Journal of Financial Economics 121 (2016) 327–349

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/finec

Market conditions, fragility, and the economics of market making[☆]

Amber Anand[a], Kumar Venkataraman[b,*]

[a] Whitman School of Management, Syracuse University, 721 University Avenue, Syracuse, NY 13244, USA
[b] Edwin L. Cox School of Business, Southern Methodist University, 6212 Bishop Boulevard, Dallas, TX 75275-0333, USA

ARTICLE INFO

Article history:
Received 19 June 2014
Revised 13 July 2015
Accepted 10 August 2015
Available online 28 March 2016

JEL classification:
G11
G12
G14
G24

Keywords:
Market makers
HFTs
Fragility
Volatility
Obligations

ABSTRACT

Using audit-trail data from the Toronto Stock Exchange, we find that market makers scale back in unison when market conditions are unfavorable, which contributes to covariation in liquidity supply, both within and across stocks. Market conditions lower aggregate participation via their impact on trading profits and risk. Contrary to regulatory view, higher stock volatility is associated with more participation and higher profits, even after controlling for other market conditions, including stock volume. Fragility concerns extend to larger stocks and to active participants. The designated market maker mitigates periodic illiquidity created by synchronous withdrawal of market makers in large and small stocks.

1. Introduction

A central tenet of the modern stock and futures market is endogenous liquidity provision, in which individual investors or for-profit enterprises supply liquidity by posting limit orders. In recent years, a dramatic increase in electronic trading has facilitated the emergence of high-frequency traders (HFTs) as active liquidity providers. Most limit order traders, including HFTs, are not obligated to supply liquidity. According to academic studies, high frequency market making is highly profitable and market quality has improved alongside the growth in electronic

☆ We thank the editor (Bill Schwert) and, in particular, an anonymous referee for many constructive suggestions. For comments, we thank Hank Bessembinder, Robert Battalio, Paul Brockman, Ekkehart Boehmer, Al Carrion, Fany Declerck (FIRS discussant), Amy Edwards, Sean Foley, Hans Heidle, Bob Jarrow, Yung-Yu Ma, Pamela Moulton, Lin Peng, Talis Putnins, Michel Robe, Gideon Saar, Avanidhar Subrahmanyam (Western Finance Association discussant), Wingwah Tham (European Finance Association discussant), Laura Tuttle, Bob Schwartz, and seminar participants at Commodity Futures Trading Commission, City University of New York - Baruch College, Cornell University, 2013 EFA conference, 2015 FIRS conference, 2013 FMA conference, Hong Kong University of Science and Technology, Lehigh University, Nanyang Technological University, National University of Singapore, Securities and Exchange Commission, Singapore Management University, 2013 WFA conference, University of Sydney, University of Technology Sydney and University of New South Wales. We are particularly grateful to James Twiss at Investment Industry Regulatory Organization of Canada (IIROC), and Abigail Etches and Judy Lee at the Toronto Stock Exchange for help in obtaining and understanding the data. Amber Anand gratefully acknowledges support from the Snyder Innovation Management Center at Syracuse University, and Kumar Venkataraman from the James M. Collins Chair in Finance at Southern Methodist University. An earlier version of the study was titled “Should exchanges impose market maker obligations?”

* Corresponding author. Tel.: +1 214 768 7005; fax: +1 214 768 4099.
E-mail address: kumar@mail.cox.smu.edu (K. Venkataraman).

http://dx.doi.org/10.1016/j.jfineco.2016.03.006

trading.[1] These results provide support for a market structure in which liquidity supply arises naturally from the profit incentive (see Glosten (1994)).

Counterbalancing these arguments is the concern highlighted by former Securities and Exchange Commission (SEC) chairman Mary L. Shapiro in her talk before the Economic Club of New York on September 7, 2010: "The issue is whether the firms that effectively act as market makers during normal times should have any obligations to support the market in reasonable ways in tough times." Specifically, since endogenous liquidity providers (ELPs) are not obligated to facilitate trading, the concern is whether ELPs scale back in unison when profit opportunities are small or market making is risky. A systematic withdrawal of liquidity when market conditions are unfavorable has the potential to destabilize markets and lower investor confidence. A joint SEC - Commodity Futures Trading Commission (CFTC) advisory committee report on the Flash Crash of May 2010 cautions that the new dynamics of electronic markets introduce market structure fragility in highly uncertain periods by "essentially eliminating rule-based market maker obligations."[2]

In this study, we use audit trail data from the Toronto Stock Exchange (TSX) to present the first empirical evidence on questions posed by these concerns: Do market makers move in and out of the market in concert with one another? If so, what are the market conditions that serve as signals and what are the economics of correlated participation? Is correlated participation a characteristic of the marginal or the more important market makers? Is it limited to small stocks or does it also affect large stocks? Our study informs a central debate in market design on whether market makers reliably supply liquidity when they have no obligations to do so.

