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

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Abstract

A poor liquidity level and a high liquidity risk raise the cost of capital for small-cap firms. Euronext allows them to contract with designated market makers (DMMs) who commit to supply a minimum liquidity *at all times*. We conduct an event study focused on 74 firms that sign up for DMMs. We find that the contract improves the liquidity level, reduces the liquidity risk, and generates an average cumulative abnormal return of 3.5%. It seems that shareholders willingly pay a DMM fee to insure against idiosyncratic future trading needs at times of low endogenous liquidity. Empirically, we find that DMMs participate in more trades and suffer a trading loss on high quoted spread days. That is, on days when their constraints are likely to bind.

Financial market development and economic growth are related. Rajan and Zingales (1998) provide evidence to suggest a causal relationship from financial market development to growth. Levine and Zervos (1998) emphasize stock market liquidity as an important attribute of financial market development in this causal relationship.

Liquidity appears to be a particularly important friction for small-cap firms that are often considered to be an engine of innovation and growth (Acs and Audretsch (1988) and Acs (1999)).[1] Cross-sectionally, small-caps exhibit lowest liquidity levels and highest liquidity risk, which both raise their cost of capital substantially. 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.[2] Both studies show that these illiquid stocks typically belong to 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 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 an ask quote which cannot be further apart than the contracted maximum spread and these quotes need to have the contracted minimum depth. Two recent studies for the French and

[1] In the introductory chapter Acs emphasizes Schumpeter's argument that one should take an evolutionary view to appreciate the importance of small firms for innovation and economic growth.

[2] 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."

Swedish market find that a DMM introduction raises a stock's liquidity level and it produces abnormal returns of roughly five percent around the introduction (see Venkataraman and Waisburd (2007) and Anand, Tanggaard, and Weaver (2008), respectively).

We conduct an event study and, contrary to previous work, focus on liquidity risk as the contract directly improves liquidity only by eliminating the most extreme illiquidity.[3] That is, hiring a broker as a "supplier of last resort" insures current shareholders against the idiosyncratic[4] risk of having to trade when liquidity is low. It also mechanically reduces co-variation with market return and market liquidity and therefore reduces systematic liquidity risk (see Acharya and Pedersen (2005)). The value is realized at times of low endogenous liquidity where the supply constraint binds and shareholders can realize a gain from trade that otherwise might be dominated by too high transaction cost. This effect should show through more volume and higher DMM participation in these 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 firms enter DMM contracts out of 101 eligible firms. We emphasize that the advantage of the exogenous system change is that we are not exposed to a potential endogenous timing bias that comes with sequential introduction, which was studied in the French and Swedish sample. If brokerage firms privately observe that future liquidity supply will 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

[3]Charitou and Panayides (2006), in their review of international stock markets, find that the "maximum spread" rule is by far the most common affirmative obligation.

[4]We assume markets to be incomplete with respect to such event.

the introduction as well as an ex-post liquidity improvement. We admit that we might still suffer from an endogenous selection bias across DMM and nonDMM stocks for which we control with a standard Heckman procedure. We find little empirical support for such bias as find that the inverse Mills ratio is not significant in our cross-sectional regressions.[5]

The novel structure of firms that pay for liquidity supply fits into a large literature on designated market makers with affirmative obligations. Most studies focus on the NYSE specialist who is subject to the Price Continuity Rule. Panayides (2007) shows this obligation to supply liquidity in order to smooth price discovery is costly to her at times when the constraint binds. In return, she enjoys trading privileges to recoup this cost at times when the constraint does not bind. One example of such privilege is that she enjoys a last-mover advantage when supplying liquidity which allows her to condition on the incoming market order and pick off uninformed orders, thereby exposing limit order traders to increased information risk (see e.g. Rock (1996)). This 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 and we are back in a pure limit order market. Other 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 privilige effectively taxes other market participants and therefore distorts incentives. In this context, the Euronext DMM system more naturally sends the bill

[5]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 support for endogenous selection in the Heckman procedure.

of liquidity support to where it ought to be i.e. with the issuer.[6]

The empirical strategy in the paper naturally falls into two parts.

