Should Exchanges impose Market Maker obligations?

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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 voluntarily because it is a profitable activity. Using Toronto Stock Exchange data, 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. ELPs maintain a market presence and supply liquidity in large stocks. For other stocks, we establish that a DMM is not only an incremental liquidity provider but also the only *reliable* counterparty available for investors. Under market conditions when profit opportunities are small or inventory risk is substantial, ELPs exercise the option to withdraw participation. Under these conditions, DMMs earn smaller trading profits, assume higher inventory risk, and commit more capital suggesting that contractual obligations require the DMMs to participate in undesirable trades. Our evidence 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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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. A central question in market design is whether it is desirable for exchanges to impose obligations on market makers, or stated alternatively, whether market makers *reliably* provide liquidity when they have no obligation to do so. We describe the latter class of market makers who supply liquidity because it is a profitable activity as Endogenous Liquidity Providers (ELPs). 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 motivated by trading profits but their participation is, at least in part, governed by contractual obligations to maintain a market presence.

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 how ELPs make trading decisions, and how their decisions differ from those made by DMMs.[1] The paucity of empirical work reflects the difficulty in obtaining detailed data on ELP participation in a market structure where ELPs and DMMs co-exist. In particular, many publicly available

[1] A well-developed empirical literature has examined the trades of the DMM, especially of the New York Stock Exchange (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.

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 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), many 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 market quality in equity markets has improved alongside the growth in algorithmic trading.[2] These findings are frequently interpreted as empirical support for a structure where exchanges impose no obligations on market makers.

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 secondary market trading 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 or demand a large bid-ask spread when liquidity supply is risky need not indicate any market failure or economic inefficiency. Nonetheless, the sudden withdrawal of liquidity increases uncertainty on whether an order can be executed, and if so, whether execution will occur with substantial delay. Within this framework, some theoretical papers describe the benefits to market participants of adopting a structure with market maker obligations. To the extent that investors are ambiguity averse, Easley and O'Hara (2010) point out 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 allocation efficiency. Their model shows that the benefits to traders, and ultimately to the listed firm via a higher IPO price, exceed the side payments necessary to compensate the DMM for liquidity provision. In support of their prediction, the empirical literature reports that the introduction of a DMM is associated with positive abnormal return in the stock (see Venkataraman and Waisburd (2007)). In this study, we contrast the behavior of ELPs and DMMs and provide evidence on circumstances when market maker obligations become binding. For many medium and small cap stocks, we establish that a DMM is not only an incremental liquidity provider but also the only *reliable* counterparty available for investors. Our results point to a possible mechanism by which the introduction of DMM reduces execution uncertainty and increases firm value.

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 relative merits of market structures as well as test theoretical predictions 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 participate on the passive side of trades, actively manage inventory risk, and maintain small overnight inventory. Further, the model ranks DMM-associated Accounts in the upper probability decile in an out-of-sample period.

Although both ELPs and DMMs implement market making strategies, we find that they differ in some important ways. For the largest market cap (Quintile 5) of stocks, ELPs participate on 79% of the stock-days and DMMs participate on 90% of stock-days with trading data. ELP participation declines to 37% for Quintile 4 stocks and declines further to 12% for small stocks. In contrast, DMMs are active on

78% of the stocks-days for small stocks. Our main finding is that, relative to DMMs, the trading strategy of ELPs in medium and small stocks appears to be 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 these 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.

A significant determinant of ELP participation over time is the market condition 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 lowest share volume (or volatility) and 82% for highest share volume (or volatility) quintile, and the majority of ELP trades (approximately 60%) are liquidity supplying. These results support that market makers voluntarily 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 volatility) stock-days and less than 5% of low volume (or 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 of liquidity providers for low capitalization stocks. Notably, in small stocks, DMMs are active in over 70% of low volume days and participate in one out of every four trades. These findings support Bessembinder, Hao and Zheng (2012)'s prediction that market maker obligations are more desirable in low capitalization stocks.

We show that market conditions influence the ELP's participation decision via its impact on trading profits, inventory risk, and capital commitments of market makers. We decompose trading profits into those attributable to passive, active, and positioning profits. 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. Furthermore, we find that DMMs earn *lower* trading profits on days when ELPs are absent in a stock. This result is unexpected because DMMs face less competition from liquidity providers on days when ELPs withdraw; therefore the profits should be higher, not lower. Alternatively, the results suggest that ELPs withdraw participation in a stock when profit opportunities are small or market making is risky.

