N.B.: This is a completely new and early draft. We welcome your comments.

How Do Designated Market Makers Create Value for Small-Caps?[1]

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April 25, 2008

[1]Please find Albert J. Menkveld at albertjmenkveld@gmail.com and Ting Wang at twang@feweb.vu.nl. This paper replaces "Designated Market Makers for Small-Cap Stocks." We thank Riccardo Calcagno, Drew Creal, Thierry Foucault, Terry Hendershott, Randi Nas, Kumar Venkataraman, Michel van der Wel, Ingrid Werner, Yuzhao Zhang, participants at the AFA 2008, the French AMF transatlantic conference 2007, CEPR Gerzensee summer symposium 2006, EFA 2006, ISB Hyderabad microstructure conference 2006, Magyar Nemzeti Bank Budapest central bank workshop 2007, and seminar participants at the New York Fed, NYSE, and Tilburg U their very useful comments. For research assistance, we are grateful to Jos van Gelder and Sunny Li. We thank Euronext as data sponsor for this project and Menkveld gratefully acknowledges NWO for a VENI grant and the College van Bestuur of VU University Amsterdam for a VU talent grant.

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

Abstract

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 level and risk changes explain the cross-sectional dispersion in abnormal returns. We further find that DMMs participate in more trades and their trading profit does not increase, yet is more volatile, at times of a high quoted spread, i.e. at times when they are likely to be constrained by their contract.

Small-cap firms care about liquidity as their stocks exhibit lowest liquidity levels and highest liquidity risk. In their oft-cited paper, 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 the small-cap firms. Pastor and Stambaugh (2003) study 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 re-introducing a designated market maker (DMM) for small-cap stocks, who commits to a minimum liquidity supply. In return, a DMM enjoys trading privileges granted by the exchange or is compensated by the issuer. Two recent studies study sequential DMM introduction in the French and Swedish market and find that the liquidity level improves (see Venkataraman and Waisburd (2007) and Anand, Tanggaard, and Weaver (2005), respectively). They both report abnormal returns of roughly five percent around the introduction date.

We study a Euronext roll-out of their Paris limit order market system to Amsterdam on October 29, 2001. Arguably the most signficant change was the possibility for small-caps to hire a DMM, as, otherwise, the system replaced an already well-functioning limit order system. One important advantage is that the exogenous system change allows for an event-type study of DMM introduction that does not suffer from potential endogenous timing when DMMs are introduced sequentially. 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. We therefore consider endogenous selection of DMM stocks unlikely, which is confirmed by the insignificance of a Heckman control variable in our empirical analysis.

Our main contribution is that, in addition to changes in liquidity level, we study whether the DMM arrangement affects liquidity risk. It is a more natural place to look as the nature of most DMM contracts is that they commit to minimum liqudity supply *unconditionally*; Charitou and Panayides (2006) find that the "maximum spread" rule is by far the most common affirmative obligation in their review of international stock markets. It might very well be that it is this guarantee that mitigates investor concern of (undiversifiable)

[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."

liquidity risk, which makes her shun small-cap stocks as an investment. We study how DMM introduction affects the liquidity betas proposed by Acharya and Pedersen (2005).

In what is essentially a difference-in-difference approach—post-event minus pre-event differenced across DMM and non-DMM stocks—we find that a DMM significantly reduces realized spread and β^{cc} risk, i.e. risk due to covariation of a stock's effective spread with market effective spread. We also find a significant cumulative return (CAR) of 3.5% around the announcement day for the 74 DMM stocks and no significant CAR for the 27 non-DMM benchmark stocks. In a cross-sectional regression, we find that both the realized spread change and the β^{cc} liquidity risk change explain abnormal returns significantly. We generate further empirical support for the liquidity guarantee channel as we find that DMMs involvement in trading is significantly higher on days of high quoted spread relative to days of low quoted spread. Their gross profits do not change significantly, but do become significantly more volatile. These findings are consistent with a DMM who is present on the inside quote involuntarily—the contracted liquidity constraint binds—and investors appreciate it as they consume liquidity.

Our findings add to the more fundamental debate on whether designated market makers create social value. Bessembinder, Hao, and Lemmon (2007) discuss an information and a noninformational mechanisms through which a DMM "maximum spread" rule could create social value. The noninformational explanation admits that the maximum spread rule is costly to society as DMM need to be compensated as they are an allocation of real resources to complete trades, but argues that this cost could be dominated by the social benefit created as the liquidity guarantee might enable more investors to capture a private value from trade that might otherwise be dominated by the transaction cost. The noninformational explanation relies on the argument of improved price discovery as the liquidity guarantee creates incentives for more investors to become informed. The improved price discovery, in turn, provides superior information for real decisions. We find that DMM introduction significantly reduces realized spread, but do not affect the adverse selection component of the spread, nor the midquote return volatility. We interpret this as some support for the noninformational mechanism. We do not find a volume increase overall for DMM stocks, but should perhaps more narrowly study volume changes on days of low endogenous liquidity pre- and post-event.

The remainder of the paper is organized as follows. Section 1 discusses the institutional background of the introduction of DMMs in the Dutch market. Section 2 discusses how DMMs can create value through the liquidity channel. Section 3 presents our data, discusses the methodology, and presents the results. Section 4 concludes.

1 Institutional background

In 2000, the exchanges in Paris, Amsterdam, and Brussels merge and the new exchange, Euronext, decides to structure all markets according to the Paris Bourse trading model: an electronic limit order book market. Orders are transmitted from 7:00 a.m. through 5:30 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 between auctions.[2] Executions in the call auction are based on the price that maximizes volume. If there is insufficient trading interest on one or both sides of the market at the time of the scheduled auctions, or if the clearing price deviates significantly from the prior auction price, the auction will not clear and no trade takes place (see Biais, Hillion, and Spatt (1999) for more details).

In 1992, the Paris Bourse introduces designated market makers, "liquidity providers," to address the, in their view, poor liquidity provided by public limit orders for some continuously traded stocks as well as some auction stocks. The exchange, however, does not mandate stocks to trade with a designated dealer, nor is it involved in the process of selecting the intermediary. Both decisions are taken by the listed firm. The exchange facilitates the process by providing firms with a list of eligible market makers and their prior performance rankings. The Bourse does, however, require a DMM to sign a contract to guarantee minimum market presence ("General Terms"), i.e. a quote at a maximum bid-ask spread and minimum depth. It monitors and rates the DMMs and may terminate the service if performance is poor.

As supplying liquidity for these, typically, infrequently traded stocks is not considered profitable[3], a DMM is compensated in, essentially, three ways. First, the exchange waives all fees on market-making related trades and quotes and recognizes the DMM as primary facilitator for block transactions in the security. In contrast with the NYSE specialist, a DMM cannot condition his price schedule on the arriving order flow and cherry-pick (uninformed) trades. That is, she does not have the last mover advantage. Second, the listed firm, in the "Special Terms" of the contract, endows the DMM with an inventory of shares for

[2]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.

[3]Otherwise, liquidity supply through two-sided limit orders in the book would have created adequate liquidity.

market-making and potentially pays an annual fee for the service. Third, considered most important by many brokers, a DMM relationship will make the broker a first contender when the listed firm needs other financial services e.g. a seasoned offering, banking services, insurance, etc.[4]

Venkataraman and Waisburd (2007) study the first seven years of trading in the new system, January 1992 through December 1998, and identify 75 firms that choose to trade with a designated market maker and use the 206 firms that only trade in call auctions as a control group. They document that adding a DMM increases trading frequency and reduces book imbalances. They also find that younger firms, smaller firms, and less volatile firms are more likely to add a DMM. And, around the announcement of a DMM introduction, they find that stocks experience an average cumulative abnormal return of nearly five percent.