In the absence of an externality or other market failure, a competitive equilibrium for liquidity provision in which the price of liquidity increases to reflect the real social cost of market making is socially optimal. Are regulators mistaken in interpreting an economically driven increase in liquidity cost as a sign of market failure? In a recent theoretical analysis, Bessembinder, Hao, and Zheng (2015) clarify that competitive liquidity provision is optimal if the fundamental uncertainty regarding firm value and the likelihood of information asymmetry are small in combination. However, for other firms or when information asymmetries are large, the competitive bid-ask spreads exceed the social costs of market making, leading to allocative inefficiencies, as some welfare-enhancing trades do not occur. Further, because investors discount share prices to reflect future illiquidity costs, early stage firms may decline to conduct an initial public offering (IPO) even though doing so would enhance social welfare. Under such conditions, the Bessembinder, Hao, and Zheng model shows that a designated market maker (DMM) with a mandate to narrow the bid-ask spread prevents market failure, improves allocation efficiency, and increases firm value and welfare because of an information-based externality. Consistent with their model, several empirical studies report positive stock valuation effects and improvements in liquidity surrounding DMM introduction in many markets.[3] Our study examines the role of obligations in mitigating failure when market conditions are unfavorable.

There is substantial regulatory interest to encourage, through incentives or regulation, market maker strategies that maintain continuous participation in the market.[4] However, there is relatively little empirical work showing that adverse market conditions lead to a synchronization of actions among market makers and that imposing obligations mitigates the problem. The lack of empirical evidence is, at least partly, due to unavailability of suitable data. By its very nature, an analysis of covariation in liquidity supply requires data on individual ELP trading. Most publicly available data sources, including the NYSE Trade and Quote (TAQ) database, do not identify user accounts associated with transactions, while other sources, such as Nasdaq data, identify HFT-associated trades but aggregate individual accounts into a single HFT classification, making it difficult to model the behavior of an individual ELP trader.

We study individual account trading in a sample of 1,286 TSX stocks in the calendar year 2006.[5] The TSX assigns a single member firm to serve as the DMM for each stock. We use account-level information of DMM trades (in their assigned and non-assigned stocks) to model the attributes of market makers and implement a propensity score matching algorithm to identify active, non-DMM accounts that behave as market makers. User accounts identified as ELPs in our analysis exhibit short holding periods, actively manage inventory, and earn the majority of trading profits from passive, liquidity supplying trades, both in- and out-of-sample, and these patterns are stable over time. Our paper is distinguished from prior work partly because the audit trail data made available by TSX allow an examination of individual account trading but mainly because we test hypotheses that other papers do not. Most notably, we present the first direct analysis of covariation in liquidity supply by market makers and identify market conditions that influence liquidity supply via their impact on trading profits and risk.

We base our analysis of ELP participation on a fragility score measure (Fragility Score), which aggregates the excess ELP participation on a trading day across all ELPs in a

[1] See, among others, Hendershott, Jones, and Menkveld (2011), Hasbrouck and Saar (2013), Hendershott and Riordan (2013), Menkveld (2013), and Baron, Brogaard and Kirilenko (2012).

[2] See summary report titled "Recommendations Regarding Regulatory Responses to the Market Events of May 6, 2010" by the joint CFTC-SEC Advisory Committee on Emerging Regulatory Issues, http://www.cftc.gov/ucm/groups/public/@aboutcftc/documents/file/jacreport_021811.pdf.

[3] Nimalendran and Petrella (2003), Venkataraman and Waisburd (2007), Anand, Tanggaard, and Weaver (2009), Perroti and Rindi (2010), Menkveld and Wang (2013), and Skjeltorp and Odegaard (2015) study DMM introduction by exchanges in several European markets.