The results support that the DMM's obligations reduce the ability to manage inventory risk. The DMMs routinely hold non-zero overnight inventory positions while ELPs consistently end the trading day at or near zero inventory. We model the ELPs decision to participate in an individual stock using a conditional logistical model. We find that ELP participation is positively associated with trading volume, return volatility, and market making profits and that ELPs choose to withdraw participation when market making is risky. To be specific, DMMs' maximum intra-day inventory position is five to ten times larger on days when ELPs do not participate than on days when ELP participate. Along similar lines, the DMMs overnight inventory is at least twice as large on days without ELP participation. That the ELPs choose not to participate when market making is less profitable or more risky is not unexpected;[4] however, the option to withdraw liquidity increases the investors' trade uncertainty, particularly when liquidity is withdrawn under market conditions when the demand for immediacy is high. On days when ELPs do not participate, DMMs absorb order imbalances by building large inventory positions in the opposite direction of the stock's daily return. These results provide an economic rationale for compensating DMMs for participating in undesirable trades that fulfill their contractual obligations.

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 additional endogenous liquidity supply that naturally arises 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

[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.

risk of a delayed trade, particularly in less active stocks. Our findings question the suitability of a pure limit order book structure for all securities and support a combination of 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

The early empirical literature on DMMs focus on 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 based on portfolio considerations. Hasbrouck and Sofianos (1993) show that the principal source of NYSE specialist's profits is the ability to predict price movements in the short horizon. 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". As compensation for these obligations, the NYSE Specialist obtains access to privileged information about the state of the limit order book and incoming order flow. Prior research has shown that these informational advantages allow the NYSE specialist to earn trading profits and control inventory risk.

Glosten (1994) models an electronic limit order market that relies on ELPs to supply liquidity and shows that, under stylized assumptions, alternate market structures including a hybrid structure with DMM cannot successfully compete with it. However, other theoretical research suggests that, under more relaxed assumptions, DMMs improve outcomes for market participants (see Seppi (1997), Viswanathan and Wang (2002), Parlour and Seppi (2003), Mao and Pagano (2011)).

In many electronic markets, the listed firm negotiates a liquidity agreement with one or more DMMs which describes the obligations and the compensation structure.[6] Empirical studies on DMMs (see, among others, Nimalendran and Petrella (2003), Venkataraman and Waisburd (2007), Anand, Tanggaard and Weaver (2009)) find that younger firms, smaller firms, less volatile firms and those likely to issue equity have a higher propensity to introduce a DMM. Around DMM introduction, the listed firm experiences an improvement in market quality and a cumulative abnormal return of around 5%. The level of DMM compensation depends on the contractual obligations for liquidity provision and the extent of preexisting relation between the listed firm and the market maker.

Our study is distinguished from prior work in part because the specialized TSX database provides 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. It is therefore impossible to track the trading behavior of market makers over time. Further, while much of the literature has focused on the role of DMMs, only a handful of studies have assessed the role of ELPs, mostly focusing on high frequency traders (HFTs), and none of the studies that we are aware of compare the trading behavior of ELPs and DMMs.[7] 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

[6] Saar (2011) provides an excellent survey of the "specialist" market and the related papers. Charitou and Panayides (2009) report the market maker obligations and compensation structure in several equity markets around the world. In addition to liquidity provision, DMMs in many markets, including Paris Bourse and Borsa Italiana, act as stock analysts and produce detailed reports about the firm (see Perotti and Rindi (2010)).

[7] Research on the trading strategies of the HFTs is building. Early empirical work reported patterns suggesting that HFTs should fit within our classification of ELPs. However, more recent work (e.g., Baron, Brogaard, and Kirilenko (2012) and Adam-Clarke (2012)) shows that only a subgroup of HFTs are liquidity providers. The most active HFTs almost always demand liquidity and these HFTs tend to be the most profitable.

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 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. Broker identification information for anonymous orders submitted by brokers is unavailable to market participants but reported in the database.

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 NYSE Specialist, the TSX DMM has 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 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.[8]

[8] 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.

C. Account classification and the sample

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 enable identification of user IDs assigned as DMMs for each stock. All principal trades executed by these user IDs (i.e., "specialist traders" or ST) in "specialist" assigned stocks are categorized under "ST-DMM" account. A DMM can also execute principal trades using its 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).[9] 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 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 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,

[9] 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.