On Monday, October 29, 2001, Euronext introduces the "Paris Bourse system" along with the option for small-caps to hire a DMM in the Dutch equity market. This DMM system raised a lot of regulatory interest, as securities markets regulation was, at that time, largely national. The Dutch regulator did not approve early proposals, as they did not offer sufficient guarantees against illegal insider trading.[5] Euronext addressed these concerns by requiring transparency i.e. all transactions of a DMM have to be reported to the local regulator.[6] After regulatory approval, Euronext introduced the system with the following (local) requirements. Euronext aims at a particalur set of small-cap stocks and therefore excludes actively traded Euronext 100 stocks and stocks that generate less than 2,500 transactions per annum. The minimum liquidity supply in the "General Terms" of the contract is set at a maximum spread of 4% and a minimum depth of €10,000 for most stocks.[7] Whereas the DMM feature was the most salient change to a system that was already a limit order market, there were some other differences. First, the designated market maker in the old system—the "hoekman"—disappeared. Her only obligaton was to provide a continuous quote (no minimum supply constraint) and keep a "fair and orderly market." Second, the

[4] Examples are: ING is DMM for Unit4Agresso and has 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 emissions for them. The brokers admit that they might have had this business without acting as DMM, but a DMM sponsorship allows them to make a bid when the firm shows interest in these products.

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

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

[7] These are 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 €5,000.

fee structure changed. Third, stocks with less than 5,000 trades per year move to the auction system, unless they decide to hire a DMM.

On the Monday before the effective day, Euronext announces that 74 small-cap firms signed up for DMMs.[8] Interestingly, the Dutch firms hired multiple market makers—3.13 on average out of a dozen brokerage firms that offered this service[9]—whereas the vast majority of French firms hired only one. We argue that Dutch brokers aggresively pursued a DMM contract for two main reasons. First, a prominent institutional feature of the Dutch brokerage market is that most brokers are part of large conglomerates, which creates opportunities for cross-selling and, as already mentioned, a DMM sponsorship is a foot in the door with the firm to offer other products. Second, the Dutch small-caps that took on a DMM are different from the French ones, as the average Dutch stock belongs to a 12 times larger firm (in terms of market cap) than the average French stock and generates 63 times more volume.[10] We will give further details on our sample when discussing the sample statistics.

2 Economic model

In this section, we discuss how Euronext DMM contracts can create value for small-cap firms. We first introduce a simple economic model that explicitly recognizes the constraint a DMM contract puts on a broker. We then analyze how this constraint affects a stock's average liquidity level and its liquidity risk. We then discuss how these contracts are likely to benefit existing shareholders through abnormal returns.

2.1 Two liquidity regimes: binding vs. non-binding DMM constraint

A maximum spread of 4% and a minimum depth of €10,000 seem to be non-binding, but for these small-cap stocks, they can be binding. As liquidity provider

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

[9]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," Sep 17, 2002

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

you lose money for sure when the market is very volatile.
—Willem Meijer, SNS Securities[11]

The DMM contract is a commitment of the broker to supply minimum liquidity *unconditionally*, which naturally introduces two liquidity regimes. In the "normal" liquidity regime, supply is competitive and the bid-ask spread in the limit order book is well within the mandated maximum spread. However, if for some reason liquidity supply is expensive, e.g. because of a highly volatile market which makes carrying non-optimal inventory through time expensive, the competitive spread might well be wider than the minimum spread. It is at these times that DMMs are the supplier of last resort and have to quote the contracted maximum spread and minimum depth. This makes the DMMs lose money at times that they are constrained by their contract.

2.2 DMM contracts improve average liquidity level and reduces liquidity risk

The DMM contract puts a lower bound on liquidity supply for a particular stock. This has two mechanical effects:

1. It improves the average liquidity level as the post-event liquidity supply at any point in time is the minimum of the contracted liquidity supply and the endogenous (competitive) liquidity supply.
2. It reduces liquidity risk as the liquidity supply lower bound reduces the time variation, but, more importantly, it is likely to reduce correlation with a systematic market liquidity factor.

We use the Acharya and Pedersen (2005) model to hypothesize how both these mechanical effects translate into lower required returns for DMM stocks. Their model makes the usual assumptions under which CAPM holds. They then apply standard CAPM analysis to *net* stock returns, i.e. net of transaction cost. This leads to:

$$E(r_t^i - c_t^i) = E(r_t^f) + \lambda \beta_i^{net}, \tag{1}$$

[11]See *Financieel Dagblad*, "Animateurs Betalen veel Leergeld," Sep 17, 2002.

where

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

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

$$E(r_t^i) = E(r_t^f) + E(c_t^i) + \lambda(\beta_i^{rr} + \beta_i^{cc} + \beta_i^{rc} + \beta_i^{cr}) \tag{2}$$

In the context of this model, the DMM contract mechanically reduces the expected liquidity level c_t^i and two of the liquidity risks, i.e. β_i^{cc} and β_i^{cr}. It might also affect the second liquidity risk β_i^{cr} if, as a result of the contract, required returns vary less with market illiquidity. One might well imagine that at times of market illiquidity investors leave the small-cap domain for more actively traded blue chip stocks causing small-cap prices to fall, but they might keep the stocks with a DMM as it comes with a minimum liquidity guarantee.

2.3 Can DMM contracts create abnormal returns?

If liquidity is priced, DMM contracts might create value as they improve liquidity level and reduce liquidity risk. However, on the balancing side, brokerage firms need to be compensated for committing to a minimum liquidity supply. The net result for the firm cannot be negative as otherwise it would not have entered the contract. But, if bargaining power resides with brokers, they will consumer all potential surplus. We believe that this is unlikely in our setting for two main reasons. First, as described in Section 1 a dozen brokerage firms offered DMM services, which is good for bargaining power at the side of the issuer. Second, the same section argues that the actual payment of a lump sum amount to the DMM does not make up for the cost. In the Dutch market, many brokers are part of financial conglomerates and take the loss on the DMM service in order to get a foot in the door with the issuer to cross-sell other products. ABN-AMRO, for example, offered to be a DMM for the stock of all their clients, free of charge.

3 Empirical results

This section contains the empirical analysis. We first present our dataset and some summary statistics. We then calculate abnormal returns around the DMM announcement day. Inspired by Acharya and Pedersen (2005), we estimate liquidity level and liquidity risk pre- and post-event and test these changed significantly. We aim to identify what drives abnormal returns through cross-sectional regressions of abnormal returns on liquidity level and risk changes. Finally, we exploit DMM activity data to find empirical support for the mechanism proposed in Section 2, i.e. they are the supplier of last resort when endogenous liquidity is poor and they lose money at those times.

3.1 Data and summary statistics

3.1.1 Data

We exploit three datasets for our empirical analysis. First, for 11 months before and after the effective date we receive intraday data that consists of (i) a quote file that contains the best bid and ask quote and (ii) a transaction file that contains price and size of all transactions along with a label that indicates whether DMM involvement. Second, for the same period we have daily data that include market capitalization for each stock. Third, we receive a file that for all DMM stocks contains the initation and termination date of a DMM service. Unfortunately, we did not get access to the contracts themselves, which might show that the issuer and broker contract on tighter minimum supply than the Euronext mandated 4% maximum spread and a €10,000 minimum depth.

