Should Exchanges impose Market Maker obligations?

Amber Anand
Syracuse University

Kumar Venkataraman
Southern Methodist University

Abstract

Using Toronto Stock Exchange data, we study the trades of Endogenous Liquidity Providers (ELPs), who supply liquidity because it is a profitable activity, and those of Designated Market Makers (DMMs), who have exchange-assigned obligations to maintain markets. We focus on concerns related to fragility and gaps in coverage when markets rely on ELPs for liquidity provision. We show that ELPs are active participants during periods of high volatility and days preceding earnings announcements. However, when market conditions reflect high inventory risk, such as periods with low volume or one-sided order flow, ELPs exercise the option to withdraw from the market. Under these conditions, DMMs earn smaller profits, assume higher inventory risk, and commit more capital, suggesting that liquidity contracts oblige DMMs to participate in undesirable trades, especially in less active stocks, where they are the only reliable counterparties available to investors. Our results document market conditions under which a hybrid market structure, comprising a limit order book and a DMM, improves outcomes for investors, and ultimately the listed firm.

First Draft: November 2012
This Draft: July 2013

Keywords: Designated market maker; HFTs; Electronic markets; DMM obligations.

* We thank Hank Bessembinder, Paul Brockman, Allen Carrion, Amy Edwards, Sean Foley, Hans Heidle, Bob Jarrow, Yung-Yu Ma, Pamela Moulton, Lin Peng, Michel Robe, Gideon Saar, Avanidhar Subrahmanyam (WFA Discussant), Laura Tuttle, Bob Schwartz, and seminar participants at the Commodity Futures Trading Commission (CFTC), CUNY-Baruch College, Cornell University, Lehigh University, Securities and Exchange Commission (SEC) and 2013 Western Finance Association (WFA) meetings for comments. We are particularly grateful to James Twiss at IIROC, and Abigail Etches and Judy Lee at TSX for help in obtaining and understanding the data. Anand gratefully acknowledges support from the Snyder Innovation Management Center at Syracuse University and Venkataraman from Fabacher Endowed Professorship at Southern Methodist University. Contact information for Amber Anand: amanand@syr.edu and Kumar Venkataraman: kumar@mail.cox.smu.edu.

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

Endogenous liquidity provision is a central tenet of the modern stock and derivative markets, where liquidity is supplied by limit orders in computerized auctions. The theoretical model in Glosten (1994) shows that, using stylized assumptions, an electronic limit order book dominates any alternative market structure. However, many observers believe that the electronic limit order book structure, which primarily relies on Endogenous Liquidity Providers (ELPs) who supply liquidity because it is profitable, is inherently fragile. Since ELPs have no obligations to maintain markets, their ability to withdraw when liquidity provision is unprofitable can exacerbate execution uncertainty, particularly when inventory risk increases in times of market stress. Along similar lines, Grossman and Miller (1988) emphasize that ELPs will not participate when profit opportunities are small relative to the opportunity cost of monitoring markets. This can lead to gaps in coverage across securities as ELPs focus on the larger, most liquid segments of the market.

A central question in market design is whether it is desirable for exchanges to impose obligations on market makers, or stated differently, whether market makers reliably supply liquidity even when they have no obligation to do so. Surprisingly, despite the importance of understanding ELP behavior, there is little empirical work describing how market conditions influence ELPs' trading decisions and how ELPs differ from intermediaries with exchange-imposed obligations, typically described as Designated Market Makers (DMMs) or Specialists.[1] DMMs are also motivated by profits but their participation is, at least in part, governed by a set of exchange assigned "affirmative" and "negative" obligations. Progress on these

[1] A well-developed empirical literature studies the trades of the New York Stock Exchange (NYSE) Specialist (see for example, Hasbrouck and Sofianos (1993), Madhavan and Sofianos (1998), and Panayides (2007)).

issues has been difficult due to the paucity of detailed data from a market where ELPs and DMMs co-exist. For example, publicly available data sources, such as NYSE's Trade and Quote (TAQ) database, do not identify the trader accounts associated with a transaction.

In this study, we use a detailed audit trail database made available by Toronto Stock Exchange (henceforth, TSX database), which assigns a single DMM to each security, to address two sets of empirical questions. First, how does ELPs' activity vary (relative to DMMs) with stock characteristics? Are DMMs active in stocks with low ELP participation? Second, how does information flow and inventory risk influence ELP activity over time within a stock? How do ELPs differ from DMMs? Evidence regarding these issues can further our understanding of the merits of market structures and shed light on regulatory concerns regarding fragility and gaps in coverage associated with a reliance on ELPs.

Our study contributes to the ongoing debate on the design of electronic markets. With the implementation of Regulation NMS and the concomitant growth in algorithmic trading, the most active market makers in U.S. markets today are High Frequency Traders (HFT), many of whom trade as ELPs with no obligations to maintain markets. According to academic studies, high frequency market making is a profitable enterprise and, more importantly, market quality has improved alongside the growth in algorithmic trading.[2] These results are frequently interpreted as support for a structure where liquidity supply will arise from the profit incentive. Conversely, as emphasized in SEC Chairman Shapiro's quotation above, many observers believe that ELPs do not participate when the risk to support markets are high; however these are also scenarios when investors place a premium on immediacy. Subsequent to the Flash Crash event of May 6, 2010 (see Kirilenko, Kyle, Samedi and Tuzun (2011)), the Joint CFTC-SEC Advisory Committee report on Emerging Regulatory Issues identified the lack of market maker obligation as an important factor that might contribute to market fragility:

[2] Recent studies conclude that algorithmic traders improve market liquidity (Hendershott, Jones and Menkveld (2011), Hasbrouck and Saar (2013)) and enhance price discovery (Hendershott and Riordan (2013)). Menkveld (2013) and Baron, Brogaard and Kirilenko (2012) report that the Sharpe ratio of HFTs exceeds 9.0, suggesting that their activities are highly profitable.

"*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 withdraw, or post a large bid-ask spread, when supplying liquidity is risky need not indicate any market failure or economic inefficiency. Nonetheless, if liquidity supply is unreliable, market participants face uncertainty about whether an order will execute, and if so, whether the execution will occur with delay. Within this framework, Foucault, Kadan and Kandel (2005) model a limit order book market where traders differ in their impatience, or waiting cost of a delayed execution, and show 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."[3] To the extent that investors are ambiguity averse, Easley and O'Hara (2010) suggest 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".

One theoretical paper that directly models the benefits of adopting a structure with market maker obligations is Bessembinder, Hao and Zheng (2012). In their model, the trading costs attributable to asymmetric information reduce the activity of uninformed investors in the market. Their model demonstrates that a "maximum spread" obligation, which requires the DMM to maintain the bid-ask spread within a specified width, induces increased trading, enhances allocation efficiency, improves price discovery, and increases firm value.

This study examines a sample of 1,286 TSX stocks traded over 245 days in the calendar year 2006. The TSX database provides user-account information on the participants associated with each transaction as well as the TSX-assigned (single) DMM for each security; however ELP accounts are not flagged in the database. We therefore develop a methodology to identify ELP accounts based on their trading behavior. Since both DMMs and ELPs are market makers, we build a model that distinguishes

[3] Another line of theoretical work relaxes the assumptions of the Glosten (1994) model and shows that DMMs can improve outcomes for market participants (see Seppi (1997), Viswanathan and Wang (2002), Parlour and Seppi (2003), Mao and Pagano (2011)).

DMM accounts from other accounts based on several market making attributes, including inventory management and passive trading. We implement a propensity matching approach and identify a subset of active, non-DMM Accounts with similar market making attributes as DMMs. These User Accounts, categorized as ELPs, participate on the passive side of trades, actively manage inventory risk, and maintain small overnight inventory, both in- and out-of-sample, and their behavior is stable over time.[4]

We examine market maker participation in the cross-section of stocks to test theoretical predictions (e.g., Grossman and Miller (1988) and Bessembinder, Hao and Zheng (2012)) that smaller, less active stocks do not attract sufficient interest from ELPs.[5] For largest market cap (Quintile 5) stocks, both ELPs (79%) and DMMs (90%) actively participate on stock-days with trading data. ELP participation declines sharply to 37% for Quintile 4 stocks and declines further to 12% for small cap stocks. In contrast, DMMs are active on 78% of stocks-days for small cap stocks. Moreover, 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 imbalance. In contrast, over 80% of DMMs' trades for these stocks are liquidity supplying and their trades tend to absorb order imbalance. The prior literature based on the NYSE specialist concludes that DMMs play an important role in small cap stocks. We find similar results for TSX-DMMs but, consistent with theory, we provide new evidence that medium and small cap stocks attract less interest from ELPs.

Market conditions are a significant determinant of an ELP's decision to participate over time in an individual stock. For each stock, we assign trading days into quintiles based on intra-day volatility. For the overall sample, ELP participation increases from 31% of stocks days when volatility is low to 42% of

[4] A DMM can execute principal trades using its own capital in other, non-assigned, stocks. As a robustness analysis, we compare the trades of DMMs in exchange-assigned stocks with the trades of DMMs in non-assigned stocks. The former captures the trader's behavior as a DMM while the latter captures the same trader's behavior as an ELP. We replicate all the analyses based on this model-free classification of ELPs and reach similar conclusions.

[5] Several recent regulatory initiatives, including the Jumpstart Our Business Startups (JOBS) Act passed by U.S. Congress in 2012, focus on small cap segment of the market. http://www.sec.gov/news/studies/2012/decimalization-072012.pdf. A post-IPO CEO survey of small firms that went public indicates that the lack of secondary market liquidity is among their most important concerns.

stocks days when volatility is high. In all quintiles, the majority of ELP trades are liquidity supplying. Across sub-samples conditional on market capitalization, or the absolute value of directional return being high or low on the trading day, we see no evidence that ELPs reduce presence on high volatility days. To address possible endogeneity, we also examine an exogenous event -- earnings announcements -- where the pending corporate news is the source of information risk. For the overall sample, ELP participation increases on days before earnings announcement as compared with participation on non-earnings announcement days for the same firm. Overall, these results do not support concerns that ELPs lower participation on days with high information flow.

However, when market conditions reflect high inventory risk, such as periods with low volume or one-sided order flow, we find that ELPs exercise the option to withdraw from the market. For the overall sample, ELP participation declines from 44% (45%) when volume (imbalance) is high to 28% (39%) when volume (imbalance) is low; however the impact for large stocks is economically small. In contrast, the impact for small stocks is significant, where participation drops from 22% (23%) on high volume (imbalance) days to 4% (11%) on low volume days; moreover, we show that ELPs are more likely to demand than supply liquidity on low volume days. Notably, in small stocks, a DMM is the only *reliable* counterparty available for investors -- they are active in over 70% of low volume days and participate in one out of every four trades.

We further show that market conditions influence ELPs' behavior via their impact on trading profits, inventory risk, and capital commitment. 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 passive, liquidity supplying trades. ELPs earn a majority of their profits from spreads on liquidity supplying trades as well, but also earn significant positioning profits. Further, DMMs earn *lower* trading profits on days when ELPs are absent in a stock. Thus, the lack of competition from ELPs does not create higher profit opportunities for DMMs, suggesting that ELPs' decision to participate is not a random outcome. Rather, these results support that ELPs reduce trading activity during market conditions when the benefits from market making do not exceed the opportunity costs of supplying liquidity.

We analyze market maker inventory and find that ELPs withdraw on trading days when market making is risky. To be specific, the maximum intra-day (overnight) inventory of DMMs is five to ten times (twice) larger on trading days when ELPs do not participate as compared to days when ELP participate.[6] On days when ELPs do not participate, we show that DMMs absorb the order imbalance by building large inventory positions in the opposite direction of the stock's daily return. While DMMs routinely hold overnight inventory positions, ELPs consistently end the trading day at or near zero inventory. These results provide an economic rationale for compensating DMMs who participate in many undesirable trades to fulfill their contractual obligations.