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% (99^{th} 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. The cross-section of TSX traders

The algorithm to identify ELP accounts exploits our ability to accurately identify User IDs of exchange-assigned DMMs. 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 therefore aggregate these accounts into a single-ST category and report descriptive statistics on their trading activity in Table 2. Also reported are descriptive statistics for user accounts representing the trades handled on behalf of clients (CL), proprietary accounts at member firms that never serve as

DMMs (FM), and an "others" category that captures infrequent identifiers such as options market makers. Overall, we identify 94 member firms of which 22 firms have user IDs associated with DMMs during the sample period.

The results in Table 2 show important differences in trading characteristics of market makers (i.e., ST accounts) versus other account types. ST accounts are concentrated with integrated and proprietary brokers and less so with institutional brokers. Client accounts (CL) are associated with larger number of trades and higher dollar and share trading volume; however, as noted earlier, Client accounts are difficult to interpret as they aggregate the orders from all clients associated with a trader. Relative to FM accounts, we find that ST accounts 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. 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 the existing inventory. These results are consistent with ST traders engaging in active inventory management. Some evidence suggests that market makers absorb order flow imbalance, as evidenced by the change in ST inventory, which is in the opposite direction of the stock daily return.[10]

B. An Algorithm to Identify ELP accounts

Market makers can be proprietary traders at brokerage firms (FM), large traders with a DMA arrangement with a prime broker (CL), or DMMs who execute trades in non-designated stocks (ST-non-DMM). For this reason the ELP identification algorithm does not focus on a specific account type. Instead we examine the trades of each User Account and identify trading patterns that are consistent with the behavior of market makers.

The database identifies a subset of market makers, namely the User Accounts associated with exchange-assigned DMMs (i.e., ST accounts in Table 2). We estimate a Probit model aggregated at the

[10] 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.

daily frequency for each user account where the dependent variable equals one if the user account is ST, and equals zero otherwise. The explanatory variables capture the user accounts propensity to supply liquidity and actively manage inventory. The specific variables are (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.

The results of the Probit analysis are presented in Panel A, Table 3. Based on model coefficients, we conclude that market makers are more likely to trade passively, exhibit more switches between long and short inventory within the day, maintain lower overnight inventory, participate in inventory reducing trades, use anonymous identifier, and be associated with proprietary and integrated brokers. We obtain a predicted probability score for each User Account for each day in our sample based on the model coefficients. We assign Accounts into decile portfolios based on the average probability score for a User Account over the sample period.

Table 3, Panel B reports the trading behavior of User Accounts in probability Deciles 1, 4, 7 and 10. The model obtains significant separation in probability scores across deciles groups - the predicted probability of being a market maker increases from 2% for the bottom decile to 71% for the top decile. We examine the range between the highest and lowest daily probability score for an Account over the sample period. The average range for User Accounts in the top and bottom decile is only 2.5% suggesting that trader behavior remains similar over the sample period. To further test persistence in trader behavior, we assign User Accounts into decile portfolios based on the first six months of the sample. We find that the patterns observed over the next six months are similar to those presented in Table 3.[11] About 79%,

[11] 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

63%, and 22% of accounts in Deciles 10, 9 and 8, respectively, are ST-DMM accounts and less than 5% in other Deciles are ST-DMM accounts.

In Table 3, Panel B, we disaggregate Decile 10 user accounts 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 (N=152) as ELPs. The DMM column reports all accounts identified as exchange-assigned DMM (ST-DMM, N=334). A notable result is that DMM accounts have a predicted probability of 0.60 while ELP accounts have a predicted probability of 0.71. That is, according to the model, the accounts identified as ELPs exhibit behavior that is more consistent with market makers than those of exchange-assigned DMMs. This result alleviates a possible concern that the accounts identified as ELPs simply represent the "weaker" market makers identified by the model.

Our approach to identifying ELPs is similar in spirit to the one used by NASDAQ to designate 26 firms as HFTs (see Brogaard, Hendershott and Riordan (2011)). Both approaches classify User Accounts based on trading activity that is aggregated across all stocks. The classification is based on the observation that a trader is unlikely to behave as a market maker in one stock and a long-horizon investor in another stock. One important distinction between NASDAQ versus TSX database is that information on individual User Account is preserved in TSX database while individual account information is aggregated into a single HFT classification in NASDAQ database. The account-level information is particularly useful for this study because we exploit the granularity of the data to estimate trading profits, inventory risk, and capital commitment of market makers. This aspect of our analysis is similar to Kirilenko, Kyle, Samedi and Tuzun (2011), who use an algorithm to classify user accounts as intermediaries if their trades exhibit short holding periods and small inventory positions.