First, we document how liquidity level and liquidity risk change with the introduction of a DMM where we uses the Acharya and Pedersen (2005) measures of liquidity risk. We use a difference-in-difference approach (i.e. post- minus pre-event differenced across DMM and nonDMM stocks) to test for any such effect. We then calculate cumulative abnormal returns around the announcement and effective date. Finally, we relate the two analyses through a cross-sectional regression since if liquidity changes drive the value creation the abnormal returns should be highest for stocks that show the largest level improvement, the largest 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 roughly €1 billion.

Second, we hunt for empirical support of value creation through the channel of investors consuming the service of a DMM as "supplier of last resort." We benefit from a dataset that identifies for each side of a trade (buy or sell) whether there was a DMM or not. We do the following. First, we characterize post-event trading days for DMM stocks as likely to be binding or nonbinding constraint days. We then test across these two types of days whether DMMs participate in more trades on binding days as they fulfill their duty of supplier of last resort. We also calculate their gross trading revenue across these two type of days to verify whether their increased participation is costly. Finally, we verify whether their service

[6] 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)).

is consumed in the sense that it indeed generates more volume. We do so by comparing the binding post-event days with similar pre-event days. We find empirical support in all three analyses.

We identify three ways in which we contribute to the literature. First, we test for a liquidity risk channel in addition to the liquidity level channel for value creation. Second, we exploit DMM identification in our trade data to test the idea that firms hire DMMs as a supplier of last resort. Third, we do not suffer from a potential endogenous timing bias that haunts the existing studies on sequential introduction.

In analyzing how DMMs create social value, Bessembinder, Hao, and Lemmon (2007) propose an alternative informational channel by which DMMs could create value.[7] 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 that the realized spread component and (ii) it does increase significantly with the addition of a DMM. We do find however that a DMM does make the daily midquote return autocorrelation less negative which is some evidence of improved price discovery.

The remainder of the paper is organized as follows. Section 1 discusses the institutional background of DMM introduction in the Dutch market. Section 2 discusses how DMMs could create value as liquidity suppliers of last resort. Section 3 presents the data, discusses

[7] They also discuss a noninformational 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.

the methodology, and reviews 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 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.[8] We refer to Biais, Hillion, and Spatt (1995) for a detailed description of the Euronext trading model.

In 1992, the Paris Bourse introduces designated market makers to address the poor liquidity supply by public limit orders for inactively traded stocks. The exchange however does not mandate stocks to trade with a DMM, nor is it involved in the process of selecting a broker who provides a DMM service. Both decisions are taken by the listed firm. The exchange only facilitates the process by providing firms with a list of DMM brokers. It does require a DMM to sign its standard contract and guarantee a minimum liquidity supply set by the exchange ("General Terms"). That is, the DMM needs to commit to always have a bid and ask quote in the market that cannot be further apart than the exchange-mandated

[8]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.

maximum spread and that each have to meet the exchange-mandated minimum depth. The issuer however is free to negotiate tighter liquidity supply with the DMM. Once the contract is in place, the exchange monitors the DMMs and may terminate the service if a DMM does not meet her commitment.

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.[9] This might be seen as a "soft" payment by the firm as these brokers now might not need 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 cherrypick (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

[9]This compensation is particularly important for the Dutch market as brokers who offer a DMM service are members of financial conglomerates. Examples of cross-sellings 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 relationship allows them to make a bid when the firm shows interest in these products.

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 introduces 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 replaces a similar well-functioning electronic limit order book. The new DMM feature 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.[10] Euronext eventually addressed these concerns by agreeing to report all DMM transactions to the local regulator.[11] Another feature unique to the Amsterdam market is that Euronext introduces the DMM option only for a subset of small-cap stocks. It excludes all Euronext 100 index stocks and stocks that generate less than 2,500 transactions per annum. It further sets the minimum liquidity supply in the "General Terms" of the contract at a maximum spread of 4% and a minimum depth of €10,000 for the majority of stocks.[12]

In addition to the DMM option as its most salient change, the new system brings 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

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

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

[12] 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.

duty nor any 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 move from the old continuous market to a twice a day electronic auction. The only way to stay in the continous 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 5).

