stock's illiquidity with the market illiquidity conditioning on the market return. The results imply that the downside illiquidity level has an overwhelming explanatory power in the cross-sectional returns.

In addition, the findings in this dissertation show that the variation and timing of liquidity is also important for investors besides the average level of liquidity. In Chapter 2 we introduce a measure of liquidity called 'liquileak probability'. It differs from other commonly used liquidity measures, such as spread, quoted depth or Kyle's lambda, as it incorporates the time dimension of liquidity. It recognizes (i) the frequency of hitting an illiquid state and (ii) the duration of that state. Liquidity leaks hurt only if both of these are large. Liquidity leaks occur either because market participants engage in panic selling or financial intermediaries withdraw from providing liquidity. Stocks that are captured by liquidity leaks are problematic for investors since they have to wait for significant time before liquidity can restore to their normal level. Chapter 2 provides evidence that liquidity leaks are associated with significantly positive return premium. Moreover, in contrast to the diminishing trend of liquidity level premium, the premium of liquileak probability has increased over time. Therefore, it becomes increasingly important to realize that investors care not only about the occurrence of low liquidity, but also about how long such situations will last.

The idea of 'liquidity leaks' addresses issues that are very important and relevant for market participants, stock exchanges and regulators. For market participants, liquidity might not be a problem in normal market conditions. However, it becomes a first-order concern when the security is trapped in a persistent illiquid state. Liquidity matters most when investors need to trade. Investors would prefer firms with relatively predictable liquidity because they are more certain about the cost of closing a position at the time they make the initial purchase decision. When a security is likely to enter an illiquid state and stay there for a long time, it increases the uncertainty attached to a position and limits the potential flexibility for investors . For example, investors who need to reduce overall exposure may face the situation of either selling shares at substantially low value or liquidating other positions. In the extreme case, there is no opportunity to enter or exit a position when liquidity suddenly disappears.

Since the earliest stock exchange was established in 1602 by the Dutch East India Company, the structure and design of trading mechanism has been subject to dynamic changes. Rising globalization, deregulation, cross listing have made the competition among exchanges greater than ever before. The primary function of a stock exchange is to provide liquidity for listed securities. Normally the performance of exchanges is measured by spreads, depths, volatility and trading volumes. This dissertation argues that exchanges should not simply focus on those static measures of liquidity. They should arguably have a strong interest in the dynamics of liquidity and extreme market conditions such as 'liquidity leaks'. At the time of liquidity leaks, the usual liquidity suppliers, for example speculators, would face funding constraints and higher margin requirement. Then they turn to be liquidity demanders instead of suppliers and market is absence of investors who are willing to take the other side of positions. Therefore, it is important to ensure the presence of liquidity suppliers in the market, especially during periods like liquidity leaks. Likewise, understanding 'liquidity leaks' is helpful for regulators to better monitor market quality and stability.

One possible solution for 'liquidity leaks' could be the designated market maker which is studied in Chapter 4 of this dissertation. Traditionally there are market makers with privileges in a order-driven market. One important feature of this system is the use of single market maker and its inherent advantage in terms of unique information over other traders on both the market orders and the limit order book. The best known example is the specialist in NYSE stock exchange. Recently some stock exchanges begin to allow firms to directly contract with market makers who commit to supply a minimum liquidity at all times. This kind of market makers differs from specialists as they have affirmative obligations of submitting continuous bid and ask orders by trading on their own account. They do not possess any monopolistic information and have to compete with investors for order flows. They are usually hired by small and mid caps with inactive-traded stocks and are subsidized by direct payment from the listed firms. Chapter 4 in this dissertation provides further understanding of the latter which is called 'designated market maker' in Euronext Amsterdam exchange. It is shown that the presence of designated market makers leads to abnormal returns, both economically and statistically significant. In essence, designated market makers play a role as a "supplier of last resort" to insure current shareholders against the idiosyncratic risk of having to trade when liquidity is low. Their presence reduces not only illiquidity level but also systematic liquidity risk. The findings show that DMM stocks have more volume and higher DMM participation in these extreme market conditions. The value of DMMs is basically realized at times of low endogenous liquidity when the supply constraint binds. Shareholders realize a gain from trade that otherwise might have met too high transaction cost (in the absence of the minimum supply guarantee).

Firms have to pay DMMs a lump-sum fee in order to get their service of providing the guaranteed liquidity. Such service reduces the liquidity friction for firms and therefore brings down their cost of capital. Thus, listed firms could weigh the costs and benefits of hiring DMMs and decide on the optimal level of liquidity. Without such arrangement, securities that most need and benefit from the presence of liquidity providers are usually ignored by market intermediaries. Nowadays, the increasing importance of market makers has become a noticeable phenomenon. According to the survey of Charitou and Panayides (2006), among twenty major developed stock exchanges in North America, Europe and Asia only three of them solely rely on a pure limit order book for liquidity provision. Our results have shown that DMMs are beneficial for small-cap firms. If these firms are indeed an engine for economic growth, regulators should consider encouraging these type of contracts.

Appendix: Liquileaks

This Appendix of Chapter 2 “Liquileaks” contains the following supplementary material:

(i) Table 2.14 redoes the second subperiod (1986-2008) Fama-MacBeth regressions after removing the financial crisis period (2007-08). The coefficient on liquileaks is higher in this new table which indicates that the increase in the coefficient on liquileaks across the two subperiods was not driven by the financial crisis.

(ii) Tables 2.15 through 2.17 redo the full sample Fama-MacBeth regressions except that the liquileak event is defined as the probability of finding the security in the illiquid state for three, ten, and fifteen days respectively.

(iii) Table 2.18 redoes the full sample Fama-MacBeth regressions except that the $illiq$ value of zero-volume days is set to the highest observed $illiq$ value in the stock-year sample.

(iv) Table 5* and 6* replicate Table 2.5 and 2.6 in the main text except that sorted portfolios are value weighted.

(v) Table 2’ through 13’ replicate Table 2 through 13 in the main text by using the price-reversal liquidity measure proposed by Pastor and Stambaugh (2003). The implementation details are discussed below.

A daily Pastor-Stambaugh illiquidity measure instead of Amihud’s ILLIQ

Pastor and Stambaugh (2003, p.647) propose a monthly liquidity measure that is based on daily price reversals. The regression they run by stock-month is:

$$r_{i,d+1,m} = \theta_{i,m} + \phi_{i,m} r_{i,d,m} + \gamma_{i,m} sign(r_{i,d,m}) v_{i,d,m} + \varepsilon_{i,d+1,m} \tag{6.1}$$

where i indexes stocks, d indexes days, and m indexes months, r is the stock return, v is dollar volume, and ε is an independent identically distributed error term. The γ estimate serves as the liquidity measure. The idea is that large price reversals per dollar traded imply that the liquidity supply side required high compensation as prices were significant 'pressured', i.e., large negative γ estimates indicate low liquidity.

Liquileak identification requires a daily measure of liquidity and the natural Pastor-Stambaugh alternative to the daily Amihud ILLIQ measure is[1] :

$$psilliq_{i,d} = -\left(\frac{r_{i,d+1,y} - \hat{\theta}_{i,y} - \hat{\phi}_{i,y} r_{i,d,y}}{sign(r_{i,d,y}) v_{i,d,y}}\right) \tag{6.2}$$

where $\hat{\theta}_{i,y}$ and $\hat{\phi}_{i,y}$ are obtained by estimating the model in equation (6.1) on a sample of daily observations for stock i in year y. This *psilliq* measure replaces the *illiq* measure in the main text after which all empirical analysis is redone.

[1] A Pastor-Stambaugh *illiquidity* (instead of liquidity) measure is trivially defined as minus γ.

Table 2.14: Fama-MacBeth regressions, 2007-2008 excluded from second sub-period 1986-2008

This table repeats Tables 2.7 and 2.8 with the 2007-08 financial crisis period removed.

Panel A: liquileak_prob and standard control variables

	(1)	(2)	(3)	(4)
liquileak_prob	12.07**			
	(3.97)			
p_1		10.18**		7.13**
		(5.36)		(3.31)
p_{11}^5			5.55**	3.22**
			(4.13)	(2.06)
illiqma	1.02**	0.96**	1.03**	0.99**
	(5.25)	(5.01)	(5.32)	(5.14)
β_{MKT}	7.95**	8.46**	7.80**	8.10**
	(2.86)	(3.03)	(2.81)	(2.92)
β_{SMB}	-2.93	-3.27	-2.82	-3.16
	(-1.47)	(-1.63)	(-1.41)	(-1.58)
β_{HML}	-1.16	-1.27	-1.12	-1.17
	(-0.63)	(-0.68)	(-0.61)	(-0.63)
intercept	2.11	0.76	1.99	1.13
	(1.49)	(0.53)	(1.40)	(0.82)

Panel B: liquileak_prob and extended set of control variables

	(1)	(2)	(3)	(4)
liquileak_prob	14.63**			
	(4.44)			
p_1		9.85**		5.42**
		(4.95)		(2.36)
p_{11}^5			6.50**	4.97**
			(4.90)	(3.23)
illiqma	0.81**	0.78**	0.82**	0.81**
	(4.44)	(4.29)	(4.48)	(4.45)
*r*100	0.66	0.48	0.83	0.56
	(0.26)	(0.19)	(0.32)	(0.22)
*r*100*yr*	-1.61	-1.77	-1.68	-1.79
	(-1.02)	(-1.12)	(-1.06)	(-1.13)
lnsize	-1.68**	-1.47**	-1.74**	-1.59**
	(-3.98)	(-3.53)	(-4.12)	(-3.80)
sdret	-2.46**	-2.27**	-2.52**	-2.53**
	(-3.09)	(-2.84)	(-3.18)	(-3.19)
divyld	0.01	0.01	0.01	0.01
	(0.31)	(0.45)	(0.33)	(0.32)
β_{MKT}	10.37**	10.54**	10.32**	10.43**
	(3.77)	(3.82)	(3.76)	(3.79)
β_{SMB}	-4.01**	-4.13**	-3.95**	-4.02**
	(-2.03)	(-2.09)	(-2.00)	(-2.04)
β_{HML}	-2.28	-2.28	-2.27	-2.27
	(-1.30)	(-1.30)	(-1.30)	(-1.30)
intercept	15.88**	12.95**	16.28**	14.65**
	(4.66)	(3.79)	(4.78)	(4.36)
#stocks*#months		1672*252		

**: Significant at a 95% level.
* : Significant at a 90% level.

Table 2.15: Fama-MacBeth regressions

This table repeats Tables 2.7 and 2.8 for the full sample while the liquileak event is defined as the probability of finding the security in the illiquid state for three days.