[4] A European Union (EU) proposal requires market makers to supply liquidity for a set number of hours each day. (See "High-frequency traders get curbs as EU reins in flash boys" - Bloomberg News, April 14, 2014). Nasdaq's Market Quality Program, approved by the SEC as a pilot study in 2013, rewards market makers who meet performance standards on quotation and trade participation in less liquid securities.

[5] Aitken, Cumming, and Zhan (2015) report the start date of HFT activity on the TSX as May 2005.

stock, where excess is defined as an ELP's deviation from its own average participation in the stock. The expected value of the stock's Fragility Score is zero if ELPs participate for idiosyncratic reasons. However, when ELPs respond to market conditions in a similar manner, Fragility Score is defined as positive in bad states and negative in good states.[6] The observed daily distribution of Fragility Score is compared with a simulated distribution based on the assumption that ELP participation is independent. The analysis shows that market makers tend to enter and exit in a correlated manner.

To study commonality in liquidity supply, we implement the methodology used in the analysis of liquidity commonality in Chordia, Roll, and Subrahmanyam [(2000); henceforth, CRS (2000)], and find statistically significant positive covariation between individual ELP participation and aggregate ELP participation within a stock, individual ELP's participation across stocks on the same day, and a stock's ELP participation and market-wide ELP participation. Coughenour and Saad (2004) find a common source of variation in the liquidity of stocks handled by the same NYSE-specialist firm. We show that market makers who are not DMMs also contribute to covariation in liquidity supply across stocks.

Our results based on multivariate, stock fixed effects regressions indicate that aggregate ELP participation is sensitive to market conditions and that market conditions influence ELP participation via their impact on trading profits and risk. However, contrary to the regulatory view, an increase in stock volatility is strongly associated with higher ELP participation, even after controlling for other possible determinants of participation, including stock volume. To rule out reverse-causality, we examine earnings announcements, an exogenous event in which the firm is the source of volatility, and find that ELP participation is higher on pre-announcement days. Higher stock volatility is associated with higher ELP participation, even under conditions when market volatility is high, where the U.S. VIX (Chicago Board Options Exchange Volatility Index) serves as an instrument for TSX volatility that is not influenced by TSX market makers. In addition, trading profits, including profits per unit of capital, are positively associated with stock and market volatility, which further mitigates concerns about reverse causality. Our results are consistent with the Handa and Schwartz's (1996) theoretical prediction that market making is more attractive when volatility is high and, to some extent, allay the regulatory concern that market makers exit during periods of high volatility.[7]

Among other determinants of Fragility Score, a stock's trading activity has the largest impact in terms of economic significance. A decrease in both stock volume and market-wide volume is associated with a higher Fragility Score. Trading volume is a principal determinant of the market maker's ability to offset an inventory position. Thus, markets are more fragile when market-wide trading volume declines because it influences the covariation in inventory risk across stocks [see CRS (2000)]. Order imbalance is positively associated with Fragility Score, which supports the Bessembinder, Hao, and Zheng (2015) prediction that ELP participation declines when information asymmetry, as reflected in one-sided order flow, is high.[8] Overall, the results provide empirical support for regulatory concerns that market makers scale back in unison when market conditions are unfavorable for supplying liquidity.

We examine whether correlated participation is a characteristic of a stock's marginal ELPs, which we define as those market makers with below median ELP participation over the sample period. An exit by marginal ELPs is less of a concern because they play a less important role in facilitating trading. We find that active ELPs are more sensitive to market conditions than marginal ELPs. Further, ELPs are active participants in large stocks, which are more profitable and less risky, but the Fragility Score sensitivity of large stocks is three to ten times larger than that of other stocks. Much regulatory attention has focused on the role of market maker obligations in small stocks, but the stronger results for large stocks indicate that DMMs mitigate periodic illiquidity created by synchronous ELP withdrawal in both large and small stocks. In addition, to the extent that capital is supplied at the brokerage firm level, an exit by an ELP is less of a concern than an exit by all ELPs from the same broker. Although ELPs are more sensitive than brokerage firms to market conditions, we find that the difference is not economically large, suggesting that unfavorable market conditions cause a reduction in market making capital from many brokerage firms at the same time.