On the Monday in the week ahead of the introduction day, Euronext publishes the list of the 74 firms that signed up with brokers for a DMM service.[13] Interestingly, Dutch small-caps contract with more than one DMM—3.13 on average out of a dozen brokerage firms that offer the service[14]—whereas the majority of French firms hire 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 creates many opportunities for cross-selling other products. Second, the average Dutch DMM stock is a fat cat relative to its French counterpart as it

[13]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.

[14]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

belongs to a 12 times larger firm (in terms of market cap) and it generates 63 times more volume.[15]

2 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[16]

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 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

[15]Based on comparing our Table 1 with Table 1 in Venkataraman and Waisburd (2007).
[16]See *Financieel Dagblad*, "Animateurs Betalen veel Leergeld," September 17, 2002.

CAPM model to returns *net* of transaction cost. Formally, it yields:

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

where

$$\begin{aligned}
\beta_i^{net} &= \frac{cov(r_t^i - c_t^i, r_t^m - c_t^m)}{var(r_t^m - c_t^m)}, \qquad (2)\\
&= \frac{cov(r_t^i, r_t^m)}{var(r_t^m - c_t^m)} + \frac{cov(c_t^i, c_t^m)}{var(r_t^m - c_t^m)} - \frac{cov(r_t^i, c_t^m)}{var(r_t^m - c_t^m)} - \frac{cov(c_t^i, r_t^m)}{var(r_t^m - c_t^m)},\\
&= \beta_i^{rr} + \beta_i^{cc} + \beta_i^{rc} + \beta_i^{cr}.
\end{aligned}$$

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

$$E(r_t^i) = E(r_t^f) + E(c_t^i) + \lambda(\beta_i^{rr} + \beta_i^{cc} + \beta_i^{rc} + \beta_i^{cr}) \tag{3}$$

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 counterparty 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.[17] 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 hunt for these volume effects in the data.

[17]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.

3 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 hunt 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.

3.1 Data and summary statistics

3.1.1 Data

We use three 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 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. 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.

[insert Figure 1]

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 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 as an appendix.

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

$$espread_{it} = 2q_{it}(p_{it} - m_{it})/m_{it}, \tag{4}$$

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 sells (buys). 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:

$$rspread_{it} = 2q_{it}(p_{it} - m_{it+15min})/m_{it} \text{ and} \tag{5}$$

$$adv\_selection_{it} = 2q_{it}(m_{it+15min} - m_{it})/m_{it}. \tag{6}$$

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

$$ILLIQ_{it} = \frac{|r_{it}|}{volume_{it}} \tag{7}$$

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

$$qspread_{it} = (ask_{it} - bid_{it})/m_{it}, \tag{8}$$

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.

[insert Table 1]

Table 1 presents summary statistics based on our panel dataset which consists of 22 trading months for 74 DMM stocks (Panel A) and 27 nonDMM stocks (Panel B).[18]The statistics lead to a couple of observations. First, we find that DMM stocks in spite of belonging to small-cap firms are still sizeable 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[19] 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

[18]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.

[19]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 2 for the mathematical definitions).

spread histograms stock by stock that many firms appear to contract on tighter spreads.[20] 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.[21] 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 19) 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.

[insert Table 2]

Table 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.

[20] 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.

[21] 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.

3.2 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):

$$y_{it} = \alpha_i + \beta_1 post_t * DMM_i + \beta_2 post_t + \beta_3' control\_vars_{it} + \gamma_t + \varepsilon_{it} \tag{9}$$

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. Our standard errors explicitly recognize commonalities across stocks through the time effect and they also control for within-stock autocorrelation and heteroskedasticity through what is effectively a Newey-West type procedure[22]. 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.

[insert Table 3]

[22] See Arellano and Bond (1991) for the details.

Table 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-diffference for effective spread is a significant -1.50%.[23] 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 also decline in an absolute sense by 0.13% (i.e. 1.37%-1.50%). These 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 these observations start to dominate the regressions.[24] We exclude the $ILLIQ$ measure from any remaining analysis given its poor statistical performance.[25]

[23]The large magnitude of the effect relative to a pre-event average effective spread for DMM stocks of 1.24% is undoubtedly the result of a general decline in liquidity in the aftermath of the September 11 attacks. So, the appropriate benchmark spread is higher and captured by the change in spread for nonDMM stocks. This is the strength of a difference-in-difference approach.