Panel A: liquileak_prob and standard control variables

	(1)	(2)	(3)	(4)
liquileak_prob	6.85**			
	(4.18)			
p_1		6.13**		4.54**
		(4.94)		(3.07)
p_{11}^3			2.84**	1.47*
			(4.01)	(1.72)
illiqma	1.60**	1.57**	1.61**	1.59**
	(8.99)	(8.80)	(9.05)	(8.82)
β_{MKT}	5.36**	5.62**	5.29**	5.49**
	(2.91)	(3.05)	(2.88)	(2.98)
β_{SMB}	-1.58	-1.75	-1.50	-1.68
	(-1.34)	(-1.48)	(-1.27)	(-1.42)
β_{HML}	-0.61	-0.65	-0.60	-0.65
	(-0.50)	(-0.54)	(-0.50)	(-0.54)
intercept	1.10	0.38	0.95	0.42
	(1.04)	(0.36)	(0.89)	(0.40)

Panel B: liquileak_prob and extended set of control variables

	(1)	(2)	(3)	(4)
liquileak_prob	8.40**			
	(4.86)			
p_1		5.63**		2.23
		(4.41)		(1.45)
p_{11}^3			3.68**	3.12**
			(5.44)	(3.82)
illiqma	1.29**	1.27**	1.31**	1.30**
	(7.48)	(7.33)	(7.53)	(7.47)
$r100$	3.13*	3.15*	3.21*	3.11*
	(1.69)	(1.71)	(1.74)	(1.68)
$r100yr$	1.23	1.19	1.15	1.09
	(1.07)	(1.03)	(1.00)	(0.95)
lnsize	-2.04**	-1.96**	-2.08**	-2.04**
	(-7.44)	(-7.12)	(-7.58)	(-7.41)
sdret	-4.63**	-4.47**	-4.69**	-4.68**
	(-7.96)	(-7.63)	(-8.05)	(-8.07)
divyld	0.06	0.07	0.06	0.06
	(1.10)	(1.19)	(1.12)	(1.08)
β_{MKT}	9.18**	9.27**	9.14**	9.19**
	(4.98)	(5.03)	(4.97)	(4.99)
β_{SMB}	-2.33**	-2.40**	-2.30**	-2.34**
	(-2.03)	(-2.08)	(-2.00)	(-2.04)
β_{HML}	-2.34**	-2.34**	-2.35**	-2.35**
	(-2.07)	(-2.07)	(-2.08)	(-2.08)
intercept	18.32**	16.86**	18.51**	17.91**
	(7.71)	(7.08)	(7.80)	(7.66)
#stocks*#months		1639*540		

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 2.16: Fama-MacBeth regressions

This table repeats Tables 2.7 and 2.8 for the full sample while the liquileak event is defined as the probability of finding the security in the illiquid state for ten days.

Panel A: liquileak_prob and standard control variables

	(1)	(2)	(3)	(4)
liquileak_prob	8.79**			
	(3.56)			
p_1		6.13**		4.04**
		(4.94)		(2.80)
p_{11}^{10}			4.12**	2.70**
			(3.82)	(2.18)
illiqma	1.61**	1.57**	1.61**	1.59**
	(9.04)	(8.80)	(9.06)	(8.84)
β_{MKT}	5.35**	5.62**	5.31**	5.47**
	(2.91)	(3.05)	(2.89)	(2.97)
β_{SMB}	-1.52	-1.75	-1.48	-1.68
	(-1.29)	(-1.48)	(-1.25)	(-1.42)
β_{HML}	-0.61	-0.65	-0.62	-0.65
	(-0.51)	(-0.54)	(-0.52)	(-0.54)
intercept	1.23	0.38	1.17	0.59
	(1.16)	(0.36)	(1.10)	(0.57)

Panel B: liquileak_prob and extended set of control variables

	(1)	(2)	(3)	(4)
liquileak_prob	10.86**			
	(4.10)			
p_1		5.63**		2.55*
		(4.41)		(1.72)
p_{11}^{10}			5.17**	4.44**
			(4.85)	(3.67)
illiqma	1.30**	1.27**	1.30**	1.29**
	(7.48)	(7.33)	(7.47)	(7.43)
*r*100	3.26*	3.15*	3.36*	3.23*
	(1.77)	(1.71)	(1.82)	(1.75)
*r*100*yr*	1.37	1.19	1.34	1.24
	(1.18)	(1.03)	(1.16)	(1.08)
lnsize	-2.07**	-1.96**	-2.11**	-2.05**
	(-7.53)	(-7.12)	(-7.67)	(-7.46)
sdret	-4.58**	-4.47**	-4.62**	-4.64**
	(-7.88)	(-7.63)	(-7.94)	(-7.97)
divyld	0.06	0.07	0.06	0.06
	(1.08)	(1.19)	(1.09)	(1.06)
β_{MKT}	9.15**	9.27**	9.14**	9.19**
	(4.97)	(5.03)	(4.96)	(4.99)
β_{SMB}	-2.31**	-2.40**	-2.30**	-2.35**
	(-2.01)	(-2.08)	(-2.00)	(-2.04)
β_{HML}	-2.33**	-2.34**	-2.34**	-2.34**
	(-2.06)	(-2.07)	(-2.07)	(-2.07)
intercept	18.54**	16.86**	18.79**	18.08**
	(7.82)	(7.08)	(7.94)	(7.73)
#stocks*#months		1639*540		

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 2.17: Fama-MacBeth regressions

This table repeats Tables 2.7 and 2.8 for the full sample while the liquileak event is defined as the probability of finding the security in the illiquid state for fifteen days.

Panel A: liquileak_prob and standard control variables

	(1)	(2)	(3)	(4)
liquileak_prob	9.60**			
	(3.28)			
p_1		6.13**		4.22**
		(4.94)		(3.02)
p_{11}^{15}			4.56**	3.08**
			(3.69)	(2.27)
illiqma	1.61**	1.57**	1.62**	1.59**
	(9.05)	(8.80)	(9.07)	(8.85)
β_{MKT}	5.37**	5.62**	5.35**	5.49**
	(2.92)	(3.05)	(2.91)	(2.98)
β_{SMB}	-1.50	-1.75	-1.47	-1.68
	(-1.27)	(-1.48)	(-1.24)	(-1.42)
β_{HML}	-0.62	-0.65	-0.63	-0.65
	(-0.51)	(-0.54)	(-0.53)	(-0.55)
intercept	1.26	0.38	1.20	0.59
	(1.19)	(0.36)	(1.13)	(0.56)

Panel B: liquileak_prob and extended set of control variables

	(1)	(2)	(3)	(4)
liquileak_prob	11.82**			
	(3.71)			
p_1		5.63**		3.13**
		(4.41)		(2.17)
p_{11}^{15}			5.56**	4.66**
			(4.48)	(3.43)
illiqma	1.30**	1.27**	1.29**	1.29**
	(7.48)	(7.33)	(7.45)	(7.42)
*r*100	3.33*	3.15*	3.42*	3.25*
	(1.81)	(1.71)	(1.86)	(1.76)
*r*100*yr*	1.41	1.19	1.39	1.28
	(1.22)	(1.03)	(1.21)	(1.11)
lnsize	-2.07**	-1.96**	-2.11**	-2.04**
	(-7.55)	(-7.12)	(-7.68)	(-7.41)
sdret	-4.54**	-4.47**	-4.57**	-4.60**
	(-7.81)	(-7.63)	(-7.84)	(-7.89)
divyld	0.06	0.07	0.06	0.06
	(1.10)	(1.19)	(1.12)	(1.09)
β_{MKT}	9.16**	9.27**	9.15**	9.21**
	(4.97)	(5.03)	(4.97)	(4.99)
β_{SMB}	-2.31**	-2.40**	-2.30**	-2.36**
	(-2.01)	(-2.08)	(-2.00)	(-2.05)
β_{HML}	-2.34**	-2.34**	-2.34**	-2.34**
	(-2.07)	(-2.07)	(-2.07)	(-2.07)
intercept	18.53**	16.86**	18.75**	17.88**
	(7.82)	(7.08)	(7.92)	(7.62)
#stocks*#months		1639*540		

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 2.18: Fama-MacBeth regressions

This table repeats Tables 2.7 and 2.8 for the full sample while the *illiq* value of zero-volume days is set to the highest observed *illiq* value in the stock-year sample.

Panel A: liquileak_prob and standard control variables

	(1)	(2)	(3)	(4)
liquileak_prob	7.61**			
	(3.99)			
p_1		6.50**		4.75**
		(5.22)		(3.19)
p_{11}^5			3.33**	1.78*
			(3.98)	(1.78)
illiqma	1.34**	1.32**	1.35**	1.33**
	(8.36)	(8.18)	(8.40)	(8.19)
β_{MKT}	5.15**	5.45**	5.09**	5.31**
	(2.81)	(2.97)	(2.78)	(2.89)
β_{SMB}	-1.35	-1.56	-1.28	-1.49
	(-1.13)	(-1.31)	(-1.08)	(-1.26)
β_{HML}	-0.52	-0.57	-0.52	-0.57
	(-0.43)	(-0.47)	(-0.43)	(-0.47)
intercept	1.48	0.62	1.39	0.75
	(1.41)	(0.59)	(1.31)	(0.72)

Panel B: liquileak_prob and extended set of control variables

	(1)	(2)	(3)	(4)
liquileak_prob	9.13**			
	(4.52)			
p_1		5.64**		2.22
		(4.41)		(1.46)
p_{11}^5			4.21**	3.63**
			(5.18)	(3.77)
illiqma	1.00**	0.98**	1.01**	1.00**
	(6.68)	(6.55)	(6.70)	(6.67)
*r*100	3.39*	3.35*	3.47*	3.36*
	(1.83)	(1.82)	(1.89)	(1.82)
*r*100*yr*	1.30	1.20	1.24	1.16
	(1.12)	(1.04)	(1.08)	(1.01)
lnsize	-2.27**	-2.17**	-2.32**	-2.27**
	(-8.37)	(-7.98)	(-8.52)	(-8.33)
sdret	-4.52**	-4.37**	-4.58**	-4.58**
	(-7.80)	(-7.50)	(-7.90)	(-7.92)
divyld	0.06	0.06	0.06	0.05
	(1.00)	(1.11)	(1.01)	(0.96)
β_{MKT}	9.04**	9.15**	9.01**	9.07**
	(4.91)	(4.97)	(4.90)	(4.92)
β_{SMB}	-2.39**	-2.46**	-2.37**	-2.41**
	(-2.08)	(-2.14)	(-2.06)	(-2.10)
β_{HML}	-2.27**	-2.28**	-2.28**	-2.29**
	(-2.01)	(-2.02)	(-2.02)	(-2.02)
intercept	20.03**	18.39**	20.28**	19.66**
	(8.55)	(7.82)	(8.67)	(8.53)
#stocks*#months	1639*540			

**: Significant at a 95% level.
* : Significant at a 90% level.

Table 5*: Excess returns single-sorted portfolios, value-weighted portfolios

This table replicates Table 2.5 except that portfolios are value weighted.

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (lowest $liquileak\_prob$)	0.59	3.06**	0.40	1.47	0.77	2.84**
2	0.72	3.47**	0.52	1.82*	0.90	3.06**
3	0.81	3.76**	0.66	2.14**	0.96	3.18**
4	0.88	3.70**	0.74	2.19**	1.01	3.03**
5 (highest $liquileak\_prob$)	1.16	4.58**	0.95	2.72**	1.36	3.74**
differential ('5-1')	0.57	4.71**	0.55	3.55**	0.59	3.19**
#stocks*#months	1639*540		1605*264		1672*276	

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 6*: Excess returns double-sorted portfolios, value-weighted portfolios

This table replicates Table 2.6 except that portfolios are value weighted.

