Should Exchanges impose Market Maker obligations?

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We study the trades of two important classes of market makers, Designated Market Makers (DMMs) and Endogenous Liquidity Providers (ELPs). The former have exchange-assigned obligations to supply liquidity while the latter do so because it is a profitable activity. We compare market maker participation in the cross-section of stocks and under different market conditions and relate the participation decision to trading profits, inventory risk, and capital commitments. Market makers maintain a reliable presence in large stocks when they have no obligation to do so and increase participation when volatility is high. For other stocks, ELP participation is sparse and reflects an active exercise of the option to withdraw when profit opportunities are small or inventory risk is high. DMMs earn relatively smaller profits, assume higher inventory risk, and commit more capital on days with no ELP participation. We show that DMMs reduce execution uncertainty by participating in undesirable trades and serve a fundamental role as providers of immediacy. Our results point to the suitability of a hybrid market structure comprising a limit order book and a DMM to trade less active securities.

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Keywords: Designated market maker; HFTs; Market design; Electronic limit order book.

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Abstract

We study the trades of two important classes of market makers, Designated Market Makers (DMMs) and Endogenous Liquidity Providers (ELPs). The former have exchange-assigned obligations to supply liquidity while the latter do so because it is a profitable activity. We compare market maker participation in the cross-section of stocks and under different market conditions and relate the participation decision to trading profits, inventory risk, and capital commitments. Market makers maintain a reliable presence in large stocks when they have no obligation to do so and increase participation when volatility is high. For other stocks, ELP participation is sparse and reflects an active exercise of the option to withdraw when profit opportunities are small or inventory risk is high. DMMs earn relatively smaller profits, assume higher inventory risk, and commit more capital on days with no ELP participation. We show that DMMs reduce execution uncertainty by participating in undesirable trades and serve a fundamental role as providers of immediacy. Our results point to the suitability of a hybrid market structure comprising a limit order book and a DMM to trade less active securities.

Keywords: Designated market maker; High frequency trader; Market design; Electronic limit order book.

We should consider the relevance today of a basic premise of the old specialist obligations - that the professional trading firms with the best access to the markets (and therefore the greatest capacity to affect trading for good or for ill) should be subject to obligations to trade in ways that support the stability and fairness of the markets.

Chairman Mary L. Shapiro, *Securities and Exchange Commission*
Economic Club of New York
September 7, 2010

Introduction

Exchange mechanisms that offer continuous trading allow for faster execution of orders. However there may be no counterparties available at a particular moment in time when a trader demands liquidity (Demsetz (1968), Garbade and Silber (1982)). Theoretical models (e.g., Grossman and Miller (1988)) show that such trading uncertainties can be mitigated by the regular presence of intermediaries (dealers or market makers) who fill the gaps arising from asynchronous order arrival. An important question in market design is whether it is desirable for exchanges to impose obligations on market makers, or stated alternatively, whether profit-motivated market participants *reliably* provide liquidity when they have no obligation to do so. Profit motivated liquidity suppliers choose to serve as Endogenous Liquidity Providers (ELPs) who implement market making strategies because it is a profitable activity. In contrast, exchanges can create a class of intermediaries, typically described as Designated Market Makers (DMM) or Specialists, who have specific "affirmative" and "negative" obligations imposed to a varying degree by the exchange. The DMMs are contractually obligated to maintain a market presence by continuously posting quotes with reasonable depth.

Although endogenous liquidity provision is a central tenet of the modern stock and derivative markets, where liquidity is supplied by limit orders in computerized auctions, to date there is little direct evidence on the strategic trading decisions made by ELPs, and how their decisions differ from those made by DMMs.[1] The lack of empirical analysis reflects the difficulty in obtaining detailed data on ELP

[1] There is however a well-developed empirical literature on the trades of the DMM, especially of the NYSE Specialist. See for example, Hasbrouck and Sofianos (1993), Madhavan and Sofianos (1998), and Panayides (2010) for NYSE Specialist, and Venkataraman and Waisburd (2007) and Anand, Tanggaard and Weaver (2009) for DMMs in electronic limit order markets.

participation in a market structure where ELPs and DMMs co-exist. Many publicly available data sources, such as NYSE's Trade and Quote (TAQ) database, do not identify the trader accounts associated with a transaction. In this study, we use a proprietary, audit trail database made available by Toronto Stock Exchange (henceforth, TSX database), which assigns a single DMM to each security. We compare the two important classes of market makers, namely ELPs and DMMs, and show how trading profits, inventory risk, and capital commitments influence the market maker's decision to supply liquidity.

Our study contributes to the ongoing debate on the design of electronic markets. The implementation of Regulation NMS, and the concomitant growth in algorithmic trading has created a market structure in the United States that relies largely on endogenous liquidity supply in electronic limit order books. The most active market makers in financial markets today are High Frequency Traders (HFT), some of whom trade as ELPs with no affirmative obligations to maintain markets. According to several academic studies, high frequency market making is a profitable enterprise and more importantly the growth in algorithmic trading has improved the market quality in equity markets.[2] These findings are frequently interpreted as empirical support for a market structure where DMMs may be unnecessary.

However, some practitioners and regulators are concerned that a market structure that relies on ELPs for liquidity supply is inherently fragile, and that the perceived fragility reduces investor confidence and market participation. The fragility concern stems from an ELP's option to participate only when it is profitable to do so. The lack of market maker obligations to post quotations can exacerbate execution uncertainty, particularly in times of market stress and in thinly traded securities, when the risks to support markets are too high, but which are also circumstances when the premium placed by investors on the immediacy attribute is particularly high.[3] Moreover, the Flash Crash event of May 6, 2010 has

[2] Recent studies conclude that the activities of the algorithmic traders improve market liquidity (Hendershott, Jones and Menkveld (2011), Hasbrouck and Saar (2011)) and the price discovery process (Hendershott and Riordan (2010)). Menkveld (2011) and Baron, Brogaard and Kirilenko (2012) estimate that the Sharpe ratio of HFTs exceeds 9.0, suggesting that their trades are highly profitable.

[3] The vast majority of stocks listed in equity exchanges today are thinly traded. The problem is more acute in the fixed income market where trading in the secondary market for the majority of corporate bonds and structured credit products is extremely sparse (see Bessembinder, Maxwell and Venkataraman (2012)).

emphasized the need to understand the drivers of market stability (see Kirilenko et al. (2010)). The report from Joint CFTC-SEC Advisory Committee on Emerging Regulatory Issues describes one of the underlying issues as the lack of market maker obligations:

> "*As reported by the Staff Study, however, some of these traders chose to withdraw on May 6 as a reaction to the level of uncertainty. Under our current rules and regulations, the benefits from making markets in good times do not come with any corresponding obligations to support markets in bad times*."

The fact that market makers choose to withdraw participation when liquidity supply is risky, or demand a large bid-ask spread when liquidity supply is costly, need not indicate any market failure or economic inefficiency. Nonetheless, the sudden withdrawal of liquidity reduces the number of counterparties and increases uncertainty on whether an order can be executed, and if so, whether execution will occur with substantial delay. In this context, a few related theoretical papers provide indirect predictions on the benefits of adopting a market structure with DMM. To the extent that investors are ambiguity averse, Easley and O'Hara (2010) assert that the regular presence of a DMM should "reduce the ambiguity attached to the "worst case" scenario, and thus induce investors to participate in the market". Foucault, Kadan and Kandel (2005) model a limit order book market where traders differ in their impatience, or the waiting cost of a delayed execution. In the absence of asymmetric information among traders, their model shows that a market structure that minimizes the dead-weight loss attributable to waiting costs is efficient. The authors (page 1209) "raise the possibility that introducing designated intermediaries in order driven markets could be efficiency enhancing."

Bessembinder, Hao and Zheng (2012) directly demonstrates how the adoption of a DMM market structure improves price discovery and enhances firm value. The authors observe that transaction costs attributable to asymmetric information reduce the trading activity of uninformed investors in secondary markets. A "maximum spread" obligation, which requires the DMM to maintain the bid-ask spread within a specified width, induces increased trading and enhances allocative efficiency. Importantly, their model shows that the benefits to traders, and ultimately to the listed firm via a higher IPO price, exceeds the side payments necessary to compensate the DMM for liquidity provision. Consistent with their theoretical predictions, the empirical literature reports that the introduction of a DMM is associated with positive abnormal returns in the underlying security. In contrasting the behavior of ELPs and DMMs, we directly show where the need for designated liquidity provision is more pressing. Furthermore, we also establish that for the less liquid securities, a DMM is not just an incremental liquidity provider, but largely the only consistent market maker present in the market. This result may help explain the magnitude of price increases (for example, 5% in Venkataraman and Waisburd (2007)) documented in the literature.

Using detailed transaction data on 1,286 stocks traded over 245 days in the calendar year 2006, we study the magnitude and determinants of ELP participation to address two sets of empirical questions. First, what are the stock characteristics associated with ELP participation, and specifically, how does ELP activity vary with market capitalization and return volatility? Are DMMs active in stocks with low ELP participation? Second, what affects ELP trading over time in an individual stock? How does participation relate to inventory risk, capital commitment, and trading profits, and how do the trades of ELPs differ from those of DMMs? Evidence regarding these issues can further our understanding of the relative merits of market structures as well as provide insights on theoretical models on market makers and the role of the DMM.

We build an algorithm to identify professional liquidity providers based on trading patterns observed for each User Account. Specifically, the TSX database reports the User Accounts of the buyer and seller associated with each transaction. . We implement a probit model where the User Accounts associated with exchange-assigned DMMs are categorized as professional liquidity providers. Based on the predicted probability scores from the model, all active, non-DMM User Accounts ranked in the upper decile on the probability scores are classified as ELPs. In out-of-sample tests, we show that ELPs tend to participate on passive side of trades, actively manage inventory risk, and carry smaller overnight inventory positions. Further, the model correctly classifies DMM-associated Accounts in the top probability decile in out-of-sample periods.

Although ELPs and DMMs exhibit similar trading patterns by design, we find that they differ in some important ways. For the largest market cap quintile of stocks, ELPs participate on 79% of the stock-days with trading data. The ELP participation drops to 37% for Quintile 4 stocks and drop further to 12% for small stocks. In contrast, DMMs participate on 78% of stocks-days for small stocks and their participation rates exceed 90% for larger stocks. Our analysis shows that ELP trading differs from DMM trading in medium and small stocks in being opportunistic. For these stocks, the percentage of ELPs' liquidity-supplying and liquidity-demanding trades are similar and the inventory changes suggest that their trades contribute to daily trade imbalance. In contrast, over 80% of DMMs' trades for all stocks are liquidity supplying and their trades tend to absorb order imbalances. The cross-sectional regression analysis confirms these results and indicates that ELPs' participation is positively associated with market cap, trading volume, return volatility, and market making profits, and inversely associated with capital commitment needed to make markets in a stock.

We document that market conditions affect ELP participation over time in an individual stock. For each stock, we assign trading days into quintiles based on daily trading volume or intra-day volatility. For large cap stocks, ELP participation across stock-days moves in a narrow range between 75% for the lowest share volume and volatility quintiles and 82% for the highest share volume and volatility quintiles, and the majority of ELP trades (approximately 60%) are liquidity supplying. These results indicate that market makers provide liquidity in large stocks when they have no obligation to do so. In contrast, for small cap stocks, ELPs participate in only 20% of high volume (or high volatility) stock-days and less than 5% of low volume (or low volatility) stock days. Moreover, ELPs are more likely to demand, than supply liquidity on low volume days. We show that DMMs play a critical role on these stock-days as liquidity providers of last resort. Notably, DMMs are active in over 70% of the low volume stock-days in the smallest market cap quintile and participate in one out of every four trades. These findings support the theoretical predictions in Bessembinder, Hao and Zheng (2012).

We find that DMMs routinely hold overnight inventory positions while ELPs consistently end the trading day at or near a zero inventory position, suggesting that DMM obligations reduce the flexibility to maintain a low inventory level. We decompose trading profits on days with and without ELP participation into those attributable to passive, active, and positioning profits and show that DMMs earn lower profits on days when ELPs are absent in a stock. Furthermore, the primary source of profits for DMMs is the spread earned on their liquidity supplying trades. ELPs earn a majority of their profits from spreads on liquidity supplying trades as well, but also earn significant positioning trading profits.