Anand, Tanggaard, and Weaver (2009) and Menkveld and Wang (2013) examine account-level data on DMM trades on Stockholm Stock Exchange and Euronext-Paris, respectively. On days with high bid-ask spreads, both studies find that DMMs participate in passive trades, absorb imbalance by building inventory, and earn lower profits than on days with low bid-ask spreads. We show that DMMs supply liquidity under circumstances when market making is not lucrative but also that DMMs play an important role as market makers when ELPs scale back on participation. Our study documents the mechanism by which DMM introduction reduces the stock's liquidity risk (see Menkveld and Wang (2013)).

[6] Brokerage houses are subject to the same regulations on margin calls, capital adequacy, and mark-to-market accounting, and implement similar risk management tools. Independent reactions to common signals can lead ELPs to have a synchronized response to market conditions.

[7] The Wall Street Journal (Meet Getco, high-frequency trade king - August 27, 2009) reports that HFT firm GETCO made record profits ($430 million) during the financial crisis in 2008. GETCO's profits fell to $16 million in 2012, which is attributed in part to the dramatic decline in market volatility after the crisis. (See "Getco profit plunges 82% amid slump in stock volumes" - Bloomberg, February 13, 2013). SEC (2010) describes the possibility that “short-term professional traders may like short-term volatility.”

[8] The Joint CFTC-SEC advisory committee report describes the exit by market making firms during the 2010 flash crash, an extreme event in which major US indexes declined by over 7% in a matter of minutes. Such a rare event is not a part of our sample but we note that the flash crash was characterized by high volatility as well as one-sided order flow. We believe that circuit breakers are an appropriate tool to handle periods of extreme stress.

The TSX DMM is responsible for maintaining two-sided markets with the bid-ask spread within a specified width, moderating price volatility, and guaranteeing executions for a specified number of shares [called a minimum guaranteed fill (MGF)]. As compensation for these obligations, the TSX allows DMMs to execute all odd-lot orders and to auto-participate in a trade ahead of other orders with time priority in a limit order book. We find that the option to auto-participate is exercised more often when market making is difficult, suggesting that this feature helps DMMs to facilitate trading in unfavorable periods. While regulators have focused on the role of market maker obligations, our study points to a related but neglected research on design of compensation contracts for participating in undesirable trades.

The rest of the paper is organized as follows. Section 2 describes the TSX market structure and the propensity score model to identify ELP accounts in the Toronto sample. Section 3 introduces Fragility Score and presents evidence on commonality in liquidity supply across stocks. Section 4 presents the main regression results that relate Fragility Score with market conditions. Section 5 reports the determinants of trading profits and the sources of risk of a market making strategy. Section 6 concludes and presents the study's implications for market design.

2. The Toronto Stock Exchange market structure and market maker identification

We obtain detailed audit trail data from the Toronto Stock Exchange for the calendar year 2006. The TSX's market structure is an electronic limit order book that closely resembles those observed in many global exchanges. The data include information on the orders, trades, and quotes for all TSX-listed securities time-stamped to millisecond resolution as well as the member firm (e.g., Goldman Sachs) and the user identification (ID) within a member firm participating on the active and passive side of each trade. Traders at the member firm are uniquely assigned a user ID, which serves as the port through which orders are submitted to TSX. Traders place orders on behalf of their own proprietary (principal) account or serve as brokers and enter orders on behalf of their clients. The TSX data identify whether an order is submitted on behalf of the proprietary account or the client. However, individual clients within a user ID are not identified in the data. The institutional details of TSX market, the database, and the sample selection are provided in the Appendix.

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. The TSX evaluates DMMs and rewards better performers with future allocations. The database does not provide information on stock-specific obligations of each DMM. When a 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 that are less than or equal to the security's MGF.[9] Auto-participation can be switched on or off at any time but it applies to subsequently arriving orders and does not confer a last-mover advantage. Auto-participation flag is reported in the TSX database, but the information is not disseminated in real time to market participants.

The TSX database identifies the user ID within a member firm assigned as DMM for each stock, which we term as Specialist Trader or ST. All principal trades executed by an ST user ID in stocks with exchange-assigned obligations are categorized as DMM accounts. User IDs identified as a DMM in some stocks execute principal trades using their own capital in other, non-assigned stocks. All principal trades executed by an ST user ID in non-assigned stocks are categorized into ST-ELP accounts. In some analyses, we use these ST-ELP accounts for an algorithm-free identification of an endogenous market maker, who trades some stocks under TSX benefits and obligations as well as other stocks without any benefits and obligations.