Panel A: Controlling for disaster state probability (p_1)

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (lowest *liquileak_prob*)	0.59	4.20**	0.77	3.92**	0.40	2.00**
2	0.77	5.36**	0.94	4.58**	0.60	2.96**
3	0.79	5.32**	0.94	4.56**	0.64	2.97**
4	0.87	5.48**	0.96	4.33**	0.78	3.42**
5 (highest *liquileak_prob*)	1.14	6.56**	1.31	5.47**	0.96	3.81**
differential (‘5-1’)	0.55	6.40**	0.54	4.36**	0.56	4.71**

Panel B: Controlling for disaster state continuation probability (p_{11}^5)

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (lowest *liquileak_prob*)	0.64	4.67**	0.86	4.48**	0.42	2.11**
2	0.69	4.71**	0.85	4.15**	0.52	2.49**
3	0.82	5.43**	0.98	4.56**	0.66	3.09**
4	0.96	5.88**	1.09	4.92**	0.82	3.43**
5 (highest *liquileak_prob*)	1.15	6.78**	1.33	5.59**	0.97	3.99**
differential (‘5-1’)	0.51	5.78**	0.47	3.64**	0.55	4.59**

Panel C: Controlling for average liquidity (illiq)

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (lowest *liquileak_prob*)	0.65	4.68**	0.84	4.39**	0.45	2.23**
2	0.88	5.69**	0.99	4.62**	0.78	3.44**
3	1.01	6.27**	1.09	5.00**	0.93	3.89**
4	1.22	6.97**	1.16	5.13**	1.29	4.77**
5 (highest *liquileak_prob*)	1.75	8.84**	1.59	6.64**	1.92	6.03**
differential (‘5-1’)	1.10	8.41**	0.75	4.42**	1.48	7.37**
#stocks*#months	1639*540		1605*264		1672*276	

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 2.2': Likelihood ratio test on one regime vs. two regimes

The table redoes Table 2.2 in the main text for the Pastor-Stambaugh liquidity measure instead of the Amihud measure.

1963-1985				1986-2008			
year	likelihood ratio	% stocks p-value < 0.01	% stocks p-value ≥ 0.01	year	likelihood ratio	% stocks p-value < 0.01	% stocks p-value ≥ 0.01
1963	34.34	60.77	39.23	1986	101.93	62.02	37.98
1964	68.36	65.07	34.93	1987	102.01	61.62	38.38
1965	83.17	71.39	28.61	1988	95.63	52.69	47.31
1966	88.84	72.96	27.04	1989	102.42	54.11	45.89
1967	100.80	75.15	24.85	1990	115.11	55.02	44.98
1968	94.75	79.16	20.84	1991	113.29	54.66	45.34
1969	101.84	79.51	20.49	1992	109.00	56.33	43.67
1970	115.21	75.31	24.69	1993	100.69	58.23	41.77
1971	114.51	76.65	23.35	1994	102.57	58.93	41.07
1972	107.10	75.91	24.09	1995	105.43	59.70	40.30
1973	98.77	68.24	31.76	1996	109.23	63.66	36.34
1974	89.51	61.38	38.62	1997	107.08	63.14	36.86
1975	101.05	61.85	38.15	1998	119.76	64.47	35.53
1976	84.44	60.45	39.55	1999	99.32	59.08	40.92
1977	82.63	61.44	38.56	2000	99.98	54.36	45.64
1978	127.45	71.57	28.43	2001	113.47	54.37	45.63
1979	110.95	68.76	31.24	2002	116.15	53.21	46.79
1980	116.33	69.80	30.20	2003	138.38	59.24	40.76
1981	108.39	70.06	29.94	2004	126.18	59.27	40.73
1982	126.54	68.36	31.64	2005	140.05	59.94	40.06
1983	112.93	71.15	28.85	2006	139.67	60.88	39.12
1984	111.35	66.01	33.99	2007	174.45	64.09	35.91
1985	106.90	62.78	37.22	2008	206.39	69.24	30.76
1963-1985	101.22	70.16	29.84	1986-2008	119.00	59.33	40.67
1963-2008	110.14	64.73	35.27				
#stocks*#years		1610*23		#stocks*#years		1671*23	

Table 2.3': Liquileak model estimates

This table redoes Table 2.3 in the main text for the Pastor-Stambaugh liquidity measure instead of the Amihud measure.

Panel A: Mean and variance parameter estimates

μ_0	-0.05	0.31	0.14	0.28	-15.59	6.84	-0.00
μ_1	1.21	1.88	1.36	1.30	0.00	7.18	0.32
σ_0	0.43	1.22	0.73	0.98	0.00	10.89	0.05
σ_1	0.81	1.61	1.05	1.23	0.00	12.58	0.16
ϕ	0.01	0.11	0.04	0.10	-0.46	1.00	-0.00
p_{00}	0.83	0.21	0.14	0.15	0.00	1.00	0.88
p_{11}	0.39	0.29	0.14	0.25	0.00	1.00	0.34
p_1	0.22	0.23	0.17	0.16	0.00	1.00	0.18
p_{11}^5	0.11	0.22	0.09	0.20	0.00	1.00	0.00
$liquileak\_prob$	0.04	0.11	0.05	0.09	0.00	1.00	0.00

Panel B: Between and within correlation parameter estimates

		μ_1	σ_0	σ_1	ϕ	p_{00}	p_{11}	p_1	p_{11}^5	$liquileak\_prob$
μ_0	ρ(between)	0.18*	-0.63*	-0.29*	-0.01	0.47*	-0.32*	-0.44*	-0.19*	-0.40*
	ρ(within)	0.01*	-0.47*	0.12*	-0.04*	0.37*	-0.17*	-0.33*	-0.17*	-0.34*
μ_1	ρ(between)		-0.28*	-0.30*	0.02	0.63*	-0.31*	-0.68*	-0.04	-0.45*
	ρ(within)		-0.00	0.12*	-0.01*	0.16*	0.03*	-0.19*	0.04*	-0.06*
σ_0	ρ(between)			0.59*	0.04	-0.67*	0.48*	0.66*	0.24*	0.52*
	ρ(within)			-0.07*	0.09*	-0.48*	0.24*	0.49*	0.20*	0.37*
σ_1	ρ(between)				-0.05*	-0.55*	0.33*	0.54*	0.06*	0.30*
	ρ(within)				-0.05*	0.09*	-0.10*	-0.11*	-0.12*	-0.17*
ϕ	ρ(between)					-0.09*	0.25*	0.15*	0.27*	0.26*
	ρ(within)					-0.17*	0.24*	0.33*	0.21*	0.33*
p_{00}	ρ(between)						-0.58*	-0.95*	-0.18*	-0.60*
	ρ(within)						-0.25*	-0.82*	-0.09*	-0.36*
p_{11}	ρ(between)							0.74*	0.80*	0.76*
	ρ(within)							0.56*	0.79*	0.56*
p_1	ρ(between)								0.37*	0.78*
	ρ(within)								0.41*	0.72*
p_{11}^5	ρ(between)									0.70*
	ρ(within)									0.68*
#stocks*#years: 1641*46										

[a]: Based on stock-specific averages, i.e., $\bar{x}_i = \frac{1}{Y}\sum_{y=1}^{Y} x_{i,y}$.

[b]: Based on deviations from stock-specific averages, i.e., $x_{i,y}^* = x_{i,y} - \bar{x}_i$.

*: Significant at a 95% level.

Table 2.4': Commonality in the liquidity state across stocks

This table redoes Table 2.4 in the main text for the Pastor-Stambaugh liquidity measure instead of the Amihud measure.

Panel A: Filtered probability of the illiquid state

	All years	1963-1985	1986-2008
1	9.37	8.74	9.96
2	2.92	2.76	3.08
3	1.75	1.55	1.94
4	1.28	1.22	1.34
5	1.09	1.02	1.15
sum	16.41	15.29	17.48

Panel B: Smoothed probability of the illiquid state

	All years	1963-1985	1986-2008
1	10.42	9.78	11.03
2	3.19	3.03	3.34
3	1.89	1.69	2.09
4	1.38	1.33	1.44
5	1.16	1.08	1.23
sum	18.04	16.91	19.12
#stocks*#years	1641*46	1610*23	1671*23

Table 2.5': Excess returns single-sorted portfolios

This table redoes Table 2.5 in the main text for the Pastor-Stambaugh liquidity measure instead of the Amihud measure.

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (lowest $liquileak\_prob$)	0.44	1.72*	0.55	1.61	0.32	0.85
2	0.55	2.66**	0.60	2.10**	0.49	1.66*
3	0.68	2.66**	0.64	1.93*	0.73	1.84*
4	0.77	2.80**	0.61	1.77*	0.94	2.17**
5 (highest $liquileak\_prob$)	1.01	3.19**	0.88	2.19**	1.15	2.33**
differential ('5-1')	0.58	4.49**	0.33	2.14**	0.83	4.09**
#stocks*#months	1641*540		1610*264		1671*276	

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 2.6': Excess returns double-sorted portfolios

This table redoes Table 2.6 in the main text for the Pastor-Stambaugh liquidity measure instead of the Amihud measure.

Panel A: Controlling for disaster state probability (p_1)

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (lowest *liquileak_prob*)	0.41	2.53**	0.55	2.47**	0.27	1.12
2	0.41	2.69**	0.64	3.00**	0.18	0.82
3	0.63	3.61**	0.51	2.32**	0.75	2.77**
4	0.60	3.48**	0.40	1.91*	0.81	2.93**
5 (highest *liquileak_prob*)	0.60	2.94**	0.47	1.83*	0.74	2.30**
differential ('5-1')	0.19	1.87*	-0.08	-0.64	0.47	3.00**

Panel B: Controlling for disaster state continuation probability to the power 5 (p_{11}^5)

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (lowest *liquileak_prob*)	0.48	2.63**	0.46	1.99**	0.49	1.75*
2	0.56	3.34**	0.59	2.60**	0.52	2.13**
3	0.63	3.61**	0.51	2.32**	0.75	2.77**
4	0.60	3.51**	0.41	1.95*	0.81	2.94**
5 (highest *liquileak_prob*)	0.58	2.82**	0.43	1.65*	0.74	2.30**
differential ('5-1')	0.10	1.88*	-0.04	-0.30	0.25	2.05**

Panel C: Controlling for average liquidity (psilliq)

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (lowest *liquileak_prob*)	0.40	2.32**	0.54	2.51**	0.25	0.92
2	0.51	3.05**	0.57	2.67**	0.45	1.73*
3	0.64	3.68**	0.48	2.16**	0.82	2.99**
4	0.66	3.55**	0.53	2.12**	0.79	2.89**
5 (highest *liquileak_prob*)	0.69	3.40**	0.46	1.88*	0.93	2.84**
differential ('5-1')	0.29	2.82**	-0.09	-0.66	0.69	4.27**
#stocks*#months	1641*540		1610*264		1671*276	

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 2.7': Fama-MacBeth regressions of stock returns on liquileak probability and standard control variables

This table redoes Table 2.7 in the main text for the Pastor-Stambaugh liquidity measure instead of the Amihud measure.