[insert Figure 1]

The empirical analysis is essentially an event study of 74 DMM stocks and 27 benchmark stocks and Figure 1 depicts the time line: a ten month pre-event period, a two months event period, and a 10 months post-event period. The 74 DMM stocks are those that hire a DMM as of the introduction day, i.e. Monday, October 29, 2001. The list of these stocks was announced on the Monday ahead of the effective day. As non-DMM benchmark stocks, we select all stocks that were eligible for DMM sponsorship but did not hire a broker on the introduction day or any time in the post-event period. We reiterate that not all listed firms are eligible stocks as, for example, all Euronext 100 stocks are not allowed to hire a DMM. We add the complete list of all DMM and non-DMM benchmark stocks in the appendix.

We use standard liquidity measures from the literature to gauge how DMMs affects liquidity levels. 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 accounts for the actual consumption of liquidity and therefore are a better measure for the transaction cost a "representative" investor actually incurred.

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

$$espread_{it} = 2q_{it}(p_{it} - m_{it})/m_{it} \tag{3}$$

where i indexes stocks, t indexes transactions, q_{it} is an indicator variable that equals +1 for market buy orders and -1 for market sells orders, p_{it} is the transaction price, and m_{it} is the midquote prevailing at the time of the trade. Trades are trivially signed in in electronic limit order markets as market buys (sells) are identified as transactions that execute above (below) the prevailing midquote. We further decompose the effective spread into two components. The adverse selection component captures the average loss of liquidity providers against informed market orders (they are on the wrong side of the trade in these transations). The realized spread component is the remaining part and therefore captures the gross profit to liquidity suppliers. These two component are identified based on the price-relevant information in the trade which is revealed through post-trade midquotes. We use 60 minutes to allow the market to fully incorporate the information into quotes. Formally, the two comoponents are defined as:

$$rspread_{it} = 2q_{it}(p_{it} - m_{it+60min})/m_{it} \text{ and} \tag{4}$$

$$adv\_sel_{it} = 2q_{it}(m_{it+60min} - m_{it})/m_{it}. \tag{5}$$

Amihud's $ILLIQ$ measure. We also calculate an illiquidity measure based on daily data as proposed by Amihud (2002):

$$ILLIQ_{it} = \frac{|r_{it}|}{volume_{it}} \tag{6}$$

where r_{it} is the return from day $t-1$ to day t and $volume_{it}$ is the trading volume in millions of euro on day t. Both ex-post measures are only defined for days with transactions and will be set to missing values for days without transactions.

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

$$qspread_{it} = (ask_{it} - bid_{it})/m_{it}, \tag{7}$$

where t indexes any time in the trading day.

We winsorize all variables in the sample and set extreme values to the 1% and 99% quantiles.

[insert Table 1]

Table 1 presents summary statistics based on panel dataset that comprises 22 trading months for 74 DMM stocks (Panel A) and 27 non-DMM stocks (Panel B).[12] The statistics lead to a couple of observations. First, we find that DMM stocks are not negligible stocks in terms of trade activity and size. The average firm has €490 million market capitalization and its stock trades 74.20 times per day. Second, the average quoted spread is 1.40% and exhibits a monthly within variation of 0.94% which shows that liquidity risk might actually be important. These statistics suggest that spreads are well within the Euronext mandated 4%, which suggests that many issuers have contracted on a narrower spread with their DMMs. Third, the average effective spread of 1.17% is smaller than the quoted spread which indicates that liquidity consumers time their trade. The decomposition shows that more than 80% of the effective spread is gross-profit for liquidity suppliers. Fourth, the average number of DMMs it hire is 3.13 with considerable cross-sectional dispersion as the within standard deviation is 1.33. Fourth, we compare trade statistics across Panels A and B and find that the pre-event mean is the same order of magnitudefor DMM and non-DMM stocks. For example, we find that the average effective spread is 1.24% for DMM stocks vs. 1.76% for non-DMM stocks, average daily volume is €680,000 per day for DMM stocks vs. €780,000 and market capitalization is €490,000 for DMM stocks vs. €2,140,000 for non-DMM stocks.

[insert Table 2]

[12] We use the monthly frequency as the point of departure for our analysis, since some series are only naturally defined on a monthly frequency, e.g. ILLIQ or volatility of daily midquote returns. For the daily spread measures, we average over all days in the month to generate estimates at the monthly frequency.

Table 2 presents overall, between, and within correlations for our liquidity proxies along with volume and volatility for both DMM stocks and non-DMM 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. Wealso find significant evidence that liquidity is negatively correlated with volatility and positively correlated with volume in both the cross-sectional and the time dimension. Interestingly, we find an insignificant within correlation for volality and volume, which suggests that there are times of high volatility and low volume where typically stocks should become illiquid. We expect that it is at these times that DMMs liquidity contraint binds and they become the liquidity supplier of last resort.

3.2 Abnormal returns around the announcement and effective day

[insert Figure 2]

Figure 2 shows DMM stocks generate significant cumulative abnormal returns (CARs) in a 21 day window around the introduction day which includes the announcement day (see also the time of Figure 1). We estimate the CARs based on daily midquote returns and post-even beta estimates. Panel A shows that DMM stocks generate a CAR over this period of 3.5%. Most of this CAR is a strong run-up in prices in the week after the Monday announcement (t=0) of the list of DMM stocks. We also find a 1.0% CAR in the week before the announcement, which indicates that some of the information might have become known to the market ahead of the announcement. We find another 0.5% on the effective day (t=5) and no significant changes afterwards. Panel B plots the CARs for non-DMM stocks which are insignificant throughout the entire period, which we interpret as further evidence that the CARs for DMM stocks are really due to DMM sponsorship for these stocks.

3.3 Pre- and post-event liquidity level and liquidity risk

A natural explanation for the DMM stock abnormal returns is that they reflect improved liquidity of the stock. The Acharya and Pedersen (2005) model discussed in Section 2 suggest two potential channels: a liquidity level change or a liquidity risk change.

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

$$y_{it} = \alpha_i + \beta_1 post_t * DMM_i + \beta_2 post_t + \beta_3' control\_vars_{it} + \gamma_t + \varepsilon_{it} \tag{8}$$

where i indexes stocks and t indexes months, α_i is the 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 in shares and volatility, γ_t is a time effect, and ε_{it} is the error term. Statistical inference explicitly recognizes commonalities across stocks through the time effect and also controls for within-stock autocorrelation and heteroskedasticity through Newey-West standard errors. In this specification, the β_1 coefficient captures the difference in difference effect. That is, it estimates how the average $y_i t$ changes in the post-event period relative to the pre-event period minus the equivalent change for non-DMM stocks. It is therefore this coefficient and its associated t-value that tests, for example, whether DMM stock effective spreads changed more than non-DMM stock effective spreads.

[insert Table 3]

Table 3 finds that liquidity levels improve for DMM stocks in the post-event period significantly relative to non-DMM stocks except for $ILLIQ$ measure. In model (1) where we exclude the control variables, fixed effects and time dummies, we find that effective spread decreases by 0.27% (i.e. from 1.37% pre-event to 1.10%) and decreases significantly relative to non-DMM stocks by 1.94%. The spread decomposition shows that the cause of the spread decrease is a reduction in gross profits for liquidity suppliers and not a reduction in adverse selection. That is, realized spreads for DMM stocks decline significantly relative to non-DMM stocks by 1.64% and the adverse selection component change is small and insignificant. The quoted spread results are similar. The $ILLIQ$ measure analysis shows qualitatively similar results, but 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 these observations start to dominate the regressions.[13] We exclude the $ILLIQ$ measure from any remaining analysis given its poor performance. All previous results are robust to including the standard control variables, fixed effects, and time dummies for liquidity changes.