Many user IDs at a member firm are not assigned as DMM in any stock in the sample period. All principal trades associated with these user IDs are categorized into Non-ST accounts. Finally, because the TSX data do not separately identify clients, all client trades within a particular user ID are grouped together in the same CL (or Client) account. For this reason, CL accounts are difficult to interpret.

2.1. Descriptive statistics

Table 1, Panel A, describes our sample. The sample contains 1,286 TSX-listed stocks traded over 245 days in 2006. We observe trading activity in approximately nine hundred stocks on an average day. Equally weighted across stocks, the daily number of trades for the average stock is 595, which aggregates to 544,482 shares, or approximately 10 million Canadian dollars (CAD). The average market capitalization across stock-days is 1.6 billion CAD, and the average quoted spread is 0.12 CAD. Between the 25th and 75th percentile of the daily distribution, the closing price varies between 13.2 CAD and 14.5 CAD, the relative spread between 2.1% and 2.4%, and the daily stock return between −0.33% and 0.43%.[10]

In Table 1, Panel B, we report descriptive statistics for user accounts under category ST, Non-ST, and CL. The results suggest that market makers (i.e., ST accounts, including ST-ELP and DMM) actively manage inventory and engage in liquidity provision. Relative to Non-ST accounts, ST accounts are active on more days, participate in more trades, and have smaller end-of-day inventory, higher proportion of zero end-of-day inventory, higher propensity to switch between long and short positions within a day (i.e., reversing inventory position), greater tendency to participate in trades that reduce inventory, higher proportion of passive executions, higher proportion of volume placed anonymously, and higher probability of affiliation with proprietary brokers.

[9] Similar to TSX, many US options exchanges allow DMMs to auto-participate (up to a maximum of 40% of the incoming order size) with small orders, which tend to be more profitable [see Anand, Hua and McCormick (2015)].

[10] Value-weighted across stocks, the quoted spread is 0.047 CAD and the relative quoted spread is 0.17%.

Table 1
Descriptive statistics on Toronto Stock Exchange (TSX) sample and account-level trading activity.

Panel A presents descriptive statistics for the overall sample used in the paper. The sample contains 1,286 TSX-listed stocks traded over 245 days in the calendar year 2006. We calculate equally weighted averages across stocks on each trading day and present the average, median, and 25th and 75th percentile statistics across days. Panel B presents summary statistics on trading activity for user identifiers (IDs) grouped into three account-type categories: (1) Specialist Trader (ST) refers to proprietary trades of user IDs who are designated market makers (DMM) for some securities but can also trade other securities (ST-ELP); (2) Non-ST are proprietary trades of user IDs who are not designated as DMM in any security; and (3) CL refers to all client trades (both retail and institutional) associated with a user ID. The Toronto Stock Exchange (TSX) data report whether the order or trade is attributed to a proprietary (i.e., principal) account or to clients of a user ID but do not provide an identifier for each client within a user ID. The reported statistics are aggregated to the stock-user-day level, then aggregated across stocks by user for each day (averages at the user level are volume-weighted), then aggregated across days (equally weighted) for each user, and then equally weighted across user IDs. In the Non-ST accounts and Client account columns, we report the statistical significance of the test of difference from ST Accounts.*,** and*** indicate statistical significance of test of difference at the 10%, 5%, and 1% level, respectively.

Panel A: Sample statistics	Mean	Median	25th percentile	75th percentile
Number of stocks per day	900	915	886	929
Average daily number of trades per stock	595	591	535	650
Average daily share volume per stock	544,482	542,384	475,096	627,090
Average daily dollar volume per stock	9,969,075	10,060,919	8,687,780	11,155,961
Average closing stock price in Canadian dollars	13.7	13.8	13.2	14.5
Market capitalization of stocks traded (thousands of Canadian dollars)	1,627,110	1,631,396	1,599,909	1,661,509
Average daily dollar spread (Canadian dollars)	0.12	0.12	0.12	0.13
Average daily relative spread	2.3%	2.3%	2.1%	2.4%
Average daily return	−0.02%	0.08%	−0.33%	0.43%
Panel B: Account-level statistics	Overall	ST accounts	Non-ST accounts	Client accounts
Number of user IDs	4861	683	2362	1792
Days per trader	93	161	60***	111***
Daily number of trades	154	143	71**	268***
Daily Canadian dollars volume (∗1,000)	2,352	1,513	1,214	4,188***
Average absolute value of ending inventory	37,560	6,492	30,467***	59,128***
Number of times inventory crosses zero	0.75	3.79	0.22***	0.28***
Zero ending inventory	9.2%	18.8%	9.2%***	5.5%***
Proportion of trades in direction of inventory	50.1%	41.0%	42.7%*	63.5%***
Proportion of passive trades	51.8%	62.6%	49.9%***	50.1%***
Proportion of volume placed anonymously	16.6%	29.7%	15.8%***	12.7%***
Users affiliated with institutional brokers	22.5%	9.4%	22.1%***	28.3%***
Users affiliated with proprietary brokers	4.4%	18.9%	2.5%***	1.4%***
Users affiliated with retail brokers	20.7%	15.5%	24.5%***	17.9%
Users affiliated with integrated brokers	48.0%	54.3%	46.7%***	46.8%***