	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
liquileak_prob	17.69**				13.55**				22.02**			
	(3.93)				(1.98)				(3.79)			
p_1		10.60**		13.43**		6.19**		7.18**		15.22**		19.96**
		(7.54)		(8.30)		(3.14)		(3.25)		(7.73)		(8.65)
p_{11}^5			6.19**	-11.72**			4.53	-4.79			7.91**	-18.96**
			(2.63)	(-4.57)			(1.36)	(-1.38)			(2.38)	(-5.09)
psilliqma	0.02	0.02	0.03	0.02	0.03	0.02	0.03	0.02	0.02	0.01	0.02	0.01
	(1.40)	(0.98)	(1.41)	(0.96)	(1.06)	(0.87)	(1.05)	(0.88)	(0.90)	(0.50)	(0.94)	(0.47)
β_{MKT}	4.68**	5.39**	4.56**	5.57**	5.40**	6.11**	5.21**	6.22**	3.93	4.64*	3.88	4.89**
	(2.63)	(2.98)	(2.57)	(3.07)	(2.08)	(2.31)	(2.02)	(2.34)	(1.62)	(1.88)	(1.60)	(1.97)
β_{SMB}	0.45	-0.67	0.60	-0.78	-0.68	-1.38	-0.53	-1.43	1.63	0.06	1.78	-0.09
	(0.37)	(-0.57)	(0.49)	(-0.65)	(-0.35)	(-0.72)	(-0.27)	(-0.75)	(1.11)	(0.04)	(1.21)	(-0.07)
β_{HML}	-0.32	-0.50	-0.29	-0.55	-1.69	-1.76	-1.65	-1.78	1.10	0.82	1.14	0.75
	(-0.27)	(-0.42)	(-0.24)	(-0.46)	(-0.96)	(-1.01)	(-0.94)	(-1.02)	(0.68)	(0.51)	(0.70)	(0.46)
intercept	2.20**	0.59	2.28**	0.36	2.67**	1.55	2.81**	1.48	1.70	-0.41	1.73	-0.81
	(2.15)	(0.56)	(2.23)	(0.34)	(2.03)	(1.10)	(2.13)	(1.05)	(1.08)	(-0.26)	(1.10)	(-0.51)
#stocks*#months	1641*540				1610*264				1671*276			

p-value of test $H_0(\ \delta(liquileak\_prob, 1964\text{-}1985) = \delta(liquileak\_prob, 1986\text{-}2008)\ )$ is 0.35

p-value of test $H_0(\ \delta(p_1, 1964\text{-}1985) = \delta(p_1, 1986\text{-}2008)\ )$ is 0.00^{**}

p-value of test $H_0(\ \delta(p_{11}^5, 1964\text{-}1985) = \delta(p_{11}^5, 1986\text{-}2008)\ )$ is 0.47

p-value of test $H_0(\ \delta(psilliqma, 1964\text{-}1985) = \delta(psilliqma, 1986\text{-}2008)\ )$ is 0.78

**: Significant at a 95% level.

*: Significant at a 90% level.

Table 2.8': Fama-MacBeth regressions on liquileak probability and extended set of control variables

This table redoes Table 2.8 in the main text for the Pastor-Stambaugh liquidity measure instead of the Amihud measure.

	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
liquileak_prob	9.48**				0.32				12.10**			
	(1.99)				(0.11)				(2.19)			
p_1		4.45**		4.65**		1.47		1.16		8.14**		9.60**
		(3.42)		(3.15)		(0.95)		(0.74)		(4.45)		(4.47)
p_{11}^5			6.02**	-1.36			0.36	-0.04			9.21**	-5.31
			(1.96)	(-0.57)			(0.40)	(-0.04)			(2.33)	(-1.57)
psilliqma	0.01	0.01	0.01	0.00	-0.00	-0.01	-0.00	-0.01	0.02	0.02	0.02	0.02
	(0.59)	(0.27)	(0.49)	(0.24)	(-0.14)	(-0.17)	(-0.14)	(-0.17)	(1.00)	(0.81)	(0.99)	(0.79)
r100	4.53**	4.17**	4.40**	4.14**	2.30	2.09	2.22	2.07	7.18**	6.65**	7.55**	6.60**
	(2.49)	(2.31)	(2.43)	(2.29)	(0.96)	(0.87)	(0.93)	(0.86)	(2.64)	(2.45)	(2.74)	(2.43)
r100yr	2.02*	1.88	1.79	1.87	-0.73	-0.78	-0.71	-0.77	5.27**	5.21**	5.28**	5.21**
	(1.74)	(1.63)	(1.52)	(1.61)	(-0.48)	(-0.51)	(-0.47)	(-0.51)	(3.19)	(3.15)	(3.17)	(3.15)
lnsize	-2.75**	-2.44**	-2.68**	-2.44**	-2.31**	-2.18**	-2.32**	-2.19**	-3.26**	-2.67**	-3.20**	-2.60**
	(-10.93)	(-9.82)	(-10.55)	(-9.67)	(-6.49)	(-6.38)	(-6.37)	(-6.30)	(-9.28)	(-7.64)	(-9.05)	(-7.27)
sdret	-4.08**	-3.92**	-3.83**	-3.90**	-1.62**	-1.61**	-1.62**	-1.62**	-6.36**	-6.27**	-6.30**	-6.19**
	(-6.89)	(-6.58)	(-6.47)	(-6.57)	(-2.19)	(-2.15)	(-2.20)	(-2.19)	(-7.27)	(-7.20)	(-7.12)	(-7.15)
divyld	0.09	0.10*	0.15**	0.11*	-0.00	-0.00	-0.00	-0.00	0.16	0.18	0.16	0.19
	(1.50)	(1.74)	(2.24)	(1.78)	(-0.12)	(-0.07)	(-0.18)	(-0.12)	(1.32)	(1.57)	(1.37)	(1.62)
β_{MKT}	8.21**	8.36**	7.96**	8.36**	6.92**	7.04**	6.94**	7.04**	8.32**	8.72**	8.12**	8.75**
	(4.41)	(4.48)	(4.24)	(4.48)	(2.52)	(2.56)	(2.53)	(2.56)	(3.27)	(3.40)	(3.18)	(3.42)
β_{SMB}	-2.16*	-2.21*	-2.02*	-2.20*	-4.88**	-4.89**	-4.87**	-4.89**	0.16	0.09	0.30	0.07
	(-1.87)	(-1.93)	(-1.75)	(-1.92)	(-2.67)	(-2.68)	(-2.66)	(-2.67)	(0.12)	(0.07)	(0.22)	(0.06)
β_{HML}	-1.98*	-2.01*	-1.88*	-2.01*	-2.59	-2.62	-2.60	-2.62	-1.24	-1.31	-1.18	-1.32
	(-1.76)	(-1.79)	(-1.67)	(-1.79)	(-1.62)	(-1.63)	(-1.62)	(-1.63)	(-0.80)	(-0.84)	(-0.75)	(-0.85)
intercept	23.51**	20.79**	22.54**	20.81**	21.15**	19.89**	21.22**	20.14**	27.12**	22.30**	26.69**	21.69**
	(10.25)	(9.22)	(9.79)	(9.14)	(6.71)	(6.52)	(6.70)	(6.63)	(8.13)	(6.81)	(7.95)	(6.57)
#stocks*#months	1641*540				1610*264				1671*276			

p-value of test $H_0(\ \delta(liquileak\_prob, 1964\text{-}1985) = \delta(liquileak\_prob, 1986\text{-}2008)\ )$ is 0.06*

p-value of test $H_0(\ \delta(p_1, 1964\text{-}1985) = \delta(p_1, 1986\text{-}2008)\ )$ is 0.01**

p-value of test $H_0(\ \delta(p_{11}^5, 1964\text{-}1985) = \delta(p_{11}^5, 1986\text{-}2008)\ )$ is 0.03**

p-value of test $H_0(\ \delta(psilliqma, 1964\text{-}1985) = \delta(psilliqma, 1986\text{-}2008)\ )$ is 0.32

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 2.9’: Which are the high-liquileak stocks?

This table redoes Table 2.9 in the main text for the Pastor-Stambaugh liquidity measure instead of the Amihud measure.

	OLS	between-OLS	within-OLS
prc	-0.22**	-0.35**	-0.04**
	(-3.97)	(-2.81)	(-2.46)
svol	-5.16**	-9.82	-1.24*
	(-2.89)	(-1.57)	(-1.95)
sdsvol	-0.93	-3.92	-0.10
	(-0.34)	(-0.56)	(-0.10)
sdret	26.70**	30.39**	20.14**
	(28.64)	(16.39)	(17.17)
mcap	0.04	0.12	0.02
	(0.50)	(0.40)	(0.94)
btm	-0.40	0.09	-0.45
	(-0.98)	(0.16)	(-1.05)
roa	-17.88**	15.28	-46.73**
	(-2.51)	(1.40)	(-4.90)
growth_asset	-0.03**	-0.25**	0.05
	(-2.28)	(-2.89)	(1.49)
leverage	0.01	0.05	0.02
	(0.18)	(0.94)	(0.61)
intercept	-12.40**	-10.98*	
	(-3.91)	(-1.68)	
#stocks*#years	1641*46		

**: Significant at a 95% level.
* : Significant at a 90% level.

Table 2.10': Raw data proxies for liquileak probability

This table redoes Table 2.10 in the main text for the Pastor-Stambaugh liquidity measure instead of the Amihud measure.

Panel A: Mean and variance raw data proxies for liquileak probability

	Mean	St.Dev.	St.Dev. Between[a]	St.Dev. Within[b]	Min	Max	Median
$freq\_psilliq$	0.14	0.15	0.13	0.08	0.00	0.71	0.07
$duration\_psilliq$	0.99	0.61	0.51	0.34	0.00	3.23	1.10
$freq\_psilliq \times duration\_psilliq$	0.21	0.27	0.23	0.14	0.00	2.29	0.08

Panel B: Between and within correlation raw data proxies for liquileak probability

		$duration\_psilliq$	$freq\_psilliq \times duration\_psilliq$	p_1	p_{11}^5	$liquileak\_prob$	$psilliq$
$freq\_psilliq$	ρ(between)	0.89*	0.99*	0.88*	0.28*	0.61*	-0.00
	ρ(within)	0.56*	0.96*	0.46*	0.09*	0.17*	0.06*
$duration\_psilliq$	ρ(between)		0.84*	0.87*	0.17*	0.59*	-0.01
	ρ(within)		0.55*	0.35*	0.03*	0.13*	0.04*
$freq\_psilliq \times duration\_psilliq$	ρ(between)			0.83*	0.28*	0.57*	0.01
	ρ(within)			0.37*	0.08*	0.14*	0.09*
p_1	ρ(between)				0.37*	0.78*	-0.02
	ρ(within)				0.41*	0.72*	0.01*
p_{11}^5	ρ(between)					0.70*	-0.02
	ρ(within)					0.68*	0.00
$liquileak\_prob$	ρ(between)						-0.03
	ρ(within)						0.00
#stocks*#years: 1641*46							

[a]: Based on the time means i.e. $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$.
[b]: Based on the deviations from time means i.e. $x_{i,t}^* = x_{i,t} - \bar{x}_i$.
*: Significant at a 95% level.