Recently, IIROC (2012) identifies HFTs in Canadian markets using account-level data. Their classification relies on order-to-trade ratio based on 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

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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.

in that IIROC is interested in identifying all HFT accounts while our approach identifies the subset of User Accounts, HFTs or non-HFTs, who act as market makers. The characteristics of traders identified as HFTs by IIROC (2012) are similar to ELPs in our sample suggesting that the typical HFT identified by IIROC acts as a market maker.

C. The Trades of Market Makers

The evidence supports that both DMMs and ELPs behave as market makers. Relative to Decile 1 accounts, both DMMs and ELPs exhibit more passive executions, smaller closing inventory, more intraday switches between long and short inventory, fewer trades in the direction of inventory, and more accounts associated with proprietary brokers. ELPs and DMMs also exhibit similar number of active days per user, daily number of trades, and closing inventory. These patterns suggest that both classes of market makers provide liquidity services and actively manage inventory risk.

DMMs and ELPs also differ in some important ways. First, relative to an ELP, a DMM trades in fewer stocks and executes more volume per stock, which is consistent with DMM obligations 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. On average, 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). Fourth, while ELPs close the trading day with zero inventory on 50% of trading days, DMMs close the trading day with zero inventory on less than 1% of trading days. In subsequent analysis, we show that DMMs participate in undesirable 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 four out of five trading days (79.4%). The participation drops to 37% for Quintile 4 stocks and further declines monotonically with firm size. For small (quintile 1) stocks, ELPs participate in only one out of eight trading days (12%).

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 almost every day (99.6%) in large stocks. The large difference in market presence between DMMs and ELPs for medium and small stocks is a novel finding of our study. We attribute the difference to affirmative obligations imposed by the exchange to maintain a market presence in the stock. To the extent that the continuous presence of a market maker reduces 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 pure limit order book market structure.

We examine the percentage of passive, or liquidity-supplying, trades for ELPs and DMMs. For ELPs, the proportions of passive trades are between 45% and 56% but for DMMs, the proportion consistently exceeds 80%. In other words, DMMs supply liquidity in four out of five trades across market cap quintiles. The evidence also supports that the trades of the DMM help alleviate temporary order flow imbalance. 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 buy the stock on trading days when the stock price declines and sell the stock on trading days when the stock price increases.

One measure of the market maker's inventory risk is the number of times that intraday inventory crosses zero. An inventory that switches often between net long and net short position is consistent with quicker reversal of positions and smaller capital commitments for market making. In large cap stocks, ELPs and DMMs switch between net long and short inventory in a stock about 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 cap stocks. Thus market makers in small cap stocks incur more inventory carrying costs and limited ability to quickly 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. As discussed earlier, ELPs participate sporadically in small stocks but conditional on participation, they close the day with no inventory on 17.5% of days. In contrast, across all quintiles, DMMs close the day with zero inventory on less than 1% of the trading days. We attribute the higher incidence of overnight inventory positions to DMM obligations that require them to participate in undesirable trades that they might avoid from a pure profit motive. In a later section of the paper, we examine the 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 participation measures: (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 into quintile portfolios based on trading volume (Table 5) or intra-day volatility (Table 6) observed for each stock. In both tables, Panel A presents participation statistics for the full sample, Panel B for small cap quintile, and Panel C for the large cap quintile. The statistics are equally weighted averages across stock-days in the respective sample.

In Panel A of Table 5, the percentage of trades involving the DMM is significantly more than those involving the ELP, particularly on days with low trading volume. Both classes of market makers participate more on high volume days than low volume days. Difference in trading behavior across market makers is more striking for the market cap sub-samples. 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 increases on high volume days, ELPs are also active in three out of four low volume days. These results support that ELPs maintain a market presence and provide liquidity in large caps when they have no obligation to do so.

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, suggesting that ELPs on demand more often than supply liquidity on low volume days. These results are consistent with Grossman and Miller's (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 interpretation that DMMs serve a fundamental role as providers of *immediacy* in small stocks. They are active in over 85% of high volume days and over 70% 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%. In other words, DMMs supply liquidity in seven out of eight transactions that they participate in. Further, on low volume days, one out of every four trades involve a DMM. These findings provide new evidence on the mechanism by which DMMs reduce execution uncertainty in less liquid stocks 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 minute 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. One result is particularly noteworthy. When we 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 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".[12]

[12] 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.

VI. Trading Profits and Inventory Risk of Market Makers

The evidence thus far suggests that ELPs participate more actively in large stocks. Within a stock, ELPs participate more on high volume and high volatility days. But what explains the ELPs' decision to participate in these stocks or under these 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 participation decision. 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.[13] 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.