Table 3 further finds that volume and volatility appear unaffected by the introduction of a DMM.

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

Liquidity risk change. We use daily observations to estimate the Acharya and Pedersen (2005) liquidity risk betas as summarized in eqn .(1). To enable direct econometric tests on beta changes, we estimate the following panel data model for daily data:

$$r_{it} = \sum_{k\in\{pre,post\}} \alpha_{ik} + \tilde{\beta}^{rr}_{ik} k_t * r^m_t + \tilde{\beta}^{rc}_{i,k} k_t * c^m_t + \varepsilon_{it} \tag{9}$$

$$c_{it} = \sum_{k\in\{pre,post\}} \alpha_{ik} + \tilde{\beta}^{cr}_{ik} k_t * r^m_t + \tilde{\beta}^{cc}_{i,k} k_t * c^m_t + \varepsilon_{it} \tag{10}$$

where i indexes stocks, t indexes days, k indexes pre- and post-event periods, k_t is a dummy that indicates either a pre- or post-event period, 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 (consistent with Acharya and Pedersen (2005)), r^m_t is the AEX index return, c^m_t is the marketcap-weighted transaction cost of the AEX index stocks. We test pre- vs. post-event beta changes for DMM stocks and the difference relative to non-DMM stocks based on cross-sectional averages, which is a linear transformation of the parameter estimates. In the procedure we use a Newey-West paramater covariance matrix to ensure that the standard errors in our test statistics are robust to stock-specific autocorrelation and heteroskedasticity. Finally, we denote use tildes to denote that these are regression beta rather than unconditional covariance betas that are used in the basic Acharya and Pedersen model (see eqn. (1)).[14]

[insert Table 4]

Table 4 finds that for DMM stocks all liquidity betas are lower in the post-event period, but only β^{cc} and, to some extent, β^{rc} are significantly lower relative to non-DMM stocks. The table reports the results for both the effective half spread and the quoted half spread measures. The results lead to a couple of observations. First, we find, consistent with Acharya and Pedersen (2005), that the market beta is an order of magnitude larger than the liquidity betas. In the basic liquidity-adjusted CAPM model, the risk premia is be assumed constant across all sources of risk (i.e. λ in eqn. (2)). In this case, liquidity

[14] In addition to facilitating straightforward econometric tests, the panel regression betas, which are essentially linear projections onto the two market factors, also allow one to leave the basic model restriction that the risk premia associated with each of the factors are the same. The linear decomposition allows for a more general multiple factor asset pricing model. In the later part of their paper, Acharya and Pedersen (2005) mention this issue and show that, indeed, the risk premium associated with the liquidity betas (β^{cc},β^{rc},β^{cr}) appear to be twice as high as the market risk premium.

risks would be dwarfed by the market risk due to the relatively low beta. If, however, the risk premium associated with liquidity risk is higher than the liquidity risk might be economically important. Second, again consistent with Acharya and Pedersen (2005), we find that all betas represent risk as β^{cc} and β^{rr} estimates are generally positive and β^{rc} and β^{cr} estimates are generally negative (which then constitutes a risk as investors receive the return and pay the transaction cost). Third, we find that for DMM stocks the β^{cc} risk decreases (i.e. β^{cc} becomes less positive) and the β^{rc} and β^{rc} risk increases (β^{rc} and β^{rc} become more negative) for the post-event period. These are the same for non-DMM stocks, except for the β^{cc} risk which also increases for the non-DMM stocks. We find this result to be the only significant difference across DMM and non-DMM stocks, i.e. it seems that DMM introduction removes β^{cc} risk. We attribute all other changes (including the reduced market risk) to the new trading system that Euronext introduces along with the DMM introduction, which affects all stocks equally.

3.4 Can liquidity changes explain the cross-section of abnormal returns?

In this section, we relate the cross-section of abnormal returns to the changes in liquidity level and liquidity risk to identify which one is the most likely channel to cause the abnormal returns. In addition, we consider an alternative explanation based on endogenous selection of DMM stocks.

We propose at least two alternative explanations for the abnormal returns based on an endogenous selection of DMM stocks. First, the significant DMM abnormal returns are 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 these costs are too high. This explanation, however, is unlikely as, in addition to positive abnormal returns for DMM stocks, it would predict negative abnormal returns for non-DMM stocks and we do not find evidence of the latter. Second, a more plausible explanation that also captures the liquidity improvement is that DMM firms have private knowledge on future liquidity conditions of the firms and only pitch aggressively for those that have good endogenous liquidity prospects, which could explain the result.

We recognize the potential endogenous selection in the cross-sectional regressions 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 that stock i given its observable characteristics was selected into the sample, i.e. the inverse Mills ratio. A high ratio for stock i indicates that it is unlikely that the stock was included because of its observable characteristics. Now, a selection bias occurs in the model that explains abnormal return in the cross-section if these unobservables (i.e. the draw of the residual in the Probit selection equation) correlate with unobservables in the cross-sectional equation. In the Heckman procedure we control for such bias by inclusion of the inverse Mills ratio. If, as in the second hypothesis, our results are driven by private information on the side of brokerage firms on future liquidity conditions, the inverse Mills ratio is collinear with liquidity changes and should make all variables insignificant.

The cross-sectional Probit regression is based on a sample of 101 stocks that include 74 DMM stocks and 27 non-DMM stocks, and it is specified as follows:

$$Pr[DMM_i = 1] = \Phi(\alpha_1 + \alpha_2 Volatility_i + \alpha_3 VolumeShare_i + \alpha_4 1/Price_i + \alpha_5 \#Shares_i)$$

The dependent variable "DMM_i" is a dummy that equals 1 if firm i hires designated market makers and 0 otherwise; $Price_i$ is the average daily closing price of stock i; $\#Shares_i$ is the number of shares outstanding of stock i; $VolumeShare_i$ is the average daily trading volume in shares of stock i; $Volatility_i$ is the average daily midquote return volatility of stock i.

[insert Table 5]

Table 5 finds that smaller firms with more volatile returns are more likely to hire a DMM. These results are consistent with the two earlier studies on DMMs, i.e. Venkataraman and Waisburd (2007) and Anand, Tanggaard, and Weaver (2005). We do not find significance for volume in shares or stock price.

[insert Table 6]

Table 6 finds that both the liquidity level change and the liquidity risk change can explain the abnormal return in the cross-section and these findings are robust to a potential endogenous selection bias. For the ex-post liquidity measure, the effective spread, we find that liquidity risk change explains the cross-section of abnormal returns, but not liquidity level change. If, however, we only include the gross profit to liquidity suppliers component, ithe realized spread, we find that its change is significant in addition to the liquidity risk change. The insignificance of the effective spread might thus be due to a noisy estimate of the adverse selection component.[15] We find these results to be robust to inclusion of the inverse Mills ratio that controls for a selection bias. For the ex-ante liquidity measure, time-weighted quoted spread, we find weak evidence in favor of a liquidity level change and no evidence for a liquidity risk change. We believe the relatively weak results for quoted spread indicate that the investors particularly appreciate those liquidity level and risk changes at times that they need it, i.e. at times that they actually traded which is the basis for the effective spread analysis.