Table 2.11': Fama-MacBeth regressions of stock returns on raw data proxies for liquileak probability and standard control variables

This table redoes Table 2.11 in the main text for the Pastor-Stambaugh liquidity measure instead of the Amihud measure.

	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$freq\_psilliq \times duration\_psilliq$	16.63**				10.81**				22.71**			
	(10.77)				(5.69)				(9.46)			
$freq\_psilliq$		27.60**		22.38**		18.95**		13.30**		36.65**		31.88**
		(10.65)		(8.01)		(5.64)		(3.47)		(9.40)		(7.96)
$duration\_psilliq$			5.16**	1.76**			4.14**	1.89**			6.23**	1.62**
			(10.21)	(3.82)			(5.78)	(2.62)			(8.79)	(2.86)
$psilliqma$	0.01	0.01	0.02	0.01	-0.01	-0.00	0.01	-0.00	0.02	0.02	0.03	0.02
	(0.50)	(0.53)	(1.09)	(0.49)	(-0.20)	(-0.06)	(0.27)	(-0.07)	(0.93)	(0.81)	(1.24)	(0.78)
β_{MKT}	5.56**	5.73**	5.71**	5.93**	6.47**	6.63**	6.60**	6.94**	4.60*	4.79*	4.78*	4.88**
	(2.96)	(3.06)	(3.09)	(3.17)	(2.28)	(2.35)	(2.40)	(2.47)	(1.89)	(1.95)	(1.95)	(1.99)
β_{SMB}	-1.90	-2.14*	-2.28*	-2.59**	-2.91	-3.17*	-3.62*	-3.66*	-0.84	-1.07	-0.87	-1.46
	(-1.64)	(-1.85)	(-1.89)	(-2.17)	(-1.59)	(-1.73)	(-1.89)	(-1.92)	(-0.60)	(-0.77)	(-0.61)	(-1.04)
β_{HML}	-0.72	-0.77	-0.72	-0.81	-1.79	-1.82	-1.85	-1.86	0.40	0.34	0.47	0.28
	(-0.60)	(-0.64)	(-0.60)	(-0.69)	(-1.01)	(-1.03)	(-1.06)	(-1.06)	(0.25)	(0.21)	(0.30)	(0.18)
$intercept$	0.07	-0.37	-1.94*	-1.27	0.45	0.15	-0.88	-0.81	-0.33	-0.91	-3.04*	-1.75
	(0.06)	(-0.34)	(-1.75)	(-1.17)	(0.31)	(0.10)	(-0.61)	(-0.57)	(-0.20)	(-0.56)	(-1.79)	(-1.06)
#stocks*#months	1641*540				1610*264				1671*276			

p-value of test $H_0(\ \delta(freq\_psilliq \times duration\_psilliq, 1964\text{-}1985) = \delta(freq\_psilliq \times duration\_psilliq, 1986\text{-}2008)\ )$ is 0.00^{**}

p-value of test $H_0(\ \delta(freq\_psilliq, 1964\text{-}1985) = \delta(freq\_psilliq, 1986\text{-}2008)\ )$ is 0.00^{**}

p-value of test $H_0(\ \delta(duration\_psilliq, 1964\text{-}1985) = \delta(duration\_psilliq, 1986\text{-}2008)\ )$ is 0.04^{**}

p-value of test $H_0(\ \delta(psilliqma, 1964\text{-}1985) = \delta(psilliqma, 1986\text{-}2008)\ )$ is 0.58

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 2.12': Fama-MacBeth regressions of stock returns on raw data proxies for liquileak probability and extended set of control variables

This table redoes Table 2.12 in the main text for the Pastor-Stambaugh liquidity measure instead of the Amihud measure.

	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$freq\_psilliq \times duration\_psilliq$	16.33**				8.19**				24.85**			
	(10.30)				(4.43)				(9.93)			
$freq\_psilliq$		26.79**		25.13**		13.56**		10.99**		40.63**		38.96**
		(9.83)		(8.86)		(4.16)		(3.13)		(9.54)		(9.11)
$duration\_psilliq$			3.00**	1.29**			2.10**	1.35**			3.94**	1.48**
			(6.68)	(2.80)			(3.32)	(2.05)			(6.23)	(2.48)
$psilliqma$	0.02	0.02	0.02	0.02	-0.00	0.00	0.01	-0.01	0.04	0.03	0.04	0.03
	(0.66)	(0.66)	(1.04)	(0.71)	(-0.14)	(0.00)	(0.36)	(-0.42)	(1.17)	(1.00)	(1.15)	(1.04)
$r100$	2.37	2.33	3.01*	2.05	1.11	1.16	1.60	0.99	3.69	3.56	4.49*	3.20
	(1.42)	(1.40)	(1.82)	(1.24)	(0.50)	(0.52)	(0.72)	(0.41)	(1.48)	(1.42)	(1.82)	(1.28)
$r100yr$	0.69	0.68	0.67	0.57	-1.72	-1.74	-1.70	-1.09	3.21**	3.21**	3.14**	3.09**
	(0.69)	(0.68)	(0.67)	(0.57)	(-1.28)	(-1.30)	(-1.27)	(-0.72)	(2.20)	(2.20)	(2.18)	(2.13)
$lnsize$	-1.65**	-1.50**	-2.31**	-1.22**	-1.22**	-1.19**	-1.44**	-1.10**	-2.11**	-1.84**	-3.22**	-1.52**
	(-6.73)	(-6.00)	(-8.68)	(-4.61)	(-3.60)	(-3.47)	(-4.01)	(-3.27)	(-5.94)	(-4.99)	(-8.32)	(-3.83)
$sdret$	-4.90**	-4.74**	-4.47**	-4.69**	-2.27**	-2.20**	-2.10**	-1.51**	-7.64**	-7.39**	-6.96**	-7.34**
	(-9.17)	(-8.93)	(-8.53)	(-8.88)	(-3.24)	(-3.14)	(-3.01)	(-2.03)	(-9.85)	(-9.60)	(-9.16)	(-9.58)
$divyld$	0.14**	0.14**	0.12**	0.14**	-0.01	-0.00	-0.00	0.01	0.28**	0.29**	0.26**	0.29**
	(2.53)	(2.55)	(2.30)	(2.64)	(-0.25)	(-0.21)	(-0.10)	(0.35)	(2.64)	(2.66)	(2.38)	(2.72)
β_{MKT}	9.41**	9.48**	8.98**	9.54**	8.12**	8.15**	7.97**	7.26**	10.76**	10.86**	10.03**	10.98**
	(5.13)	(5.16)	(4.92)	(5.20)	(3.00)	(3.02)	(2.98)	(2.63)	(4.36)	(4.38)	(4.06)	(4.43)
β_{SMB}	-2.19*	-2.27**	-2.53**	-2.35**	-3.69**	-3.80**	-4.10**	-4.89**	-0.62	-0.66	-0.88	-0.75
	(-1.90)	(-1.97)	(-2.19)	(-2.03)	(-1.99)	(-2.06)	(-2.21)	(-2.67)	(-0.46)	(-0.49)	(-0.66)	(-0.55)
β_{HML}	-2.59**	-2.59**	-2.42**	-2.59**	-2.86*	-2.86*	-2.81*	-2.64	-2.31	-2.30	-2.01	-2.35
	(-2.33)	(-2.33)	(-2.18)	(-2.33)	(-1.76)	(-1.76)	(-1.73)	(-1.64)	(-1.53)	(-1.52)	(-1.33)	(-1.55)
$intercept$	15.46**	13.90**	18.40**	11.13**	12.12**	11.56**	12.90**	10.16**	18.94**	16.36**	24.15**	13.35**
	(6.56)	(5.79)	(7.76)	(4.49)	(3.78)	(3.59)	(4.18)	(3.29)	(5.48)	(4.57)	(6.72)	(3.52)
#stocks*#months	1641*540				1610*264				1671*276			

p-value of test $H_0(\delta(freq\_psilliq \times duration\_psilliq, 1964\text{-}1985) = \delta(freq\_psilliq \times duration\_psilliq, 1986\text{-}2008))$ is 0.00**

p-value of test $H_0(\delta(freq\_psilliq, 1964\text{-}1985) = \delta(freq\_psilliq, 1986\text{-}2008))$ is 0.00**

p-value of test $H_0(\delta(duration\_psilliq, 1964\text{-}1985) = \delta(duration\_psilliq, 1986\text{-}2008))$ is 0.04**

p-value of test $H_0(\delta(psilliqma, 1964\text{-}1985) = \delta(psilliqma, 1986\text{-}2008))$ is 0.24

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 2.13': Fama-MacBeth regressions, excluding January effects

This table redoes Table 2.13 in the main text for the Pastor-Stambaugh liquidity measure instead of the Amihud measure.

Panel A: liquileak_prob

	(1)	(2)	(3)	(4)
liquileak_prob	30.52**			
	(2.69)			
p_1		3.73**		4.17**
		(2.77)		(2.70)
p_{11}^5			5.89*	-2.45
			(1.90)	(-1.01)
psilliqma	-0.01	-0.01	0.01	-0.01
	(-0.24)	(-0.34)	(0.52)	(-0.37)
r100	9.30**	8.64**	4.34**	8.60**
	(5.50)	(5.18)	(2.40)	(5.14)
r100yr	2.52**	2.39**	1.81	2.38**
	(2.07)	(2.03)	(1.54)	(2.02)
lnsize	-2.26**	-2.13**	-2.67**	-2.12**
	(-9.02)	(-8.70)	(-10.55)	(-8.44)
sdret	-3.94**	-3.93**	-3.83**	-3.90**
	(-6.53)	(-6.55)	(-6.47)	(-6.52)
divyld	0.08	0.03	0.15**	0.04
	(1.23)	(0.54)	(2.23)	(0.58)
β_{MKT}	6.04**	6.45**	7.95**	6.45**
	(3.15)	(3.39)	(4.24)	(3.38)
β_{SMB}	-2.91**	-3.07**	-2.04*	-3.07**
	(-2.45)	(-2.61)	(-1.78)	(-2.60)
β_{HML}	-2.45**	-2.58**	-1.87*	-2.57**
	(-2.17)	(-2.27)	(-1.66)	(-2.26)
intercept	21.27**	20.13**	22.56**	20.04**
	(8.96)	(8.77)	(9.80)	(8.59)

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Panel B: raw data proxy for liquileak probability: $freq\_illiq \times duration\_illiq$				
	(1)	(2)	(3)	(4)
$freq\_psilliq \times duration\_psilliq$	12.75**			
	(8.36)			
$freq\_psilliq$		21.21**		18.76**
		(8.04)		(6.83)
$duration\_psilliq$			3.05**	1.83**
			(6.57)	(3.84)
$psilliqma$	0.01	0.01	0.02	0.01
	(0.61)	(0.56)	(0.82)	(0.60)
$r100$	6.85**	6.78**	7.10**	6.41**
	(4.55)	(4.51)	(4.70)	(4.27)
$r100yr$	1.57	1.55	1.47	1.40
	(1.57)	(1.55)	(1.47)	(1.40)
$lnsize$	-1.53**	-1.38**	-1.79**	-0.98**
	(-6.22)	(-5.47)	(-6.97)	(-3.70)
$sdret$	-5.02**	-4.91**	-4.69**	-4.85**
	(-9.29)	(-9.12)	(-8.82)	(-9.04)
$divyld$	0.08	0.08	0.07	0.08
	(1.42)	(1.44)	(1.26)	(1.54)
β_{MKT}	7.34**	7.41**	7.14**	7.52**
	(3.90)	(3.94)	(3.83)	(4.00)
β_{SMB}	-2.98**	-3.03**	-3.29**	-3.17**
	(-2.53)	(-2.58)	(-2.77)	(-2.67)
β_{HML}	-3.13**	-3.13**	-3.03**	-3.14**
	(-2.76)	(-2.76)	(-2.68)	(-2.77)
$intercept$	16.54**	15.02**	16.45**	11.08**
	(6.87)	(6.11)	(6.80)	(4.36)
#stocks*#months	1641*495			

**: Significant at a 95% level.

* : Significant at a 90% level.