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 are calculated as the inventory position multiplied by the change in price. To be consistent with the first methodology, we close out the 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

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

of maximum intraday inventory, and the signed closing inventory position. The inventory measures are normalized by monthly stock trading volume. The maximum intraday inventory measure will be small if market makers selectively participate in trades to maintain inventory close to zero. It is possible that DMM obligations reduce the ability to manage intraday inventory levels, particularly on low volume days. We estimate a signed inventory position which accounts for the direction of trade relative to the direction of stock return on the day. The measure is positive when market makers increase inventory (i.e., buy) on negative return days and decrease inventory (i.e., sell) on positive return days. On the other hand, the measure is negative when market makers build 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 latter aggregation captures the total profits of the ELP group.

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 ELPs are higher than those earned by DMMs. The trading profits of DMMs are almost entirely attributed to passive trades and almost none to positioning profits. ELPs also earn the majority of trading profits from passive trades, which suggests that the probit model has correctly identified professional liquidity providers. There is some evidence that ELPs earn higher positioning profits than DMMs. Thus ELPs behave both as liquidity providers, who earns the spread, and active investors, who exhibit timing skill, while DMMs rely primarily on liquidity provision to generate their profits.

Both sets of market makers earn sufficient passive profits to cover the cost of active trades. The unprofitable active trades likely reflect the market maker's need to control inventory risk by trading out of undesirable inventory. On average, the end-of-day closing inventory for DMMs is twice as large as that held by ELP and the maximum intraday inventory is almost three times as large as that held by ELP's.

The DMM's overnight inventory is more than the inventory aggregated across all ELPs on a stock-day, which reflects the ELPs' preference to hold no overnight inventory position.

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 almost 60 percent lower than on days with ELP participation.[14] This result is surprising because DMMs are expected to make higher, not lower, profits on days when they face less competition for liquidity provision from ELPs. However, we also find that DMMs face higher inventory risk on days without ELP participation as compared to days with ELP participation. The absolute value of closing inventory is four times as large on days without ELP participation; the number of times that intraday inventory crosses zero is only 1.17, as compared to 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 as compared to 1.75% on days with ELP participation. These results suggest that trading days without ELP participation are characterized by large order flow imbalance, and under these conditions, market makers have difficulty in reversing 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. An important implication is that DMMs absorb the order imbalance and stabilize prices by trading in the direction opposite to the stock's return.

Results in Panel C suggests that both classes of market makers earn more profits in large stocks than small stocks.[15] Notably, ELPs earn large positioning profits in large stocks while making positioning losses in small stocks, suggesting ELPs have a comparative advantage in predicting short horizon price movement of large cap stocks. More work remains to be done to better understand the reasons for the cross-sectional variation in positioning profits. The smaller trading profits for small stocks is consistent

[14] In results not reported in the paper, we estimate that DMMs in aggregate earn $19 million from 77,400 stock-days with ELP participation and only $11 million from 123,136 stocks days without ELP participation.
[15] Consistent with our results, Coughenour and Harris (2003) find positive NYSE specialist profits for small stocks in their analysis.

with Grossman and Miller (1988), who observe that market making profits are small relative to the cost of maintaining a market presence in small stocks.

In every market cap quintile, DMM profits on days without ELP participation are smaller than profits on days with ELP participation;[16] 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. The significant capital commitment necessary to make markets under stressful conditions might cause participants to withdraw if they have no affirmative obligations. Our results support 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

A. Cross-sectional Analysis of Market Maker activity

It is clear that market capitalization is an important determinant of ELP participation. Madhavan and Sofianos (1998) show that trading activity, return volatility and bid-ask spreads explain the behavior of NYSE Specialist. The impact of volatility on market maker participation is ambiguous. It is possible that inventory risk consideration cause 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. 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.

[16] The lower profits reflect the market conditions – fewer profit opportunities and higher inventory risk - that caused the ELPs to withdraw participation rather than the lower ELP participation influencing the profits and risk. As discussed earlier, trading profits should be higher not lower when competitors withdraw from a market.

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:

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

and

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

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 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.[17] Daily regression coefficients based on 245 days of trading data are used to calculate the t-

[17] 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.

statistics using Newey-West standard errors with five lags. In Table 8, Panel A, equation (1) focuses on stock characteristics while equation (2) includes variables that capture inventory risk, capital commitment and trading profits. Equation (1) estimates indicate that ELP participation is positively associated with market capitalization (consistent with Table 5) and trading activity in the stock. Actively traded securities are attractive to ELPs because, as shown in Table 4, market makers can more easily reverse positions in these securities. ELPs are more likely to participate in stocks with tighter quoted spreads, which indicates a preference for liquid 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 Handa and Tiwari (1996) prediction that volatile securities offer marker makers with more opportunities for short-horizon trading profits.