We find that ELPs do not participate when liquidity provision is more risky. To be specific, DMMs' maximum intra-day inventory position is five to ten times larger on days without ELP participation, than on days with ELP participation, and the overnight inventory position is at least twice as large. That the ELPs do not participate on stock-days when market making is less profitable or more risky is easy to understand;[4] however, the option to withdraw participation introduces execution uncertainty for investors, particularly when liquidity is withdrawn in response to an imbalance in the demand for immediacy. On days when ELPs do not participate in trading, we show that DMMs absorb order imbalances by building large inventory positions in the opposite direction of the stock's daily return. A conditional logit analysis with stock fixed-effects indicates that ELP participation in an individual stock is positively associated with trading volume, return volatility, and trading profits from market making.

Grossman and Miller (1988) predict that smaller, less active stocks have difficulty in attracting interest from market makers because profit opportunities are small relative to market making costs.[5] We contribute to the literature by contrasting the obligated liquidity supply of DMMs and the endogenous liquidity supply that would naturally exist in the market. Our results support theoretical predictions that the DMM's continuous presence and the willingness to absorb imbalance reduce the investor's price risk of a delayed trade, particularly in less active stocks. Further, we show that DMMs play a valuable role not only for small stocks but also for many medium cap stocks, and point to a possible mechanism by which the introduction of a DMM increases firm value. Our findings question the suitability of a limit order

[4] Bid-ask spreads are wider on trading days with no ELP participation as compared with trading days with ELP participation in the same stock. Thus, although market making compensation is higher, the trading profits for DMMs are lower because liquidity provision is more risky/costly on days with no ELP participation.
[5] In Grossman and Miller (1988), the cost of supplying liquidity includes the direct costs of executing trades and the opportunity cost of maintaining a continuous presence in the market. The latter is modeled as a fixed cost and plays a key role in determining the supply of immediacy and market making services.

book structure for all securities and are supportive of a market structure which combines a limit order book structure with a DMM to trade less active securities.

The rest of the paper is organized as follows. Section II presents a literature review, describes the institutional details of the TSX market and the data source. Section III describes the algorithm to identify ELPs. Section IV presents the cross-sectional analysis of market maker participation and Section V presents the impact of market conditions on the participation decision. Section VI presents the risk and return of market maker activity. Section VII presents the multivariate regression analysis of market maker participation. In Section VIII, we discuss the implications of our study and summarize the main results.

II. Related Literature and Data Sources

A. The literature on Designated Market Makers

Much of the early empirical literature on DMMs examines the trading behavior of the floor-based New York Stock Exchange (NYSE) "specialist". Using proprietary NYSE data, Madhavan and Smidt (1993) show that the specialist acts both as a dealer, who manages inventory and as an active investor, who maintains a long-term position in the stock based on portfolio considerations. Hasbrouck and Sofianos (1993) decompose the trading profits of the NYSE specialist and show that the principal source of profits is short horizon information. Madhavan and Sofianos (1998) find that specialist participation is inversely related to trading volume and that specialists tend to participate more in small trades and when the bid-ask spread is wide. The NYSE requires the specialist to maintain a market presence and to promote a "fair and orderly market". In compensation for performing this function, the specialist enjoys access to privileged information on limit order book and incoming order flow. The informational advantages enhance the specialists' ability to earn short-horizon profits and control inventory risk.

Recent empirical work has focused on electronic limit order markets that rely primarily on public orders to supply liquidity. Less active firms in many electronic exchanges are allowed to negotiate a private liquidity arrangement with one or more designated market makers, who supplement the public supply of liquidity.[6] Several studies examine the change in market quality and possible valuation effects when a DMM is introduced. Nimalendra and Petrella (2003) report that trading volume increases and bid ask spreads decline after DMM introduction in the Italian Stock Exchange. In the Paris Bourse, Venkataraman and Waisburd (2007) show that DMMs are more often introduced by younger firms, smaller firms and less volatile firms. Around the announcement of DMM introduction, they document that stocks experience a cumulative abnormal return of nearly 5% that is positively correlated with improvements in liquidity. Anand, Tanggaard and Weaver (2009) find that firms are more likely to introduce DMMs around equity issuance. They study DMM agreements on the Stockholm Stock Exchange and show that contracted liquidity parameters and preexisting relationships are significant determinants of LP compensation.

Our study is distinguished from prior work in part because the specialized TSX database allows us to examine the actual trading records of DMMs and ELPs. Unlike the TSX database, the available public databases do not contain account-level identifiers associated with the buy and sell side of each transaction and thus makes it impossible to track the trading behavior of market makers over time. Further, much of the focus has been on the role of DMM but only a few studies have assessed the role of ELPs, mostly focusing on high frequency traders, and none of the studies that we are aware of compare the trading behavior of ELPs and the DMM in the same stock. We exploit the detailed account-level data to compare the participation rates of market makers and relate the trading behavior to risk and return associated with market making activities.

B. Institutional Details of TSX and the Data

The Toronto Stock Exchange (TSX) is organized as an electronic limit order book, where information on the best bid and ask quotes, the orders in the book away from best quotes, and the broker identifications associated with these orders are disseminated in real time to market participants. We obtain the data from the Toronto Stock Exchange for the calendar year 2006. The data include information on

[6] Saar (2011) provides an excellent survey of the "specialist" market and the related papers.

the orders, trades and quotes for all TSX listed securities. In addition to time-stamped transaction price and size and the bid and ask quotes, the data contain information on the active and passive side of the trade, the member firm and user IDs within a firm on both sides of the trade, and whether an order originated from member firm's proprietary account or from a client. Brokers can choose to submit orders anonymously. For anonymous orders, we have access to the broker identification which is unavailable to the market.

We use the information in member firm identifiers, user IDs and account type to identify trading specific to each type of account. The user IDs are uniquely assigned to traders at the member firm and serve as the ports through which orders are submitted to the TSX. The data also enable identification of user IDs (or traders) associated with each stock's DMM. We categorize proprietary orders from DMMs in stocks associated with "specialist" obligation under "ST-DMM" account. A DMM can also execute principal trades using own capital in other, non-assigned, stocks, which we categorize under "ST-Non-DMM" account. Many traders at a member firm are not assigned as DMM in any stock during the sample period. Proprietary orders associated with these traders are categorized as "FM" (or Firm) accounts.

Traders at the member firms also serve as brokers and enter orders on behalf of their clients. We use the TSX/IIROC member firm type classification to assign member firms into retail, institutional, proprietary, integrated and certain less frequent categories, such as "managed accounts", "corporate finance" and "discount" (we aggregate these into an "others" category).[7] Because the TSX data do not separately identify each client associated with a broker at a member firm, all client trades with a particular trader are grouped together in the "client" category. For our purposes, one possible solution to this problem would be to eliminate all client trades from our analysis. However, TSX member firms also offer direct market access (DMA) to their larger clients, and it is possible that some large traders serve as professional liquidity providers. Therefore, similar to IIROC (2012), we do not exclude client accounts

[7] The Investment Industry Regulatory Organization of Canada (IIROC) is the Canadian self-regulatory organization which oversees all investment dealers and trading activity in debt and equity markets in Canada.

from our analysis but we note that the ELP identification yields only a small number of client accounts as ELPs. The results are similar when these accounts are excluded from the ELP sample.

All retail and institutional orders are routed through a trader at a member firm. The trader can internalize the order; that is, execute the order against their own account as a principal trade, or execute against another client's order, but internalized orders must offer price improvement, as per IIROC rules. The need for price improvement results in most client orders being routed to the limit order book. Once placed on the book, the rules allow the broker to violate time priority and trade with the client's order as long as the broker's ID is displayed to market participants. For this reason, large brokers with considerable client volume are less likely to use anonymous orders.

The TSX assigns a single member firm to serve as the DMM for each stock. The TSX monitors the portfolio of securities assigned to each member firm and maintains a mix of more and less actively traded stocks. DMMs are responsible for maintaining two sided markets, moderating price volatility, guaranteeing executions for odd lot orders, and for a specified number of shares (called a Minimum Guaranteed Fill, or MGF order). Unlike the New York Stock Exchange (NYSE) Specialist studied extensively in the literature, the TSX DMMs have no access to privileged information on order flow but they have the ability to automatically interact with incoming order flow. Specifically, when the DMM chooses to participate with incoming order flow, the DMM is allocated 40% of any subsequent order with an order size up to the MGF in the security. Thus, the ability to trade ahead of orders with higher time priority is the primary benefit of being the DMM. The DMM can choose to participate on the bid, or offer side (or both) at any moment in time.

All trades, quotes, and orders are time-stamped to the millisecond resolution. We only include trades that occur during regular trading hours (9.30 a.m. – 4.00 p.m.). We restrict our analysis to common stocks and delete months when a stock is associated with a corporate event such as an initial listing, delisting, stock split, merger or acquisition, stock ticker change, name change, rights offering, etc. We obtain information on corporate events as well as shares outstanding from the monthly *Toronto Stock Exchange Review* publications. If the stock has multiple classes, we retain the most liquid class of a stock unless the multiple classes are part of a stock index (S&P 60, Mid-cap or Small-cap indices). Activity is dramatically lower on days when U.S. markets are closed and Canadian markets are open. We exclude these days from our sample. We also limit the sample to stock-days with an absolute return of less than 12% (99th percentile of stock-day returns). For the quotes data, we delete observations where the difference between the bid and ask quotes is greater than $5.

Table 1 describes our sample. The sample includes 1,286 stocks traded over 245 days, with approximately 900 stocks traded on an average day. The average stock-day has 595 trades for 544,481 shares representing approximately CAD$ 10 million. The average market capitalization across stock-days is CAD$ 1.6 billion, and the average quoted spread is CAD$ 0.12 which is 2.3% in relative terms. We also present the distribution across days. The day with the smallest average number of trades has 367 trades per stock while the day with the highest average number of trades has more than 800 trades per stock. The average closing price varies between CAD$ 11.1 and 15.3, and the average relative spread between 1.9% and 3%. The average daily stock return is -0.02% but varies from -3.29% to 2.74% over the sample period.

III. Identifying Endogenous Liquidity providers

A. Descriptive statistics on trader behavior

The algorithm to identify ELP accounts exploits our ability to accurately identify User IDs of exchange-assigned DMMs. Since these traders are professional liquidity providers who use their own capital to serve as DMMs (ST-DMM) in some stocks and execute proprietary trades (ST-non-DMM) in other stocks, we aggregate these accounts into ST category and report descriptive statistics on their trading activity in Table 2. We also summarize trading activity by account type, for trades handled on behalf of clients (CL), for other proprietary accounts at member firms (FM) and an “others” category that captures infrequent identifiers such as options market makers. In results not reported in the paper, we identify 94 member firms during the sample period of which 22 firms have user IDs associated with DMMs.

The results in Table 2 show important differences in trading characteristics of ST accounts versus other account types. In terms of trading frequency, Client accounts are associated with larger number of trades and higher dollar and share trading volume. Also, the average client account is associated with trading in 14 stocks per day. However, as noted earlier, Client accounts aggregate the orders from all clients associated with a trader. Relative to FM accounts, we find that ST traders tend to be active on more days (161 days for ST versus 60 days for FM), concentrate in fewer stocks and trade actively in these stocks. We also calculate various metrics that capture the trader's propensity to provide liquidity in the short horizon. ST accounts are associated with smaller end-of-day inventory levels, higher proportion of zero end-of-day inventories, higher propensity to switch between long and short positions (3.79 times) within a day, and a greater tendency to participate in trades that reduce their existing inventory position.

The preliminary evidence supports ST traders' role in absorbing order flow imbalance. ST traders participate more often on the passive side of trades (62.6%). ST accounts have zero inventory or inventory change against the stock daily return on 63% of trading days.[8] Specialist traders are more likely to use anonymous orders, which is consistent with these traders not being concerned about internalizing client orders. Specialist accounts are concentrated with integrated and proprietary brokers and less so with institutional brokers. Overall, the results suggest that ST traders control inventory risk, supply liquidity and reduce trade imbalance.