This study contributes to the literature by contrasting the obligated liquidity supply of DMMs with the endogenous liquidity supply that naturally arises in the market. We identify market conditions when a hybrid market structure, comprising a limit order book and a DMM, improves outcomes for investors. Both cross-sectional and time series results discussed above are observed in a multivariate regression analysis. Further, our multivariate model describing the trading behavior of ELPs contributes to several strands of related literature. Among others, we show that ELP participation (relative to DMMs) is positively associated with the prior month return, which is consistent with liquidity dry-ups observed during down markets, and that a larger relative tick size is associated with more ELP presence, which supports U.S. regulatory initiatives aimed at increasing the tick size for small cap stocks.[7]

The rest of the paper is organized as follows. Section II presents a literature review, and describes the institutional details of the TSX market and the data. Section III describes the algorithm to identify ELPs. Section IV presents a cross-sectional analysis of market maker participation and Section V presents a time-series analysis of market maker participation. Section VI presents results on the risk and return of

---

[6] Within a stock, the bid-ask spread is wider on days when ELPs do not participate as compared to days when ELPs participate. Thus, although market making compensation is higher, the results are consistent with the higher spreads proxying for higher liquidity risk on such days.

[7] Many securities do not enjoy sufficient public interest to make purchases and sales feasible on short notice. The optimal market design for these securities remains an open question. Such securities include not only the vast majority of listed stocks but also fixed income securities, such as corporate bonds and structured credit products, where the secondary market activity is extremely sparse (see Bessembinder, Maxwell and Venkataraman (2013)).

market making. 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 empirical literature on Designated Market Makers

The early empirical literature examines the floor-based NYSE "specialist" based on 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. Madhavan and Sofianos (1998) find that specialists tends to participate more in less liquid stocks, retail-sized trades and when the bid-ask spread is wide. Hasbrouck and Sofianos (1993) show that the NYSE specialist's positions predict short term price movements, which is a principal source of profits. Under the NYSE model, the Specialist has access to information about the state of the book and the incoming order flow. The literature concludes that privileged information allows the Specialist to earn trading profits and control inventory risk.

Recent empirical work examines electronic limit order markets, where DMMs have no informational advantage but instead negotiate a liquidity agreement with the listed firm. Based on Stockholm data, Anand, Tanggaard and Weaver (2009) show that DMMs are compensated based on the contractual obligations described in the liquidity agreement and the nature of preexisting relation between the DMM and the listed firm. Using French stock market data, Venkataraman and Waisburd (2007) find that younger firms, smaller firms, and less volatile firms choose to introduce a DMM. Surrounding DMM introduction, the study documents a positive abnormal return of nearly 5% in the underlying stock. Other studies document that DMM introductions are associated with an improvement in market quality (Nimalendran and Petrella (2003)) and a reduction in liquidity risk (Menkveld and Wang (2013)).[8] Saar (2011) provides an excellent literature review of the related papers.

---

[8] 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)).

Our study is distinguished from prior work because the specialized TSX database allows an examination of the trading records of DMMs and ELPs. Unlike the TSX database, other public databases do not contain account-level identifiers associated with buy and sell side of each transaction. It is therefore difficult to model the behavior of market makers. Further, while the majority of empirical studies have focused on DMMs, only a handful of studies have studied ELPs, mostly focusing on high frequency traders (HFTs), and none of the studies that we are aware of compare ELPs with DMMs.[9] We exploit the detailed account-level data to assess whether the hybrid market structure, comprising a limit order book with a DMM, improves outcomes for investors.

B. Institutional Details of TSX and the Data

The Toronto Stock Exchange (TSX) is organized as an electronic limit order book, where 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 TSX 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 member firm on both sides of the trade, and whether an order originated from a member firm's proprietary account or from a client. Broker ID information for anonymous orders submitted by brokers is not available to market participants but reported in the database.

The TSX assigns a single member firm to serve as the DMM for each stock. Each member firm is typically assigned a mix of more and less actively traded stocks. DMMs are responsible for maintaining two-sided markets, and stock-specific maximum spreads, moderating price volatility, and guaranteeing executions for a specified number of shares (called a Minimum Guaranteed Fill (MGF)), including odd lot

[9] Research on the trading strategies of HFTs is building. The early empirical work suggested that HFTs primarily trade as liquidity providers and should fit within our classification of ELPs. However, recent work (e.g., Baron, Brogaard, and Kirilenko (2012) and Clark-Joseph (2012)) based on account-level data shows that only a subset of HFTs are liquidity providers. The trades of active HFTs, who are also the most profitable, tend to demand liquidity.

orders. The TSX evaluates the DMMs and rewards better performers with future allocations. Unlike the Euronext-Paris DMMs, the TSX DMMs do not receive an annual fee or cross-subsidy in the form of investment banking business from the stock issuer. Unlike the NYSE Specialists, the TSX DMMs do not enjoy privileged information on order flow. The main advantages offered to the TSX DMM are in the more favorable trading fees, and in their ability to trade ahead of orders with higher time priority at the best quotes. Specifically, when the DMM chooses to automatically ("auto") participate on the bid, or offer side (or both) with incoming order flow, the DMM is allocated 40% of incoming orders up to the security's MGF. Auto-participation can be turned on or off at any moment but does not confer a last-mover advantage as the flag applies for subsequent orders only.[10]

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.[11] The need for price improvement results in most client orders being routed to the limit order book.[12]

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. We identify 94 member firms of which 22 firms have user IDs associated with DMMs. 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 assigned stocks are categorized as "ST-DMM" accounts. A DMM can also execute principal trades using its own capital in other, non-assigned, stocks, which we categorize as "ST-Non-DMM" accounts. Many

[10] Auto-participation flag is not disseminated in real time to market participants. The 40% participation feature is similar to that observed in the U.S. Options exchanges. Anand, McCormick and Serban (2013) present an analysis of market-maker incentives in the U.S. options markets.

[11] 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.

[12] 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.

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.[13] Because the TSX data do not separately identify each client associated with a broker at a member firm, all client trades with a particular user ID are grouped together in the same "client" account. One possible solution to this problem would be to eliminate all client accounts from our analysis. However, TSX member firms also offer direct market access (DMA) to their larger clients, and it is possible that some large client accounts serve as ELPs. Therefore, similar to IIROC (2012), we do not exclude client (CL) accounts from our analysis but we note that our ELP identification algorithm yields only a small number of client accounts as ELPs. The results are similar when these accounts are excluded from the 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, delisting, stock split, merger or acquisition, stock ticker change, name change, rights offering, etc. We obtain information on corporate events as well as shares outstanding from the monthly *Toronto Stock Exchange Review* publications. If the stock has multiple classes, we retain the most liquid class of a stock unless the multiple classes are part of a stock index (S&P 60, Mid-cap or Small-cap indices). Activity is dramatically lower on days when U.S. markets are closed and Canadian markets are open. We exclude these days from our sample. We also limit the sample to stock-days with an absolute return of less than 12% (99th percentile of stock-day returns). For the quotes data, we delete observations where the difference between the bid and ask quotes is greater than $5.

Table 1 describes our sample. The sample includes 1,286 stocks traded over 245 days, with approximately 900 stocks traded on an average day. The average stock-day has 595 trades, aggregated to

[13] 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).

544,481 shares, or 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. The average closing price varies between CAD$ 11.1 and 15.3, the average relative spread between 1.9% and 3%, and the average daily stock return between -3.29% to 2.74% over the sample period.

III. Identifying Endogenous Liquidity providers

A. The cross-section of TSX traders

Exchange-assigned DMMs use their own (or firm) 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, representing professional liquidity providers. In Table 2, we report descriptive statistics for user accounts under category ST, FM, CL, and an "others" category that captures infrequent identifiers such as options market makers. As noted earlier, CL accounts are difficult to interpret as they aggregate the orders from all clients associated with a broker.

Results in Table 2 indicate that market makers differ from other traders in important ways. Relative to FM accounts, 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 within a day, and a greater tendency to participate in trades that reduce existing inventory. ST accounts are concentrated with integrated and proprietary brokers and less so with institutional brokers. Thus our results suggest that market makers engage in active inventory management and participate on the passive side of the trade.

These distinguishing characteristics of market makers enable the identification of traders who, similar to STs, act as professional liquidity providers. We note that our approach uniquely identifies market makers based on a combination of these characteristics. For example, many patient buy-side institutions accumulate large positions using limit orders; although these accounts trade passively, they do not exhibit reversals in inventory positions that exemplify market making. Similarly, short horizon momentum traders frequently reverse inventory positions but primarily use market orders to quickly build positions; these accounts are not identified under our approach to be market makers.

B. An Algorithm to Identify ELP accounts

The algorithm to identify ELP accounts exploits our ability to model the trading behavior of exchange-assigned DMM accounts. We use propensity score matching to identify active, non-ST user accounts whose trading characteristics are similar to ST accounts.[14] These players can be proprietary traders at brokerage firms (FM) or large traders with a DMA arrangement with a prime broker (CL). For this reason our ELP identification algorithm does not focus on a specific account type.

We implement a Probit model, aggregated at a daily frequency, for each user account where dependent variable equals one for ST accounts, and zero otherwise, and the explanatory variables capture the account's propensity to supply liquidity and manage inventory risk. Following Table 2, the 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 Table 3, Panel A. Consistent with Table 2, the coefficients indicate that market makers are more likely to trade passively, exhibit more switches between long and short intraday inventory, maintain small overnight inventory, participate in inventory reducing trades, use anonymous identifier, and be associated with proprietary and integrated brokers. For each User Account, the daily propensity score is the predicted probability score based on model coefficients. We assign a daily decile rank to a User Account, and then categorize User Accounts, regardless of account type, into decile portfolios based on average propensity score rank over the sample period.

[14] Propensity score matching attempts to identify a sample that did not receive the treatment but is comparable in all observed covariates to the sample that received the treatment. Propensity score is the estimated probability from a probit or a logit model that is used to identify the treatment sample (see Kennedy (2003)).

Table 3, Panel B reports the characteristics of User Accounts in propensity score Deciles 1, 4, 7 and 10. As expected, all attributes used to identify market makers show monotonic trends across deciles. For example passive trades constitute 40% of trades for Decile 1 traders and 66% of trades for Decile 10 traders. Within the highest rank decile, we report characteristics by account types that are candidates for ELP classification: ST-Non-DMM, FM and CL. We delete accounts with less than 50 trading days of data and classify the remaining Decile 10 accounts as ELPs. The DMM column includes DMMs in assigned stocks (ST-DMM) regardless of their propensity scores.

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 (2013)). Both approaches classify User Accounts based on trading activity that is aggregated across all stocks – the reasoning being 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 individual account information is preserved in TSX database while the information is aggregated into a single HFT classification in NASDAQ database. In this study, we exploit the granularity of account-level TSX data to estimate profits and inventory risk of market makers. This aspect of our analysis is similar to Kirilenko et al. (2011), who 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 observation that HFTs are characterized by large number of order submissions relative to order execution. The focus of the IIROC study differs from ours in that IIROC is interested in identifying all HFT accounts while our approach identifies the subset of User Accounts, HFTs or non-HFTs, who act as market makers. The characteristics of traders identified as HFTs by IIROC (2012) are similar to ELPs in our sample suggesting that many HFTs identified by IIROC act as market makers.

The studies discussed above identify market makers based on a set of pre-specified criteria (e.g., short holding periods or reversal in inventory positions) and implicit assumptions about the importance of each criteria. Our approach exploits information on DMM accounts to identify a subset of active, non-

DMM Accounts with similar attributes. For example, relative to Decile 1 accounts, both DMMs and ELPs more often supply liquidity (more passive trades) and actively manage inventory risk (small closing inventory, more intraday inventory switches, more inventory reducing trades). ELPs and DMMs exhibit similar number of active days per user, daily number of trades, and closing inventory.

Relative to ELP accounts, DMM accounts trade in fewer stocks and executes more volume per stock, consistent with a DMM's focus on assigned stocks. The proportion of passive executions is higher for DMMs than it is for ELPs.[15] ELPs are more likely to post anonymous orders and are more often associated with proprietary brokers. ELPs are less likely than DMMs to trade against the daily stock return (i.e., buy on negative return days, and vice-versa) and more likely to end the trading day with zero inventory position.