Stock price is commonly included in trading cost models as a control for relative tick size. However, the variable itself is of interest for the analysis due to two arguments relating to ELP participation. First, there is an increasing impetus in the US markets to increase tick sizes to encourage market making in illiquid securities.[18] Harris (1998) for example observes that higher relative tick size 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. This is consistent with anecdotal evidence that HFTs are more active in low priced stocks.[19]

In model (2), 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

[18] See *Wall Street Journal* article, "SEC weights bringing back fractions in stock prices", Oct 27th, 2012.
[19] http://blogs.reuters.com/felix-salmon/2012/06/13/wall-streets-preference-for-low-priced-stocks/

participate in stocks with higher DMM trading profits. These findings are 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

We further explore the factors influencing ELP participation within a stock. In Figure 1, Panels A through D, we plot the number of trades, relative bid-ask spreads, intraday volatility, and trade imbalances, for days with and without ELP participation. Similar to earlier analysis, DMMs participate on all trading days included in the analysis. Panel A shows that, for all market cap quintiles, trading activity on days with ELP participation is significantly higher than days without ELP participation. Thus, even in large stocks, where ELPs participate on approximately 80% of the stock days, ELPs tend to avoid days with lower trading activity.

Results in Panel B suggest that relative spreads are larger on days without ELP participation than days with ELP participation. Thus, the results do not support that the compensation for liquidity provision is lower on days when 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 using a fixed-effects logit estimation. The (stock) fixed-effects model controls for omitted stock specific attributes and examines within stock variation in ELP participation. 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 for market makers. Following the recommendation in Allison (2005), we use a conditional maximum likelihood methodology for the estimation which avoids a possible bias in coefficients due to 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

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

$$\beta_5 . relspread_{i,t} + \beta_6 . abs(imbal_{i,t}) + \ \beta_7 . DMMInv_{i,t} + \ \beta_8 . TimesInv_{i,t} + \ \beta_9 . DMMprofit_{i,t}$$

$$(4)$$

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. We find that ELP participation is positive associated with price-inverse variable, suggesting that ELPs prefer higher relative tick sizes. ELP participation is strongly negatively associated with trade imbalances suggesting that ELPs are more active when the order flow is two-sided, possibly reflecting the ease of controlling inventory risk. In unreported results, we estimate a model separating out positive and negative imbalances to test for asymmetric preference for order flow. 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 capital commitment necessary for liquidity provision is small, and when inventory risk is small. Thus, the results based on the univariate analysis 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 proprietary trading desks who are willing to supply liquidity when it is profitable to do so. However, as noted by SEC Chairman Shapiro, these participants have no obligations to maintain a market presence and/or stabilize markets. The lack of obligations raises the possibility that a market structure that relies on market makers 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 and relate their participation to trading profits, inventory risk, and capital commitments.. Unlike publicly available databases, the proprietary TSX database that we examine provides detailed account-level information on counterparties to a trade. For large stocks, we find that ELPs are active participants who supply liquidity under various market conditions. However, for medium and small cap stocks, ELP participation is 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 profitable days.

The results support theoretical predictions (see Grossman and Miller (1988), Bessembinder, Hao and Zheng (2012)) that liquidity is less likely to arise endogenously in smaller, less active securities. For these stocks, we find that DMMs are active in over 70% of low volume days and supply liquidity in majority of transactions. Therefore DMMs serve as providers of immediacy who reduce the investors' execution uncertainty by maintaining a market presence. These results point to the 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 to close the trading day with no inventory. They also prefer to participate on trading days with balanced order flow which allows them to reverse inventory positions within a trading day. Such a strategy differs substantially from market making opportunities observed in illiquid securities, suggesting that the ELPs' business model is generally not supportive of active participation in less liquid segments of the market. These observations are consistent with Boehmer, Fong and Wu (2012), who assess the impact of algorithmic trading (AT) on liquidity in 38 stock exchanges around the world. They find that more AT reduces liquidity in small stocks and that AT provide less liquidity on days when market making is difficult.