[24]Table 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.

[25]We have also added "DMM×Post×#DMM" to capture a potential difference-in-difference effect from the *number* of DMMs a firm hires. We find a significantly negative coefficient only for the effective spread in the amount of 0.07% (i.e. no significant effect for quoted spread or $ILLIQ$). In the effective spread decomposition, we find that the adverse selection component is significantly reduced, not the realized spread component. The effect is substantially smaller than the DMM-or-not effect as captured by the "DMM×Post" variable. We therefore ignore it in the remainder of the analysis.

Table 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 1).

Liquidity risk change. We measure liquidity risk through the Acharya and Pedersen (2005) liquidity risk betas as summarized in equation (1). To enable direct econometric tests on beta changes, we estimate the following panel data model based on daily data:

$$
\begin{aligned}
r_{it} &= \sum_{k \in \{pre, post\}} \alpha_{ik}^{rr} + \tilde{\beta}_{ik}^{rr} k_t * r_t^m + \varepsilon_{it}^{rr} && (10) \\
r_{it} &= \sum_{k \in \{pre, post\}} \alpha_{ik}^{rc} - \tilde{\beta}_{ik}^{rc} k_t * c_t^m + \varepsilon_{it}^{rc} && (11) \\
c_{it} &= \sum_{k \in \{pre, post\}} \alpha_{ik}^{cr} - \tilde{\beta}_{ik}^{cr} k_t * r_t^m + \varepsilon_{it}^{cr} && (12) \\
c_{it} &= \sum_{k \in \{pre, post\}} \alpha_{ik}^{cc} + \tilde{\beta}_{ik}^{cc} k_t * c_t^m + \varepsilon_{it}^{cc} && (13)
\end{aligned}
$$

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_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. In the procedure we use a Newey-West type procedure to ensure that the standard errors in our test statistics are robust to stock-specific autocorrelation and heteroskedasticity.[26] 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 (1)). In reporting our results, we scale the regression betas with the appropriate covariance ratio to arrive at the AP betas.[27] 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 (2)).

[insert Table 4]

Table 4 finds that only the β^{cc} liquidity risk is significantly reduced for DMM stocks relative to nonDMM stocks. 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 (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

[26] See Arellano and Bond (1991) for details.

[27] Stock by stock we multiply the regression beta with $(var(r_{it})/var(r_t^m - c_t^m))$ for equation (10) and (11) and $(var(c_{it})/var(r_t^m - c_t^m))$ for equation (12) and (13).

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, i.e. a security's transaction cost covaries less with market transaction cost after hiring a designated market maker.

[insert Figure 2]

Cumulative abnormal returns. Figure 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 1). We estimate CARs based on daily midquote returns and post-event market beta estimates.[28] 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,

[28] 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 1).

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 and only pitch aggressively to those firms with good liquidity prospects.[29] 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

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

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):

$$\begin{aligned} Pr[DMM_i = 1] = \ & \Phi(\alpha_1 + \alpha_2 volatility_i + \alpha_3 volume_i + \alpha_4 price_i + \\ & \alpha_5 nr\_shares\_outstanding_i + \alpha_6 auction\_threat_i), \end{aligned} \tag{14}$$

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, and $auction\_threat$ 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. The reason for including the last 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.

[insert Table 5]

Table 5 finds that smaller firms and firms with more volatile stock 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 (2008). We do not find any significance for volume, stock price, or the auction threat dummy.

[insert Table 6]

Table 6 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.[30] 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. 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. 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.[31]

[30] 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 3).

[31] We believe the weak results for quoted spread relative to effective spread indicate that investors only appreciate liquidity level and liquidity risk changes if they coincide with the time of their trading need which

3.3 Binding vs. nonbinding liquidity regimes

In this second set of empirical analyses, we hunt 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 (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

explains the stronger results for the ex-post measure.

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:

$$GTR_{it} = (S_{it} - B_{it} + p_{it}I_{it} - p_{i,t-1}I_{i,t-1})/nr\_shares\_transacted_{it}, \tag{15}$$

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.[32]

[32] 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.