3.5 Further evidence to relate liquidity changes to DMMs

We exploit a DMM identifier in our transactions data to generate further empirical support for our hypothesized mechanism, i.e. the DMM is "liquidity supplier of last resort" on low endogenous liquidity. We do not observe the contracted minimum liquidity supply, but decide to analyze DMM activity and gross trading profit at days of high quoted spread and benchmark it against days of low quoted spread. We use quoted spread to distinguish the two regimes, as this is what we know the issuer and broker contract on. We identify these regimes based on stock-specific quantiles q_i and identify days with an average quoted spread below (above) the q_i (1-q_i) quantile as low (high) spread days. For q_i we use 0.10, 0.33, and 0.50.

For each day in the sample we calculate DMM participation rate and her gross trading profit and use a panel data model to analyze any difference across the two liquidity regimes. We define participation rate as the ratio of the number of transactions that have a DMM on one side of the trade and the total number of transactions. Inspired by Sofianos (1995) we calculate the gross trading profit per trade (GTP) in stock i on day t by marking to market the DMMs starting and ending inventories and adding the gross profits due to buys and sells:

$$GTP_{it} = (S_{it} - B_{it} + p_{it}I_{it} - p_{i,t-1}I_{i,t-1})/trades_{it} \tag{11}$$

where p_{it} is the midquote of stock i at the end of day t, I_{it} is the specialist inventory in shares of stock i at the end of day t, S_{it} is the total euro value of stock i sold on day t, B_{it} is the total euro value of shares bought, and $trades_{it}$ captures the number of transactions with DMM

[15]If we only include the adverse selection component, we find it not be significant, which is no surprise as it did not change significantly due to DMM introduction (see Table 3).

on one side of the transaction. We do not observe DMM inventory and therefore assume that they are zero at the start of the data sample. We further assume that DMMs do all their trading through the system so that the inventory at any point is time is the cumulative sum of their signed trade sizes in shares when they trade as a liquidity provider. As we are ultimately interested in testing for GTP mean and GTP variance across two liquidity regimes, any random shifts due to missing DMM transactions will affect these estimates but is unlikely to affect the difference across regimes. We estimate the following panel data model to test for differences across liquidity regimes:

$$y_{it} = \alpha_i + \beta_{low} low\_qspread_{it} + \beta_{high} high\_qspread_{it} + \varepsilon_{it}, \tag{12}$$

where low_spread_{it} is a dummy that indicates that quoted spread on day t for stock i falls below the stock-specific q_i quantile and $high\_spread_{it}$ is defined analogously. We also estimate the model with the squared residuals of the GTP regression to estimate whether GTP volatility is different across the two regimes.

[insert Table 7]

Table 7 finds that DMMs participate in more trades with unchanged gross trading profit per trade, but with significantly higher trading profit variance. Not surprisingly, we find the strongest results for the lowest quantile q_i=0.10. We find that DMM participation rate in the high regime is 0.29, which is a significant 0.12 higher than her participation rate in the low quoted spread regime. She earns €73.80 per trade in the high spread regime which is €60.78 less than in the low spread regime, but the difference is not significant. We find that the standard deviation in the profit per trade is €6,900 in the high spread regime, which is a significant €1,950 higher than in the low spread regime.[16] These results are consistent with a binding liquidity supply constraint as the higher participation does not seem voluntary as the increased gross profit risk, if not perfectly diversifiable, is costly to a DMM. The results are qualitatively similar but less pronounced across the other the other two quantiles q_{it}=033 and q_{it}=0.50. The results are not driven by a trade size change across the two regimes as we find that the results are unchanged when we multiply all trades in the denominator by the trade size in euro before summing.

[16]We perform the econometric test on the variance difference, but prefer to also report the standard deviation.

3.6 Discussion of the results

The results thus far emphasize a mechanism where DMMs at time of low endogenous liquidity hit the minimum supply constraint and become supplier of last resort. This puts a lower bound on liquidity level and thus decreases the average liquidity level and reduces liquidity risk. The finding that DMMs are more active on low liquidity days with gross trading profits that are unchanged, yet more volatile supports this mechanism.

An alternative explanation for the liquidity level improvement is that DMM brokers do not pay fees on limit order submissions. In our sample period, Euronext charged all participants a fee for limit order submission. As discussed in Section 1, they waive these fees for designated market makers to create incentives for DMM sponsorship. This could explain the liquidity level changes, in particular the realized spread reduction, but not the liquidity risk results.

4 Conclusion

We analyze a 22 month window around the announcement and introduction of designated market makers by Euronext-Amsterdam. 74 small-cap firms hire DMMs and we identify 27 firms that are eligible to hire a DMM, but did not hire one in our sample period. In an event-type analysis, we document the following results:

1. DMM stocks generate a significant cumulative abnormal return of 3.5% in a 21 day window around the introduction day. We find that most of it occurs in the week after the list of DMM stocks is announced. In aggregate, this amounts to value creation of about €1 billion.[17]

2. In what is essentially a difference in difference approach—post-event minus pre-event differenced across DMM and non-DMM stocks—we find that the effective spread declines, but only find statistical significance for the realized spread (i.e. gross profit to liquidity suppliers) component of the effective 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 note that this critically depends on the ex-post nature of the effective

[17] 74 stocks * 3.5% * €0.49 billion market cap (see Table 1).

spread as we do not find any significance for a similar analysis based on time-weighted quoted spread.

3. We find that the realized spread change and the effective spread market covariation change are significant in explaining the cross-section of abnormal returns and together explain 11% of this variation. In the regressions, we use a Heckman procedure to control for endogenous selection.

4. We further find that DMMs are significanlty more active on days when the (time-weighted) quoted spread is high relative to days that it is low. For example, we find that that they participate in 29% of the trades on the highest decile days relative to 17% of the trades on the low decile days. We also find that their gross trading profit does not increase on these days, but does become significantly more volatile.

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Appendix: List of All Stocks

We select DMM stocks as stocks that hire one or more DMMs on the introduction day, i.e. October 29, 2001. Non-DMM stocks are benchmark stocks that were eligible for DMM sponsorship but did not hire a broker in the entire post-event period. In total, we have 74 DMM stocks and 27 non-DMM 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: non-DMM stocks, N=27		
A O T	HAL TRUST	RANDSTAD
AAB HOLD	HEINEKEN HOLDING	ROOD TESTHOUSE
ANTONOV PLC	HITT	SIMAC TECHNIEK
ATHLON	ISPAT INTERNATIONA	SOPHEON PLC
BAAN	MANAGEMENT SHARE	TIE HOLDING
CAP GEMINI SA	NEWCONOMY	TULIP COMPUTERS
CARDIO CONTROL	OPEN TV	UNILEVER PREF
DEUTSCHE BK	PHARMING GRP	VAN DER MOOLEN
EVC INT	RABO CAP FND TRUST	VIA NET.WORKS

Table 1: Summary statistics panel data

This table presents overall, between and within summary statistics on the 74*22 "stock-months" for DMM stocks in Panel A and 27*22 "stock-months" for non-DMM stocks in Panel B. All data are obtained from Euronext Paris with a time period from Dec 1st 2000 to Sep 30th 2002. The data set includes monthly average of: share-weighted effective spread (Espread), time-weighted quoted spread (Qspread), share-weighted realized spread, 60 minute (Rspread), share-weighted adverse selection component spread, 60 minute (AdvSelection), Amihud's ILLIQ measure, the volatility of daily midquote returns, daily volume in euros, daily volume in shares, daily closing price, the daily number of trades, market capitalization and the number of registered designated market makers (DMMs). We winsorize the data using upper 99% percentile and lower 1% percentile. DMM stocks are stocks with designated market makers and non-DMM stocks are stocks without DMMs.