2.2. An algorithm to identify market makers

We build a propensity score model to identify active, Non-ST user accounts that behave as market makers.[11] Examples include proprietary traders employed by brokerage houses or institutional traders (e.g., a hedge fund) trading via a DMA arrangement with a prime broker. The probit model is estimated at a daily frequency, in which the dependent variable *ST* equals one for an ST account and equals zero otherwise. Based on Table 1, Panel B, we include several explanatory variables that capture an account's propensity to behave as a market maker.

The results of the probit model are presented in Table 2, Panel A. Consistent with Table 1, the regression coefficients indicate that market makers are more likely to trade passively, exhibit more switches between long and short intraday inventory, place volume anonymously, maintain smaller overnight inventory, participate in inventory-reducing trades, associate with proprietary brokers, and are less likely to associate with retail and institutional brokers. For each user account, the propensity score for the stock-day is the predicted probability based on model coefficients and the attributes of the user account. We rank user accounts each day based on propensity score and then categorize them into decile portfolios based on the accounts average propensity score rank over the sample period.

Table 2, Panel B, presents the attributes for user accounts in Deciles 1, 4, 7, and 10. Results in Columns 1–4 suggest that the model obtains significant cross-sectional separation in propensity scores. The scores increase from 2% for Decile 1 accounts to 71% for Decile 10 accounts. The rank range, defined as [High-Low] rank during the sample period, averages 2.5 for the top and bottom deciles, indicating that the relative rank of accounts is stable over time. Many explanatory variables exhibit monotonic patterns across deciles. For example, the number of zero inventory crosses increases from 0.1 in Decile 1 to 5.5 in Decile 10; the proportion of passive executions increases from 40.3% in Decile 1 to 66.3% in Decile 10; and the proportion of zero inventory days increases from 1.7% in Decile 1 to 23.0% in Decile 10. In column 5–7, we present the attributes of user accounts in Decile 10 for the account types: ST-ELP, Non-ST, and CL. From this group, we classify

[11] 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 2
Propensity score matching algorithm to identify endogenous liquidity providers (ELPs).

Panel A presents the estimates from a probit model on the trading behavior of market makers. The dependent variable *ST* equals one for a user identifier (ID) designated as a Specialist Trader (ST) account and equals zero otherwise. Specialist Trader (ST) refers to proprietary trades of user IDs who are designated market makers (DMM) for some securities but can also trade other securities (ST-ELP). The probit analysis is based on observations aggregated at the user-day level (similar to Table 1, Panel B) and includes all user-days with five or more trades. The explanatory variables are the proportion of passive trades, the number of times inventory position crosses zero within the day, the absolute value of the end-of-the-day inventory positions, the proportion of trades that are executed anonymously, and the proportion of trades that increase the current inventory position in the stock. "Institutional broker", "Proprietary broker," "Retail broker," and "Integrated" broker are indicator variables that equal one for the corresponding member firm type [identified by Toronto Stock Exchange (TSX)] and equals zero otherwise. The member firm type, “Integrated” broker, is the omitted indicator variable. Panel B presents participation and inventory patterns for user accounts grouped by propensity scores deciles from the probit model in Panel A. The probit model 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 a number of trading characteristics for each decile. The reported statistics are aggregated to the stock-user-day level, then aggregated across stocks by user for each day (averages at the user level are volume-weighted), then aggregated across days (equally weighted) for each user, and then equally weighted across user IDs. We report statistics that are equally weighted across users within the same propensity score decile (Columns 1–4) and further within account type (Columns 5–7). The final classification in Column 8 is based on trading activity of DMMs in their designated stocks with obligations and does not depend on propensity rank. The final classification in Column 9 refers to non-DMM user accounts ranked in the highest decile on propensity scores (Columns 5–7) and trade on 50 or more days in the sample period. Column 4 reports on test of difference from Column 1, and Column 9 reports on test of difference from Column 8. *, ** and *** indicate statistical significance of test of difference at the 10%, 5%, and 1% level, respectively.