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 et al. (2008)). The first inventory-neutral component is defined as:

$$RTR_{it} = min(s_{it}, b_{it})(\overline{p}^s_{it} - \overline{p}^b_{it}), \tag{16}$$

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:

$$ITR_{it} = (p_{it} - \overline{p}^b_{it})(b_{it} - s_{it})^+ + (\overline{p}^s_{it} - p_{it})(s_{it} - b_{it})^+ + I_{i,t-1}(p_{it} - p_{i,t-1}), \tag{17}$$

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:

$$GTR_{it} = RTR_{it} + ITR_{it} \tag{18}$$

for each day in the sample.

We estimate the following panel data model for all variables of interest:

$$y_{it} = \alpha_i + \beta_{low} low\_qspread_{it} + \beta_{high} high\_qspread_{it} + \varepsilon_{it}, \tag{19}$$

where i indexes stocks and t indexes days, $low\_qspread_{it}$ is a dummy that is one for the days that are labeled "low spread days", zero otherwise, $high\_qspread_{it}$ is defined analogously.

[insert Table 7]

Table 7 compares high to low quoted spread days and finds that DMMs participate in more trades 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. 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. Panels B and C show that these results are robust to changing the quantile from 0.10 to 0.33 or 0.50, respectively.

Table 7 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 (9)).

[insert Table 8]

Table 8 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.[33]

4 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:

1. 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.[34]

2. 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

[33] We also find an overall volume increase in the difference-in-difference analysis of Table 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 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.

[34] 74 stocks * 3.5% * €0.49 billion market cap (see Table 1).

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.

3. 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.

4. 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.

5. Finally, 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.

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.[35]

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[35]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.

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Appendix: 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

Table 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 12/1/00 trough 9/20/02. 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*), volatility 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(σ)	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(σ)	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. $x^*_{i,t} = x_{i,t} - \bar{x}_i$.

Table 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.

Table 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 were 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.

	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*
	(-3.69)	(-3.90)	(-3.23)	(-3.47)	(-0.84)	(-0.83)	(-3.72)	(-3.84)	(0.02)	(0.17)	(0.98)	(0.11)	(2.90)
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*
	(3.38)	(3.78)	(2.06)	(2.33)	(0.90)	(0.85)	(3.16)	(3.35)	(0.31)	(0.15)	(-0.15)	(-1.44)	(-2.51)
price		-0.01		-0.01		0.01		0.01		-0.02*			
		(-1.13)		(-1.81)		(0.21)		(0.93)		(-4.96)			
volume		-0.00*		-0.00*		0.01		-0.00		-0.00*			
		(-2.23)		(-3.47)		(1.02)		(-0.21)		(-2.21)			
volatility		0.15*		0.24*		-0.67		0.03		0.12*			
		(6.63)		(6.57)		(-1.69)		(0.91)		(4.85)			
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.

Table 4: 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*460 stock-day panel dataset to estimate the following model specification:

$$r_{it} = \sum_{k\in\{pre,post\}} \alpha_{ik}^{rr} + \tilde{\beta}_{ik}^{rr} k_t * r_t^m + \varepsilon_{it}^{rr} \quad (1)$$

$$r_{it} = \sum_{k\in\{pre,post\}} \alpha_{ik}^{rc} - \tilde{\beta}_{ik}^{rc} k_t * c_t^m + \varepsilon_{it}^{rc} \quad (2)$$

$$c_{it} = \sum_{k\in\{pre,post\}} \alpha_{ik}^{cr} - \tilde{\beta}_{ik}^{cr} k_t * r_t^m + \varepsilon_{it}^{cr} \quad (3)$$

$$c_{it} = \sum_{k\in\{pre,post\}} \alpha_{ik}^{cc} + \tilde{\beta}_{ik}^{cc} k_t * c_t^m + \varepsilon_{it}^{cc} \quad (4)$$

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_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 seperately, and it equals $(var(r_{it})/var(r_t^m - c_t^m))$ for equation (1) and (2) and $(var(c_{it})/var(r_t^m - c_t^m))$ for equation (3) and (4). We add t-values in parentheses.