B. An Algorithm to Identify ELP accounts

The ELP identification algorithm does not focus on a specific account type since ELPs can be proprietary traders at brokerage firms, large traders with a DMA arrangement with a prime broker, or DMMs who execute trades in non-designated stocks. Instead, we examine the trading behavior of each User Account and identify trading patterns that are consistent with professional liquidity provision. Specifically, the ST accounts discussed in Table 2 serve as the benchmark for the identification. We fit a

[8] Stated differently, the changes to the end-of-day inventories of ST traders are more likely to be against the direction of stock's daily return; That is, an increase in daily inventory position when the stock has a negative return day and a decrease in daily inventory position when the stock has a positive return day.

probit model where the dependent variable equals one if the User Account is ST, and equals zero otherwise. The model is estimated over trading data aggregated at the daily frequency for each user account. The explanatory variables include (a) the number of times the trader's inventory switches between long and short positions each day, (b) the proportion of passive trades, (c) the absolute value of daily ending inventory, (d) the proportion of trades in direction of existing inventory, (e) the proportion of anonymous trades, and (f) dummy variables for broker type (the omitted type is integrated brokers) associated with the account. Our objective is to identify other active User Accounts whose trading behavior is similar to those observed for ST accounts.

Table 3 presents the results of the Probit analysis. Consistent with Table 2, the model coefficients show that professional liquidity providers are more likely to trade passively, exhibit more switches between long and short inventory within the day, maintain lower overnight inventory, execute trades that reduce inventory, use anonymous identifier, and be associated with proprietary and integrated brokers. Based on model coefficients, we obtain a predicted probability score for each User Account for each day in our sample. We calculate the average probability score for a User Account over the sample period, and assign Accounts into decile portfolios based on average score. User Accounts in the top decile based on probability score with at least 50 days of trading are classified as ELPs.

Our approach to identifying ELPs is similar in spirit to the approach used by NASDAQ to designate 26 firms as HFTs (see Brogaard, Hendershott and Riordan (2011)). Both approaches classify User Accounts based on trading activity aggregated across all stocks. An important assumption underlying the classification is that a trader is unlikely to be a liquidity provider in one stock and a long-horizon investor in another stock. An important difference between the NASDAQ versus the TSX database is that information on individual User Account is preserved in the TSX database while individual account information is aggregated into a single HFT classification in the Nasdaq database. Information on User Accounts is particularly useful for this study since we exploit the granularity of the data to estimate the inventory risk, capital commitment, and the trading profits of market makers. Our approach is similar to Kirilenko, Kyle, Samedi and Tuzun (2011) who use an algorithm to classify traders as intermediaries if they have short horizons, both buy and sell frequently, and maintain small inventory positions. Recently, IIROC (2012) classifies User Accounts in Canadian markets as HFTs based on the order-to-trade ratio under the assumption that HFTs are characterized by large number of order submissions relative to order execution. The focus of the IIROC study differs from ours in that IIROC is interested in identifying all HFT accounts while our approach identifies the subset of User Accounts, HFTs or non-HFTs, who trade in a manner consistent with liquidity provision. The characteristics of traders identified as HFTs by IIROC (2012) are similar to ours, suggesting that the average IIROC identified HFT User Account supplies liquidity services.

C. The Trades of Market Makers

Table 3, Panel B reports the trading patterns of User Accounts in four of the probability deciles. The model obtains significant separation in probability scores across decile portfolios - the predicted probability of being a market maker increases from 2% for the bottom decile to 71% for the top decile. We perform several additional analyses to test the robustness of the model. First, we rank-order User Accounts based on the daily probability score and examine the range between the highest and lowest rank for an Account over the sample period. The average range for User Accounts in the top and bottom decile is relatively small. Second, in unreported analysis, we estimate the Probit model over the first six months of our sample, use predicted probabilities to assign User Accounts to decile portfolios, and then examine trading patterns over the next six months of the sample. In this out-of-sample analysis, we find that 79%, 63%, and 22% of trader accounts in Deciles 10, 9 and 8, respectively, are ST-DMM accounts and less than 5% of trader accounts in other Deciles are ST-DMM accounts. Further, the out-of-sample analysis yields trading patterns that are similar to those presented in Table 3, B. These results show that the trading patterns for User Accounts persist over time.[9]

[9] For example, in the out-of-sample analysis, the average absolute value of ending inventory for the top decile users is CAD$ 9,408 compared to CAD$ 54,989 for the bottom decile and the proportion of passive executions are 68% for the top decile compared to 47% for the bottom decile. The top decile traders switch between long and short positions 5.9 times a day on average compared to 0.1 times for the bottom decile, and are much less likely to trade in

In Table 3, Panel B, we disaggregate the User Accounts in Decile 10 by account types, ST-Non-DMM, FM and CL. We delete accounts with less than 50 trading days of data and classify the remaining accounts as ELPs. We also report all trader accounts identified as exchange-assigned DMM accounts (ST-DMM) in a separate column labeled DMM. A notable result is that DMM accounts have a predicted probability of 0.60 while ST-Non-DMM, FM and CL accounts have a predicted probability of 0.75, 0.65, and 0.65, respectively. In other words, the model indicates more confidence in classifying ELP accounts as endogenous liquidity providers as compared to DMM accounts. Therefore, the results address a possible concern that ELPs simply represent the "weaker" User Accounts identified by the model.

Relative to the lowest decile, both DMMs and ELPs have a higher percentage of passive executions, smaller closing inventory, more intraday switches between long and short inventory, smaller proportion of trades in the direction of inventory, and a larger proportion of accounts associated with proprietary brokers. ELPs and DMMs also exhibit similar number of active days per user, daily number of trades, and closing inventory. The results show that both classes of market makers provide liquidity services and actively manage inventory risk.

Although both ELPs and DMMs are professional liquidity providers, we show that they differ in some important ways. First, relative to an ELP, a DMM trades in fewer stocks and executes more volume per stock. This result is consistent with the DMM obligation to maintain a market presence in assigned stocks. Second, ELPs are more likely to post anonymous orders and more often associated with proprietary brokers. Third, ELPs are less likely than DMMs to trade against the daily stock return (i.e., buy on negative return days, and vice-versa) and participate on the passive side of a trade. Specifically, DMMs provide liquidity in three out of four trades (proportion of passive execution is 78.7 percent) while ELPs provide liquidity in two out of four trades (corresponding statistic is 54 percent).

A striking difference between DMMs and ELPs is observed in the the propensity to close the trading day with zero inventory. While ELPs have zero inventory position on 50% of trading days,

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the direction of their existing inventories. Furthermore, with very minor exceptions, the trends are monotonic even in the out-of-sample analysis.

DMMs have zero inventory on 1% of trading days. In subsequent analysis, we show that DMMs serve an important need of investors by participating in trades that create risky overnight inventory positions.

IV. Cross-sectional analysis of market maker participation

Table 4 presents univariate statistics on ELP and DMM participation for the cross-section of stocks. We assign stocks to quintile portfolios based on their market capitalization at the end of month prior to the trading day. We find that ELP participation varies significantly across stocks. For large cap (Quintile 5) stocks, ELPs participate in trading on four out of five trading days (79.4%). However, the participation drops significantly for Quintile 4 stocks, to 37.1%. We observe a further monotonic decline such that ELPs participate in only one out of eight trading days (12%) for small (Quintile 1) stocks. In contrast, DMMs participate in four out of five trading days (78.4%) in small cap stocks. DMMs further increase participation with market capitalization and trade on almost every day (99.6%) in large stocks. The sharp differences in market presence between DMMs and ELPs for medium to small stocks are a novel finding of our study. We attribute the difference to the affirmative obligations imposed by the exchange on the DMM to maintain a market presence in the stock. To the extent that the continuous presence of a market maker helps lower execution uncertainty that investors face in market interactions, the results point to a simple mechanism by which a hybrid market structure with a DMM improves over a market structure with no market maker obligations.

We also examine the percentage of passive, or liquidity-supplying, trades for ELPs and DMMs. For ELPs, a majority of trades are passive for small and large cap stocks, while a majority are active in mid cap stocks. In all cases, the proportions of passive trades of ELPs are between 45% and 56%. In contrast, DMMs' proportion of passive trades is consistently above 80%, or stated differently, four out of five trades are liquidity supplying, across market cap quintiles. In comparison to ELPs, the change in DMMs daily inventory is more likely against the daily stock return. To the extent that daily return is correlated with daily order flow imbalance, the results suggest that DMMs absorb the imbalances by buying the stock when the stock price declines and selling the stock when the stock price increases.

One measure of a stock's inventory risk for a market maker is the number of times that the intraday inventory crosses zero. More zero crossing of inventory is consistent with quicker reversal of positions and lower inventory carrying cost. In large cap stocks, ELPs and DMMs switch between net long and short position in a stock over six to ten times within the day. The statistic drops sharply to between one and 2.45 times for stocks in Quintile 4, and the statistic is less than 0.5 for small stocks. These results suggest that market makers in small stocks incur high inventory carrying costs and reduced ability to trade out of an inventory position.

ELPs and DMMs differ markedly in the percentage of days when the overnight inventory position is zero. In large stocks, ELPs end the trading day with no inventory on 57 percent of trading days. ELPs participate sporadically in small stocks but conditional on their participation, they close the day with no inventory on 17.5% of days. However, across all quintiles, we estimate that the closing inventory of DMMs is zero less than 1% of the time. We attribute the higher incidence of overnight inventory positions to DMM obligations that might force them to participate in trades that they might be unwilling to participate from a pure profit motive. In a later section of the paper, we further examine trading profits and inventory risk associated with market maker obligations.

V. Impact of market conditions on market maker participation

We examine market making activity over time in an individual stock. We report statistics on three measures of market maker participation: (a) the percentage of stock-days with market maker participation, (b) the percentage of trades involving the market maker, and (c) conditional on participation, the percentage of trades on the passive side of the trade. For each stock, we assign trading days in the sample into quintile portfolios based on trading volume (Table 5) or intra-day volatility (Table 6). The quintile assignments are made separately for each stock. In both tables, Panel A presents participation statistics for the full sample, Panel B for stocks in the lowest market cap quintile, and Panel C for stocks in the largest market cap quintile. The statistics are equally weighted averages across stock-days in the respective sample.

In Panel A of Table 5, we observe that both classes of market makers participate more on high volume trading days than low volume days. Further, the percentage of trades involving the DMM is significantly more than those involving the ELP, particularly on days with low trading volume. Differences in trading behavior across the two classes of market maker are more striking when we examine stocks in highest and lowest market cap quintiles. In Panel C (large stocks), ELPs are active participants who trade on a significant percent of stock days and the majority of their trades are supplying liquidity. Although participation is higher on high volume days, ELPs are active in three out of four low volume days and primarily supply liquidity. We conclude that market makers maintain a market presence and provide liquidity in large caps when they are under no obligation to do so. These results suggest that DMMs may be less important in the market structure required for trading large stocks.

For small stocks (Panel B), ELP participation appears to be sparse at best, averaging about one in five high volume days and less than one in 20 low volume days. Further, the percentage of passive ELP trades declines from 55.5% on high volume days to 43.9% on low volume days. Thus, ELPs on low volume days demand more often than supply liquidity, which is more consistent with opportunistic trading than with liquidity provision. These findings confirm predictions from Grossman and Miller (1988) that small stocks, particularly on low volume days, are characterized in equilibrium with relatively few ELPs and high effective cost of immediacy.

The results support the notion that DMMs serve a fundamental role as providers of *immediacy* by maintaining a market presence. DMMs are active in over 85% of high volume days and over 70.9% of low volume days. The percentage of passive DMM trades, which exceeds 80% in all quintiles, is highest on low volume days, averaging 88.1%; that is, when DMMs participate in a trade, they supply liquidity in seven out of eight transactions. On low volume days, their role as liquidity providers is more critical, as they provide liquidity in one out of four transactions on average. Since immediacy is an important attribute of market quality, our results indicate that the presence of a DMM enhances market quality in medium and small cap stocks. These findings provide direct evidence on the mechanism by which a market maker with obligations can reduce execution uncertainty and serve the important needs of investors.