Appendix: How Do Designated Market Makers Create Value for Small-Caps?

This Appendix of Chapter 4 “How Do Designated Market Makers Create Value for Small-Caps” contains the following supplementary material:

(i) Table 4.10 extends Table 4.3 in the main text by including an additional dummy variable ($MuiltiDMM$) to examine whether there is an additional effect of multiple DMMs on liquidity level over the DMMs-or-not binary variable.

(ii) Table 4.11 runs cross-sectional regressions to examine whether there is an additional effect of multiple DMMs on price discovery, abnormal returns, and DMM trading activities.

(iii) Table 4.12 examines post-event DMM passive trades on days with price downturns and upturns.

(iv) Table 4.3’ replicates Table 4.3 in the main text but does the liquidity level diff-in-diff at the (aggregate) industry level as opposed to the stock level.

(v) Table 4.5’ uses the estimation results of Table 4.5 in the main text to conduct a diff-in-diff analysis for liquidity risk at the industry level.

(vi) Table 4.7’ replicates Table 4.7 in the main text except that changes in all three liquidity risk betas are included.

(vii) Tables 4.3*, 4.5*, 4.7*, 4.9* replicate the analysis of Tables 4.3, 4.5, 4.7, 4.9 in the main text respectively, except that the September 2001 month is removed from the data.

Table 4.10: Multiple DMMs and post-event change in liquidity level and nonliquidity variables

This table presents the effect of multiple DMMs on liquidity level and some nonliquidity variables. It extends Table 4.3 by adding an additional independent variable, $post_t * MultiDMM_i$, where $MultiDMM_i$ is a dummy for stocks that have more than one DMM.

	Liquidity variables										Nonliquidity variables		
	espread		*qspread*		*ILLIQ*		*rspread*		*adv_selection*		*volume*	*volatility*	*ret_autocorr*
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(1)	(1)
$post * MultiDMM$	0.01	-0.02	0.29	0.25	0.36	0.44	0.06	0.07	-0.04	-0.09	12.93	0.21	-0.02
	(0.09)	(-0.15)	(1.18)	(1.08)	(0.17)	(0.22)	(0.41)	(0.50)	(-0.43)	(-0.99)	(1.44)	(1.39)	(-0.50)
$post * DMM$	-1.51**	-1.46**	-1.54**	-1.45**	-5.19	-5.49	-1.56**	-1.59**	0.04	0.13	-5.81	-0.16	0.08**
	(-3.34)	(-3.53)	(-3.11)	(-3.28)	(-0.87)	(-0.86)	(-3.65)	(-3.74)	(0.14)	(0.45)	(-0.62)	(-0.65)	(2.60)
$post$	1.37**	1.37**	0.81**	0.80**	5.18	5.21	1.28**	1.33**	0.09	0.04	-0.77	-0.32*	-0.05**
	(3.35)	(3.70)	(1.99)	(2.21)	(0.96)	(0.90)	(3.18)	(3.33)	(0.32)	(0.16)	(-0.15)	(-1.65)	(-3.31)
$price$		-0.01		-0.01*		0.01		0.01		-0.02**			
		(-1.17)		(-1.84)		(0.22)		(0.96)		(-3.83)			
$volume$		-0.00**		-0.00**		0.01		-0.00		-0.00**			
		(-2.62)		(-3.67)		(0.97)		(-0.31)		(-2.32)			
$volatility$		0.15**		0.24**		-0.67		0.03		0.12**			
		(9.00)		(5.27)		(-1.51)		(0.95)		(6.13)			
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	277	277	280	280	244	244	277	277	277	277	280	280	280

**: Significant at a 95% level.
* : Significant at a 90% level.

Table 4.11: Multiple DMMs and post-event change in price discovery, abnormal returns and DMM trading activities

This table presents the effect of multiple DMMs on price discovery, abnormal returns and DMM trading activities. We estimate the following cross-sectional regression:

$$y_i = \alpha + \beta_0 MultiDMM_i + \beta_1 DMM_i + \beta_2' \Delta control\_vars_i + \varepsilon_i$$

where i indexes stocks, $MultiDMM_i$ is a dummy for stocks that have more than one DMM, DMM_i is a dummy for DMM stocks, and $control\_vars_i$ is a vector of control variables, including changes in price, volume and volatility. For the measures of price discovery (σ_w, σ_ε and $\frac{\sigma_\varepsilon}{1-\phi^2}$), y_i is their changes calculated as the post-event average minus the pre-event average. For abnormal returns, we take the three week cumulative abnormal return (CAR) as the dependent variable y_i. Regarding to DMM trading activities, we calculate the average of DMM participation rate, GTR per share, ITR per share and RTR per share, and set them as the dependent variable (note: these observations are only available for DMM stocks in the post-event period). We add t-values in parentheses.

	$\Delta\sigma_w$	$\Delta\sigma_\varepsilon$	$\Delta\frac{\sigma_\varepsilon}{1-\phi^2}$	*CAR*	*DMM_particip_rate*	*DMM_GTR_pershare*	*DMM_ITR_pershare*	*DMM_RTR_pershare*
MultiDMM	0.56	-0.13	0.04	-1.08	5.46	-6.86	-7.73	0.86*
	(0.67)	(-0.19)	(0.04)	(-0.21)	(0.67)	(-0.05)	(-0.05)	(1.74)
DMM	-1.97**	-0.32	-0.87	3.94	19.41**	-0.97	-2.03	1.00**
	(-2.23)	(-0.45)	(-0.94)	(0.73)	(2.40)	(-0.01)	(-0.01)	(2.05)
$\Delta price$	-0.01	0.01	0.01	-0.22**	0.02	4.27	4.26	0.01
	(-0.64)	(0.67)	(0.68)	(-1.96)	(0.08)	(0.89)	(0.89)	(0.33)
$\Delta volume$	0.02**	-0.00	-0.00	-0.06	-0.02	2.21	2.22	-0.00
	(2.41)	(-0.04)	(-0.12)	(-1.20)	(-0.18)	(1.32)	(1.32)	(-0.49)
$\Delta volatility$	-0.89**	0.96**	1.20**	-2.55	-6.45	161.46*	160.93*	0.46
	(-3.40)	(4.63)	(4.42)	(-1.59)	(-1.28)	(1.95)	(1.95)	(1.50)
intercept	2.55**	0.24	0.48	-1.29				
	(6.76)	(0.79)	(1.22)	(-0.56)				
#Observations	101	101	101	101	74	74	74	74

**: Significant at a 95% level.

*: Significant at a 90% level.

Table 4.12: Post-event DMM passive trades in price downturns and upturns

This table presents an analysis on whether DMMs are suppliers of last resort in the sense that they are passive buyer (seller) on days with price downturns (upturns). For each stock, we calculate the daily open-to-close return in the post-event period. We then label days with a negative (positive) open-to-close return as "price downturn days" ("price upturn days"). We define DMM as a passive buyer if he/she is on the buy side of a seller-initiated trade. Correspondingly, DMM is defined as a passive seller if he/she is on the sell side of a buyer-initiated trade. DMM passive buying and selling are measured by the number of trades, trading volume in shares and trading volume in euros, denoted as *_trades*, *_shares*, and *_trans* respectively. We use the following panel data regression to test for differences across return regimes:

$$y_{it} = \alpha_i + \beta_{down} price\_downturn_{it} + \beta_{up} price\_upturn_{it} + \varepsilon_{it}$$

where $price\_downturn_{it}$ is a dummy for the negative return days and $price\_upturn_{it}$ is a dummy for the positive return days. We add t-values in parentheses, where the standard errors are corrected for both firm and time clustering.

	Price downturn (1)	Price upturn (2)	Difference (2)-(1)	#Observations
DMM_passive_buy_trades	4.71	3.61	-1.09 **	8,762
	(104.20)	(46.34)	(-8.91)	
DMM_passive_buy_shares	3.57	2.34	-1.23 **	8,762
	(83.52)	(29.33)	(-10.01)	
DMM_passive_buy_trans	53.21	35.50	-17.71 **	8,762
	(95.07)	(32.83)	(-10.55)	
DMM_passive_sell_trades	4.05	5.70	1.65 **	8,459
	(64.06)	(106.65)	(13.15)	
DMM_passive_sell_shares	2.44	4.29	1.85 **	8,459
	(34.75)	(75.05)	(14.15)	
DMM_passive_sell_trans	36.28	70.99	34.70 **	8,459
	(22.63)	(50.07)	(11.30)	

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 4.3': Designated market makers and post-event change in liquidity level and nonliquidity variables

This table replicates Table 4.3 except that the analysis is conducted on the industry level. We use the Standard Industrial Classification Historical (SICH) from the Compustat Global database of Wharton Research Data Services (WRDS). In total we identify 7 industries that contain both DMM and nonDMM stocks. We calculate the industry average of our liquidity and nonliquidity variables and conduct the difference-in-difference analysis using the 14*20 industry-month panel dataset.

	Liquidity variables										Nonliquidity variables		
	espread		*qspread*		*ILLIQ*		*rspread*		*adv_selection*		*volume*	*volatility*	*ret_autocorr*
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(1)	(1)
$post * DMM$	-1.88**	-1.58**	-2.06**	-1.66**	-3.61**	-2.62	-1.15	-1.26	-0.74	-0.32	13.21	-0.62*	0.04
	(-2.86)	(-2.41)	(-3.10)	(-2.72)	(-1.99)	(-1.30)	(-1.51)	(-1.62)	(-1.43)	(-0.67)	(0.96)	(-1.81)	(1.29)
post	1.72**	1.78**	1.50**	1.60**	3.23**	2.80**	0.88	1.19	0.84*	0.59	-11.32	0.16	-0.02
	(2.72)	(2.97)	(2.47)	(3.03)	(2.38)	(2.14)	(1.20)	(1.53)	(1.66)	(1.26)	(-0.94)	(0.66)	(-1.13)
price		-0.00		-0.00		-0.00		0.01*		-0.01**			
		(-0.53)		(-0.62)		(-0.37)		(1.79)		(-4.76)			
volume		-0.00		-0.01		-0.01		-0.00		-0.00			
		(-0.69)		(-0.81)		(-0.77)		(-0.17)		(-1.11)			
volatility		0.54**		0.71**		0.74		0.33*		0.21**			
		(2.80)		(3.35)		(0.76)		(1.80)		(2.59)			
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	277	277	280	280	244	244	277	277	277	277	280	280	280

**: Significant at a 95% level.
* : Significant at a 90% level.

Table 4.5': Designated market makers and post-event change in liquidity risk

This table presents the effect of DMMs on Acharya and Pedersen (2005) liquidity risk betas on the industry level. We use the Standard Industrial Classification Historical (SICH) from the Compustat Global database of Wharton Research Data Services (WRDS). In total we identify 7 industries that contain both DMM and nonDMM stocks. We use the estimation results of individual stock beta and liquidity risk betas in the pre- and post-event period as presented in Table 4.5. Then we calculate the industry average of these betas and conduct the following cross-sectional regression:

$$y_i = \alpha + \beta_1 post_i * DMM_i + \beta_2 post_i + \varepsilon_i$$

where i indexes industries, *post* is a dummy for the post-event period, and *DMM* is a dummy for DMM industries. We add t-values in parentheses.