	DMM stocks				nonDMM stocks				DMM stocks - nonDMM stocks			
	β^{rr} ($\times10^{-2}$)	β^{cc} ($\times10^{-4}$)	β^{rc} ($\times10^{-4}$)	β^{cr} ($\times10^{-4}$)	β^{rr} ($\times10^{-2}$)	β^{cc} ($\times10^{-4}$)	β^{rc} ($\times10^{-4}$)	β^{cr} ($\times10^{-4}$)	β^{rr} ($\times10^{-2}$)	β^{cc} ($\times10^{-4}$)	β^{rc} ($\times10^{-4}$)	β^{cr} ($\times10^{-4}$)
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	-26.98*	0.01*	1.31	-11.98
	(27.81)	(4.38)	(0.32)	(1.65)	(27.32)	(1.47)	(2.72)	(0.93)	(9.63)	(2.96)	(1.68)	(1.89)
post-event	27.03*	0.01*	0.56*	3.32	39.31*	0.03*	0.36*	22.28*	-12.27*	-0.02	0.21*	-18.96
	(23.24)	(11.17)	(14.27)	(1.19)	(20.42)	(17.32)	(5.46)	(4.57)	(9.34)	(0.13)	(9.40)	(1.46)
post-event − pre-event	-15.74*	-0.02*	0.48	9.37	-30.45*	0.01	1.58*	16.35	14.71	-0.03*	-1.11	-6.98
	(8.16)	(2.71)	(1.73)	(2.03)	(9.52)	(1.16)	(3.47)	(2.04)	(2.05)	(2.91)	(0.31)	(0.62)
#Observations	43,925											
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	-26.99*	-0.02*	0.19*	-8.25
	(27.81)	(21.13)	(5.08)	(0.20)	(27.32)	(25.19)	(1.24)	(2.26)	(9.63)	(5.11)	(3.70)	(1.00)
post-event	27.03*	0.01*	0.64*	3.56	39.30*	0.04*	0.41*	21.61*	-12.27*	-0.02	0.23*	-18.05
	(23.24)	(21.02)	(13.68)	(2.03)	(20.42)	(32.84)	(5.36)	(7.33)	(9.34)	(0.81)	(8.95)	(2.10)
post-event − pre-event	-15.74*	-0.01*	0.31*	3.09	-30.46*	-0.00	0.28	12.89*	14.71	-0.00*	0.03	-9.79
	(8.16)	(4.81)	(3.95)	(1.06)	(9.53)	(0.87)	(2.13)	(2.66)	(2.05)	(3.66)	(2.27)	(0.47)
#Observations	45,539											

* : Significant at a 99% level.

Table 5: 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:

$$Pr[DMM_i = 1] = \Phi(\alpha_1 + \alpha_2 volatility_i + \alpha_3 volume_i + \alpha_4 price_i + \alpha_5 nr\_shares\_outstanding_i + \alpha_6 auction\_threat)$$

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, and $auction\_threat$ 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. The Probit regression is based on 101 stocks (74 DMM stocks and 27 nonDMM stocks). We use maximum likelihood to estimate the model parameters.

	Coefficient	t-stat
volatility	-0.54	-4.23*
volume	0.00	0.91
price	-0.00	-0.28
nr_shares_outstanding	-11.00	-3.60*
auction_threat	0.22	0.55
intercept	2.43	4.47*
#Observations	101	

* : Significant at a 95% level.

Table 6: 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 Tables 3 and 4) 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 is the only one that significantly changes with the introduction of a DMM. The IMR is based on the Probit model estimate of Table 5. 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 **	-2.81 **
	(-3.43)		(-2.38)	(-2.50)
$\Delta adv\_selection^a$	0.62		1.18	0.66
	(0.55)		(1.00)	(0.52)
$\Delta\beta^{cc}(\times 10^2)$		-74.71 **	-53.61 *	-53.58 *
		(-2.77)	(-1.85)	(-1.85)
IMR				10.74
				(1.00)
intercept	2.76 **	1.65	2.10 *	-2.09
	(2.60)	(1.50)	(1.88)	(-0.48)
R^2	0.12	0.07	0.15	0.16
#Observations	101	101	101	101
Panel B: Quoted spread as the liquidity measure				
	(1)	(2)	(3)	(4)
$\Delta qspread$	-2.02 **		-2.46 **	-2.82 **
	(-2.40)		(-2.61)	(-2.42)
$\Delta\beta^{cc}(\times 10^2)$		-2.13	57.12	60.94
		(-0.04)	(1.09)	(1.15)
IMR				5.51
				(0.53)
intercept	2.06 *	2.32 **	2.25 **	-0.02
	(1.91)	(2.04)	(2.04)	(-0.00)
R^2	0.05	0.00	0.07	0.07
#Observations	101	101	101	101

**: 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.

Table 7: Post-event participation and trading revenues of DMMs 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 particitpate in more trades and suffer lower trading revenues 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 and DMM gross trading revenue (GTR) 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. 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.