In Table 6, we report results on market maker participation for trading days sorted into volatility quintiles. Daily intraday volatility is calculated as the standard deviation of 15 minutes returns based on bid-ask quote midpoints. The trading patterns in Table 6 are similar to those reported in Table 5. Participation rates for ELPs and DMMs are positively correlated with daily volatility. In fact, when we specifically examine trading days that rank above the 95 percentile on within-firm daily return volatility, we find that ELP (and DMM) participation exceeds those observed in less volatile periods and the majority of the trades are passive, or liquidity supplying. SEC (2010) acknowledges the possibility that, "short-term professional traders may like short-term volatility…", while at the same time raising related questions regarding the value of affirmative obligations, and the activities of ELPs during times of market "stress".[10]

VI. The Risk and Return of Market Makers Activity

The evidence thus far suggests that ELPs participate more actively in large stocks. Within a stock, ELPs participate on high volume and high volatility days. But what explains the ELPs' decision to participate in some stocks or under certain market conditions? In Table 7, we use the granular account-level transaction data to examine whether trading profits, capital commitments, and inventory risk can explain the ELPs' decision to be active on a stock-day. Specifically, we compare the profitability and inventory positions of market makers on stock-days when both DMMs and ELPs participate versus stock-days when DMMs participate but ELPs do not.[11] Panel A presents unconditional results for the full sample, Panel B presents results on trading days with and without ELP participation, and Panel C presents the results by market cap quintiles.

[10] The two discussions are on pages 33 and 48 of SEC, "Concept release on equity market structure," 17 CFR part 242, Release No. 34-61358; File No. S7-02-10.

[11] Trading days when ELPs participate but DMMs do not represent less than 1% of the sample observations and are ignored in the analysis.

For each stock-day for an account, we implement three methodologies to calculate profits. First, we mark the day's transactions to the closing quote midpoint and aggregate the dollar profit or loss over all positions for the day. Hasbrouck and Sofianos (1993) and Menkveld (2010) discuss two alternative methodologies for profit calculation – cash flow profits calculated as the change in inventory associated with a trade multiplied by the price; and mark-to-market profits calculated as the inventory position multiplied by the change in prices. Consistent with the first methodology, we close out remaining inventory positions at the end of the day for cash-flow and mark-to-market profits. All three methodologies yield identical profit measures. Following Hasbrouck and Sofianos (1993) and Menkveld (2010), we decompose trading profits into three components: *passive* is the half-spread earned on trades that provide liquidity; *active* is the half-spread paid on trades that demand liquidity; and *positioning* profit is the profit calculated using quote midpoints rather than traded prices, which removes the effect of supplying or demanding liquidity. Large positioning profits are consistent with successful timing of trades over a short horizon.

As proxies for inventory risk, we report the number of times the intraday inventory switches between long and short positions, the absolute value of end-of-day closing inventory, the absolute value of maximum intraday inventory, and the signed closing inventory position. The inventory measures are normalized by monthly stock trading volume. The maximum intraday inventory will be small if market makers actively manage participation to maintain inventory close to zero. Alternatively, the obligations of DMM might reduce the flexibility to manage intraday inventory risk, particularly on low volume days, and lead to high absolute intraday inventory levels. The signed inventory position accounts for the direction of trading relative to the direction of return in the stock on the day. We sign the inventory as positive when market makers increase inventory (i.e., buy) on negative return days and decrease inventory (i.e., sell) on positive return days. Negative signed inventories indicate positions in the direction of the stock's return. The statistics are equally weighted averages across stock-days in the respective sample. We present results averaged across stock-days at the individual market-maker level, as well as across stock days at the market-maker type level. The latter aggregation does not substantively affect the

DMMs since there is one DMM per stock-day, but yields different results for ELPs as it aggregates all ELPs active in a stock on a day. By doing so, the market maker type aggregation for ELPs captures the total profits to endogenous liquidity provision.

Results in Panel A suggest that the average DMM account earns daily trading profits that are more than twice as large as the average ELP account. However, the total profits to endogenous liquidity provision are higher than those captured by DMMs. The trading profits of DMMs are almost entirely attributed to passive trades and almost none to positioning profits. The largest proportion of ELPs' profits is attributed to passive trades, which provides additional support for the Table 3 algorithm reliably identifying professional liquidity providers. However, ELPs earn significantly higher positioning profits than DMMs. In other words, ELPs trade opportunistically to provide liquidity as well as to earn profits via timing skill while DMMs rely primarily on liquidity provision to generate their profits.

Both sets of market makers earn sufficient passive profits to pay for demanding liquidity on active trades. The unprofitable active trades likely reflect the market maker's need to control inventory risk by trading out of undesirable inventory. We estimate that the end-of-day closing inventory for DMMs (a measure of overnight inventory risk) is twice as large as that held by the average ELP and the maximum inventory (a measure of intraday inventory risk) is almost three times as large as the average ELP's. The DMM overnight inventory is higher than the combined inventory held across all ELPs on a stock-day, which reflects the ELPs' preference to hold no overnight inventory positions.

In Panel B, we report the trading profits and inventory risk of DMMs on trading days with and without ELP participation. A striking result is that DMM profits on days without ELP participation are over 60 percent lower than on days with ELP participation, which can be attributed in part to smaller revenues from passive trades.[12] The results also show higher inventory risk on days without ELP participation as compared to days with ELP participation. Specifically, the absolute value of closing inventory is four times as large on days without ELP participation; the number of times that intraday

[12] In results not reported in the paper, we estimate that DMMs in aggregate make $19 million from 77,400 stock-days with ELP participation and only $11 million from 123,136 stocks days without ELP participation.

inventory crosses zero is 1.17, compared with 7.45 on days with ELP participation; and the absolute value of maximum inventory exceeds 7% of monthly trading volume on days without ELP participation. The significant drop in number of times intraday inventory crosses zero indicates that trading days without ELP participation are characterized by high order flow imbalance and market makers have difficulty in reversing the inventory positions. We also estimate that DMMs exhibit large positive signed inventory (0.46%) on days without ELP participation as compared to days with ELP participation (0.11%). On the other hand, ELPs' signed inventories are small and close to zero. The results are supportive that DMMs absorb imbalance and play a stabilizing role by trading in the direction opposite to the stock's return.

In every market cap quintile (panel C), DMM profits on days without ELP participation are smaller than on days with ELP participation;[13] the number of times that intraday inventory crosses zero is lower by one-half; the absolute value of end-of-day closing inventory is more than twice as large; the absolute value of maximum inventory is almost five times as large; and the signed inventory is almost twice as large. As an example, in the case of large stocks, the overnight inventory position carried by a DMM on days without ELP participation exceeds 0.15% of monthly trading volume, as compared with 0.03% for days with ELP participation. Thus, the significant capital commitment might cause market makers to withdraw when they have no obligations to maintain markets. We also show that it is more profitable to make markets in large stocks as compared with small stocks.[14] Grossman and Miller (1988) observe that market making profits is small relative to the costs of maintaining a market presence in small, less active stocks. We provide empirical support for this prediction in Table 7. We conclude that ELPs participate in financial market when the activity is profitable and/or less risky, and withdraw participation when the converse is true.

VI. Multivariate Regression Analysis of Market Maker participation

[13] The lower profits likely reflect the market conditions that led to lower ELP participation, rather than being caused by their lower participation.

[14] Consistent with our results, Coughenour and Harris (2003) find positive NYSE specialist profits for small stocks in their analysis.

A. Cross-sectional Analysis of Market Maker activity

It is clear that market capitalization is an important factor in determining ELP participation. Prior research has shown that trading activity, return volatility and bid-ask spreads are also important considerations for a market maker. Therefore, it is possible that ELPs avoid less active and more volatile stocks. On the other hand, limit order strategies such as volatility capture are more profitable in volatile securities (Handa and Tiwari (1996)) and bid-ask spreads are inversely proportional to trading activity and return volatility. The larger compensation for liquidity provision might attract market makers to riskier stocks. Moreover, market makers care about not only trading profits but also the capital commitment necessary to supply liquidity. All else the same, an increase in capital commitment should reduce participation by market makers.

To better understand the contribution of various factors affecting ELP participation in a particular stock on a day, we estimate two daily Fama-MacBeth logit regressions of the form:

$$\log\left(\frac{p_i}{1-p_i}\right) = \mu + \beta_1.STVol_i + \beta_2.\log(mktcap_i) + \beta_3.\log(dailyvolume_i) + \beta_4.numtrades_i + \beta_5.\left(\frac{1}{price_i}\right) + \beta_6.relspread_i + \beta_7.LTVol_i \qquad (1),$$

and

$$\log\left(\frac{p_i}{1-p_i}\right) = \mu + \beta_1.STVol_i + \beta_2.\log(mktcap_i) + \beta_3.\log(dailyvolume_i) + \beta_4.numtrades_i + \beta_5.\left(\frac{1}{price_i}\right) + \beta_6.relspread_i + \beta_7.LTVol_i + \beta_8.DMMInv_i + \beta_9.TimesInv_i + \beta_{10}.DMMprofit_i \qquad (2)$$

where p_i is the probability that *ELP* equals 1, which denotes ELP participation on a stock-day. *ELP* equals zero on stock-days with no ELP participation; *price* is the midpoint of the stock's closing bid-ask quote;

mktcap is the market cap in the month in which the stock-day occurs; *dailyvolume* and *numtrades* are the daily dollar volume and number of trades in the stock; *LTVol* represents the long-term volatility in the stock and is calculated as the standard deviation of daily returns in the month; *STVol* is a measure of intraday volatility calculated as the standard deviation of 15 minutes returns based on bid-ask midpoints; *relspread* is the time-weighted quoted percentage spread on the stock-day; *DMMInv* is the absolute value of DMM closing inventory on the stock-day divided by monthly volume, which proxies for market maker capital commitment; *TimesInv* is the number of times the DMM inventory crosses zero and proxies for the ease of unwinding intraday inventory positions; *DMMprofit* is a measure of trading profits proxied by DMM profits divided by the highest absolute value of intraday inventory held by the DMM, and ε represents the error term. The regression is estimated over all stock-days with DMM participation; therefore, the regression coefficients reflect the likelihood that ELP participate on a stock day, conditional on DMM participation.[15] Daily regression coefficients based on 245 days of trading data are used to calculate the t-statistics using Newey-West standard errors with five lags.

We present results separately for equations (1) and (2) in Table 8, Panel A. Equation (1) focuses on stock characteristics while equation (2) introduces additional variables that proxy for inventory risk, capital commitment and trading profits. Equation (1) estimates indicate that ELP participation is positively associated with market capitalization, which is consistent with Table 5. We also find that ELPs participate more in stocks with higher volume or a greater number of trades. These securities are attractive because market makers can quickly move in and out of positions in active securities. Controlling for other stock characteristics, ELPs exhibit a preference for stocks with high return volatility measured both at daily and intra-day levels. These findings support the prediction that volatile securities provide limit order traders with more opportunities for short-horizon trading profits. We find that ELPs are more likely to participate in stocks with lower quoted spreads, which indicates a preference for liquid securities.

[15] As mentioned earlier, stock-days when ELPs participate but DMMs do not represent less than 1% of the sample. We do not include any trading day when the DMM does not participate in the regression.

Our inclusion of the inverse of the price in the regression is commonplace in the literature as a control for the relative tick size. However, the variable itself is of interest in the analysis due to two arguments relating to ELP participation. First, there is an increasing impetus to increase tick sizes to encourage market making in illiquid securities in the US markets.[16] Harris (1998) for example observes that higher relative tick sizes increase the cost of stepping ahead of standing limit orders and thereby encourages participants to supply liquidity services. However, as SEC (2010) notes, ELPs, with ready access to the markets, may be in a better position to employ such "order anticipation" strategies. Therefore the impact of larger tick size on ELP participation is an empirical question. We find that the price-inverse measure is positively related to ELP participation, which indicates a preference for higher relative tick sizes, or for lower priced securities, holding all the other variables constant.

In equation (2), we note that the relationships between ELP participation and stock characteristics are similar when additional variables are included. We find that ELP participation is inversely associated with average DMM capital commitment, and positively associated with the ease of unwinding intraday inventory positions, which is proxied by the the number of times intraday inventory crosses zero. ELPs are also more likely to participate in stocks with higher DMM trading profits. The result is reasonable since market makers are expected to maximize trading profits per unit of invested capital.