C. Model sensitivity

Our tests confirm that the behavior of an account does not change over time. In Table 3, Panel B, the propensity scores increase from 2% for the lowest decile to 71% for the highest decile suggesting that the model obtains significant separation in scores across groups. The range, defined as the highest minus lowest propensity score rank for a User Account within the sample period, averages only 2.5 for both top and bottom propensity score deciles. A notable result is that DMM accounts have a propensity score of 0.60 while ELP accounts have a propensity score of 0.71. In other words, according to our model, the accounts identified as ELPs exhibit behavior that is more consistent with market makers than exchange-assigned DMMs. The higher propensity score alleviates, to some extent, the concern that the accounts classified by the model as ELPs simply represent a pool of "weaker" market makers. As a robustness check, we assign User Accounts into decile portfolios based on a probit estimation using January-June 2006 data and calculate account characteristics observed over the next six months. The patterns are

[15] In addition to earning the bid-ask spread, market makers actively manage inventory and takes strategic positions based on return predictability in the short horizon. For these reasons, it is expected that market makers demand liquidity in many instances, which lower the proportion of passive executions.

similar to those reported in Table 3.[16] In a subsequent analysis, we show that ELPs earn the majority of profits from passive trading, which further lends support to the model identifying market makers.

Finally, to address concerns on model specification, we compare the trades of DMMs in assigned stocks (i.e., ST-DMM) with the trades of DMMs in non-assigned stocks (i.e., ST-non-DMM). The former involve exchange-assigned obligations while the latter do not. Moreover, the analysis accounts for unobservable member-firm characteristics that might influence participation. For this model-free classification of ELPs, we replicate the analyses reported in the study and reach similar conclusions. These results are not reported in the paper in the interest of brevity but are available from the authors.

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 market capitalization on the last trading day of the prior month. 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%). The participation drops sharply to 37% for Quintile 4 stocks and further declines monotonically with firm size. For small cap (quintile 1) stocks, ELPs participate in one out of eight trading days (12%). In contrast, DMMs participate in four out of five trading days (78%) in small stocks and almost all days (99%) in large stocks. The ELPs' proportion of passive or liquidity-supplying trades, conditional on participation, is between 45% and 56% while the comparable statistic for DMMs exceeds 80%. Relative to ELPs, the change in DMMs' daily inventory is more often against the daily stock return. Chordia and Subrahmanyam (2004) show that daily returns are correlated with daily order imbalances. Thus, our results suggest that DMMs absorb the temporary order imbalance by buying (selling) on trading days when the stock price declines (increases).

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

One measure of inventory risk is the number of times intraday inventory crosses zero. Frequent switches between net long and net short is consistent with quick reversal of positions and a smaller capital commitment for market making. In large cap stocks, ELPs' and DMMs' inventory crosses zero about six to ten times within the day. The statistic drops sharply to between one and 2.45 times for Quintile 4 stocks, and further to less than 0.5 for small cap stocks. These results suggest that market makers in small stocks incur higher inventory risk and a limited ability to quickly trade out of an acquired position. Since DMMs are more active than ELPs in small stocks, we conclude that DMMs assume more inventory risk than ELPs. ELPs and DMMs differ markedly in the percentage of days when overnight inventory position is zero. In large stocks, conditional on participation, ELPs close with zero inventory on 57% of trading days. ELPs participate sporadically in small stocks but conditional on participation, the overnight inventory is zero on 17.5% of days. In contrast, across all quintiles, DMMs close the day with zero inventory on less than 1 percent of trading days. We verify that the differences between DMMs and ELPs are statistically significant using double clustered standard errors at the stock and day level.

These results support the Grossman and Miller (1988) prediction that small cap stocks attract less interest from ELPs. The large difference in market presence between DMMs and ELPs for medium and small cap stocks is a novel finding of our study. We attribute the difference to exchange-imposed obligations to maintain a market presence. To the extent that the market presence lowers execution uncertainty that investors face in market interactions, the results point to a simple mechanism by which a hybrid market structure improves outcomes for investors.

V. Impact of market conditions on market maker participation

A. The Impact of Volatility and Information Flow

One regulatory concern attributed to ELPs is the reduction in trading activity in response to heightened information asymmetry. In Table 5, Panel A, we assign trading days into quintiles based on intra-day volatility for each stock and present results for the full sample, large cap stocks and small cap stocks. We report statistics on three participation measures: the percentage of stock-days, the percentage of trades involving market makers, and conditional on participation, the percentage of passive trades. Reported statistics are equally weighted averages across stock-days in the respective sample. We find that ELP participation rates are positively correlated with daily volatility. For the overall sample, ELP participation increases from 31% of stocks days when volatility is low to 42% of stocks days when volatility is high. In all quintiles, the majority of ELP trades are liquidity supplying. Similar patterns are observed for both large cap and small cap stocks.[17]

One possibility is that market makers are active when volatility is non-directional but withdraw when volatility is directional. For example, Handa and Schwatrz (1996) show that a 'volatility capture' strategy, which involves submitting limit orders on both sides of the book, is profitable when intraday volatility is high but the absolute value of daily return is small. In Table 5, Panel B, we report ELP participation for intraday volatility quintiles, conditional on the absolute value of the daily return being large or small. Consistent with theory, for both small and large stocks, we find that ELP activity increases with intraday volatility when the magnitude of daily return is small. When the magnitude of daily return is large, ELP activity increases with intraday volatility for small stocks but we observe no significant change for large stocks. Thus we find no evidence that ELPs withdraw on high volatility days.

Another concern is that, while we treat intraday volatility as exogenous, the causality goes in the opposite direction; i.e., the active participation by ELPs contribute to the higher intraday volatility. To address possible endogeneity, we examine an exogenous event -- earnings announcements -- where the pending corporate news is a well known source of information risk. In Table 5, Panel C, we compare ELP activity on the day preceding earnings announcement (Day[-1]) benchmarked against control days (Day[-5,-15]) for the same firm. The sample consists of 592 stocks with a total of 1,532 announcements, ranging from 61 for small cap stocks to 653 for large cap stocks. For the overall sample, we find that ELP

---

[17] In unreported results, we examine 2-sigma (95th percentile) and 3-sigma (99th percentile) days based on volatility and find similar results – ELP participation increases and the majority of trades are liquidity supplying. Our analysis only considers trading days when DMMs participate. Further, our sample period does not include six-sigma events, along the lines of 2010 Flash Crash event. Most exchanges, including the TSX, rely on trading halts to stabilize markets during extreme events since it is not economically viable for DMMs to stabilize highly stressed markets.

participation increases on days before earnings announcement, from 48.7% to 51%. The increase is significant using double clustered standard errors at the stock and day level. For both large and small stocks, the increase on pre-announcement day relative to control days is not statistically significant, possibly reflecting the small sample for the small stocks. Overall, the results in Table 5 do not support the concern that ELPs withdraw from the market on days with high information flow.

B. The Impact of Inventory Risk

The patterns in Table 3, Panel B, indicate that ELPs have a strong preference to end the trading day with zero inventory. In Table 6, we examine whether market conditions that affect inventory risk influence ELP participation. We report results for daily trading volume quintiles in Panel A and daily trade imbalance quintiles in Panel B. The quintile assignments are made separately for each stock. Trading days with high volume or low imbalance are associated with two-sided order flow, thus lowering the inventory risk of market makers.

For the overall sample in Panel A, ELP participation declines from 44% when volume is high to 28% when volume is low. For large cap stocks, the decline in activity is more modest, from 83% on high volume days to 75% on low volume days. Consistent with Table 4, ELP participation in small cap stocks is sparse, averaging about one in five high-volume trading days and less than one in 20 low-volume trading days. Further, the percentage of passive ELP trades declines from 56% on high-volume days to 44% on low-volume days, suggesting that ELPs demand, more often than supply, liquidity on low volume days. Similar patterns in ELP participation are observed in Panel B when quintiles are formed based on order flow imbalance. Based on these results, we conclude that ELPs tend to withdraw participation when market conditions reflect high inventory risk.

Notably, in small stocks, a DMM is the only *reliable* counterparty available for investors -- they are active on over 85% of high volume days and over 70% of low volume days; the percentage of passive trades, which exceeds 80% in all quintiles, increases to 88% on low volume days, suggesting that DMMs supply liquidity in seven out of eight transactions in which they participate. Further, on low volume days, one out of every four trades involves a DMM as the counterparty.

VI. Trading Profits and Inventory Risk of Market Makers

The evidence thus far describes how ELP participation varies by stock characteristics and market conditions. In the next two sections, we present additional analysis to investigate potential endogeneity in ELP participation and market outcome. In Table 7, we examine granular account-level transaction data to study whether trading profits, capital commitments, and inventory risk explain the participation decision. Specifically, we compare stock-days when both DMMs and ELPs participate versus stock-days when DMMs participate but ELPs do not.[18] Panel A presents statistics for the full sample, Panel B presents conditional results based on ELP participation, and Panel C presents 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 (2013) discuss two alternative methodologies – 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 price. To be consistent with the first methodology, we close out the open inventory positions at the closing price for both cash-flow and mark-to-market profits. All three methodologies yield identical profit measures. Following earlier work, 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 instead of trade prices, which removes the effect of bid-ask spread. 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 crosses zero, the absolute value of end-of-day inventory, the absolute value of maximum intraday inventory, and the signed closing inventory. The inventory measures are normalized by monthly stock trading volume. The maximum intraday inventory measure will be small if market makers supply and demand liquidity such

---

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

that the magnitude of inventory remains close to zero. The signed closing inventory accounts for daily change in inventory relative to the daily stock return. 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. 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 for an individual market-maker, as well as across stock-days for a *type of* market-maker. The *type* aggregation does not affect DMMs since there is one DMM per stock-day but yields different results for ELPs as it aggregates across all ELPs active in a stock on a day. By doing so, the *type* measure captures the total profits of ELPs as a group.

Results in Table 7, Panel A suggest that DMMs earns daily trading profits that are twice as large as individual ELP accounts. However total profits for ELPs are higher than those earned by DMMs. DMM profits are almost entirely attributed to passive trades and almost none to positioning profits. ELPs also earn the majority of profits from passive trades but earn higher positioning profits than DMMs. Spreads earned on passive trades of both classes of market makers are sufficient to cover the spreads paid on active trades. The DMMs daily closing inventory is twice as large as ELPs and the maximum intraday inventory is almost three times as large as ELPs. Notably, the (single) DMM's overnight inventory is larger than the aggregate overnight inventory across all ELPs, which reflects ELPs' strong preference to close the day with no inventory position.

In Table 7, Panel B, we report the results conditional on whether ELPs, as a group, are active on a trading day. A striking result is that DMM profits on trading days when ELPs withdraw are almost 60 percent lower than trading days when ELPs participate.[19] If ELPs' participation across trading days is random and their participation drives the observed differences in market outcomes (e.g., volume or volatility), then market making profits for DMMs should be higher on days when they face less competition from ELPs. We find the opposite result suggesting that ELPs' participation is not random but

[19] 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.

instead reflects an active choice to avoid trading days with lower profit potential. These results support that market conditions drive the ELP participation decision, and not vice-versa; however DMMs continue to participate on low profit days to fulfill their exchange-assigned obligations.

Additional evidence based on inventory risk is consistent with these interpretations. We find that inventory risk is significantly higher on days when ELPs withdraw relative to days when ELPs participate. To be specific, the maximum intra-day (overnight) inventory of DMMs is five to ten times (twice) larger on trading days when ELPs do not participate as compared to days when ELP participate. These results suggest that ELPs withdraw when market conditions reflect one-sided order flow because under these conditions, it is difficult to reverse inventory positions. In support of this interpretation, we find that DMMs hold larger positive signed inventory (0.12%) on days when ELP withdraw as compared to days when ELPs participate (0.03%). Thus, DMMs absorb order imbalances and stabilize prices by trading in the direction opposite of the stock's return.