	β^{rr} $(\times 10^{-2})$	β^{cc} $(\times 10^{-4})$	β^{rc} $(\times 10^{-4})$	β^{cr} $(\times 10^{-4})$
Panel A: Effective spread as the liquidity measure				
$post * DMM$	21.05	-0.01	0.89	1.76
	(1.53)	(-0.87)	(1.03)	(0.12)
post	16.68	0.02*	-0.92	1.00
	(1.40)	(1.90)	(-1.23)	(0.08)
intercept	37.74**	0.01**	0.14	10.92
	(5.49)	(2.29)	(0.34)	(1.49)
#Observations	28	28	28	28
Panel B: Quoted spread as the liquidity measure				
$post * DMM$	21.05	-0.02**	-0.12	-3.18
	(1.53)	(-2.49)	(-0.49)	(-0.35)
post	16.68	0.03**	0.22	13.74*
	(1.40)	(4.64)	(1.00)	(1.73)
intercept	37.74**	0.01**	0.45**	5.55
	(5.49)	(3.68)	(3.59)	(1.21)
#Observations	28	28	28	28

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 4.7': Determinants of cross-sectional dispersion in cumulative abnormal returns

This table replicates Table 4.7 except that changes in all three liquidity risk betas are included.

Panel A: Effective spread as the liquidity measure				
	(1)	(2)	(3)	(4)
$\Delta rspread^a$	-2.80 **		-1.75 *	-2.09 **
	(-3.43)		(-1.88)	(-2.07)
$\Delta adv\_selection^a$	0.62		1.56	1.43
	(0.55)		(1.28)	(1.16)
$\Delta\beta^{cc}(\times 10^4)$		-65.63**	-53.96*	-53.56*
		(-2.42)	(-1.86)	(-1.85)
$\Delta\beta^{rc}(\times 10^4)$		-0.58	-0.30	-0.40
		(-1.33)	(-0.68)	(-0.88)
$\Delta\beta^{cr}(\times 10^4)$		-0.03	-0.03	-0.04
		(-1.20)	(-1.20)	(-1.37)
IMR				7.34
				(0.87)
intercept	2.76 **	2.52 **	2.57 **	-0.04
	(2.60)	(2.12)	(2.18)	(-0.01)
R^2	0.12	0.10	0.17	0.18
#Observations	101	101	101	98
Panel B: Quoted spread as the liquidity measure				
	(1)	(2)	(3)	(4)
$\Delta qspread$	-2.02 **		-2.32 **	-2.11 **
	(-2.40)		(-2.42)	(-2.08)
$\Delta\beta^{cc}(\times 10^4)$		46.11	85.18	79.77
		(0.80)	(1.46)	(1.35)
$\Delta\beta^{rc}(\times 10^4)$		1.81	1.95	2.40
		(0.95)	(1.05)	(1.21)
$\Delta\beta^{cr}(\times 10^4)$		-0.07	-0.04	-0.03
		(-1.36)	(-0.78)	(-0.66)
IMR				-5.68
				(-0.69)
intercept	2.06 *	2.35 *	2.01	4.04
	(1.91)	(1.80)	(1.57)	(1.26)
R^2	0.05	0.03	0.08	0.09
#Observations	101	101	101	98

**: Significant at a 95% level.

* : Significant at a 90% level.

[a] : We prefer to use the two components of effective spread rather effective spread itself to trace down which component drives CARs. If, however, we include effective spread instead, we find its coefficient to be significantly negative in all models.

Table 4.3*: Designated market makers and post-event change in liquidity level and nonliquidity variables

This table replicates Table 4.3 except that the month 'September 2001' is excluded.

	Liquidity variables										Nonliquidity variables		
	espread		*qspread*		*ILLIQ*		*rspread*		*adv_selection*		*volume*	*volatility*	*ret_autocorr*
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(1)	(1)
post ∗ DMM	-1.60**	-1.56**	-1.41**	-1.34**	-5.00	-5.25	-1.57**	-1.59**	-0.03	0.03	5.19	-0.01	0.06**
	(-3.73)	(-3.91)	(-3.28)	(-3.46)	(-0.83)	(-0.82)	(-3.84)	(-3.96)	(-0.10)	(0.12)	(0.88)	(-0.05)	(3.08)
post	1.50**	1.46**	1.01**	0.93**	5.55	5.69	1.38**	1.44**	0.13	0.03	0.78	-0.14	-0.04**
	(3.65)	(3.95)	(2.51)	(2.63)	(0.99)	(0.93)	(3.48)	(3.69)	(0.47)	(0.11)	(0.16)	(-0.68)	(-2.70)
price		-0.01		-0.02*		0.01		0.01		-0.02**			
		(-1.12)		(-1.87)		(0.25)		(1.05)		(-4.47)			
volume		-0.00**		-0.00**		0.01		-0.00		-0.00**			
		(-2.26)		(-2.76)		(1.32)		(-0.26)		(-2.28)			
volatility		0.15**		0.23**		-0.72		0.04		0.11**			
		(7.95)		(4.28)		(-1.52)		(1.05)		(6.43)			
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	1,904	1,904	1,919	1,919	1,805	1,805	1,904	1,904	1,904	1,904	1,919	1,919	1,919

**: Significant at a 95% level.
*: Significant at a 90% level.

Table 4.5*: Designated market makers and post-event change in liquidity risk

This table replicates Table 4.5 except that the month ‘September 2001’ is excluded.

	DMM stocks				nonDMM stocks				DMM stocks - nonDMM stocks		
	β^{rr} ($\times 10^{-2}$)	β^{cc} ($\times 10^{-4}$)	β^{rc} ($\times 10^{-4}$)	β^{cr} ($\times 10^{-4}$)	β^{rr} ($\times 10^{-2}$)	β^{cc} ($\times 10^{-4}$)	β^{rc} ($\times 10^{-4}$)	β^{cr} ($\times 10^{-4}$)	β^{cc} ($\times 10^{-4}$)	β^{rc} ($\times 10^{-4}$)	β^{cr} ($\times 10^{-4}$)
Panel A: Effective spread as the liquidity measure											
pre-event	37.12**	0.02**	-0.35*	-9.77**	83.77**	0.01**	-1.37**	3.68	0.02**	1.02**	-13.46**
	(24.32)	(4.93)	(-1.66)	(-2.62)	(90.73)	(2.80)	(-10.70)	(1.60)	(2.74)	(4.11)	(-3.07)
post-event	27.03**	0.01**	0.56**	3.32	39.31**	0.03**	0.36**	22.28**	-0.02**	0.21**	-18.96**
	(31.17)	(14.66)	(19.27)	(1.57)	(75.09)	(62.32)	(20.21)	(16.41)	(-21.07)	(6.06)	(-7.54)
post-event − pre-event	-10.09**	-0.01**	0.92**	13.09**	-44.47**	0.02**	1.73**	18.60**	-0.03**	-0.81**	-5.51
	(-5.75)	(-2.84)	(4.28)	(3.05)	(-41.89)	(6.19)	(13.36)	(6.95)	(-5.67)	(-3.24)	(-1.09)
#Observations	38,000										
Panel B: Quoted spread as the liquidity measure											
pre-event	37.12**	0.01**	0.16**	-2.34	83.77**	0.01**	0.26**	-0.89	-0.00	-0.09	-1.45
	(24.32)	(8.42)	(2.35)	(-0.93)	(90.73)	(14.22)	(6.12)	(-0.59)	(-0.09)	(-1.16)	(-0.49)
post-event	27.03**	0.01**	0.64**	3.56**	39.30**	0.04**	0.41**	21.61**	-0.02**	0.23**	-18.05**
	(31.17)	(25.39)	(18.48)	(2.51)	(75.09)	(108.69)	(19.82)	(24.83)	(-35.03)	(5.58)	(-10.84)
post-event − pre-event	-10.09**	0.00**	0.48**	5.90**	-44.47**	0.03**	0.16**	22.50**	-0.02**	0.32**	-16.60**
	(-5.75)	(3.75)	(6.17)	(2.04)	(-41.90)	(36.40)	(3.37)	(12.90)	(-15.57)	(3.53)	(-4.92)
#Observations	39,114										

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 4.7*: Determinants of cross-sectional dispersion in cumulative abnormal returns

This table replicates Table 4.7 except that the month 'September 2001' is excluded when we calculate the liquidity level and liquidity risk changes.

Panel A: Effective spread as the liquidity measure				
	(1)	(2)	(3)	(4)
$\Delta rspread^a$	-2.88 **		-2.61 **	-2.73 **
	(-3.46)		(-2.96)	(-2.71)
$\Delta adv\_selection^a$	1.06		1.46	1.40
	(0.81)		(1.06)	(1.00)
$\Delta\beta^{cc}(\times 10^4)$		-29.99**	-19.82**	-19.75**
		(-2.59)	(-2.01)	(-2.00)
IMR				2.02
				(0.25)
intercept	2.92 **	2.17 *	2.71 **	1.97
	(2.72)	(1.96)	(2.45)	(0.62)
R^2	0.12	0.03	0.13	0.13
#Observations	98	98	98	98
Panel B: Quoted spread as the liquidity measure				
	(1)	(2)	(3)	(4)
$\Delta qspread$	-1.99 **		-1.46	-1.46
	(-2.53)		(-1.59)	(-1.55)
$\Delta\beta^{cc}(\times 10^4)$		-88.61**	-52.34	-52.72
		(-2.24)	(-1.15)	(-1.09)
IMR				0.20
				(0.02)
intercept	2.42 **	3.24 **	2.94 **	2.86
	(2.26)	(2.78)	(2.51)	(0.88)
R^2	0.06	0.05	0.07	0.07
#Observations	98	98	98	98

**: Significant at a 95% level.

* : Significant at a 90% level.

[a] : We prefer to use the two components of effective spread rather effective spread itself to trace down which component drives CARs. If, however, we include effective spread instead, we find its coefficient to be significantly negative in all models.

Table 4.9*: Pre- and post-event volume in high quoted spread regime

This table replicates Table 4.9 except that the month ‘September 2001’ is excluded.