B. Time Series Variation in Market Maker activity within a stock

The results in tables 5 and 6 document the variation in ELP participation based on market conditions within a stock. In this subsection, we further explore the factors influencing ELP participation. In Figure 1, Panels A through D, we plot market characteristics for days with and without ELP participation, within market cap quintiles. Specifically, the figures compare the number of trades, relative bid-ask spreads, intraday volatility and trade imbalances for days when ELPs choose to participate with those when ELPs do not participate. We note that DMMs participate on all the days covered in the figures. Panel A shows that the number of trades on the days with ELP participation is significantly

[16] See *Wall Street Journal* article, "SEC weights bringing back fractions in stock prices", Oct 27th, 2012.

higher than days without ELP participation. This pattern is observed across all market cap quintiles. Thus, even in large stocks, where ELPs participate on approximately 80% of the stock days, they tend to avoid days with lower trading activity. In Panel B, we show that relative spreads are smaller on days with ELP participation than days without ELP participation. Therefore, the results do not support the argument that the compensation for liquidity provision is lower on days when the ELPs choose to withdraw. Panel C on trade imbalances indicates that ELPs choose to withdraw on trading days with higher trade imbalance in all market cap quintiles; and in Panel D for intraday volatility where, similar to the results in Table 6, we find that days with ELP participation have higher intraday volatility relative to days without ELP participation.

We model the ELPs' activity over time within an individual stock more carefully using a fixed-effects logit estimation. The (stock) fixed-effects model controls for all stock specific attributes and focuses only on within stock variation. Accordingly, we include variables in this estimation which are likely to vary within a stock over time. The participation rate of market makers is most likely affected by trading activity, volatility, bid-ask spreads, order imbalances and price movements. Further, the results in Table 7 suggest that trading profits, inventory risk and capital commitments are important determinants of market maker participation on a stock-day. We follow the recommendation in Allison (2005) in using a conditional maximum likelihood methodology for the estimation which avoids a possible bias in coefficients due to the incidental parameters problem. Specifically, we model the ELP participation using two logistical regressions with stock fixed effects estimated over all stock-days as:

$$\log\left(\frac{p_{i,t}}{1-p_{i,t}}\right) = \propto_i + \beta_1.STVol_{i,t} + \beta_2.\log\left(dailyvolume_{i,t}\right) + \beta_3.numtrades_{i,t} + \beta_4.\left(\frac{1}{price_{i,t}}\right)$$
$$+ \beta_5.relspread_{i,t} + \beta_6.abs(imbal_{i,t}) \qquad (3),$$

and

$$\log\left(\frac{p_{i,t}}{1-p_{i,t}}\right) = \propto_i + \beta_1.STVol_{i,t} + \beta_2.\log\left(dailyvolume_{i,t}\right) + \beta_3.numtrades_{i,t} + \beta_4.\left(\frac{1}{price_{i,t}}\right) + \beta_5.relspread_{i,t} + \beta_6.abs(imbal_{i,t}) + \beta_7.DMMInv_{i,t} + \beta_8.TimesInv_{i,t} + \beta_9.DMMprofit_{i,t} \tag{4}$$

where p_i is the probability that *ELP* equals 1, which denotes ELP participation on a stock-day. *ELP* equals zero on stock-days with no ELP participation; α_i are stock specific and capture all stable differences across stocks; *price, dailyvolume, numtrades, STVol, relspread, DMMInv*, *TimesInv* and *DMMprofit* are defined above; and *imbal* is the buy-sell trade imbalance (in shares) normalized by the traded volume on a stock-day. Since our data identify the active and passive side of the trade, we are able to accurately identify buyer and seller initiated trading volume.

The results for equation (3) show that, within a stock, ELPs are more likely to participate on high volume and more volatile days. ELP participation tends to be higher on days with tighter quoted spread. The latter is a bit surprising since tighter spreads are associated with lower market maker compensation. However, tighter spreads might capture exposure to an omitted risk factor for liquidity provision, such as availability of dealer capital, or lower risks of liquidity provision, which might explain higher ELP participation. We find that ELP participation is higher when the price-inverse variable is higher, which may reflect a preference for higher relative tick sizes. ELP participation is strongly negatively associated with trade imbalances. ELPs are more likely to participate when the absolute value of the imbalance is low. In unreported results, we estimate a model separating out positive and negative imbalances to examine whether ELPs are more averse to imbalances on one side than another. The coefficients on the positive and negative imbalance variables are similar in magnitude indicating that ELPs avoid days with high levels of imbalance in either direction. In equation (4), we introduce DMM inventory and profitability variables in addition to stock level variables used in equation (3). We find that ELP participation is more likely when market makers earn higher profits, when the capital commitment necessary for liquidity provision is small, and when inventory risk is smaller as indicated by the DMMs' ability to unwind their intraday inventories. Thus, the results based on the univariate analysis in the prior tables are robust to the inclusion of control variables in the regression analysis.

VII. Discussions and Conclusion

The role of market makers in financial markets has come under increased scrutiny in recent years. Increased competition among trading venues and improvements in technology have vastly expanded the pool of market participants monitoring markets and providing liquidity when it is profitable to do so. However, as noted by SEC Chairman Shapiro, professional liquidity providers have no obligations to maintain a market presence and/or stabilize markets. The lack of obligations leads some practitioners and regulators to assert that a market structure that relies on market participants with no obligations is inherently fragile. Under current SEC regulation, U.S. based issuers are not permitted to enter into long-term liquidity enhancing contracts with market making firms. A recent bill introduced in the U.S. Congress encourages stock exchanges to allow small listed issuers to directly pay market makers for liquidity provision.

In this study, we examine the trades of two important classes of market makers in the same security. Unlike publicly available databases, the proprietary TSX database that we examine provides detailed account-level information on the counterparties to a trade. We compare the participation decision of DMMs and ELPs in the cross-section of stocks and under different market conditions and relate the decision to trading profits, inventory risk, and capital commitments.

We find that market makers create a liquid market in large stocks when they have no obligation to do so. Specifically, ELPs are active participants, the majority of their trades are liquidity supplying, and ELP participation does not vary significantly with market conditions. In medium and small cap stocks, ELP participation tends to be sparse and opportunistic - ELPs selectively participate on a small percentage of trading days; the percentage of liquidity-supplying and liquidity-demanding trades are similar; their trades contribute to rather than absorb daily trade imbalance; and ELP participation declines on less active or less volatile days. The results support theoretical predictions (see Grossman and Miller (1988), Bessembinder, Hao and Zheng (2012)) that endogenous liquidity provision is less likely in small, less active securities. For these stocks, DMMs are more likely than ELPs to absorb order imbalances and supply liquidity. Notably, DMMs are active in over 70% of low volume days for small stocks, and supply liquidity in the majority of transactions. Thus DMMs reduce the investors' execution uncertainty by maintaining a market presence and point to their fundamental role as providers of immediacy. Our results provide new evidence on the specific mechanism by which the adoption of a DMM market structure meets the needs of investors.

While our analysis has the advantage of directly comparing ELPs and DMMs, we are unable to directly address whether ELPs will behave differently, or behave more like DMMs, when they do not face competition from DMMs. We note that ELPs exhibit a strong preference for small to zero daily ending inventories and selectively participate on trading days with balanced order flow which allows them to flip inventory positions within a trading day. Such a strategy differs substantially from market making opportunities observed in illiquid securities, suggesting that ELPs' business model is generally not supportive of active participation in less liquid segments of the market. Further, DMMs earn smaller trading profits, assume higher inventory risk, and commit more capital on days with no ELP participation as compared to days with ELP participation. Therefore, while the ELPs' trading strategy reflects an active exercise of the option to withdraw participation when profit opportunities are small or inventory risk is substantial, the obligations of DMM force them to participate in many undesirable trades. For this reason, DMMs are typically compensated for their services. The compensation arrangements observed in markets can be summarized as (see Saar (2009)):

- The floor-based NYSE system provides the Specialist with access to order flow information such that (a) liquid stocks subsidize illiquid stocks and (b) non-stress periods subsidize stressful periods (see Glosten (1989)).
- The TSX, in certain cases, allows the DMM to trade ahead of orders with higher time priority in the book. DMMs accept obligations in a portfolio of liquid and illiquid stocks.

- In Euronext-Paris and Stockholm, the listed firm pays an annual fee via a liquidity contract with the DMM. The contracting arrangement, which is currently illegal in United States, is modeled by Bessembinder, Hao and Zheng (2012).
- Some U.S.-based market centers compensate DMMs using fees from data feeds, or providing higher credits for posting limit orders in the book.

The optimal design of DMM contracts and its implications for market quality remains an important avenue for future research. The trading profits of TSX DMMs are positive for all stocks, suggesting that large stocks need not subsidize small stocks. However, we acknowledge the difficulty in accounting for inventory risk, the fixed cost of maintaining a market presence, and the cost of capital associated with market making. By assigning a portfolio of liquid and illiquid stocks to DMMs, the TSX effectively lowers the marginal cost of maintaining a presence in illiquid securities.

We find that ELP participation increases on trading days with high volatility. In fact, on trading days with extreme intraday volatility, ELPs are more active and increase the percentage of liquidity supplying trades. Although, this result appears to be at odds with anecdotal evidence from 2010 Flash Crash, when HFTs withdrew participation, the result is consistent with discussions in several press articles that market maker (or HFT) profits are positively correlated with market volatility.[17] It is also important to consider the nature of the "market stress" during the 2010 Flash Crash event. According to the CFTC-SEC report, the event period was associated with a market decline possibly triggered by large sell imbalances responding to global anxiety on European markets. As the report notes, individual market participants based their trade assessments on,

"*whether observed severe price moves could be an artifact of erroneous data; the impact of such moves on risk and position limits; impacts on intraday profit and loss ("P&L"); the potential for trades to be broken, leaving their firms inadvertently long or short on one side of the market; and the ability of their systems to handle the very high volume of trades and orders they were processing that day. In addition, a number of participants reported that because prices simultaneously fell across many types of*

[17] For example, the WSJ article "Meet Getco, High-Frequency Trade King", August 27, 2009, reports that Getco made a profit of $400 million during the peak of the financial crisis and represented more than 10% of trading volume in U.S. equities in October 2008.

securities, they feared the occurrence of a cataclysmic event of which they were not yet aware, and that their strategies were not designed to handle."[18]

This study documents new evidence on the behavior of ELPs under stressful market conditions. Specifically, we show that ELPs are less likely to trade on stock-days with high order imbalances, stocks days when ELPs have difficulty in reversing intraday inventory, and exhibit a strong preference to end the day at or near zero inventory. To the extent that the Flash Crash event is characterized by sustained order imbalance and higher inventory risk, the results of our study are consistent with HFT participation patterns observed during the Flash Crash. Further, our study provides new insights on a number of questions raised in SEC's Equity Market Structure Concept Release (2010).

> *How important are affirmative and negative obligations to market quality in today's market structure? Are they more important for any particular equity type or during certain periods, such as times of stress? Should some or all proprietary firms be subject to affirmative or negative trading obligations that are designed to promote market quality and prevent harmful conduct? Is there any evidence that proprietary firms increase or reduce the amount of liquidity they provide to the market during times of stress?"*

[18] Page 4 of "Findings regarding the market events of May 6, 2010. Report of the staffs of the CFTC and SEC to the joint advisory committee on emerging regulatory issues", September 30, 2010.

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Table 1

The table presents descriptive statistics for the overall sample and for different user types. "Client" trades refer to customers of broker-dealers. These can be retail or institutional. "Firm" refers to proprietary trades of broker-dealers. "Specialists" are those users who are designated as specialists for certain securities. These specialists can also trade other non-designated securities for their proprietary accounts. These are all grouped together under the "Specialist" designation. The "Other" category includes infrequently seen categories such as options market makers. To calculate the numbers, first the data are aggregated to the stock-user-day level. The averages presented are then calculated by aggregating by stock and day across users, then across stocks each day and then across days. percentiles reflect the respective daily average across stocks. The sample contains 1,286 stocks traded over 245 days in the calendar year 2006.