Panel A: Regression coefficients	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 volume placed anonymously	0.51	0.00
Institutional broker dummy	−0.60	0.00
Proprietary broker 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^2	0.33	

Panel B: Account-level trading activity	Propensity score decile				Highest decile accounts with account-type			Final classification	
	Lowest decile (1)	4 (2)	7 (3)	Highest decile (4)	ST-ELP (5)	Non-ST (6)	Client (7)	Designated market maker (8)	Endogenous liquidity provider (9)
Number of accounts	424	425	425	424	115	93	23	334	152
Propensity score	0.02	0.10	0.19	0.71***	0.75	0.65	0.65	0.60	0.71 ***
Propensity rank range	2.5	6.4	6.8	2.7	2.6	3.1	3.7	3.5	3.7
Days per user	53	114	109	144 ***	157	77	87	166	169
Daily Canadian dollar volume (∗1,000)	4,370	2,963	1,805	2,168 ***	1,825	1,234	9,610	1,337	3,395 **
Average absolute value of ending inventory	67,089	53,261	36,834	5,757 ***	4,265	9,519	15,944	6,232	7,245
Number of times inventory crosses zero	0.1	0.2	0.3	5.5 ***	4.0	1.9	5.1	5.6	4.4 ***
Zero ending inventory	1.7%	3.8%	7.4%	23.0% ***	42.6%	42.7%	26.3%	1.1%	49.7% ***
Inventory against days stock return	46.1%	46.8%	48.1%	41.1% ***	32.3%	28.6%	35.0%	52.6%	27.4% ***
Proportion of passive executions	40.3%	48.9%	52.2%	66.3% ***	51.5%	57.3%	51.9%	78.7%	54.0% ***
Proportion of trades in direction of inventory	70.3%	61.8%	51.3%	38.9% ***	36.0%	30.1%	42.7%	42.9%	34.4% ***
Proportion of volume placed anonymously	9.1%	11.0%	16.1%	42.2% ***	56.1%	42.2%	45.3%	25.0%	51.9% ***
Users affiliated with institutional brokers	56.6%	21.9%	12.2%	3.3% ***	0.9%	2.2%	4.3%	9.3%	2.0% *
Users affiliated with proprietary brokers	0.0%	0.0%	0.0%	39.2%***	53.0%	32.3%	60.9%	19.2%	41.4%***
Users affiliated with retail brokers	9.4%	26.8%	22.1%	8.0%	2.6%	18.3%	0.0%	15.6%	9.2%
Users affiliated with integrated brokers	12.3%	49.2%	62.6%	49.1% ***	43.5%	47.3%	26.1%	54.2%	46.1% *

the set of accounts that meet the threshold of 50 days of trading data in the sample period as ELPs (Column 9). To facilitate comparison, we report the attributes for DMM accounts in their assigned stocks in Column 8. The propensity score for ELP accounts [0.71 in Column 9] is higher than those observed for DMM accounts [0.60 in Column 8], which alleviates, to some extent, the concern that the model classifies weaker market makers as ELPs.

The propensity score model identifies market makers using a combination of desirable attributes. Some buy-side institutions primarily use limit orders to build large positions but do not exhibit multiple zero crossing of inventory. Other traders implement short horizon momentum strategies that result in frequent reversal of inventory but primarily use aggressive orders to enter and exit positions. The model avoids selecting such traders by using several important attributes of market makers. In an out-of-sample robustness analysis, we identify ELP accounts based on a propensity score model that uses data from the first half of the sample period. Trading attributes of these accounts in the second half of the sample period are similar to those reported in Table 2, Panel B. The results are not reported but are available from the authors upon request.