	Pre-event high quoted spread regime[a] (1)	Post-event high quoted spread regime[b] (2)	Difference (2)-(1)
Panel A: q=0.10 quantile to identify liquidity regimes			
DMM stocks	34.31**	43.81**	9.50**
	(4.21)	(5.31)	(2.59)
NonDMM stocks	42.11**	37.23**	-4.88
	(15.90)	(3.51)	(-0.60)
DMM stocks - NonDMM stocks	-7.79	6.58	14.37*
	(-0.74)	(0.36)	(1.65)
#Observations	6,593		
Panel B: q=0.33 quantile to identify liquidity regimes			
DMM stocks	36.15**	43.18**	7.02**
	(5.17)	(6.24)	(2.63)
NonDMM stocks	38.14**	37.63**	-0.51
	(15.97)	(4.04)	(-0.07)
DMM stocks - NonDMM stocks	-1.99	5.55	7.53
	(-0.21)	(0.34)	(1.03)
#Observations	15,984		
Panel C: q=0.50 quantile to identify liquidity regimes			
DMM stocks	40.99**	48.51**	7.52**
	(10.27)	(12.45)	(2.67)
NonDMM stocks	38.76**	34.88**	-3.88
	(27.43)	(6.60)	(-1.00)
DMM stocks - NonDMM stocks	2.22	13.63	11.40**
	(0.42)	(1.53)	(2.47)
#Observations	22,116		

[a]: The pre-event volume of DMM stocks is calculated as $\frac{1}{74}\sum_{i=1}^{74}\alpha_i+\beta_{DMM}$. For nonDMM stocks, it is $\frac{1}{27}\sum_{i=75}^{101}\alpha_i$.

[b]: The post-event volume of DMM stocks is calculated as $\frac{1}{74}\sum_{i=1}^{74}\alpha_i+\beta_{DMM}+\beta_{post\_DMM}$. For nonDMM stocks it is $\frac{1}{27}\sum_{i=75}^{101}\alpha_i+\beta_{post\_nonDMM}$

**: Significant at a 95% level.

* : Significant at a 90% level.

Samenvatting (Summary in Dutch)

Dit hoofdstuk bevat Nederlandstalige samenvattingen van de hoofdstukken 2 t/m 4 van dit proefschrift.

In hoofdstuk 2, stellen we een maatstaf voor liquiditeit voor die liquiditeitslekken afvangt, en we onderzoeken de prijsstelling in de cross-section van de aandelenrendementen. Bestaande literatuur suggereert dat de liquiditeit tijd afhankelijk is en er goede redenen zijn om te geloven dat er een niet-liquide regime en een liquide regime bestaat. Wanneer een aandeel een lange periode van de niet-liquide regime heeft, zeggen we dat het vast zit in een liquiditeits-lek (of liquileak) situatie. Liquiditeitslekken hebben dus twee dimensies, een lage liquiditeit niveau en een lange duur van gebrek aan liquiditeit. Risicomijdende beleggers moeten vragen om een hoog rendement ter compensatie van de verliezen die zij kunnen realiseren in een liquiditeits-lek situatie. Wij stellen voor om de liquiditeitslekken te meten door de liquileak waarschijnlijkheid, dat is de kans dat een aandeel blijft steken in de niet-liquide situatie voor vijf opeenvolgende beursdagen, geschat door het Markov-regime switching model. De veronderstelde relatie tussen liquileak waarschijnlijkheid een het vereiste rendement van een aandeel wordt getest op twee conventionele manieren: portfolio soorten en Fama-MacBeth regressies. De portefeuille soort analyse toont dat een trading strategie die lang is bij hoge liquileak voorraden en korte bij lage liquileak aandeel een significant gemiddelde extra rendement op jaarbasis van 3,36% oplevert. Om te onderzoeken of dit positief rendement alleen te wijten is aan een van de twee factoren van de liquileak waarschijnlijkheid (dat wil zeggen, de frequentie of duur) of alleen te wijten is aan de (onvoorwaardelijke) gemiddelde liquiditeit niveau, we dubbel sorteren en vinden dat het rendementsverschil tussen lage en hoge liquileak aandeel nog steeds duidelijk positief is. De Fama-MacBeth regressie maakt het mogelijk om de standaard Fama-Franse factoren en andere aandeel karakteristiek te controleren. We vinden een positief rendement premie voor de Liquileak waarschijnlijkheid. Een een standaarddeviatie verhoging van de liquileak kans verhoogt het jaarlijkse rendement met 1,33%. Deze regressies worden herhaald voor de twee ever lange sub-perioden en de resultaten geven aan dat de liquileak waarschijnlijkheid belangrijker is geworden voor rendementen over de tijd terwijl, in overeenstemming met eerdere literatuur, het liquiditeitsniveau minder belangrijk is geworden.

In de robuustheid cheque, stellen we een alternatieve maatstaf voor liquiditeit lekken, die rechtstreeks wordt berekend op basis van ruwe data zonder enige model specificatie. We proxy het voortbestaan van de niet-liquide regime van de gemiddelde duur dat een aandeel in de niet-liquide regime en de frequentie van de niet-liquide regime met het percentage van de dagen dat een bestand is in de niet-liquide regime meer dan het totale aantal handelsdagen. Dienovereenkomstig, de interactie van deze twee variabelen is de maatstaf voor liquiditeit lekken. Ook hier vinden we consistent bewijs is dat deze maatregel van liquiditeit lekken ook een significant positieve relatie met aandelenrendementen heeft. Daarnaast zijn onze resultaten zijn robuust op de januari-effect en de financile crisis periode 2007-2008.

Hoofdstuk 3 onderzoekt de prijsstelling van de keerzijde liquiditeit. We stellen dat de beleggers nadeel markt anders te beschouwen van ondersteboven markt, en aandelen die een hoge liquiditeit en laag liquiditeitsrisico in nadeel markt zijn bijzonder waardevol voor beleggers. In een dalende markt, zijn beleggers zeer waarschijnlijk getroffen hun financiering beperking en moeten hun voorraden liquideren. Dus ze liever bestanden die kunnen worden uitgevoerd tegen lage kosten in de markt dalingen vast te houden en zou een hoger rendement eisen voor aandelen die een hoge liquiditeit keerzijde te hebben. We stellen het gemiddelde marktrendement als een cut-off niveau en definiren van een markt is in een nadeel (ondersteboven) indien haar rendement lager (hoger) dan dit cutoff niveau. Amihud ILLIQ maatregel wordt gebruikt als ons dagelijks illiquiditeit maatregel. Het downside (upside) de geringe liquiditeit wordt gedefinieerd als het gemiddelde van de dagelijkse ILLIQ maatregel in een downside (upside) markt. Het downside en upside liquiditeit beta is de comovement van illiquiditeit voorraad het niveau met de markt illiquiditeit niveau conditioning op het marktrendement.

We gebruiken twee benaderingen om de relatie tussen de downside liquiditeit en de aandelenrendementen in de cross-section te onderzoeken. Een is de portefeuille sorterings benadering, die eenvoudig te interpreteren rendementen geef haalbare bij gangbare beleggingsstrategieen.. We sorteren individuele aandelen in vijf Quintiles op basis van de hun downside (en upside) iliquiditeit niveau en de upside (en dwonside) liquiditeit beta, en vinden dat de aandelen met een hoge downside iliquiditeit niveau en de beta een hoger rendement hebben dan aandelen met een lage downside iliquiditeit niveau en beta . Bijvoorbeeld, een trading strategie die long in aandelen met een hoge downside iliquiditeit en short in aandelen met een lage downside illiquiditeit niveau leveren een gemiddelde maandelijkse hoger return van ongeveer 0,94%. Het rendement terugkeer verschil tussen de twee uiterste downside liquiditeit beta Quintiles is 0,74% per maand. Om de effecten van downside en upside iliquiditeit niveau en beta differentiren, we gebruiken we verder een dubbele sortering analyse. Na controle voor de upside illiquiditeit niveau vinden we nog steeds dat rendement spread van de portefeuilles gesorteerd op de downside iliquiditeit significant positief is. Ook de toenemende rendement patroon van lage downside liquiditeit beta naar hoge downside liquiditeit beta blijft na de eerste soort van upside liquiditeit beta. De andere aanpak is de Fama-MacBeth regressie, die ons in staat stelt om cross-sectional excess rendement direct op de downside illiquiditeit niveau en de bta te regress en ons mogelijk maakt om te controleren voor andere bekende determinante. De regressie wordt uitgevoerd op bedrijfsniveau. We vinden aanwijzingen dat de downside illiquiditeit niveau en de beta een significant positief effect op de aandelenrendementen in de cross-section te hebben. Bijvoorbeeld, een verhoging van een standaarddeviatie in het downside liquiditeit niveau zal de maandelijkse rendementen met 0,15% verhogen. Het is ongeveer 1,8% op jaarbasis, die geeft ook de economische betekenis aan. De downside liquiditeit beta heeft ook een significant positief effect op aandelenrendementen. Echter, wanneer de downside liquiditeit niveau, de upside illiquiditeit niveau, de downside en upside liquiditeit beta gezamenlijk worden opgenomen in het cross-sectional regressie, heeft alleen de downside liquiditeit niveau nog een significant positieve cofficint op het rendement. In de robuustheid cheque, vinden we dat onze resultaten robuust zijn op het januari-effect.

In hoofdstuk 4 onderzoeken we het effect van designated market makers (DMMs) op de small-caps in de Euronext Amsterdam markt. Bedrijven geven om de liquiditeit van het aandeel omdat het invloed heeft op de kosten van kapitaal. Small-caps geven hier het meest om omdat hun aandelen laagste liquiditeit niveau en de hoogste liquiditeitsrisico vertoont. Euronext stelt hen in staat een DMM te contracten, die vervolgens minimumliquiditeit onvoorwaardelijk moeten leveren. In Amsterdam, aanmelden 74 small-caps van de 101 verkiesbaar bedrijven zich op de introductiedag. Wij analyseren 11 maanden voor en na de introductie van DMMs en vinden dat DMM aandelen een significant cumulatief abnormaal rendement van 3,5% in een drie weken venster dat de aankondiging en de effectieve dag bevat te genereren. Het grootste deel hiervoor doet zich voor in de week na dat Euronext de lijst van DMM aandelen publiceert. In totaal komt dit neer op een waarde creren van ongeveer 1 miljard euros. Op basis van difference-in-difference approach, vinden we dat de effectieve verspreiding significant daalt en de effectieve verspreiding covarieerd beduidend minder met de markt effectieve verspreiding (dat wil zeggen in Acharya en Pedersen (2005)). Wij stellen dat DMMs de liquiditeit niveau te verbeteren en het liquiditeitsrisico verminderen. Bovendien zijn zowel de liquiditeit niveau verandering en het liquiditeitsrisico verandering zijn belangrijke verklarende variabelen voor de positieve abnormale rendementen geassocieerd met DMM aandelen. We zien verder dat DMMs in meer trades participeren en verlies lopen op hoge quoted-verspreid dagen, dat wil zeggen, op dagen waarop hun beperking is waarschijnlijk te bindend zijn. Tot slot vinden we dat DMMs fouten in dagelijks prijsstellingen verminderen.

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