Results in Table 7, Panel C suggest that market makers earn positive profits in every stock quintile but significantly more profits in large stocks.[20] Figure 1, Panel A shows that ELPs earns almost 90% of profits from large stocks, and in particular, from top 5th percentile (T5) based on market capitalization. Figure 1, Panel B, shows that ELPs earn large positioning profits in large stocks, particularly from T5 stocks, while making positioning losses in small stocks. In other words, ELPs enjoy a comparative advantage over DMMs in predicting short-term price movements in large stocks.[21] We consider two explanations -- first, that DMMs are less skilled in predict short-term price movements, and second, that DMM obligations limit the implementation of trading strategies that would allow lead to positioning profits. In unreported analysis, we find that ST-non-DMM accounts exhibit significant positioning profits that is similar to ELPs, suggesting that the latter explanation is more likely.

[20] Coughenour and Harris (2003) also report positive NYSE specialist profits for small cap stocks.
[21] Our conversations with market participants suggest that ELPs prefer large stocks because (a) they have more data to build their algorithms and (b) the two sided order flow helps lowers the inventory risk.

Table 7, Panel C shows that, in every market cap quintile, DMM profits on days without ELP participation are smaller than profits on days with ELP participation; 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. Our results provide an economic rationale for compensating DMMs who participate in undesirable trades to fulfill contractual obligations.

VI. Multivariate Regression Analysis of Market Maker participation

A. Cross-sectional Analysis of Market Maker activity

Madhavan and Sofianos (1998) model the cross-sectional participation of NYSE Specialists based on a stock's trading activity, return volatility, and bid-ask spread. Along similar lines, we expect that inventory risk should cause ELPs to avoid less active and more volatile stocks; however limit order strategies are more profitable in volatile securities and bid-ask spreads increase with return volatility. All else equal, an increase in capital commitment should reduce participation by market makers. In Table 8, we present results of a multivariate regression analysis based on daily Fama-MacBeth logit regressions. The multivariate analysis builds on the univariate results reported in earlier tables by assessing the marginal contribution of each explanatory variable on ELP participation. Daily regression coefficients based on 245 days of trading data are used to calculate the t-statistics using Newey-West standard errors with five lags. The functional form is as follows:

$$\log\left(\frac{p_{i,t}}{1-p_{i,t}}\right) = \mu + \beta_1 . STVol_{i,t-1} + \beta_2 . \log\left(mktcap_{i,t-1}\right) + \beta_3 . \log\left(dailyvolume_{i,t-1}\right) + \beta_4 . numtrades_{i,t-1} + \beta_5 . \left(\frac{1}{price_{i,t-1}}\right) + \beta_6 . relspread_{i,t-1} + \beta_7 . LTVol_{i,t-1} + \beta_8 . DMMInv_{i,t-1} + \beta_9 . TimesInv_{i,t-1} + \beta_{10} . DMMpass\_profit_{i,t-1} \quad (1)$$

where p_i is the probability that *ELP* participates on a stock-day. The dependent variable *ELP* equals one when one or more ELPs participate on a stock-day with DMM participation, and equals zero otherwise; therefore, the regression coefficients explain the likelihood that ELPs participate, conditional on DMM participating on the trading day. To correct for potential endogeneity in ELP participation and market outcomes, we implement an instrumental variable approach following Roll, Schwartz and Subrahmanyam (2010), where all explanatory variables are one-day lagged values.[22] Specifically, *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 standard deviation of daily returns in the month and *STVol* is the standard deviation of 15 minute returns based on quote midpoints; *relspread* is the time-weighted quoted percentage spread on the stock-day; *DMMInv* is the absolute value of DMMs' closing inventory on stock-day divided by monthly volume; *TimesInv* is the number of times the DMM inventory crosses zero; *DMMpass_profit* is log of DMM market-making (passive) profits, and ε represents the error term.

In Table 8, Panel A, model (1) includes stock characteristics, model (2) includes proxies for market making risk and profits, and model (3) includes all variables. From model (1) coefficients, we conclude that ELPs are more likely to participate in larger stocks, those with higher trading volume and tighter quoted spreads, suggesting a preference for liquid securities, and those with higher daily return volatility. These results are consistent with the univariate statistics reported in the earlier tables.

Some observers argue that decimalization, which introduced a tick size of one cent, has lowered the incentives for liquidity provision. Harris (1996) notes that higher relative tick size increases the cost of stepping ahead of standing limit orders and thereby encourages participants to supply liquidity. For this reason, there is an increasing impetus in US markets to increase tick sizes to encourage market making in illiquid securities.[23] Since the minimum tick size on TSX is one-cent for all stocks, the relative tick size is inversely proportional to the stock price. The positive coefficient on the price-inverse variable indicates

[22] Roll, Schwartz and Subrahmanyam (2010) observe that "There are few obvious good instruments and we follow common practice in simply using a one-day lagged value; this has the virtue of being unrelated cross-sectionally to the regression disturbances on the next trading day." Additionally, the analysis of ELP behavior surrounding earnings announcement alleviates the endogeneity concern to some extent. More broadly, we show in Table 7 that ELPs avoid days with low profit potential and high inventory risk, thus documenting the economics underlying the ELPs decision to participate on a trading day.

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

that ELP participation is indeed higher in stocks with higher relative tick size. This result is also consistent with popular press reports that HFTs are more active in lower priced stocks.[24] In model (2), we find that ELP participation declines with capital commitment and intraday inventory risk and increases with DMM profits. Thus these results suggest that market makers increase activity in stocks that offer more risk-adjusted profits for each dollar of capital. Model (3) includes all variables in one specification and yields results similar to those described above.

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

We further explore the factors influencing ELP participation within a stock. In Figure 2, Panels A through D, we plot the (one-day lagged) number of trades, relative bid-ask spreads, intraday volatility, and trade imbalances, for days with and without ELP participation. DMMs participate on all trading days included in the analysis. Panel A shows that, for all market cap quintiles, we observe higher number of trades on days when ELPs participate. Even in large stocks, where ELPs participate on approximately 80% of stock days, ELPs reduce participation on days with lower trading volume.

Panel B shows that relative bid ask spreads are tighter on days when ELPs participate than on days when ELPs withdraw. The results in Table 7 shows that DMMs earn lower profits and bear higher inventory risk on days when ELPs withdraw; collectively these results suggest that the higher spreads are indicative of the higher risk of liquidity provision on these days. Further evidence regarding market conditions is offered in Panel C, where trade imbalance is higher on days when ELPs withdraw than on days when ELPs participate; suggesting that ELPs withdraw on days when inventory risk is high. Finally Panel D shows that the days when ELPs withdraw have lower intraday volatility, suggesting that profit opportunities do not justify the opportunity cost of maintaining market on these days.

We model the time series of ELP behavior using a logistical regression with stock fixed effects estimated over all stock-days. The (stock) fixed-effects model controls for omitted stock specific attributes and examines within stock variation in ELP participation. Accordingly, we include within-stock

[24] http://blogs.reuters.com/felix-salmon/2012/06/13/wall-streets-preference-for-low-priced-stocks/

variables such as trading activity, past stock and market returns, volatility, bid-ask spreads, order imbalances and price movements, and proxies for trading profits, inventory risk, and capital commitments. 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 estimate three models based on the following specification:

$$\log\left(\frac{p_{i,t}}{1-p_{i,t}}\right) = \propto_i + \beta_1.STVol_{i,t-1} + \beta_2.\log\left(dailyvolume_{i,t-1}\right) + \beta_3.numtrades_{i,t-1} + \beta_4.\left(\frac{1}{price_{i,t-1}}\right) + \beta_5.relspread_{i,t-1} + \beta_6.abs(imbal_{i,t-1}) + \beta_7.DownMarket_{i,t-1} + \beta_8.DownStock_{i.t-1} + \beta_9.DMMInv_{i,t-1} + \beta_{10}.TimesInv_{i,t-1} + \beta_{11}.DMMpass\_profit_{i,t-1} \quad (2)$$

where p_i is the probability that *ELP* equals 1. ELP equals one when one or more ELPs participate on a stock-day, and equals zero otherwise; α_i is the stock specific fixed effect; *price, dailyvolume, numtrades, STVol, relspread, DMMInv*, *TimesInv* and *DMMpass_profit* are defined earlier; *imbal* is the lagged absolute value of buy-sell trade imbalance normalized by trading volume; and *DownMarket (DownStock)* equals one when the market (stock) return cumulated over the previous 30 calendar days (not including the stock-day) is negative, and equals zero otherwise.

The results for Panel B, Model (1) show that, within a stock, ELPs are more likely to participate on high volume days, more volatile days, and days with tighter quoted spread. ELP participation is positively associated with the price-inverse variable suggesting that ELPs prefer higher relative tick sizes. The negative coefficient on trade imbalance suggests that ELPs are more active when order flow is two-sided, consistent with inventory risk. The negative coefficient on *DownMarket* (*DownStock*) indicates that ELPs reduce participation following a sustained market (stock) decline.

Recent studies (e.g., Hameed, Kang and Viswanathan (2010), Comerton-Forde, Hendershott, Jones, Moulton and Seasholes (2010)) document that the NYSE specialists are less willing to provide liquidity when they lose money on inventories following a downturn. Since our estimation only includes days with DMM participation, our results add to this evidence by showing that ELPs exhibit an even greater sensitivity to past returns than DMMs. From Model (2), we observe that ELP participation is more likely when market making profits are large, when capital commitment is small, and when inventory risk is low. In Model (3), we include all the variables in one specification and find results largely in line with the ones discussed above.

C. Fee Structure and Market Maker Participation

We exploit a change in TSX make/take pricing structure that occurred in 2006 to investigate the impact of fee structure on liquidity supply. From January 1 to June 30, 2006, stocks in TSX operated under one of two make/take fee structures – value-based and volume-based. Beginning July 1, 2006, all TSX stocks traded under a revised volume-based fee structure.[25] For ease of exposition, we designate stocks that switched from the value system to the volume system on July 1, 2006 as *Value* firms, and the remaining TSX stocks which switched from one volume system to another as *Volume* firms. Benchmarking *Value* firms against *Volume* firms is important since TSX stocks experienced a 20% reduction in price followed by an almost complete recovery between April and August 2006.

Figure 3 presents the time series variation in ELP participation and the percentage of ELP's passive trades for *Value* and *Volume* firms. Because *Value* firms include a large cross-section of firms, including small firms, we see that, consistent with Table 4, ELP participation is lower for *Value* than *Volume* firms; however both groups exhibit no significant change in ELP participation after new fee structure is introduced. Consistent with the new fee structure providing incentives for liquidity provision, we observe that both groups of firms experience an increase in passive trades in the second half of 2006.

[25] The TSX switched 113 stocks to the Volume system prior to January 2006. All other stocks were traded under the Value system until July 2006. Pricing in the value system is based on the dollar value of trade while pricing in the volume system is based on number of shares. Specifically, before July 1, 2006, passive trades received a rebate of 0.275 pennies per share and paid a fee of 0.40 pennies per share under the volume system. Under the value system, there were no fees/rebates for passive trades but a fee of 1/60 of 1% of the value of an active trade. There were discounts based on trading activity in the month going up to 80% of the fees in the value system. After July 1, 2006, passive trades are paid a rebate between 0.20 - 0.30 pennies per share and active trades pay a fee between 0.32 – 0.36 pennies per share depending on trading activity in the month. Overall, the fee changes are consistent with higher incentives to supply rather than demand liquidity after July 1, 2006.

Table 8, Panel C presents the results of a panel regression of ELP participation surrounding the fee change for *Value* and *Volume* firms after controlling for other determinants of the participation decision. The specification includes stock and day fixed effects. The *Value* dummy equals one for *Value* firms, and equals zero otherwise; the *Post* dummy equals one after July 1, 2006, and equals zero otherwise. The coefficients on control variables are consistent with those reported in Panel B. The positive coefficient on *Post* dummy indicates that ELP participation increased after the new fee structure was introduced. However, the coefficient on the *Post**Value* variable, which tests for difference-in-differences between *Value* and *Volume* stocks, is not statistically significant at the 5% level. Thus, the fee structure affected both *Value* firms and *Volume* firms in a similar manner. Overall, these results yield mixed conclusions by establishing a change for all stocks around the fee structure change, but at the same time there are no incremental changes for the sample most affected by the change in the fee structure.