	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
	(23.54)	(39.42)	(8.07)	
$DMM\_GTR\_pershare$	0.95	-1.10	-2.04 *	2,628
	(1.86)	(-2.62)	(-2.20)	
$DMM\_ITR\_pershare$	0.94	-1.12	-2.05 *	2,628
	(1.85)	(-2.66)	(-2.21)	
$DMM\_RTR\_pershare$	0.01	0.02	0.01 *	2,638
	(6.42)	(20.88)	(5.86)	
$rspread$	0.32	0.56	0.24 *	2,324
	(20.60)	(30.65)	(7.00)	
Panel B: q=0.33 quantile to identify liquidity regimes				
$DMM\_particip\_rate$	0.21	0.31	0.10 *	11,193
	(32.97)	(48.06)	(7.79)	
$DMM\_GTR\_pershare$	0.27	-1.15	-1.42 *	8,855
	(0.96)	(-4.52)	(-2.65)	
$DMM\_ITR\_pershare$	0.26	-1.17	-1.43 *	8,855
	(0.92)	(-4.60)	(-2.66)	
$DMM\_RTR\_pershare$	0.01	0.02	0.01 *	8,900
	(17.32)	(31.98)	(6.32)	
$rspread$	0.34	0.49	0.15 *	7,557
	(31.28)	(41.19)	(6.70)	
Panel C: q=0.50 quantile to identify liquidity regimes				
$DMM\_particip\_rate$	0.22	0.30	0.08 *	16,712
	(48.22)	(64.32)	(8.34)	
$DMM\_GTR\_pershare$	-0.15	-1.32	-1.17 *	13,360
	(-0.75)	(-6.99)	(-2.99)	
$DMM\_ITR\_pershare$	-0.17	-1.34	-1.18 *	13,360
	(-0.82)	(-7.08)	(-3.00)	
$DMM\_RTR\_pershare$	0.01	0.02	0.01 *	13,444
	(26.05)	(39.38)	(5.53)	
$rspread$	0.35	0.46	0.11 *	11,364
	(41.15)	(51.01)	(6.49)	

* : Significant at a 95% level.

Table 8: 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 7) 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.

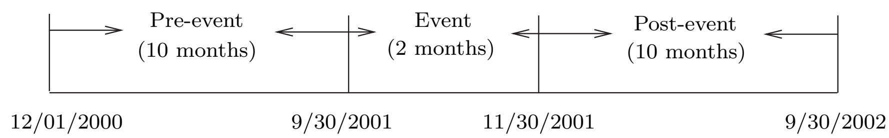
	Pre-event high quoted spread regime[b] (1)	Post-event high quoted spread regime[c] (2)	Difference[a] (2)-(1)
Panel A: q=0.10 quantile to identify liquidity regimes			
DMM stocks	43.81	48.70	4.89
	(7.90)	(8.17)	(1.47)
NonDMM stocks	42.10	32.32	-9.78
	(19.36)	(4.23)	(-1.79)
DMM stocks - NonDMM stocks	1.71	16.38	14.67*
	(0.22)	(1.23)	(2.29)
#Observations	7,728		
Panel B: q=0.33 quantile to identify liquidity regimes			
DMM stocks	41.87	46.96	5.09*
	(5.76)	(6.37)	(2.07)
NonDMM stocks	41.83	33.81	-8.02
	(14.41)	(3.34)	(-1.11)
DMM stocks - NonDMM stocks	0.03	13.14	13.11
	(0.00)	(0.76)	(1.72)
#Observations	17,556		
Panel C: q=0.50 quantile to identify liquidity regimes			
DMM stocks	42.54	48.39	5.85*
	(8.75)	(9.73)	(2.35)
NonDMM stocks	43.03	34.96	-8.06
	(22.86)	(5.12)	(-1.63)
DMM stocks - NonDMM stocks	-0.48	13.43	13.91*
	(-0.07)	(1.15)	(2.51)
#Observations	23,837		

[a]: We use a Wald test to test for significant differences.