Under market conditions when profit opportunities are small or inventory risk is substantial, ELPs exercise the option to withdraw participation. Under these conditions, we show that DMMs earn smaller trading profits, assume higher inventory risk, and commit more capital. These findings suggest that liquidity agreements require the DMMs to participate in many undesirable trades. For this reason, DMMs are typically compensated for their services but the compensation arrangements vary across markets (see Saar (2009) and Charitou and Panayides (2009)):

- The NYSE Specialist had access to order flow information such that profits from (a) liquid stocks subsidize illiquid stocks and (b) non-stress periods subsidize stressful periods (see Glosten (1989) for theory and Cao, Choe and Hatheway (1997) for empirical evidence).
- 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.

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.[20] It is also important to consider the nature of the "market stress" during the 2010 Flash Crash event. According to CFTC-SEC report, 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 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*."[21]

[20] 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.
[21] 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.

This study presents new evidence on how proprietary trades behave under stressful market conditions. An important driver of ELP participation is inventory risk management. We show that ELPs are more likely to withdraw when order flow imbalance makes it difficult to reverse the intraday inventory, or end the day at or near zero inventory. To the extent that the Flash Crash 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, this study advances our understanding on many important issues 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?"*

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Table 1

The table presents descriptive statistics for the overall sample. The sample contains 1,286 stocks traded over 245 days in the calendar year 2006.The averages presented are calculated by averaging across stocks each day and then across days. Percentiles reflect the respective daily average across stocks.

	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 CAD $ (midpoint)	13.7	11.1	13.2	13.8	14.5	15.3
Market cap. of stocks traded (CAD $ 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 (CAD $) 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	**Client Accounts (CL)**	**Proprietary Trader Accounts (FM)**	**Specialist Trader Accounts (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 $ CAD 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	Client (CL)	Proprietary Trader (FM)	Specialist Trader (ST- Non DMM)	Designated Market Maker (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	2,963	1,805	2,168	*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	53,261	36,834	5,757	*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.

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		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.

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.

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

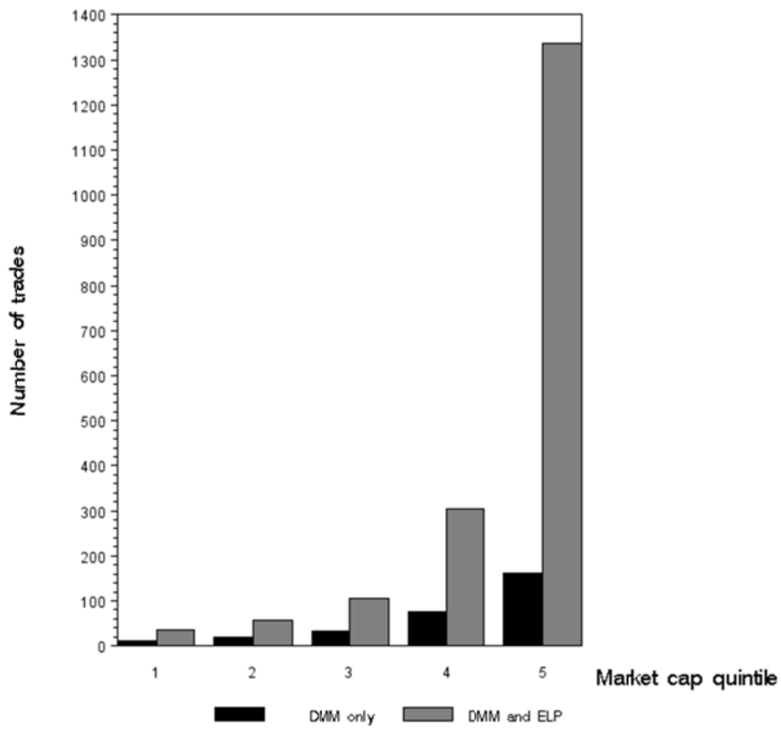
	Model 1			Model 2		
	Average Estimate	p-value	Average Odds ratio	Average Estimate	p-value	Average Odds ratio
Intercept	-4.595	*0.00*		-4.174	*0.00*	
ST volatility (intraday)	0.654	*0.00*	2.013	0.671	*0.00*	2.048
Log (market cap)	0.048	*0.01*	1.062	0.034	*0.06*	1.047
Log (daily $ volume)	0.139	*0.00*	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