VII. Discussions and Conclusion

Increased competition among trading venues and improvements in technology have vastly expanded the pool of proprietary trading desks who serve as market makers. However, these participants have no obligations to maintain a market presence, which points to a concern that a trading mechanism that relies on endogenous liquidity provision is inherently fragile. Further, a recent IPO Task Force Report concludes that market structure initiatives in recent years favor endogenous liquidity provision in large, more liquid segments at the expense of smaller capitalization stocks.

In this study, we model the behavior of the two important classes of market makers -- ELPs and DMMs -- and show how information flow and inventory risk influence their decision to supply liquidity Our results support theoretical predictions that liquidity is less likely to arise endogenously in smaller, less actively traded securities. We show that ELPs enhance market quality by increasing the supply of liquidity in periods with high volatility. However, when market conditions reflect inventory risk, ELPs withdraw from the market, thus introducing execution uncertainty. Under these conditions, the DMM’s continuous presence and the willingness to absorb imbalance reduce the investor’s price risk of a delayed trade, particularly in less active stocks. Our results point to a mechanism by which a DMM structure meets the needs of investors and increases the firm value around DMM introduction.

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 show that ELPs' strategy is especially sensitive to inventory risk – they consistently close the trading day with zero inventory and actively avoid trading days with one-sided order flow. 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 an increase in AT lowers the liquidity in small cap stocks and that ATs provide less liquidity on days when market making is difficult. Our results are also consistent with Hendershott, Jones and Menkveld (2011), who find that the benefits of increased AT primarily accrue to large stocks.

While our study highlights the importance of DMMs, the design of liquidity contracts and its impact on market quality remains an important avenue for future research. The nature of the market maker compensation, which varies widely across markets (see Saar (2011) , can be summarized as:

- The NYSE Specialist had privileged access to order flow information such that profits from (a) liquid stocks subsidize the illiquid stocks in the portfolio, and (b) non-stress periods subsidize stressful periods (see Glosten (1989) for theory and Cao, Choe and Hatheway (1997) for empirics).
- The TSX DMM is allowed to trade ahead of standing orders with higher time priority at the best quotes. The DMM accepts obligations in a portfolio of liquid and illiquid stocks.
- In Euronext-Paris and Stockholm, the listed firm pays an annual fee to the DMM via a liquidity contract. The contracting arrangement is modeled by Bessembinder, Hao and Zheng (2012).
- Some U.S.-based market centers compensate the DMMs using data feed fees, or provide higher credits for posting limit orders in the book.

Our study contributes to two recent regulatory debates on market structure. The multivariate regression analysis suggests that higher relative tick size is positively associated with ELP participation after controlling for other stock characteristics. This result supports regulatory initiatives to re-examine the impact of tick size on the economic incentives to supply liquidity, particularly in small cap stocks.[26] Second, we find that ELPs are active on trading days with high volatility. Although, this result appears to be at odds with anecdotal evidence from the 2010 Flash Crash, when HFTs withdrew participation, the result is consistent with popular press reports that market maker profits are positively correlated with volatility.[27] According to CFTC-SEC report on Flash Crash, market participants based their participation decision during the Flash Crash event 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.*"[28]

We show that ELPs are particularly sensitive to inventory risk considerations and actively avoid market conditions characterized by one-sided order flow which makes it difficult to reverse inventory. To the extent that market conditions during the Flash Crash signaled a sustained order imbalance, the observed behavior of HFTs is consistent with the main conclusions of our study. More broadly, this study advances our understanding on a number of issues raised in SEC's Equity Market Structure Concept Release (2010), such as:

> *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?"*

---

[26] The Jumpstart Our Business Startups (JOBS) Act, signed into law by U.S. Congress on April 5, 2012, requires the SEC to conduct a study on the impact of decimalization on secondary market liquidity, and consequently on the number of initial public offerings, of small capitalization stocks.

[27] For example, the WSJ article "Meet Getco, High-Frequency Trade King", August 27, 2009, reports that Getco made a profit exceeding $400 million during the peak of the financial crisis and participated in more than 10% of trading volume in U.S. equities in October 2008. SEC (2010) acknowledges the possibility that, "short-term professional traders may like short-term volatility…".

[28] 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.

References

Allison, P., "Fixed effects regression methods for longitudinal data," Cary, NC, SAS Institute Inc. (2005).

Anand, A., Tanggaard, C., and D. Weaver, "Paying for market quality." *Journal of Financial and Quantitative Analysis*, 44 (2009), No. 6, 1427-1457.

Anand, A., McCormick, T., and L. Serban, "Incentives for liquidity provision: Is the make-take structure the answer?" working paper (2013), Syracuse University.

Baron, M., Brogaard, J., and A. Kirilenko, "The trading profits of high frequency trades", working paper (2012), Princeton University.

Bessembinder, H., Hao, J., and K. Zheng, "Market making obligations and firm value", working paper (2012), University of Utah.

Bessembinder, H., Maxwell, W., and K. Venkataraman, "Introducing Daylight to Structured Credit Products." *Financial Analysts Journal*, forthcoming (2013).

Boehmer, E., Fong, K.L., and J. Wu. "International Evidence on Algorithmic Trading." Working paper (2012), EDHEC Business School.

Brogaard, J., Hendershott, T., and R. Riordan, "High Frequency Trading and Price Discovery." Working paper (2013), University of Washington.

Cao, C., Choe, H., and F. Hatheway. "Does the Specialist Matter? Differential Execution Cost and Inter-Security Subsidization on NYSE." *Journal of Finance,* 52 (1997), 1615–1640.

Charitou, A., and M. Panayides. "Market making in international capital markets: challenges and benefits of its implementation in emerging markets." *International Journal of Managerial Finance*, 5 (2009), 50-80.

Chordia, T., and A. Subrahmanyam. "Order imbalance and individual stock returns: Theory and evidence." *Journal of Financial Economics*, 72 (2004), 485-518.

Clark-Joseph, A., "Exploratory Trading." Working paper (2012), University of Illinois at Urbana-Champaign.

Comerton-Forde, C., Hendershott, T., Jones, C., Moulton, P., and S. Seasholes, "Time variation in liquidity: the role of market-maker inventories and revenues." *Journal of Finance,* 65 (2010), 295-331.

Coughenour, J., and L. Harris. "Specialist Profits and the Minimum Price Increment." Working paper. University of Delaware (2003).

Easley, D., and M. O'Hara, "Microstructure and Ambiguity." *Journal of Finance*, 65 (2010), 1817-1846.

Foucault, T., Kadan, O., and E. Kandel, "Limit order book as a market for liquidity." *Review of Financial Studies,* Vol. 18 (2005), 1171-1217.

Glosten, L. “Insider Trading, Liquidity, and the Role of the Monopolistic Specialist.” *Journal of Business,* 62 (1989), 211–236.

Glosten, L. “Is the Electronic Open Limit Order Book Inevitable?” *Journal of Finance,* 49 (1994), 1127–1161.

Grossman, S., and M. Miller. “Liquidity and Market Structure.” *Journal of Finance,* 43 (1988), 617–633.

Hameed, A., Kang, W., and S. Viswanathan, “Stock market declines and liquidity.” *Journal of Finance* 65 (2010), 257-294.

Handa, P., and R. Schwartz, “Limit order trading.” *Journal of Finance,* 51 (1996), 1835-1861.

Harris, L., “Does a large minimum price variation encourage order display? Working paper (1996), USC.

Hasbrouck, J., and G. Saar, “Low-latency trading,” *Journal of Financial Markets*, forthcoming (2013).

Hasbrouck, J., and G. Sofianos. “The Trades of Market Makers: An Analysis of NYSE Specialists.” *Journal of Finance,* 48 (1993), 1565–1594.

Hendershott, T., Jones, C., and A., Menkveld, “Does algorithmic trading improve liquidity?” *Journal of Finance*, 66 (2011), 568-604.

Hendershott, T., and R. Riordan, “Algorithmic trading and Price Discovery”, *Journal of Financial and Quantitative Analysis*, 2013, forthcoming.

IIROC, “The HOT Study, Phases I and II of IIROC’s Study of High Frequency Trading Activity on Canadian Equity Marketplaces,” (2012), Trading Review and Analysis – Analytics Group, Investment Industry Regulatory Organization of Canada, Toronto, Ontario

Kennedy, P., “A guide to Econometrics.” The MIT Press; 5th edition (2003).

Kirilenko, A., Kyle, A., Samadi, M., and T. Tuzun, “The flash crash: the impact of high frequency trading on an electronic market, working paper (2011), MIT.

Madhavan, A., and S. Smidt. “An Analysis of Changes in Specialist Quotes and Inventories.” *Journal of Finance,* 48 (1993), 1595–1628.

Madhavan, A., and G. Sofianos. “An Empirical Analysis of NYSE Specialist Trading.” *Journal of Financial Economics,* 48 (1998), 189–210.

Menkveld, A., “High frequency trading and the new market makers”, *Journal of Financial Markets*, forthcoming (2013).

Menkveld, A. and T. Wang, “How do designated market makers create value for small-caps?” *Journal of Financial Markets*, forthcoming (2013).

Mao, W., and M.S. Pagano. “Specialists as risk managers: The competition between intermediated and non-intermediated markets” *Journal of Banking and Finance*, 35 (2011), 51-66.

Nimalendran, M., and G. Petrella. “Do ‘Thinly-Traded’ Stocks Benefit from Specialist Intervention?” *Journal of Banking and Finance,* 27 (2003), 1823–1854.

Panayides, M., “Affirmative Obligations and Market Making with Inventory," *Journal of Financial Economics*, 86 (2007), 513-542.

Parlour, C., and D. Seppi. “Liquidity-Based Competition for Order Flow.” *Review of Financial Studies,* 16 (2003), 301–343.

Perotti, P. and B. Rindi ., "Market Makers as Information Providers: the Natural Experiment of Star". Journal of Empirical Finance, 17 (2010), 895-917.

Roll, R., Schwartz, E., and A. Subrahmanyam, “O/S: The relative trading activity in options and stock.” *Journal of Financial Economics*, 96 (2010), 1-17.

Saar, G., “Specialist Markets,” Encyclopedia of Quantitative Finance, (2011).

Seppi, D. “Liquidity Provision with Limit Orders and a Strategic Specialist.” *Review of Financial Studies,* 10 (1997), 103–150.

Venkataraman, K., and A. Waisburd, “The value of a Designated Market Maker.” *Journal of Financial and Quantitative Analysis*, 42 (2007), No. 3, 735-758.

Viswanathan, S., and J. Wang. “Market Architecture: Limit-Order Books versus Dealership Markets.” *Journal of Financial Markets,* 5 (2002), 127–167.

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.

						Statistical tests		
	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*
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 based on propensity scores from the probit in Table 3.a. The probit models provides a propensity score for each user each day. We rank users based on their scores each day, average the ranks across days for each user, and then assign users into deciles based on average ranks. Reported are average propensity scores, the average propensity rank range for an account during the sample period and various trading characteristics for each decile. The data are first aggregated at the stock-user-day level. We then 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. User accounts are placed in categories as follows. User accounts associated with designated market makers for assigned stocks are designated as DMMs regardless of their propensity score. Other user accounts in the highest ranking decile based on propensity scores and trade on at least 50 days during the sample period are categorized as Endogenous Liquidity Providers (ELPs). The Highest Ranking Accounts column includes tests of differences between Decile 1 and Decile 10 accounts. The ELP column includes statistical tests of difference between DMM and ELP accounts. *, @ and # indicate statistical significance at the 1%, 5% and 10% level respectively based on tests of differences on data aggregated at the user level.