	Mean	Minimum	25th percentile	Median	75th percentile	Maximum
Number of stocks per day	899.8	763.0	886.0	915.0	929.0	967.0
Average daily Number of trades per stock	595.3	367.1	535.0	591.3	649.5	832.4
Average daily share volume per stock	544,481.6	261,148.9	475,096.2	542,383.9	627,090.3	863,383.8
Average daily Dollar volume per stock	9,969,075.2	4,279,950.1	8,687,780.9	10,060,919.3	11,155,961.2	14,915,292.7
Average closing stock price $ (midpoint)	13.7	11.1	13.2	13.8	14.5	15.3
Market cap. of stocks traded ($ thousands)	1,627,110.2	1,506,065.5	1,599,908.5	1,631,396.1	1,661,508.7	1,728,463.8
Average daily dollar spread	0.12	0.10	0.12	0.12	0.13	0.16
Average daily relative spread	2.3%	1.9%	2.1%	2.3%	2.4%	3.0%
Average daily return	-0.02%	-3.29%	-0.33%	0.08%	0.43%	2.74%

Table 2

This table presents summary statistics on the users trading on the Toronto Stock Exchange. "CL" trades refer to clients or customers of broker-dealers. These can be retail or institutional. "FM" refers to proprietary trades of broker-dealers. "ST" traders are those users who are designated as specialists for certain securities. These specialists can also trade other non-designated securities for their proprietary accounts. These are all grouped together under the "ST" designation. The "Other" category includes infrequently seen categories such as options market makers. To calculate the numbers, first the data are aggregated to the stock-user-day level. We aggregate across stocks by user for each day (averages at the user level are volume weighted), and aggregate across days (equally weighted) for each user. The user level data are summarized below using equally weighted means. The sample contains 1,286 stocks traded over 245 days in the calendar year 2006.

	Overall	**CL**	**FM**	**ST**	**Other**	**CL=FM**	**CL=ST**	**FM=ST**
Number of traders	4861	1792	2362	683	24			
Days per trader	93.3	110.8	60.2	160.6	128.0	*0.00*	*0.00*	*0.00*
Stocks per day per trader	7.79	13.63	4.50	3.99	4.63	*0.00*	*0.00*	*0.59*
Daily Number of trades	153.7	268.2	70.9	142.8	45.5	*0.00*	*0.00*	*0.02*
Daily Share volume (*1,000)	121.9	222.4	61.3	71.1	24.9	*0.00*	*0.00*	*0.48*
Daily Dollar volume (*1,000)	2,351.7	4,187.7	1,213.6	1,512.5	932.5	*0.00*	*0.00*	*0.36*
Average absolute value of ending inventory	37,559.6	59,128.3	30,466.7	6,492.1	6,810.6	*0.00*	*0.00*	*0.00*
Number of times inventory crosses zero	0.75	0.28	0.22	3.79	0.53	*0.51*	*0.00*	*0.00*
Proportion of passive executions	51.8%	50.1%	49.9%	62.6%	58.3%	*0.78*	*0.00*	*0.00*
Proportion of trades in direction of inventory	50.1%	63.5%	42.7%	41.0%	44.3%	*0.00*	*0.00*	*0.07*
Proportion of volume placed anonymously	16.6%	12.7%	15.8%	29.7%	11.6%	*0.00*	*0.00*	*0.00*
Zero ending inventory	9.2%	5.5%	9.2%	18.8%	6.5%	*0.00*	*0.00*	*0.00*
Inventory against day's stock return	45.5%	45.9%	45.4%	43.8%	66.9%	*0.42*	*0.03*	*0.09*
Users affiliated with institutional brokers	22.5%	28.3%	22.1%	9.4%	4.2%	*0.00*	*0.00*	*0.00*
Users affiliated with proprietary brokers	4.4%	1.4%	2.5%	18.9%	0.0%	*0.08*	*0.00*	*0.00*
Users affiliated with retail brokers	20.7%	17.9%	24.5%	15.5%	0.0%	*0.00*	*0.19*	*0.00*
Users affiliated with integrated brokers	48.0%	46.8%	46.7%	54.3%	91.7%	*0.99*	*0.00*	*0.00*

Table 3.a

This table presents the results of a probit used to identify users who behave like the specialist traders in our sample. The dependent variable equals one for "Specialist" users and zero otherwise. The probit is run on data aggregated at the user-day level (similar to Table 2 above). User-days included in the probit are required to have at least five trades. The independent variables are chosen to correlate with liquidity supplying trading behavior. Liquidity suppliers are assumed to trade more passively, flip their inventory position during the day, not hold large end of the day positions, and trade opposite to their existing intraday inventory. Due to the internalization rules in Canada, traders who are hoping to trade with their client order flow are more likely to display their broker IDs whereas traders with lesser client order flow and greater proprietary trading are more likely to be anonymous. We also use the broker types that the user is affiliated with. "Integrated" brokers are the omitted dummy.

	Estimate	**p-value**
Intercept	-0.39	*0.00*
Number of times inventory crosses zero	0.08	*0.00*
Proportion of passive trades	1.21	*0.00*
Absolute value of ending inventory (*100,000)	-0.63	*0.00*
Proportion of trades in direction of inventory	-1.62	*0.00*
Proportion of anonymous trades	0.51	*0.00*
Institutional broker dummy	-0.60	*0.00*
Proprietary trading firm dummy	1.38	*0.00*
Retail broker dummy	-0.31	*0.00*
Other broker dummy	-1.14	*0.00*
Likelihood Ratio		*0.00*
Wald		*0.00*
R-Square	0.3309	

Table 3.b

This table presents characteristics of users differentiated on the predicted probability from the probit in Table 3.a. The probit provides a predicted probability for each user each day. We average the probabilities across days for each user, and then assign users into deciles based on the average probability. The average probability of users in a decile and the average probability rank range are presented along with the other summary variables for each decile. We use the decile rankings to assign users into the following categories. Users who are designated as market makers ("Specialists") for a particular stock are designated as DMMs for their trading in designated stocks only regardless of their probability score. Users who are in decile 10 and trade on at least 50 days during the year are designated as Endogenous Liquidity Providers (ELPs). To calculate the numbers, first the data are aggregated to the stock-user-day level. We aggregate across stocks by user for each day (averages at the user level are volume weighted), and aggregate across days (equally weighted) for each user. The user level data are summarized below using equally weighted means.

	Probability Ranking Deciles					**Decile 10**					
	1 (Lowest)	**4**	**7**	**10 (Highest)**	**1=10**	**CL**	**FM**	**ST- Non DMM**	**DMM**	**ELP**	**DMM= ELP**
Number of users	424	425	425	424		23	93	115	334	152	
Probability	0.02	0.10	0.19	0.71	*0.00*	0.65	0.65	0.75	0.60	0.71	*0.00*
Probability rank range	2.5	6.4	6.8	2.7	*0.36*	3.7	3.1	2.6	3.5	3.7	*0.38*
Days per user	52.8	114.0	108.6	143.8	*0.00*	87.4	76.9	157.2	165.5	168.8	*0.69*
Stocks per day per user	6.9	11.3	6.6	4.7	*0.17*	13.5	6.1	4.1	3.2	7.1	*0.08*
Daily Number of trades	288.0	196.0	72.6	213.9	*0.14*	750.8	102.3	97.9	203.3	235.0	*0.64*
Daily Share volume (*1,000)	179.3	189.7	89.6	95.4	*0.00*	236.8	101.0	97.2	64.3	152.2	*0.00*
Daily Dollar volume (*1,000)	4,370.0	2,963.3	1,805.0	2,168.7	*0.00*	9,610.0	1,233.6	1,825.0	1,336.9	3,395.2	*0.01*
Average absolute value of ending inventory	67,089.4	53,261.9	36,834.1	5,757.7	*0.00*	15,943.8	9,518.5	4,264.6	6,232.0	7,244.6	*0.92*
Number of times inventory crosses zero	0.1	0.2	0.3	5.5	*0.00*	5.1	1.9	4.0	5.6	4.4	*0.00*
Proportion of passive executions	40.3%	48.9%	52.2%	66.3%	*0.00*	51.9%	57.3%	51.5%	78.7%	54.0%	*0.00*
Proportion of trades in direction of inventory	70.3%	61.8%	51.3%	38.9%	*0.00*	42.7%	30.1%	36.0%	42.9%	34.4%	*0.00*
Proportion of volume placed anonymously	9.1%	11.0%	16.1%	42.2%	*0.00*	45.3%	42.2%	56.1%	25.0%	51.9%	*0.00*
Users affiliated with institutional brokers	56.6%	21.9%	12.2%	3.3%	*0.00*	4.3%	2.2%	0.9%	9.3%	2.0%	*0.06*
Users affiliated with proprietary brokers	0.0%	0.0%	0.0%	39.2%	*0.00*	60.9%	32.3%	53.0%	19.2%	41.4%	*0.00*
Users affiliated with retail brokers	9.4%	26.8%	22.1%	8.0%	*0.60*	0.0%	18.3%	2.6%	15.6%	9.2%	*0.11*
Users affiliated with integrated brokers	12.3%	49.2%	62.6%	49.1%	*0.00*	26.1%	47.3%	43.5%	54.2%	46.1%	*0.09*
Zero ending inventory	1.7%	3.8%	7.4%	23.0%	*0.00*	26.3%	42.7%	42.6%	1.1%	49.7%	*0.00*
Inventory against day's stock return	46.1%	46.8%	48.1%	41.1%	*0.00*	35.0%	28.6%	32.3%	52.6%	27.4%	*0.00*

Table 4: Market cap. quintiles

This table presents results by market capitalization quintiles of stocks for the Non MM, DMM and ELP categories for our sample. Market capitalization is calculated as of the end of the month prior to the trading date. "% of stock days" indicates the proportion of days with DMM or ELP (as a group) trading. We present the participation rates for DMMs and ELPs both as a proportion of the number of trades and volume. We calculate the participation rate in two ways – conditional on trading in a particular stock-day, and unconditionally where we fill in a zero participation if DMMs or ELPs do not trade on the stock-day. We also present the proportion of all trades that are passive, and are marked as anonymous. "Trades with inv." Presents the proportion of trades in the day which are in the direction of the trader's existing intraday inventory. "Times inv. Crosses zero" measures the number of times the trader's inventory changes sign. "Zero Inv." and "Inv. against return" show the proportion of days where a trader ends the stock-days with zero inventories, and inventory positions against the stock's return on the day. The numbers are equally weighted averages across stock-user-days. *indicates that all numbers in the column are significant at the 5% level. For the columns for which this is not true, statistical significance is indicated by numbers in bold.

Rank	**Type**	**Stock user days**	**% of stock days**	**Part. rate-trades (cond.)***	**Part. rate-volume (cond.)***	**Part. rate-trades (uncond.)***	**Part. rate-volume (uncond.)***	**Passive trades***	**Anonymous volume***	**Trades with inv.***	**Times inv. Cross zero***	**Zero inv.***	**Inv. against return***
(Low)	DMM	28210	78.4%	23.4%	14.9%	18.4%	11.7%	84.0%	25.2%	33.4%	0.45	1.5%	46.9%
1 (Low)	ELP	5052	12.0%	13.4%	15.6%	1.6%	1.9%	52.9%	58.9%	32.1%	0.35	17.5%	35.8%
1 (Low)	DMM=ELP		*0.00*	*0.00*	*0.09*	*0.00*	*0.00*	*0.00*	*0.00*	*0.01*	*0.00*	*0.00*	*0.00*
2	DMM	36995	86.0%	20.8%	12.8%	17.9%	11.0%	82.7%	20.3%	36.9%	0.77	1.6%	51.4%
2	ELP	10554	19.5%	8.5%	9.3%	1.7%	1.8%	45.2%	52.6%	35.3%	0.30	19.6%	39.0%
2	DMM=ELP		*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
3	DMM	42725	91.9%	18.9%	11.4%	17.4%	10.5%	82.5%	22.4%	41.5%	1.23	1.4%	53.8%
3	ELP	14194	22.7%	5.9%	6.3%	1.3%	1.4%	44.1%	52.2%	36.3%	0.39	26.6%	34.7%
3	DMM=ELP		*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
4	DMM	47009	96.4%	16.1%	9.6%	15.6%	9.3%	81.8%	21.3%	45.8%	2.45	1.1%	55.6%
4	ELP	29389	37.1%	3.8%	3.8%	1.4%	1.4%	50.7%	57.2%	33.6%	1.00	40.5%	28.5%
4	DMM=ELP		*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
5 (High)	DMM	49908	99.6%	12.3%	6.8%	12.3%	6.8%	82.9%	26.6%	48.7%	10.28	0.6%	56.4%
5 (High)	ELP	152355	79.4%	5.4%	4.6%	4.3%	3.6%	56.6%	64.5%	33.6%	6.66	56.5%	23.4%
5 (High)	DMM=ELP		*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*

Table 5: This table presents the participation rates of DMMs and ELPs for stock days sorted into daily share volume quintiles. The quintile assignments are made separately for each stock. Participation rates are unconditional (fill in a zero for days with no trading). The numbers are equally weighted averages across stock- days. Panel A presents the results for the overall sample, Panel B for stocks in the lowest market cap quintile and Panel C for stocks in the highest market cap quintile. *indicates that all numbers in the column are significant at the 1% level. For the columns for which this is not true, statistical significance is indicated by numbers in bold.