	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(%)	0.97	1.09	0.87	0.71	0.50	0.07	7.60	0.69
AdvSelection(%)	0.20	0.15	0.46	0.24	0.39	-3.93	4.45	0.19
ILLIQ (%/mln)	2.50	2.33	9.80	4.68	8.61	0.00	181.33	0.14
Volatility(σ)	1.99	2.13	1.23	0.90	0.83	0.11	8.43	1.70
VolumeEuro(€mln)	0.64	0.68	1.06	0.93	0.50	0.00	9.63	0.22
VolumeShare(mln)	0.04	0.04	0.07	0.06	0.03	0.00	0.78	0.01
Price(€)	19.56	21.48	13.45	12.47	5.06	0.38	72.83	16.42
#Trades	74.20	88.06	111.33	100.50	47.90	1.95	1017.34	31.67
MktCap(€bln)	0.49	0.49	0.70	0.70	0.00	0.02	5.25	0.34
#DMMs	3.13	0.00	1.44	1.33	0.56	1.00	8.00	3.00
Panel B: 27 non-DMM 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(%)	1.91	1.36	1.89	1.12	1.52	0.07	15.24	1.30
AdvSelection(%)	0.51	0.40	1.54	0.98	1.19	-6.07	13.61	0.33
ILLIQ (%/mln)	7.89	5.04	38.49	14.84	35.51	0.00	478.93	0.52
Volatility(σ)	3.46	3.50	2.67	1.82	1.96	0.17	18.44	3.00
VolumeEuro(€mln)	0.65	0.78	1.78	1.61	0.74	0.00	18.41	0.06
VolumeShare(mln)	0.05	0.05	0.08	0.06	0.04	0.00	0.67	0.02
Price(€)	13.94	17.23	25.79	23.01	11.64	0.06	194.34	3.21
#Trades	76.94	97.64	124.96	110.12	59.06	0.05	983.43	25.91
MktCap(€bln)	2.14	2.14	7.30	7.30	0.00	0.00	38.64	0.07
#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. $x^*_{i,t} = x_{i,t} - \bar{x}_i$.

Table 2: Overall, between, and within correlation liquidity proxies

This table presents overall, between, and within correlation for share-weighted effective spread, time-weighted quoted spread, Amihud's ILLIQ measure, the volatility of midquote returns and volume in euros. Observations are in monthly frequency and detailed definitions can be found in Table 1. Panel A uses the sample of 74 DMM stocks and Panel B uses the sample of 27 non-DMM stocks.

		Qspread	ILLIQ	Volatility	VolumeEuro
Panel A: 74 DMM stocks					
Espread	ρ(overall)	0.87*	0.44*	0.42*	-0.41*
	ρ(between)	0.95*	0.80*	0.45*	-0.49*
	ρ(within)	0.68*	0.26*	0.41*	-0.17*
Qspread	ρ(overall)		0.46*	0.44*	-0.41*
	ρ(between)		0.85*	0.42*	-0.53*
	ρ(within)		0.26*	0.47*	-0.10*
ILLIQ	ρ(overall)			0.13*	-0.15*
	ρ(between)			0.31*	-0.34*
	ρ(within)			0.04	-0.01
Volatility	ρ(overall)				0.11*
	ρ(between)				0.17
	ρ(within)				0.02
Panel B: 27 non-DMM stocks					
		Qspread	ILLIQ	Volatility	VolumeEuro
Espread	ρ(overall)	0.92*	0.24*	0.46*	-0.31*
	ρ(between)	0.97*	0.37	0.77*	-0.45*
	ρ(within)	0.85*	0.14*	0.17*	-0.03
Qspread	ρ(overall)		0.28*	0.48*	-0.34*
	ρ(between)		0.48*	0.71*	-0.48*
	ρ(within)		0.15*	0.26*	-0.04
ILLIQ	ρ(overall)			0.08	-0.08*
	ρ(between)			0.27	-0.21
	ρ(within)			-0.04	-0.00
Volatility	ρ(overall)				-0.14*
	ρ(between)				-0.25
	ρ(within)				0.03

[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 3: Designated market makers and post-event liquidity level change

This table presents the panel regressions of effective spread, quoted spread, Amihud's ILLIQ measure, volume and volatility. We use our 20*101 stock-months panel dataset to estimate various perturbations of 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 the 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 with control variables, γ_t is a time effect, and ε_{it} is the error term. Price, volume in shares and volatility are used as control variables. Model (1) applies the OLS overall estimation and Model (2) and (3) use within estimation, i.e. add fixed effects. In order to further check robustness, we add control variables in Model (2) and (3) and time dummies in Model (3).

	Espread			Qspread			ILLIQ		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
DMM×Post	-1.94*	-1.47*	-1.48*	-2.21*	-1.21*	-1.23*	-6.90	-4.67	-5.10
	(-4.10)	(-3.89)	(-3.90)	(-4.35)	(-3.47)	(-3.47)	(-1.34)	(-0.78)	(-0.83)
Post Dummy	1.67*	1.36*	1.37*	1.49*	0.77	0.80	6.53	4.77	5.21
	(3.83)	(3.81)	(3.78)	(3.22)	(2.34)	(2.33)	(1.32)	(0.79)	(0.85)
Constant	1.37*			1.87*			2.98*		
	(15.33)			(13.51)			(3.76)		
Price		-0.01	-0.01		-0.02*	-0.01		-0.04	0.01
		(-1.65)	(-1.13)		(-2.69)	(-1.81)		(-0.73)	(0.21)
VolumeShare		-2.51*	-1.66		-4.12*	-2.98*		-2.56	6.11
		(-2.60)	(-2.23)		(-3.52)	(-3.47)		(-0.45)	(1.02)
Volatility		0.21*	0.15*		0.31*	0.24*		-0.30	-0.67
		(7.58)	(6.63)		(10.23)	(6.57)		(-0.72)	(-1.69)
Time Dummy	No	No	Yes	No	No	Yes	No	No	Yes
Fixed Effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

* : Significant at a 99% level.

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	Rspread			AdvSelection			Volume		Volatility	
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(1)	(2)
DMM×Post	-1.64*	-1.45*	-1.48*	-0.30	-0.01	-0.00	0.10	0.21	-1.35*	0.02
	(-4.45)	(-3.53)	(-3.61)	(-1.90)	(-0.04)	(-0.01)	(0.37)	(1.47)	(-3.96)	(0.11)
Post Dummy	1.32*	1.24*	1.27*	0.36	0.11	0.10	-0.17	-0.25	0.69	-0.32
	(3.59)	(3.05)	(3.09)	(2.11)	(0.36)	(0.33)	(-0.94)	(-1.88)	(2.50)	(-1.44)
Constant	1.16*			0.22			0.70*		2.50*	
	(12.97)			(2.36)			(5.35)		(17.35)	
Price		0.00	0.01		-0.01*	-0.02*				
		(0.19)	(1.32)		(-4.41)	(-4.77)				
VolumeShare		-1.42	-0.32		-1.10	-1.34				
		(-1.55)	(-0.41)		(-1.83)	(-2.05)				
Volatility		0.13*	0.06		0.08*	0.10*				
		(3.25)	(1.50)		(3.40)	(3.59)				
Time Dummy	No	No	Yes	No	No	Yes	No	No	No	No
Fixed Effects	No	Yes	Yes	No	Yes	Yes	No	Yes	No	Yes

* : Significant at a 99% level.