	Propensity Score Decile				**Highest Ranking accounts**			**Final Classification**	
	Lowest ranking accounts	**4**	**7**	**Highest ranking accounts**	**Client (CL)**	**Proprietary Trader (FM)**	**Specialist Trader (ST- Non DMM)**	**Designated Market Maker (DMM)**	**Endogenous Liquidity Provider (ELP)**
Number of users	424	425	425	424	23	93	115	334	152
Probability	0.02	0.10	0.19	0.71*	0.65	0.65	0.75	0.60	0.71*
Probability rank range	2.5	6.4	6.8	2.7	3.7	3.1	2.6	3.5	3.7
Days per user	52.8	114.0	108.6	143.8*	87.4	76.9	157.2	165.5	168.8
Stocks per day per user	6.9	11.3	6.6	4.7	13.5	6.1	4.1	3.2	7.1#
Daily Number of trades	288.0	196.0	72.6	213.9	750.8	102.3	97.9	203.3	235.0
Daily Share volume (*1,000)	179.3	189.7	89.6	95.4*	236.8	101.0	97.2	64.3	152.2*
Daily Dollar volume (*1,000)	4,370	2,963	1,805	2,168*	9,610.0	1,233.6	1,825.0	1,336.9	3,395.2@
Average absolute value of ending inventory	67,089	53,261	36,834	5,757*	15,943.8	9,518.5	4,264.6	6,232.0	7,244.6
Number of times inventory crosses zero	0.1	0.2	0.3	5.5*	5.1	1.9	4.0	5.6	4.4*
Proportion of passive executions	40.3%	48.9%	52.2%	66.3%*	51.9%	57.3%	51.5%	78.7%	54.0%*
Proportion of trades in direction of inventory	70.3%	61.8%	51.3%	38.9%*	42.7%	30.1%	36.0%	42.9%	34.4%*
Proportion of volume placed anonymously	9.1%	11.0%	16.1%	42.2%*	45.3%	42.2%	56.1%	25.0%	51.9%*
Users affiliated with institutional brokers	56.6%	21.9%	12.2%	3.3%*	4.3%	2.2%	0.9%	9.3%	2.0%#
Users affiliated with proprietary brokers	0.0%	0.0%	0.0%	39.2%*	60.9%	32.3%	53.0%	19.2%	41.4%*
Users affiliated with retail brokers	9.4%	26.8%	22.1%	8.0%	0.0%	18.3%	2.6%	15.6%	9.2%
Users affiliated with integrated brokers	12.3%	49.2%	62.6%	49.1%*	26.1%	47.3%	43.5%	54.2%	46.1%#
Zero ending inventory	1.7%	3.8%	7.4%	23.0%*	26.3%	42.7%	42.6%	1.1%	49.7%*
Inventory against day's stock return	46.1%	46.8%	48.1%	41.1%*	35.0%	28.6%	32.3%	52.6%	27.4%*

Table 4: Market Maker behavior across Market Value 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 trades 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. *, @ and # indicate that ELP and DMM estimates differ at the 1%, 5% and 10% level respectively based on double clustered standard errors at the stock and day 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
Small cap	DMM	28210	78.4%	23.4%	14.9%	18.4%	11.7%	84.0%	25.2%	33.4%	0.45	1.5%	46.9%
stocks	ELP	5052	12.0%*	13.4%*	15.6%	1.6%*	1.9%*	52.9%*	58.9%*	32.1%	0.35@	17.5%*	35.8%*
2	DMM	36995	86.0%	20.8%	12.8%	17.9%	11.0%	82.7%	20.3%	36.9%	0.77	1.6%	51.4%
2	ELP	10554	19.5%*	8.5%*	9.3%*	1.7%*	1.8%*	45.2%*	52.6%*	35.3%	0.30*	19.6%*	39.0%*
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%*
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%*
Large cap	DMM	49908	99.6%	12.3%	6.8%	12.3%	6.8%	82.9%	26.6%	48.7%	10.28	0.6%	56.4%
stocks	ELP	152355	79.4%*	5.4%*	4.6%*	4.3%*	3.6%*	56.6%*	64.5%*	33.6%*	6.66*	56.5%*	23.4%*

Table 5: Impact of Volatility on Market Maker participation

This table presents the participation rates of DMMs and ELPs for stock days sorted into intraday volatility quintiles, and for pre-earnings announcement days. The quintile assignments are made separately for each stock. Intraday volatility is the standard deviation of 15 minutes return based on quote midpoints. Participation rates are unconditional (fill in a zero for days with no trading). All measures are reported for the overall sample, for stocks in the lowest market cap (small cap) quintile and for stocks in the highest market cap (large cap) quintile. Panel A examines the impact of unconditional volatility on DMM and ELP participation. Panel B examines the impact of directional versus non-directional volatility on ELP participation for large and small stocks. Panel C examines participation on trading day preceding earnings announcements (Day[-1]) benchmarked against control days (Days[-5,-15]). Earnings announcements date is obtained from I/B/E/S database. I/B/E/S data are matched to TSX data by ticker. The sample consists of 592 stocks with a total of 1,532 announcements, ranging from 61 for small cap stocks and 653 for large cap stocks. If the announcement time is before the market open or during market hours, then the pre-announcement day is the day prior to the announcement date. For announcements after market close the pre-announcement day is the same as the announcement day. *, @ and # indicate that (a) ELP and DMM estimates differ in Panel A, (b) ELP participation across high and low directional return quintiles differs in Panel B, and (c) market maker participation differs between pre-earnings announcement days and control days, at the 1%, 5% and 10% level respectively based on double clustered standard errors at stock and day level.

Panel A: Daily Intraday Volatility Quintile (within stock ranking)

DMM	Low volatility days	2	3	4	High volatility days	p-value: test q1=q5
A.1. Overall Sample						
DMM						
% of stock days	87.37%	89.69%	92.42%	92.74%	94.30%	*0.00*
Participation rate-trades	16.91%	16.28%	16.21%	15.73%	15.48%	*0.00*
Passive trades	85.91%	83.74%	82.48%	81.39%	80.28%	*0.00*
ELP						
% of stock days	30.84%*	33.41%*	35.86%*	37.77%*	41.77%*	*0.00*
Participation rate-trades	1.88%*	1.99%*	2.10%*	2.17%*	2.36%*	*0.00*
Passive trades	53.90%*	53.71%*	53.81%*	53.74%*	53.50%*	*0.00*
A.2. Small cap stocks						
DMM						
% of stock days	70.47%	74.67%	80.64%	81.67%	85.22%	*0.00*
Participation rate-trades	19.97%	18.63%	18.99%	17.50%	16.72%	*0.00*
Passive trades	89.03%	86.17%	83.49%	81.92%	80.40%	*0.00*
ELP						
% of stock days	5.86%*	9.06%*	11.67%*	14.68%*	18.84%*	*0.00*
Participation rate-trades	1.15%*	1.44%*	1.59%*	1.82%*	2.04%*	*0.00*
Passive trades	46.10%*	49.92%*	51.82%*	51.92%*	55.75%*	*0.00*
A.3. Large Cap stocks						
DMM						
% of stock days	99.33%	99.56%	99.79%	99.59%	99.71%	*0.00*
Participation rate-trades	12.82%	12.45%	12.30%	12.12%	11.79%	*0.00*
Passive trades	85.20%	83.55%	83.01%	81.99%	80.98%	*0.00*
ELP						
% of stock days	76.68%*	78.33%*	79.63%*	80.50%*	81.78%*	*0.00*
Participation rate-trades	4.06%*	4.19%*	4.35%*	4.38%*	4.49%*	*0.00*
Passive trades	62.04%*	61.98%*	61.80%*	61.09%*	59.78%*	*0.00*

Panel B. Directional Vs. Non-Directional Volatility and ELP Participation (within stock ranking)

Market cap quintile	Directional return	Variable	Intraday Volatility quintile: Low volatility	2	3	4	High volatility	p-value: q1=q5
	Low	**% of stock days**	5.62%	8.57%	10.92%	14.39%	17.33%	*0.00*
	Low	**Participation rate-trades**	1.06%	1.44%	1.57%	1.71%	2.09%	*0.00*
	Low	**Passive trades**	45.14%	47.43%	51.90%	50.42%	61.27%	*0.00*
Small cap stocks	**High**	**% of stock days**	6.52%	9.94%	12.35%@	14.85%	19.44%#	*0.00*
	High	**Participation rate-trades**	1.39%#	1.43%	1.62%	1.88%	2.02%	*0.00*
	High	**Passive trades**	48.36%	53.77%#	51.76%	52.72%	53.79%*	*0.23*
	Low	**% of stock days**	75.24%	76.95%	79.24%	80.40%	83.56%	*0.00*
	Low	**Participation rate-trades**	3.87%	4.08%	4.34%	4.49%	4.86%	*0.00*
Large cap stocks	**Low**	**Passive trades**	62.55%	62.63%	62.25%	60.94%	59.56%	*0.00*
	High	**% of stock days**	80.41%*	80.25%*	79.98%	80.57%	80.97%*	*0.68*
	High	**Participation rate-trades**	4.54%*	4.33%*	4.36%	4.30%	4.33%*	*0.20*
	High	**Passive trades**	60.80%*	61.12%*	61.39%	61.19%	59.88%	*0.26*

Panel C. Market Maker Participation surrounding Earnings Announcement Days

	DMMs			ELPs		
	Overall	**Small cap stocks**	**Large cap stocks**	**Overall**	**Small cap stocks**	**Large cap stocks**
Pre-Earnings announcement Day[-1]						
% of stock days	95.95%	88.52%	100.00%	51.17%	16.39%	81.47%
Participation rate-trades	14.91%	23.99%	11.85%	2.81%	1.89%	4.72%
Passive trades	82.17%	81.80%	82.66%	54.67%	35.28%	55.59%
Control Days[-5,-15]						
% of stock days	95.27%	82.10%#	99.71%@	48.68%#	13.35%	81.36%
Participation rate-trades	15.05%	19.66%@	12.35%@	2.69%	1.59%	4.80%
Passive trades	82.34%	80.91%	82.94%	55.78%	52.92%	56.53%

Table 6: Impact of Inventory Risk on Market Maker participation

This table presents participation rates of DMMs and ELPs for stock days sorted into daily share volume (Panel A) quintiles and daily trade imbalance 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. Each panel presents the results for the overall sample, for stocks in the lowest market cap (small cap) quintile and for stocks in the highest market cap (large cap) quintile. * indicates that ELP estimates are statistically different from DMM estimates at the 1% level based on double clustered standard errors at the stock and day level.

Panel A: Daily Intraday Share Volume Quintile (within stock ranking)

DMM	Low volume days	2	3	4	High volume days	p-value: test q1=q5
A.1. Overall Sample						
DMM						
% of stock days	86.92%	89.87%	91.82%	93.10%	94.41%	*0.00*
Participation rate-trades	19.80%	17.08%	15.78%	14.71%	13.33%	*0.00*
Passive trades	85.05%	83.17%	82.29%	81.65%	81.60%	*0.00*
ELP						
% of stock days	27.96%*	32.46%*	35.67%*	38.96%*	44.19%*	*0.00*
Participation rate-trades	1.94%*	2.02%*	2.10%*	2.15%*	2.29%*	*0.00*
Passive trades	55.96%*	54.75%*	53.72%*	52.86%*	52.29%*	*0.00*
A.2. Small cap stocks						
DMM						
% of stock days	70.90%	74.82%	78.38%	81.82%	85.98%	*0.00*
Participation rate-trades	24.33%	19.70%	17.62%	16.17%	14.04%	*0.00*
Passive trades	88.14%	85.57%	83.53%	81.99%	81.61%	*0.00*
ELP						
% of stock days	4.21%*	7.35%*	11.01%*	14.79%*	22.58%*	*0.00*
Participation rate-trades	1.06%*	1.27%*	1.64%*	1.84%*	2.23%*	*0.00*
Passive trades	43.93%*	49.20%*	49.85%*	52.90%*	55.55%*	*0.00*
A.3. Large cap stocks						
DMM						
% of stock days	99.12%	99.56%	99.71%	99.80%	99.76%	*0.00*
Participation rate-trades	14.10%	12.76%	12.15%	11.62%	10.88%	*0.00*
Passive trades	84.47%	83.12%	82.54%	82.27%	82.36%	*0.00*
ELP						
% of stock days	75.42%*	78.73%*	79.25%*	80.74%*	82.68%*	*0.00*
Participation rate-trades	4.43%*	4.37%*	4.28%*	4.21%*	4.17%*	*0.00*
Passive trades	63.25%*	62.02%*	61.38%*	60.41%*	59.78%*	*0.00*