A. Overall Sample: Daily Intraday Share Volume Quintile (within stock ranking)

DMM	**Quintile 1 (lowest)**	**2**	**3**	**4**	**Quintile 5 (highest)**	**p-value: test q1=q5**	**5th percentile**	**95th percentile**	**p-value: test p5=p95**
% of stock days	86.92%	89.87%	91.82%	93.10%	94.41%	*0.00*	86.09%	95.18%	*0.00*
Participation rate-trades	19.80%	17.08%	15.78%	14.71%	13.33%	*0.00*	22.57%	12.64%	*0.00*
Passive trades	85.05%	83.17%	82.29%	81.65%	81.60%	*0.00*	87.21%	81.72%	*0.00*
ELP									
% of stock days	27.96%	32.46%	35.67%	38.96%	44.19%	*0.00*	25.19%	48.18%	*0.00*
Participation rate-trades	1.94%	2.02%	2.10%	2.15%	2.29%	*0.00*	1.88%	2.39%	*0.00*
Passive trades	55.96%	54.75%	53.72%	52.86%	52.29%	*0.00*	57.60%	52.04%	*0.00*
p-values: test DMM=ELP									
% of stock days	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	
Participation rate-trades	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	
Passive trades	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	

B. Lowest market value quintile stocks: Daily Intraday Share Volume Quintile (within stock ranking)

DMM	**Quintile 1 (lowest)**	**2**	**3**	**4**	**Quintile 5 (highest)**	**p-value: test q1=q5**	**5th percentile**	**95th percentile**	**p-value: test p5=p95**
% of stock days	70.90%	74.82%	78.38%	81.82%	85.98%	*0.00*	72.02%	88.29%	*0.00*
Participation rate-trades	24.33%	19.70%	17.62%	16.17%	14.04%	*0.00*	29.41%	12.71%	*0.00*
Passive trades	88.14%	85.57%	83.53%	81.99%	81.61%	*0.00*	92.82%	81.45%	*0.00*
ELP									
% of stock days	4.21%	7.35%	11.01%	14.79%	22.58%	*0.00*	2.64%	28.66%	*0.00*
Participation rate-trades	1.06%	1.27%	1.64%	1.84%	2.23%	*0.00*	0.90%	2.46%	*0.00*
Passive trades	43.93%	49.20%	49.85%	52.90%	55.55%	*0.00*	37.21%	56.34%	*0.00*
p-values: test DMM=ELP									
% of stock days	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	
Participation rate-trades	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	
Passive trades	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	

C. Highest market value quintile stocks: Daily Intraday Share Volume Quintile (within stock ranking)

DMM	**Quintile 1 (lowest)**	**2**	**3**	**4**	**Quintile 5 (highest)**	**p-value: test q1=q5**	**5th percentile**	**95th percentile**	**p-value: test p5=p95**
% of stock days	99.12%	99.56%	99.71%	99.80%	99.76%	*0.00*	98.73%	99.79%	*0.00*
Participation rate-trades	14.10%	12.76%	12.15%	11.62%	10.88%	*0.00*	15.26%	10.53%	*0.00*
Passive trades	84.47%	83.12%	82.54%	82.27%	82.36%	*0.00*	85.62%	82.45%	*0.00*
ELP									
% of stock days	75.42%	78.73%	79.25%	80.74%	82.68%	*0.00*	72.89%	84.18%	*0.00*
Participation rate-trades	4.43%	4.37%	4.28%	4.21%	4.17%	*0.00*	4.40%	4.10%	*0.00*
Passive trades	63.25%	62.02%	61.38%	60.41%	59.78%	*0.00*	63.72%	58.48%	*0.00*
p-values: test DMM=ELP									
% of stock days	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	
Participation rate-trades	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	
Passive trades	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	

Table 6: This table presents the participation rates of DMMs and ELPs for stock days sorted into intraday volatility quintiles. The quintile assignments are made separately for each stock. Intraday volatility is calculated as the standard deviation of 15 minutes returns based on bid-ask midpoints. Participation rates are unconditional (fill in a zero for days with no trading).The numbers are equally weighted averages across stock- days. Panel A presents the results for the overall sample, Panel B for stocks in the lowest market cap quintile and Panel C for stocks in the highest market cap quintile. *indicates that all numbers in the column are significant at the 1% level. For the columns for which this is not true, statistical significance is indicated by numbers in bold.

A. Overall Sample: Daily Intraday Volatility Quintile (within stock ranking)

DMM	Quintile 1 (lowest)	2	3	4	Quintile 5 (highest)	p-value: test q1=q5	5th percentile	95th percentile	p-value: test p5=p95
% of stock days	87.37%	89.69%	92.42%	92.74%	94.30%	*0.00*	89.10%	95.62%	*0.00*
Participation rate-trades	16.91%	16.28%	16.21%	15.73%	15.48%	*0.00*	16.46%	15.21%	*0.00*
Passive trades	85.91%	83.74%	82.48%	81.39%	80.28%	*0.00*	87.02%	79.93%	*0.00*
ELP									
% of stock days	30.84%	33.41%	35.86%	37.77%	41.77%	*0.00*	33.47%	45.37%	*0.00*
Participation rate-trades	1.88%	1.99%	2.10%	2.17%	2.36%	*0.00*	1.98%	2.51%	*0.00*
Passive trades	53.90%	53.71%	53.81%	53.74%	53.50%	*0.00*	54.25%	53.62%	*0.00*
p-values: test DMM=ELP									
% of stock days	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	
Participation rate-trades	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	
Passive trades	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	

B. Lowest market value quintile stocks: Daily Intraday Volatility Quintile (within stock ranking)

DMM	Quintile 1 (lowest)	2	3	4	Quintile 5 (highest)	p-value: test q1=q5	5th percentile	95th percentile	p-value: test p5=p95
% of stock days	70.47%	74.67%	80.64%	81.67%	85.22%	*0.00*	71.30%	87.34%	*0.00*
Participation rate-trades	19.97%	18.63%	18.99%	17.50%	16.72%	*0.00*	19.84%	16.01%	*0.00*
Passive trades	89.03%	86.17%	83.49%	81.92%	80.40%	*0.00*	90.28%	80.55%	*0.00*
ELP									
% of stock days	5.86%	9.06%	11.67%	14.68%	18.84%	*0.00*	6.58%	22.32%	*0.00*
Participation rate-trades	1.15%	1.44%	1.59%	1.82%	2.04%	*0.00*	1.31%	2.15%	*0.00*
Passive trades	46.10%	49.92%	51.82%	51.92%	55.75%	*0.00*	48.50%	56.45%	*0.00*
p-values: test DMM=ELP									
% of stock days	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	
Participation rate-trades	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	
Passive trades	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	

C. Highest market value quintile stocks: Daily Intraday Volatility Quintile (within stock ranking)

DMM	Quintile 1 (lowest)	2	3	4	Quintile 5 (highest)	p-value: test q1=q5	5th percentile	95th percentile	p-value: test p5=p95
% of stock days	99.33%	99.56%	99.79%	99.59%	99.71%	*0.00*	99.15%	99.75%	*0.00*
Participation rate-trades	12.82%	12.45%	12.30%	12.12%	11.79%	*0.00*	13.05%	11.40%	*0.00*
Passive trades	85.20%	83.55%	83.01%	81.99%	80.98%	*0.00*	86.27%	80.28%	*0.00*
ELP									
% of stock days	76.68%	78.33%	79.63%	80.50%	81.78%	*0.00*	75.45%	82.79%	*0.00*
Participation rate-trades	4.06%	4.19%	4.35%	4.38%	4.49%	*0.00*	3.96%	4.52%	*0.00*
Passive trades	62.04%	61.98%	61.80%	61.09%	59.78%	*0.00*	61.94%	58.28%	*0.00*
p-values: test DMM=ELP									
% of stock days	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	
Participation rate-trades	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	
Passive trades	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*	*0.00*	

Table 7: This table presents the profitability and inventory positions of market makers on stock-days when both DMMs and ELPs participate versus stock-days when DMMs participate but ELPs do not. Panel A presents unconditional results for the full sample, Panel B presents results on trading days with and without ELP participation, and Panel C presents the results for each of the market cap quintiles, conditional on ELP participation.. For each stock-day for an account, we calculate profits using three methodologies -- by marking the day's transactions to closing quote midpoint and aggregating the dollar profit over the day; cash flow profits calculated as the change in inventory associated with a trade multiplied by the price; and mark-to-market profits calculated as the inventory position multiplied by the change in prices. We close out remaining inventory positions at the end of the day for each of the three methodologies. All three methodologies yield identical profit measures. We decompose trading profits into three components: passive is the half-spread earned on trades that provide liquidity; active is the half-spread paid on trades that demand liquidity; and positioning profits is the profit calculated using quote midpoints rather than traded prices. As proxies for inventory risk, we report the number of times the inventory switches between long and short positions, the absolute value of closing inventory, the absolute value of maximum inventory within the day, and the signed closing inventory position normalized by monthly stock trading volume. The statistics are equally weighted averages across stock-days in the respective sample. We present results averaged across stock-days at the individual market-maker level, as well as across stock days at the market-maker type level. The latter aggregation aggregates all ELPs active in a stock on a day.

			Analysis by User Account Per Stock Per Day								**Analysis by User Type (ELPs aggregated) Per Stock Per Day**					
			Trading Profits					**Inventory/month volume**			**Trading Profits**				**Inventory/month volume**	
		Stock-days	**Profit**	**Passive**	**Active**	**Positioning**	**Times inv crosses zero**	**Abs (end inv)**	**Signed inv.****	**Abs (max inv)**	**Profit**	**Passive**	**Active**	**Positioning**	**Abs (end inv)**	**Signed inv.****
A. All stocks																
	DMM	200536	150.89	255.81	103.64	0.10	3.59	0.3296%	0.0831%	5.04%	153.36	260.52	105.98	0.29	0.3313%	0.0833%
	ELP	78813	68.86	119.15	62.72	13.19	4.92	0.1749%	-0.0026%	1.57%	309.35	421.80	244.27	134.35	0.2144%	-0.0021%
	DMM=ELP		*0.00*	*0.00*	*0.00*	*0.07*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
B. All stocks, conditional on ELP participation																
DMM only	**DMM**	123136	92.64	137.60	45.14	1.30	1.17	0.4674%	0.1201%	7.10%	93.37	138.61	45.52	1.40	0.4693%	0.1203%
Both	**DMM**	77400	243.56	441.15	195.36	-1.78	7.45	0.1104%	0.0275%	1.75%	248.80	451.66	200.77	-1.46	0.1118%	0.0276%
Both	**ELP**	77387	69.70	119.84	62.83	13.41	5.01	0.1554%	-0.0033%	1.45%	314.59	427.63	247.48	136.70	0.1951%	-0.0027%
Both	**DMM=ELP**		*0.00*	*0.00*	*0.00*	*0.18*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*