Table 4: Designated market makers and post-event liquidity risk change

This table presents the estimation results of the Acharya and Pedersen (2005) liquidity risk betas. We use our 460*101 stock-days panel dataset to estimate the following model:

$$r_{it} = \sum_{k\in\{pre,post\}} \alpha_{ik} + \tilde{\beta}^{rr}_{ik} k_t * r^m_t + \tilde{\beta}^{rc}_{i,k} k_t * c^m_t + \varepsilon_{it}$$
$$c_{it} = \sum_{k\in\{pre,post\}} \alpha_{ik} + \tilde{\beta}^{cr}_{ik} k_t * r^m_t + \tilde{\beta}^{cc}_{i,k} k_t * c^m_t + \varepsilon_{it}$$

where i indexes stocks, t indexes days, k indexes pre- and post-event periods, k_t is a dummy that indicates either a pre- or post-event period, 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 (consistent with **?**)), r^m_t is the AEX index return, c^m_t is the marketcap-weighted transaction cost of the AEX index stocks. We test pre- vs. post-event beta changes for DMM stocks and the difference relative to non-DMM stocks based on cross-sectional averages, which is a linear transformation of the parameter estimates. Panel (a) measures each stock's transaction cost c_{it} and market transaction cost c^m_t using effective spread while Panel (b) uses quoted spread. In parenthesis we report the p-value of the Wald test.

	DMM stocks				NonDMM stocks				DMM stocks - NonDMM stocks			
	β^{RR} (×100)	β^{CC} (×10,000)	β^{RC} (×10,000)	β^{CR} (×10,000)	β^{RR} (×100)	β^{CC} (×10,000)	β^{RC} (×10,000)	β^{CR} (×10,000)	β^{RR} (×100)	β^{CC} (×10,000)	β^{RC} (×10,000)	β^{CR} (×10,000)
Panel A: Espread as liquidity measure												
Pre	42.77	0.03	-0.53	6.05	69.76	0.02	1.72	-5.93	-26.98	0.01	-2.25	11.98
Post	27.03	0.01	-0.57	-3.32	39.31	0.03	-0.36	-22.28	-12.27	-0.02	-0.21	18.96
$Post - Pre$	-15.74*	-0.02*	-0.04	-9.37	-30.45*	0.01	-2.08	-16.35	14.71	-0.03*	2.04	6.98
	(0.00)	(0.01)	(0.95)	(0.04)	(0.00)	(0.25)	(0.04)	(0.04)	(0.04)	(0.00)	(0.30)	(0.53)
Panel B: Qspread as liquidity measure												
Pre	42.78	0.02	-0.33	-0.47	69.76	0.04	-0.13	-8.72	-26.99	-0.02	-0.19	8.25
Post	27.03	0.01	-0.64	-3.56	39.30	0.04	-0.41	-21.61	-12.27	-0.02	-0.23	18.05
$Post - Pre$	-15.74*	-0.01*	-0.31*	-3.09	-30.46*	-0.00	-0.28	-12.89*	14.71	-0.00*	-0.03	9.79
	(0.00)	(0.00)	(0.00)	(0.29)	(0.00)	(0.39)	(0.03)	(0.01)	(0.04)	(0.00)	(0.02)	(0.64)

* : Significant at a 99% level.

Table 5: Probit analysis of decision to hire a DMM in the cross-section of eligible small-caps

The table presents the estimation results of a cross-sectional probit model. The estimation equation is:

$$Pr[DMM_i = 1] = \Phi(\alpha_1 + \alpha_2 Volatility_i + \alpha_3 VolumeShare_i + \alpha_4 Price_i + \alpha_5 \#Shares_i)$$

The dependent variable "DMM_i" is a dummy that equals 1 if firm i hires designated market makers and 0 otherwise; $Price_i$ is the average daily closing price of stock i; #Shares is the number of shares outstanding of stock i; $VolumeShare_i$ is the average daily trading volume in shares of stock i; $Volatility_i$ is the average daily midquote return volatility of stock i. The regression is based on a sample of 101 stocks (74 DMM stocks and 27 non-DMM stocks) and is estimated using maximum likelihood.

	Coefficient	t-stat
Constant	2.75	5.04*
Volatility	-0.67	-4.55*
VolumeShare	3.11	1.21
Price	-0.00	-0.32
#Shares	-11.67	-3.86*

*: Significant at a 95% level.

Table 6: Determinants of cross-sectional dispersion of post-event cumulative abnormal returns

The table regresses CAR on changes in liquidity level, changes in liquidity risk, and Inverse Mills Ratio. The estimation of CAR is described in section 3.2 and we use CAR on day +15 (15 days after the announcement day) as dependent variable. Changes in liquidity level are calculated by taking the difference after and before the event. Changes in liquidity risk, ΔLR_{CC} is $\Delta\beta_{cc}$ calculated in section 3.3. Inverse Mills Ratio is based on the estimation of the Probit model in table 5. Panel A and B uses effective spread and quoted spread as measures for liquidity respectively.

Panel A: Espread as liquidity measure					
	(1)	(2)	(3)	(4)	(5)
$\Delta Espread$	-1.05		-0.18	-0.47	
	(-1.26)		(-0.20)	(-0.37)	
$\Delta Rspread$					-2.74 **
					(-2.48)
$\Delta LR_{CC}(10^4)$		-75.65 **	-72.83 **	-73.04 **	
		(-2.56)	(-2.21)	(-2.21)	
IMR				4.38	9.42
				(0.33)	(0.85)
Intercept	3.07 **	2.10 *	2.17 *	0.47	-0.67
	(2.52)	(1.73)	(1.70)	(0.09)	(-0.15)
R^2	0.02	0.06	0.06	0.06	0.06
N	101	101	101	101	101
Panel B: Qspread as liquidity measure					
	(1)	(2)	(3)	(4)	(5)
$\Delta Qspread$	-1.37		-2.03 *	-2.30 *	
	(-1.47)		(-1.96)	(-1.76)	
$\Delta LR_{CC}(10^4)$		36.28	85.22	86.54	
		(0.69)	(1.47)	(1.49)	
IMR				4.03	
				(0.34)	
Intercept	2.60 **	2.94 **	2.88 **	1.22	
	(2.17)	(2.37)	(2.36)	(0.24)	
R^2	0.02	0.00	0.04	0.04	
N	101	101	101	101	

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

Table 7: Post-event DMM activity and gross trading profit in high and low quoted spread regimes

This table compares DMM participation rate and his gross trading profit in low and high quoted spread regime using our 230*74 stock-days panel dataset. We define participation rate as the ratio of the number of transactions that have a DMM on one side of the trade and the total number of transactions. We calculate the gross trading profit per trade (GTP) in stock i on day t as follows:

$$GTP_{it} = (S_{it} - B_{it} + p_{it}I_{it} - p_{i,t-1}I_{i,t-1})/trades_{it} \tag{1}$$

where p_{it} is the midquote of stock i at the end of day t, I_{it} is the specialist inventory in shares of stock i at the end of day t, S_{it} is the total euro value of stock i sold on day t, B_{it} is the total euro value of shares bought, and $trades_{it}$ captures the number of transactions with DMM on one side of the transaction. We do not observe DMM inventory and therefore assume that they are zero at the start of the data sample. We further assume that DMMs do all their trading through the system so that the inventory at any point is time is the cumulative sum of their signed trade sizes in shares. We estimate the following panel data model to test for differences across liquidity regimes:

$$y_{it} = \alpha_i + \beta_{low} low\_qspread_{it} + \beta_{high} high\_qspread_{it} + \varepsilon_{it}, \tag{2}$$

where low_spread_{it} is a dummy that indicates that quoted spread on day t for stock i falls below the stock-specific q_i quantile and $high\_spread_{it}$ is defined analogously. We also estimate the model with the squared residuals of the GTP regression to estimate whether GTP volatility is different across the two regimes.