Panel B: Daily Imbalance Quintile (within stock ranking)

DMM	Low imbalance days	2	3	4	High imbalance days	p-value: test q1=q5
B.1. Overall Sample						
DMM						
% of stock days	97.58%	97.56%	97.39%	97.17%	95.96%	*0.00*
Participation rate-trades	15.16%	15.19%	15.17%	15.10%	15.38%	*0.01*
Passive trades	82.52%	82.56%	82.77%	82.94%	83.92%	*0.00*
ELP						
% of stock days	45.38%*	44.65%*	43.63%*	42.78%*	38.55%*	*0.00*
Participation rate-trades	2.46%*	2.42%*	2.37%*	2.32%*	2.14%*	*0.00*
Passive trades	54.13%*	53.72%*	54.24%*	53.69%*	53.83%*	*0.49*
B.2. Small cap stocks						
DMM						
% of stock days	92.93%	93.50%	92.85%	91.77%	90.48%	*0.00*
Participation rate-trades	16.78%	16.81%	16.95%	17.23%	18.37%	*0.00*
Passive trades	85.01%	84.10%	85.13%	85.04%	87.38%	*0.00*
ELP						
% of stock days	22.87%*	21.80%*	19.84%*	18.50%*	11.26%*	*0.00*
Participation rate-trades	2.31%*	2.17%*	2.04%*	1.91%*	1.33%*	*0.00*
Passive trades	56.26%*	54.30%*	53.74%*	50.11%*	50.49%*	*0.06*
B.3. Large cap stocks						
DMM						
% of stock days	99.84%	99.82%	99.87%	99.82%	99.72%	*0.08*
Participation rate-trades	12.04%	12.06%	12.11%	12.16%	12.33%	*0.01*
Passive trades	82.69%	82.73%	82.76%	82.89%	83.47%	*0.00*
ELP						
% of stock days	81.18%*	80.91%*	80.26%*	80.02%*	78.78%*	*0.00*
Participation rate-trades	4.40%*	4.40%*	4.34%*	4.32%*	4.19%*	*0.00*
Passive trades	61.28%*	61.02%*	61.42%*	61.60%*	61.43%*	*0.74*

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. *p-values* are calculated based on double clustered standard errors at the stock, and day level, and presented for tests comparing DMM measures on days with and without ELP presence, and DMMs and ELPs.

			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*	*0.22*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.01*	*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%
	DMM with=w/o		*0.00*	*0.00*	*0.00*	*0.87*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.88*	*0.00*	*0.00*
	DMM=ELP		*0.00*	*0.00*	*0.00*	*0.45*	*0.00*	*0.00*	*0.00*	*0.01*	*0.15*	*0.45*	*0.08*	*0.01*	*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 with=w/o		*0.09*	*0.00*	*0.00*	*0.02*	*0.00*	*0.00*	*0.00*	*0.00*	*0.10*	*0.00*	*0.00*	*0.02*	*0.00*	*0.00*
	DMM=ELP		*0.38*	*0.00*	*0.00*	*0.31*	*0.00*	*0.00*	*0.02*	*0.00*	*0.03*	*0.00*	*0.00*	*0.19*	*0.00*	*0.03*
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 with=w/o		*0.00*	*0.00*	*0.00*	*0.59*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.60*	*0.00*	*0.00*
	DMM=ELP		*0.00*	*0.00*	*0.23*	*0.58*	*0.00*	*0.00*	*0.00*	*0.02*	*0.04*	*0.02*	*0.04*	*0.35*	*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 with=w/o		*0.01*	*0.00*	*0.00*	*0.12*	*0.00*	*0.00*	*0.00*	*0.00*	*0.01*	*0.00*	*0.00*	*0.10*	*0.00*	*0.00*
	DMM=ELP		*0.00*	*0.00*	*0.06*	*0.03*	*0.00*	*0.00*	*0.00*	*0.06*	*0.02*	*0.00*	*0.42*	*0.07*	*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 with=w/o		*0.00*	*0.00*	*0.00*	*0.93*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.92*	*0.00*	*0.00*
	DMM=ELP		*0.00*	*0.00*	*0.00*	*0.97*	*0.00*	*0.16*	*0.00*	*0.99*	*0.00*	*0.00*	*0.51*	*0.74*	*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 with=w/o		*0.00*	*0.00*	*0.00*	*0.53*	*0.00*	*0.00*	*0.00*	*0.02*	*0.00*	*0.00*	*0.00*	*0.53*	*0.00*	*0.00*
	DMM=ELP		*0.00*	*0.00*	*0.00*	*0.60*	*0.00*	*0.00*	*0.00*	*0.00*	*0.02*	*0.58*	*0.08*	*0.01*	*0.00*	*0.00*

Table 8: This table analyzes the determinants of ELP participation in cross-sectional and panel frameworks. In all panels, the dependent variable equals one if there is ELP trading on a stock-day and zero otherwise. Panel A presents the results from a Fama-MacBeth style daily logit estimation. 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 C presents the results of a linear panel regression examining the impact of fee structure on ELP participation.

Panel A: Fama-MacBeth logit estimation

	Model 1		**Model 2**		**Model 3**	
	Average Estimate	**p-value**	**Average Estimate**	**p-value**	**Average Estimate**	**p-value**
Intercept	-5.174	*0.00*	-1.597	*0.00*	-4.832	*0.00*
Lag (ST volatility (intraday))	0.296	*0.00*			0.324	*0.00*
Lag (Log (daily $ vlm))	0.056	*0.00*			0.067	*0.00*
Lag (Number of trades)	0.006	*0.00*			0.006	*0.00*
Lag (Price inverse)	0.103	*0.00*			0.093	*0.00*
Lag (% quoted spread)	-0.203	*0.00*			-0.181	*0.00*
Lag (Log (market cap))	0.141	*0.00*			0.128	*0.00*
Lag (LT volatility (daily, measured each month))	0.174	*0.00*			0.162	*0.00*
Lag (DMM inventory/month volume (abs. value))			-1.428	*0.00*	-0.390	*0.00*
Lag (Log(passive profits))			0.228	*0.00*	-0.043	*0.00*
Lag (Times inventory crosses zero)			0.178	*0.00*	0.010	*0.00*
Average Pseudo R-square	0.38		0.24		0.39	
Average Rescaled Pseudo R-square	0.52		0.32		0.53	

Panel B: Conditional logit with stock fixed effects

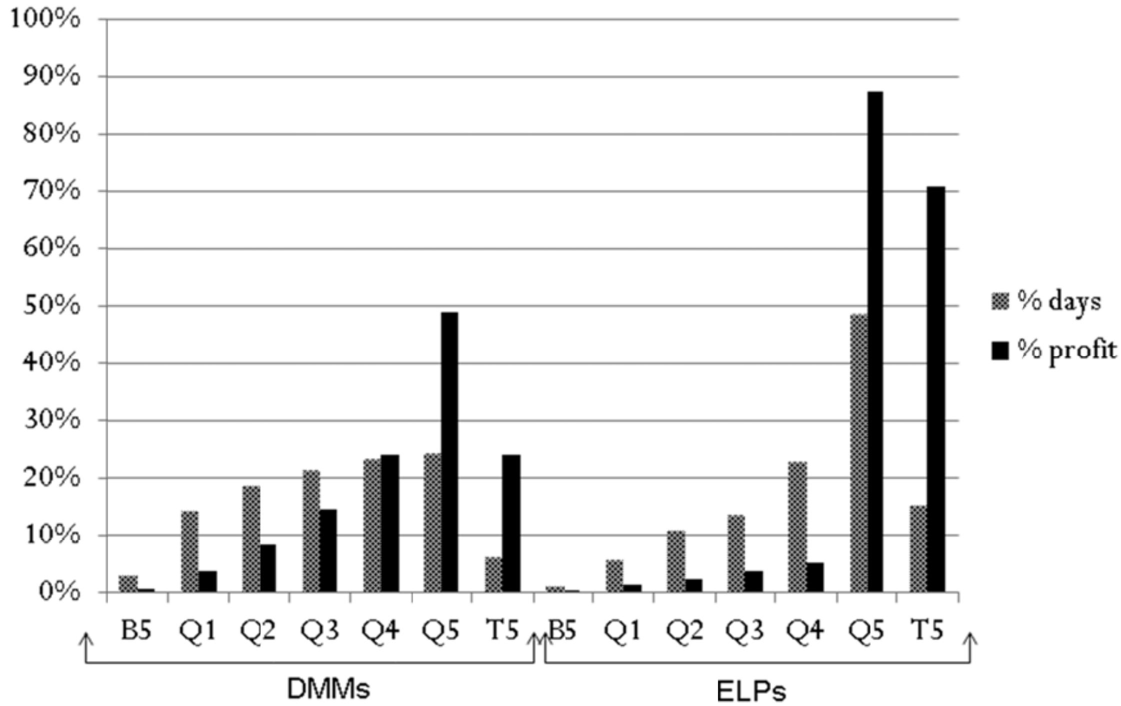
	Model 1		**Model 2**		**Model 3**	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Lag (ST volatiltity (intraday))	0.088	*0.00*			0.086	*0.00*
Lag (Log (daily $ vlm))	0.156	*0.00*			0.154	*0.00*
Lag (Number of trades)	0.002	*0.00*			0.002	*0.00*
Lag (Price inverse)	0.076	*0.00*			0.081	*0.00*
Lag (% quoted spread)	-0.060	*0.00*			-0.062	*0.00*
Lag (Abs (order imbalance))	-0.130	*0.00*			-0.117	*0.00*
Cumulative past month market return<0%	-0.081	*0.00*			-0.083	*0.00*
Cumulative past month stock return<0%	-0.072	*0.00*			-0.065	*0.00*
Lag (DMM inventory/month volume (abs. value))			-0.170	*0.00*	-0.150	*0.00*
Lag (passive profits)			0.096	*0.00*	0.023	*0.00*
Lag (Times inventory crosses zero)			0.038	*0.00*	0.000	*0.86*
Average Pseudo R-square	0.01		0.00		0.02	
Average Rescaled Pseudo R-square	0.03		0.01		0.03	

Panel C: Fee Structure and ELP participation

	Estimate	p-value
Post dummy*Value dummy	0.00760	*0.11*
Post dummy	0.07719	*0.00*
Lag (Log (daily $ vlm))	0.02399	*0.00*
Lag (ST volatility (intraday))	0.01709	*0.00*
Lag (% quoted spread)	-0.00509	*0.00*
Lag (Number of trades)	0.00002	*0.00*
Lag (Price inverse)	0.00795	*0.00*
Lag (Abs (order imbalance))	-0.01210	*0.00*
R-square	0.54	
Stock fixed effects	Yes	
Day fixed effects	Yes	

Figure 1: We provide the source of DMM and ELP profits by market cap quintile in Panel A, and the contribution of positioning profits to total profits in Panel B. "Q1" through "Q5" refer to market cap quintiles, while "B5" and "T5" refer to the bottom and top 5th percentiles of market cap.