			Analysis by User Account Per Stock Per Day								Analysis by User Type Per Stock Per Day					
			Trading Profits					Inventory/month volume			Trading Profits				Inventory/month volume	
		Stock-days	Profit	Passive	Active	Positioning	Times inv crosses zero	Abs (end inv)	Signed inv.**	Abs (max inv)	Profit	Passive	Active	Positioning	Abs (end inv)	Signed inv.**
C. Market Cap. quintiles, conditional on ELP participation																
Quintile 1	**DMM w/o ELP**	24121	41.39	59.59	18.71	1.39	0.44	0.9125%	0.2446%	4.63%	41.49	59.75	18.76	1.36	0.9143%	0.2443%
(Low)	**DMM with ELP**	3793	52.71	93.02	29.21	-10.46	0.91	0.4833%	0.1471%	0.62%	52.75	93.32	29.33	-10.62	0.4873%	0.1490%
	ELP	3784	61.66	136.64	51.50	-22.01	0.60	0.8625%	0.0418%	1.16%	81.38	187.96	68.63	-36.14	0.9527%	0.0492%
	DMM=ELP		*0.24*	*0.00*	*0.00*	*0.18*	*0.00*	*0.00*	*0.01*	*0.00*	*0.00*	*0.00*	*0.00*	*0.03*	*0.00*	*0.02*
Quintile 2	**DMM w/o ELP**	28825	62.25	90.91	29.18	1.26	0.69	0.5615%	0.1421%	7.18%	62.50	91.23	29.30	1.32	0.5641%	0.1426%
	DMM with ELP	7795	105.88	169.19	59.64	-3.45	1.46	0.2869%	0.0627%	0.93%	107.31	171.03	60.15	-3.35	0.2893%	0.0628%
	ELP	7793	47.62	98.56	52.32	3.27	0.52	0.4491%	-0.0016%	1.34%	71.42	135.15	72.48	9.75	0.5159%	-0.0013%
	DMM=ELP		*0.00*	*0.00*	*0.00*	*0.36*	*0.00*	*0.00*	*0.00*	*0.01*	*0.00*	*0.00*	*0.00*	*0.16*	*0.00*	*0.00*
Quintile 3	**DMM w/o ELP**	31947	93.51	131.96	41.75	4.03	1.06	0.3622%	0.1009%	6.27%	94.36	132.96	42.11	4.24	0.3640%	0.1008%
	DMM with ELP	10119	142.71	242.50	80.14	-19.54	2.19	0.1707%	0.0427%	1.40%	143.75	245.16	80.97	-20.33	0.1731%	0.0422%
	ELP	10119	55.08	99.28	61.11	16.09	0.66	0.2554%	-0.0313%	2.13%	90.08	161.57	90.07	18.20	0.3009%	-0.0351%
	DMM=ELP		*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.01*	*0.00*	*0.00*
Quintile 4	**DMM w/o ELP**	28468	128.98	188.17	64.83	6.17	1.72	0.2203%	0.0551%	7.94%	129.91	189.81	65.49	6.10	0.2219%	0.0555%
	DMM with ELP	17560	209.22	339.38	134.83	4.75	3.98	0.0857%	0.0216%	1.58%	212.10	345.21	137.40	4.38	0.0868%	0.0218%
	ELP	17558	40.64	97.97	63.62	5.41	1.71	0.0999%	-0.0046%	1.58%	72.93	200.07	122.23	-6.44	0.1308%	-0.0079%
	DMM=ELP		*0.00*	*0.00*	*0.00*	*0.96*	*0.00*	*0.00*	*0.00*	*0.99*	*0.00*	*0.00*	*0.00*	*0.53*	*0.00*	*0.00*
Quintile 5	**DMM w/o ELP**	9775	200.02	330.50	108.28	-21.77	3.18	0.1553%	0.0500%	13.26%	202.83	333.79	109.45	-21.07	0.1560%	0.0501%
(High)	**DMM with ELP**	38133	333.27	630.18	297.70	1.11	12.31	0.0326%	0.0095%	2.21%	342.01	647.70	307.15	2.14	0.0334%	0.0097%
	ELP	38133	92.28	137.77	66.09	21.74	9.04	0.0243%	0.0004%	1.26%	558.27	681.03	397.05	274.20	0.0559%	0.0033%
	DMM=ELP		*0.00*	*0.00*	*0.00*	*0.34*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*

Table 8: This table analyzes the determinants of ELP participation in cross-sectional and panel frameworks. Panel A presents the results from a Fama-MacBeth style daily logit estimation where the dependent variable equals one if there is ELP trading on a stock-day and zero otherwise. All included stock-days have DMM participation. Daily coefficients (over 245 days) are used to calculate t-statistics using Newey-West standard errors with five lags. Panel B presents the results of a conditional logit estimated over the entire panel of stock-days with stock fixed effects.

Panel A: Fama-MacBeth logit estimation

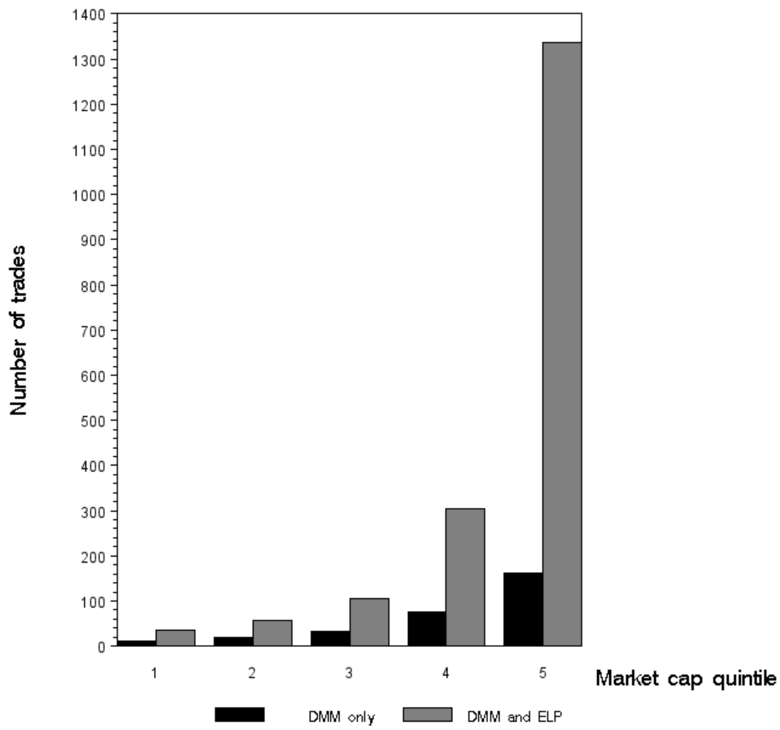
	Model 1			Model 2		
	Average Estimate	**p-value**	**Average Odds ratio**	**Average Estimate**	**p-value**	**Average Odds ratio**
Intercept	-4.595	*0.00*		-4.174	*0.00*	
ST volatility (intraday)	0.654	*0.00*	2.013	0.671	*0.00*	2.048
Log (market cap)	0.048	*0.01*	1.062	0.034	*0.06*	1.047
Log (daily $ volume)	0.139	*0.00*	1.155	0.133	*0.00*	1.147
Number of trades	0.007	*0.00*	1.007	0.007	*0.00*	1.007
Price inverse	0.094	*0.00*	1.103	0.091	*0.00*	1.099
% quoted spread	-0.207	*0.00*	0.819	-0.204	*0.00*	0.821
LT volatility (daily, measured each month)	0.139	*0.00*	1.152	0.130	*0.00*	1.141
DMM inventory/month volume (abs. value)				-0.295	*0.00*	0.780
Times inventory crosses zero				0.006	*0.03*	1.007
DMM profit/highest absolute intraday inventory				0.013	*0.00*	1.014
Average Pseudo R-square	0.40			0.41		
Average Rescaled Pseudo R-square	0.54			0.55		

Panel B: Conditional logit with stock fixed effects

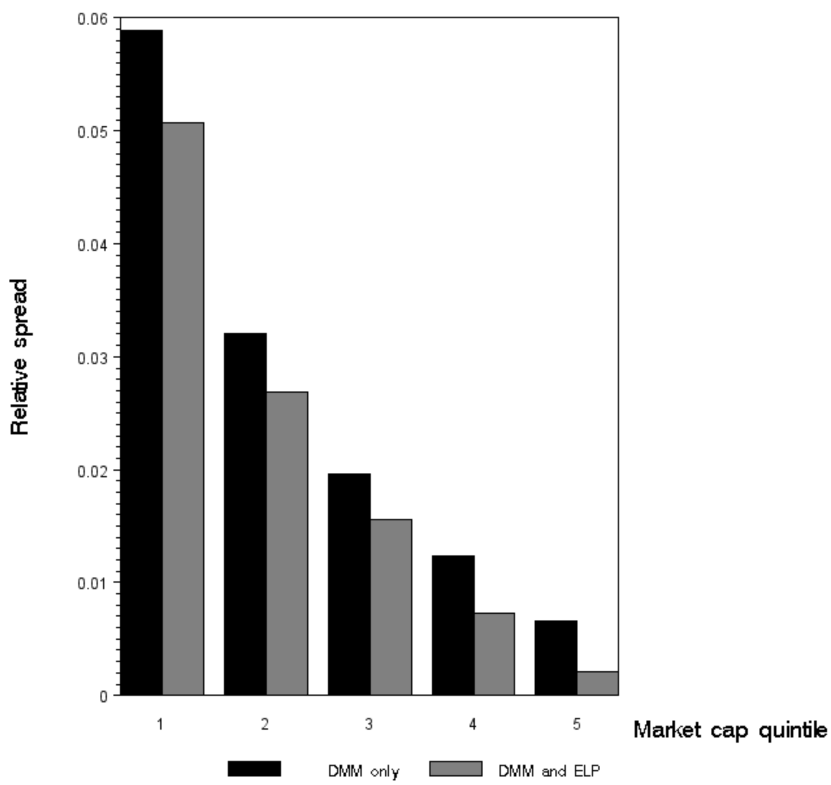
	Model 1			Model 2		
	Estimate	**p-value**	**Odds Ratio**	**Estimate**	**p-value**	**Odds Ratio**
ST volatility (intraday)	0.410	*0.00*	1.506	0.412	*0.00*	1.509
Log (daily $ volume)	0.351	*0.00*	1.421	0.351	*0.00*	1.421
Number of trades	0.003	*0.00*	1.003	0.003	*0.00*	1.003
Price inverse	0.091	*0.00*	1.095	0.091	*0.00*	1.096
% quoted spread	-0.058	*0.00*	0.943	-0.062	*0.00*	0.940
Abs (order imbalance)	-0.512	*0.00*	0.599	-0.504	*0.00*	0.604
DMM inventory/month volume (abs. value)				-0.051	*0.00*	0.950
Times inventory crosses zero				0.007	*0.03*	1.007
DMM profit/highest absolute intraday inventory				0.009	*0.00*	1.009
Average Pseudo R-square	0.05			0.05		
Average Rescaled Pseudo R-square	0.10			0.10		

Figure 1: We study the stock characteristics, within market cap quintiles, on days without and with ELP participation. Panel A presents the average number of trades, Panel B presents the average spreads, Panel C the average imbalance and Panel D the average intraday volatility. Averages are taken over stock-days

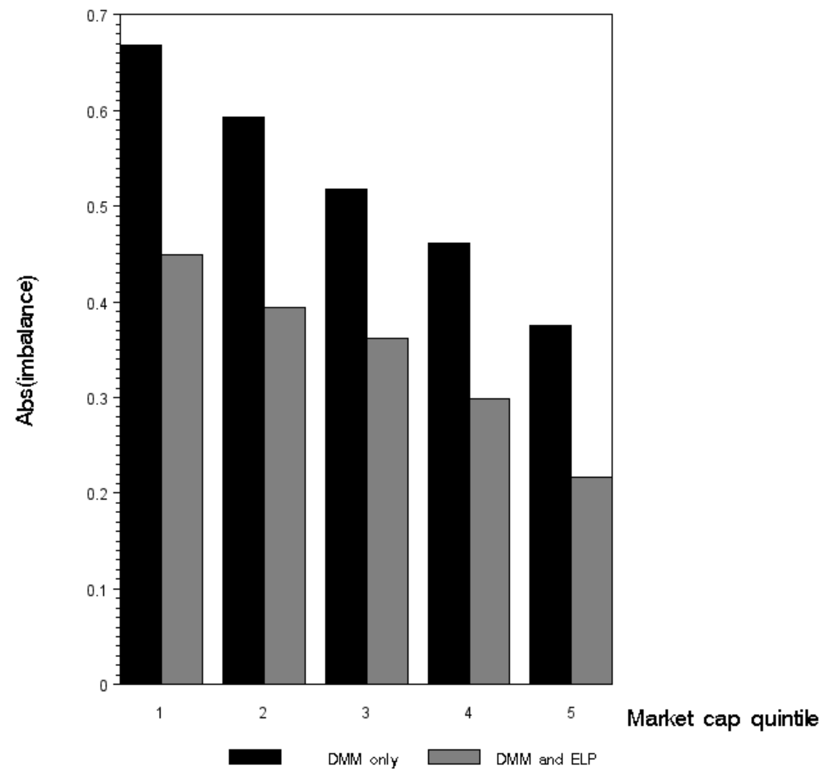
Panel A: Number of trades



Panel B: Relative spread



Panel C: Abs (order imbalance)



Panel D: Intraday volatility