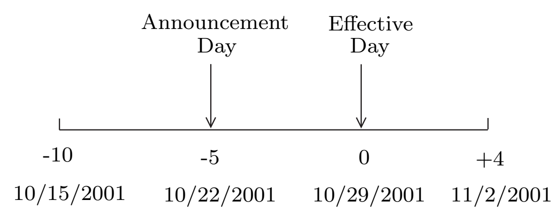
[b]: The pre-event volume of DMM stocks is calculated as $\frac{1}{74}\sum_{i=1}^{74}\alpha_i + \beta_{DMM}$. For nonDMM stocks, it is $\frac{1}{27}\sum_{i=75}^{101}\alpha_i$.

[c]: 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.



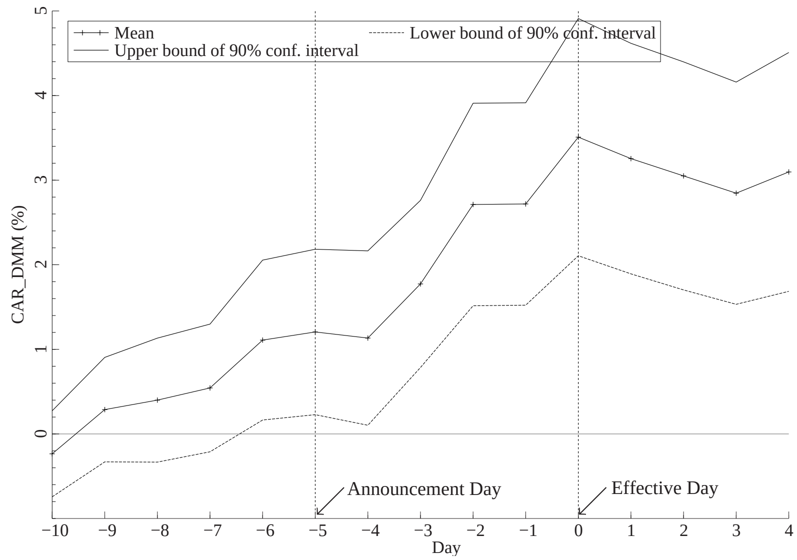
Panel A: Sample period (22 months)



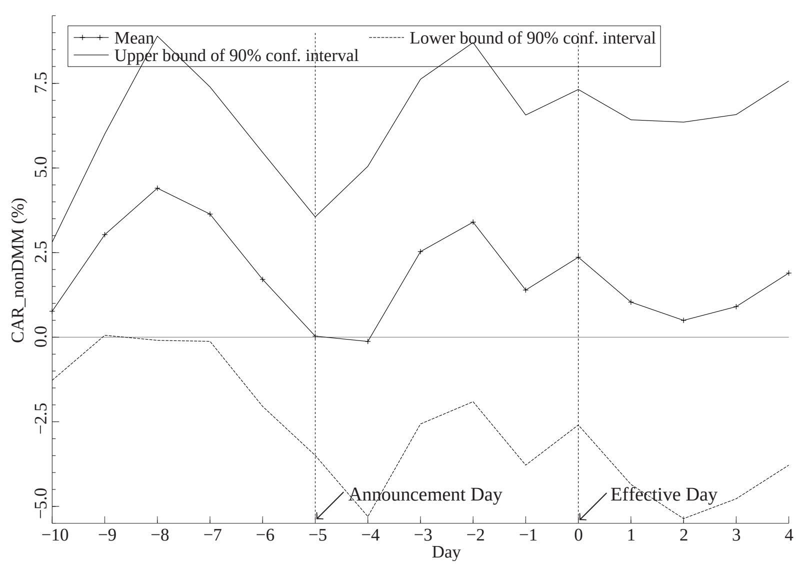
Panel B: Event window (15 days)

Figure 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.



Panel A: Cumulative abnormal return of DMM stocks



Panel B: Cumulative abnormal return of nonDMM stocks

Figure 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.