Panel A: Participation and profits, by market cap



Panel B: Positioning profits as proportion of total

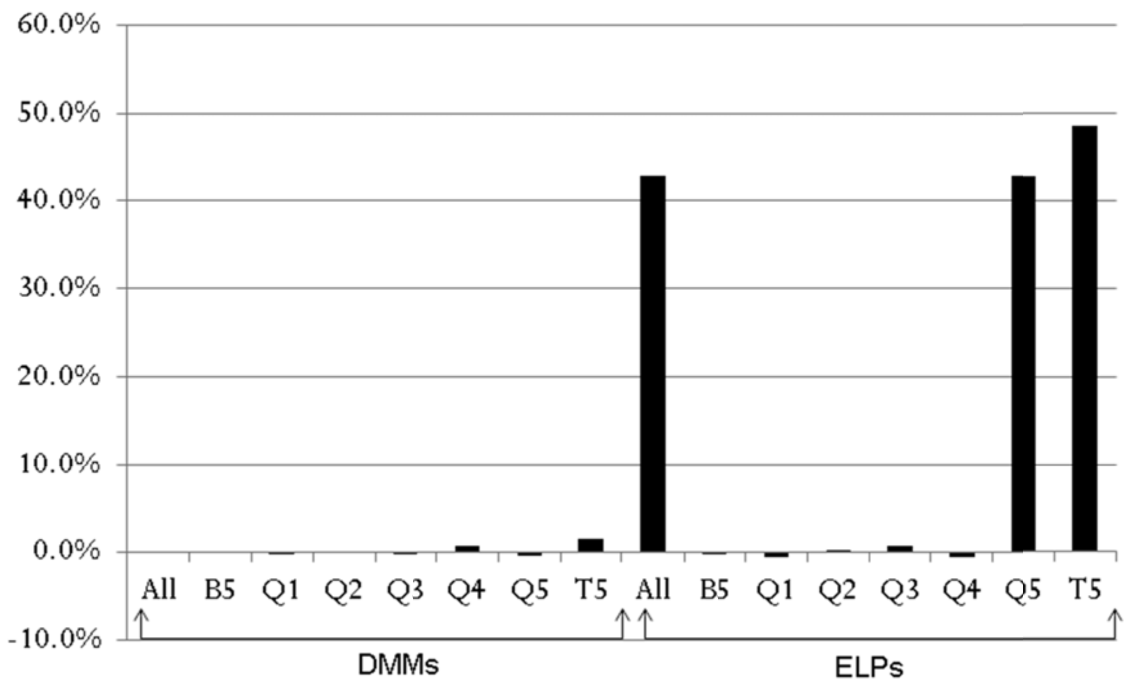
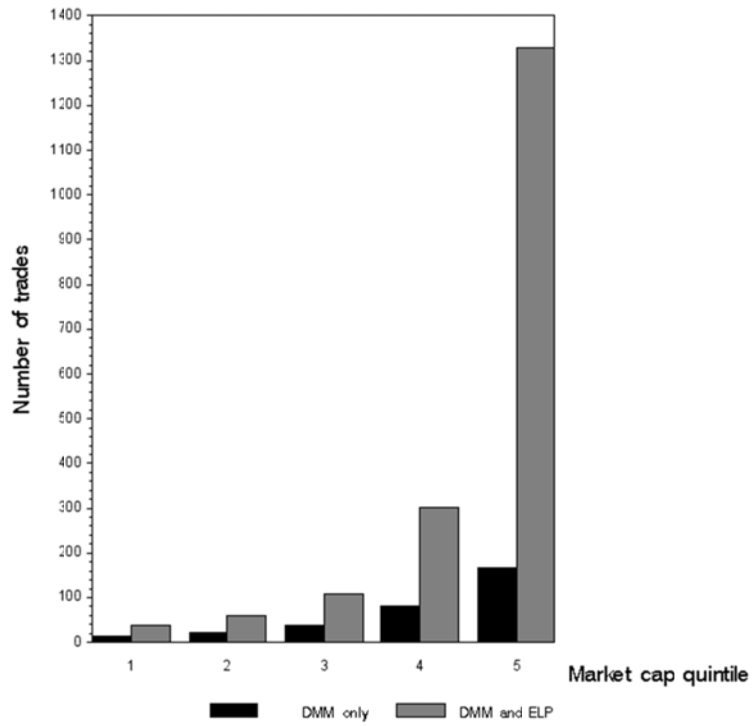
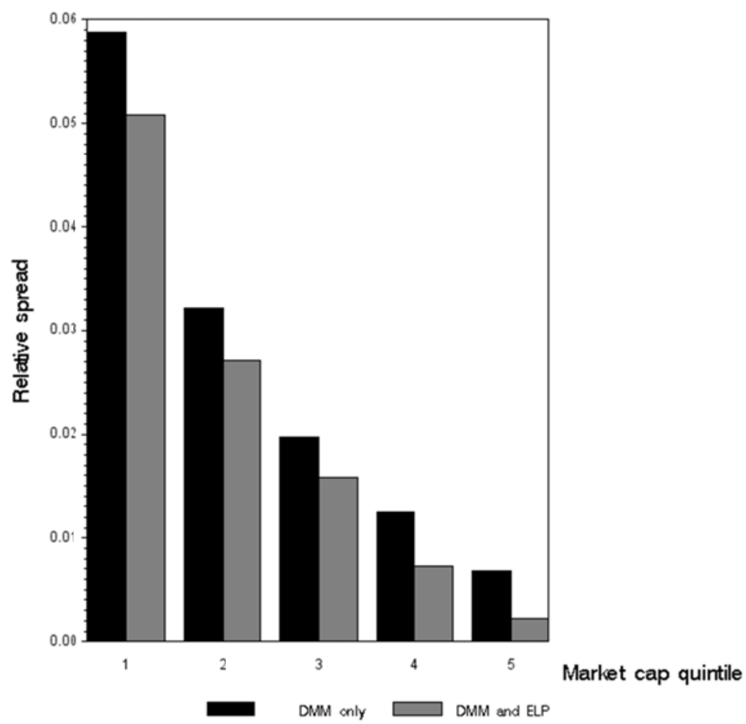


Figure 2: We study the stock characteristics, within market cap quintiles, on days without and with ELP participation. Previous day values of the plotted variables are used as instruments of current day activity. Panel A presents the average number of trades, Panel B presents the average spreads, Panel C the average imbalance and Panel D the average intraday volatility. Averages are taken over stock-days

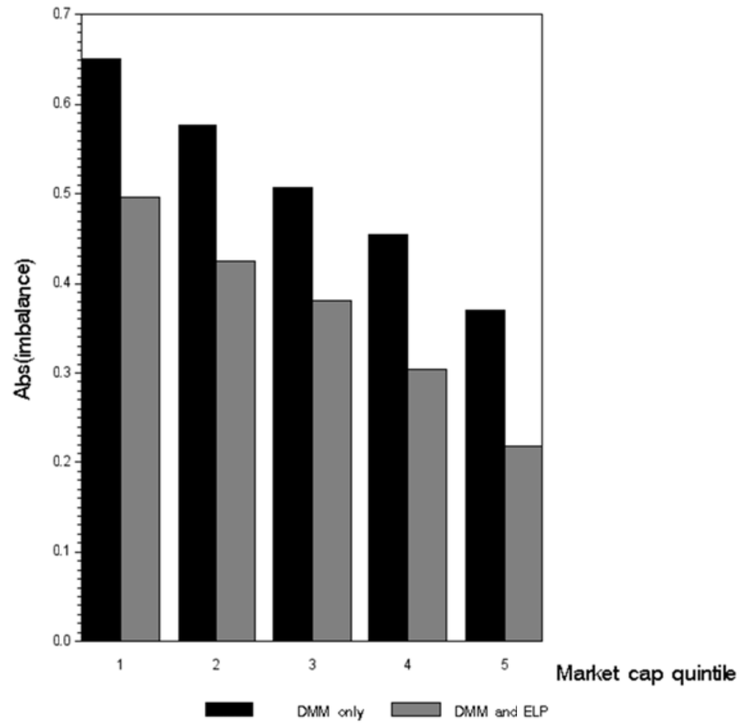
Panel A: Number of trades



Panel B: Relative spread



Panel C: Abs (order imbalance)



Panel D: Intraday volatility

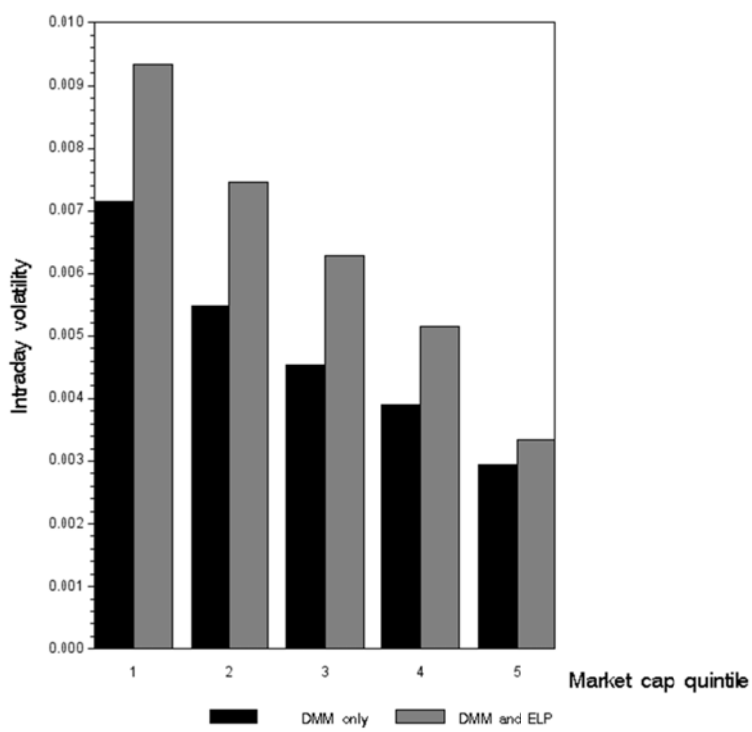
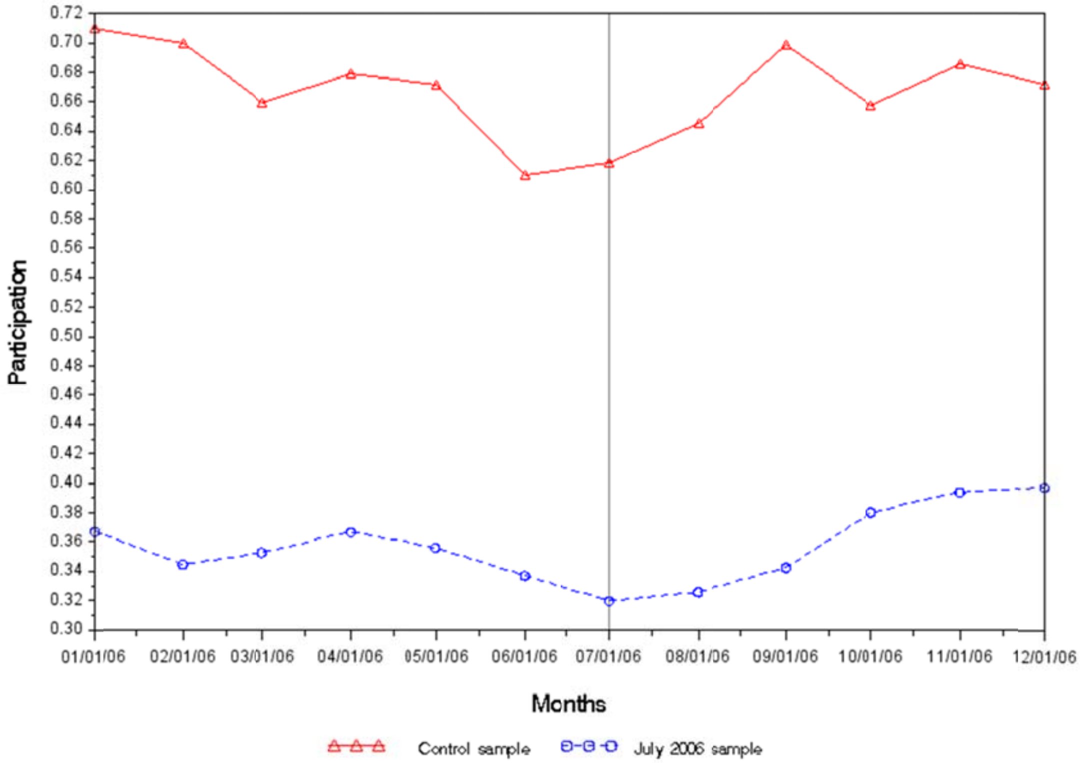


Figure 3: We study the impact of fee Structure on ELP Participation in Panel A, and on passive trades in Panel B.

Panel A: ELP Participation



Panel B: Proportion of ELP Trades that are passive.