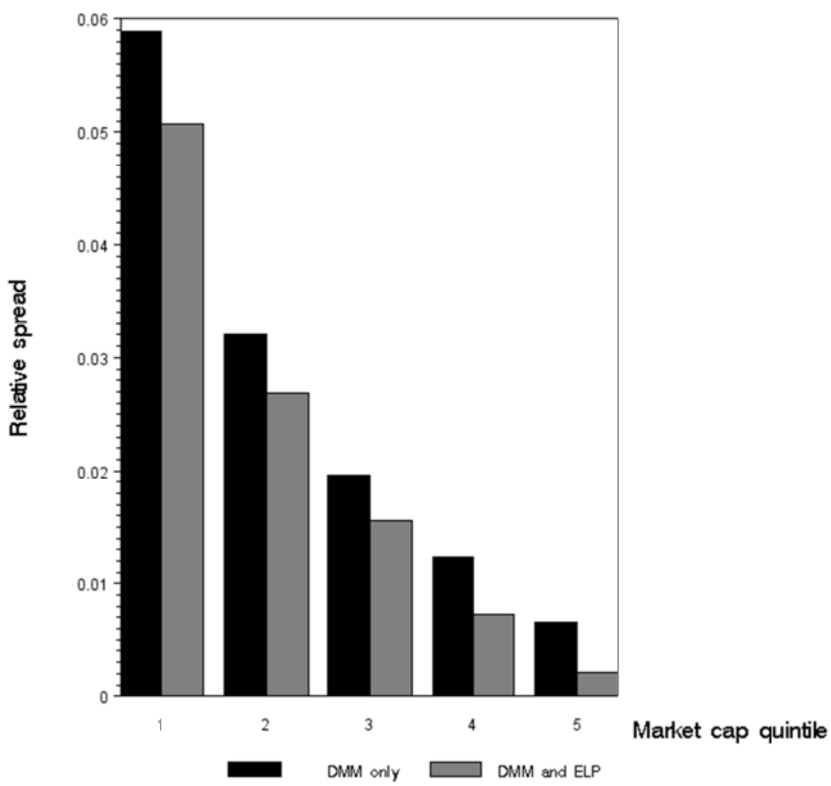
	Model 1			Model 2		
	Estimate	p-value	Odds Ratio	Estimate	p-value	Odds Ratio
ST volatility (intraday)	0.410	*0.00*	1.506	0.412	*0.00*	1.509
Log (daily $ volume)	0.351	*0.00*	1.421	0.351	*0.00*	1.421
Number of trades	0.003	*0.00*	1.003	0.003	*0.00*	1.003
Price inverse	0.091	*0.00*	1.095	0.091	*0.00*	1.096
% 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

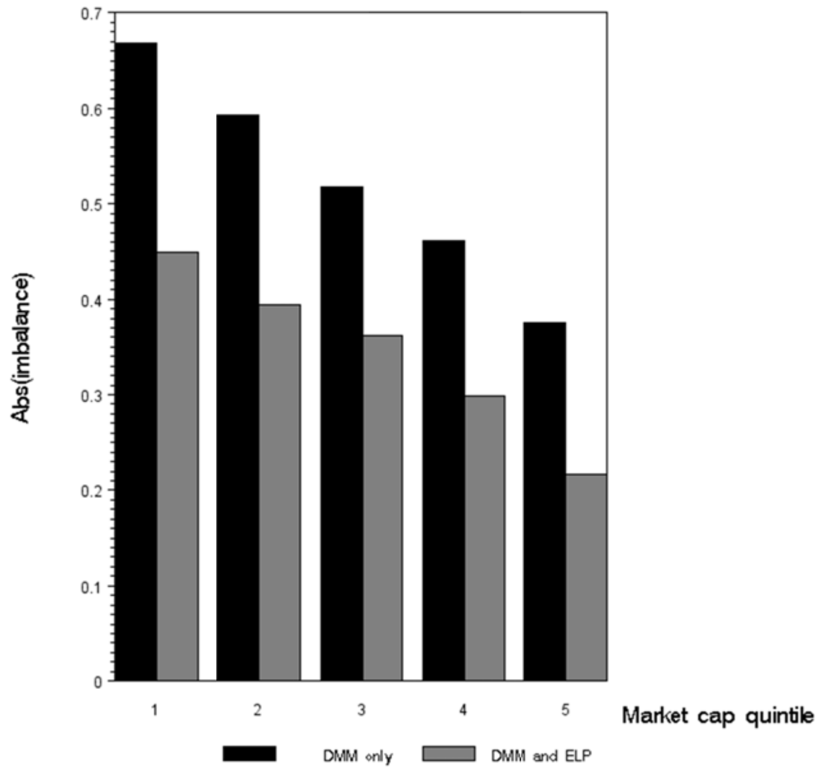
Panel A: Number of trades



Panel B: Relative spread



Panel C: Abs (order imbalance)



Panel D: Intraday volatility