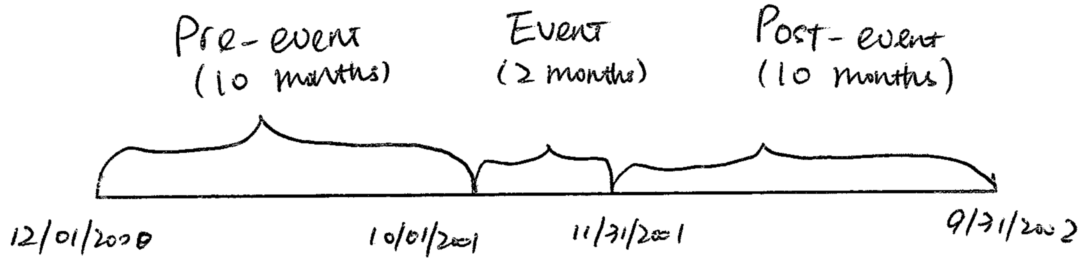
	low quoted spread regime [a] (1)	high quoted spread regime [a] (2)	difference (2)-(1)
Panel A: Quantile cutoff level Q to identify regime is 0.10.			
Participation rate	0.17	0.29	0.12 *
	(0.01)	(0.01)	(0.02)
Profit per trade	134.58	73.80	-60.78
	(139.22)	(205.05)	(272.55)
Variance profit per trade(10^6)	24.50	47.61	23.12 *
	(3.58)	(4.27)	(5.76)
Standard deviation profit per trade(10^3)	4.95	6.90	1.95 *
	(0.36)	(0.31)	-
Panel B: Quantile cutoff level Q to identify regime is 0.33.			
Participation rate	0.19	0.28	0.09 *
	(0.01)	(0.01)	(0.01)
Profit per trade	134.21	51.25	-82.96
	(65.59)	(82.53)	(136.16)
Variance profit per trade	27.24	39.26	12.02 *
	(1.75)	(2.22)	(3.60)
Standard deviation profit per trade	5.22	6.27	1.05 *
	(0.17)	(0.18)	-
Panel C: Quantile cutoff level Q to identify regime is 0.50.			
Participation rate	0.20	0.27	0.07 *
	(0.00)	(0.00)	(0.01)
Profit per trade	126.32	116.69	-9.63
	(61.52)	(55.62)	(117.12)
Variance profit per trade	28.30	36.14	7.84 *
	(1.33)	(1.20)	(2.54)
Standard deviation profit per trade	5.32	6.01	0.69 *
	(0.13)	(0.10)	-

[a]: we classify days with a time-weighted quoted spread less (more) than the stock-specific Q (1-Q) quantile as the low (high) qutoed spread regime.

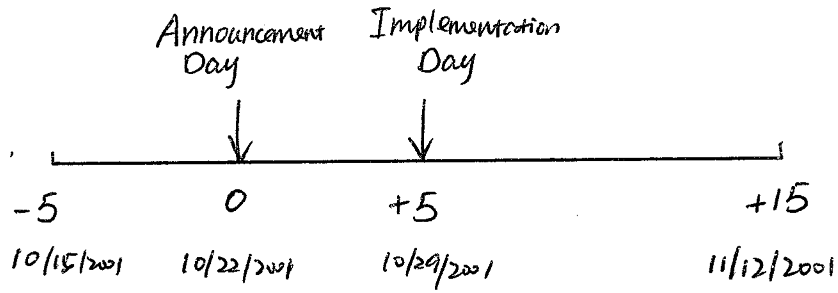
* : Significant at a 99% level.

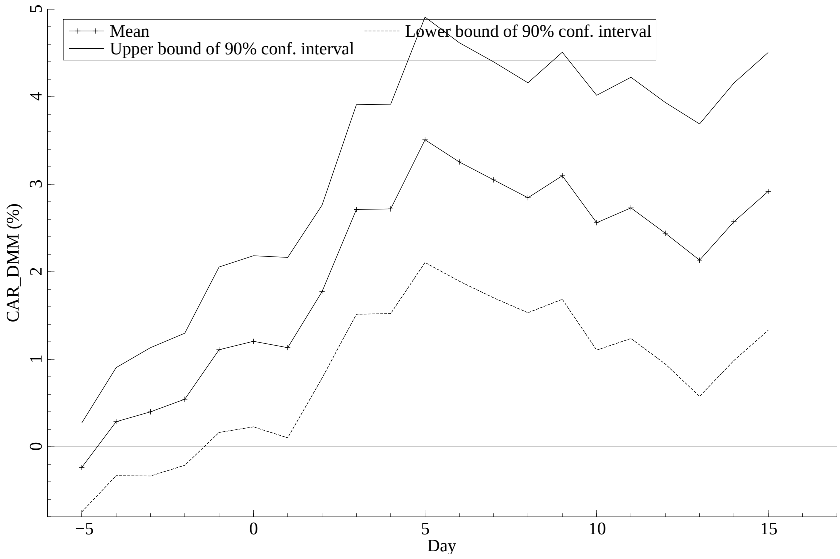
Figure 1: Calendar

Panel A: Sample Period (22 months)

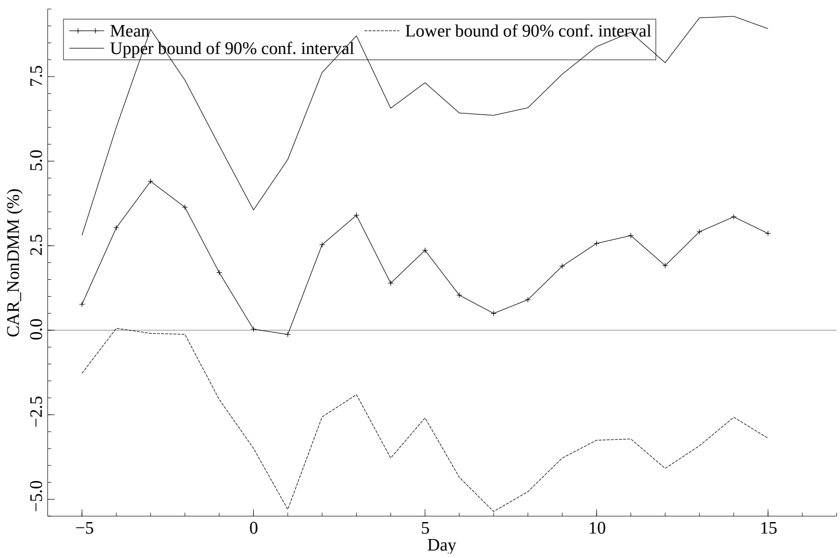


Panel B: Event Window (21 days)





(a) Cumulative abnormal return of DMM stocks



(b) Cumulative abnormal return of non-DMM stocks

Figure 2: Cumulative abnormal returns in the event period

This figure presents the average cumulative abnormal return with the 90% confidence interval during a period from 5 days before the announcement of designated market makers (day 0) to 15 days after. Panel (a) reports CAR of DMM stocks; Panel (b) reports CAR of non-DMM stocks. Confidence intervals are calculated using robust standard errors.