Our identification strategy is along the lines of several studies using Nasdaq data (see Brogaard, Hendershott and Riordan (2014)), in which market makers are identified based on trading activity across all stocks. This approach is based on the reasoning that a trader is unlikely to behave as market maker in one stock and long-horizon investor in another stock. One important distinction is that individual account information is preserved in TSX database while information is aggregated into a single HFT classification across 26 HFT firms in Nasdaq data. Other studies identify market makers based on information from the exchange or using trading attributes selected by authors.[12] These studies report considerable variation in HFT strategies, with some HFTs acting as market makers and other HFTs demanding liquidity. The focus of our study is to understand obligated liquidity supply versus the endogenous liquidity supply that arises naturally in a market.

3. Analysis of correlated trading by market makers

The combined influence of risk management and the regulatory environment governing margin calls, capital adequacy and mark-to-market accounting can lead market makers to withdraw participation at the same time. This is because the economics of market making provide incentives to increase participation in good states and reduce participation in bad states. Does the synchronized withdrawal by ELPs to unfavorable market conditions lead to fragility in liquidity supply?

Panels A and B of Fig. 1 illustrate the issue with two ELPs in one stock. In the base case scenario (Panel A), the ELPs participate for idiosyncratic reasons, and the combined ELP participation in the stock is relatively stable. Panel B presents a scenario in which both ELPs increase participation in favorable states and withdraw participation in unfavorable states. This scenario leads to greater variation in the combined ELP participation and higher instability in unfavorable states, when neither of the ELPs supplies liquidity. Both panels hold constant the level of each ELP's participation and focus on within-ELP deviation from expected (the time series average represented by dotted line) stock participation.

As further illustration, we present an analysis of trading data in Barrick Gold Corporation (ticker: ABX). Barrick is a large capitalization stock with trades observed on all 245 trading days in 2006. Panel C of Fig. 1 plots the distribution of number of ELPs participating in a trade on a stock-day in 2006. The observed distribution (dotted line) shows that the minimum number of ELPs is six, the maximum is 19, and about 20% of trading days involve 11 ELPs. The two most active ELPs participate on 244 and 242 days, respectively, and the ELP ranked 25th participates on 28 days.

In Panel C, the observed distribution is compared with a simulated distribution of number of ELPs (solid line). Using each ELP's average stock participation observed in 2006, we draw all possible outcomes based on independent arrival of ELPs and plot the simulated distribution of the number of ELPs on a stock-day.[13] When market conditions exert a common influence across market makers, we expect more ELPs to show up in good states (right tail) and more ELPs to withdraw in bad states (left tail) relative to the simulated distribution. Consistent with this expectation, the observed frequency in Panel C lies above the simulated frequency in both the left and right tail of the distribution. Further, the observed distribution has a higher standard deviation than the simulated distribution, indicating more weight in the tails of the observed distribution. In unreported regression analysis (available upon request), we show that these patterns extend to the full sample of stocks.

3.1. A measure of ELP participation

To formalize the patterns in Panels A and B of Fig. 1, we propose a Fragility Score, which aggregates the excess ELP participation across all ELPs S in stock i on day t:

$$\text{Fragility Score } FS_{(i,t)} = (-1) * \sum_{(s=1)}^{S} (L_{(i,s,t)} - \bar{L}_{(i,s)}), \quad (1)$$

where excess is defined as deviation from ELP's average stock participation and multiplied by (-1) to convert excess participation into a fragility measure. When ELPs participate for idiosyncratic reasons, the expected value of Fragility Score is zero. When ELPs offer a similar response to market conditions, Fragility Score is expected to be positive in bad states and negative in good states.[14]

3.2. Importance of DMM participation

We present a complementary measure (*MMPct*) that incorporates both the extent of participation and the

[12] For example, Kirilenko, Kyle, Samadi, and Tuzun (2011), Baron, Brogaard, and Kirilenko (2012) and Clark-Joseph (2012) classify user accounts based on holding periods and inventory positions. Raman, Robe and Yadav (2014) identify market makers in crude oil futures markets using account-level data on trading activity relative to end-of-day positions. IIROC (2012) identifies HFTs in Canadian markets using account-level order-to-trade ratio.

[13] For example, the top-ranked ELP participates on 244 days [99%] and the 25th ranked ELP participates on 28 days [11%]. The simulation considers all possible combinations of ELP participation while matching the average participation rate observed in data for each ELP. The simulated distribution based on independent arrival of market makers serves as a benchmark to assess correlated participation.

[14] In a robustness analysis, we consider an alternative measure of ELP participation: the daily percentage of trades involving an ELP on one side of the trade (as a proportion of double-counted trades) and find similar results.

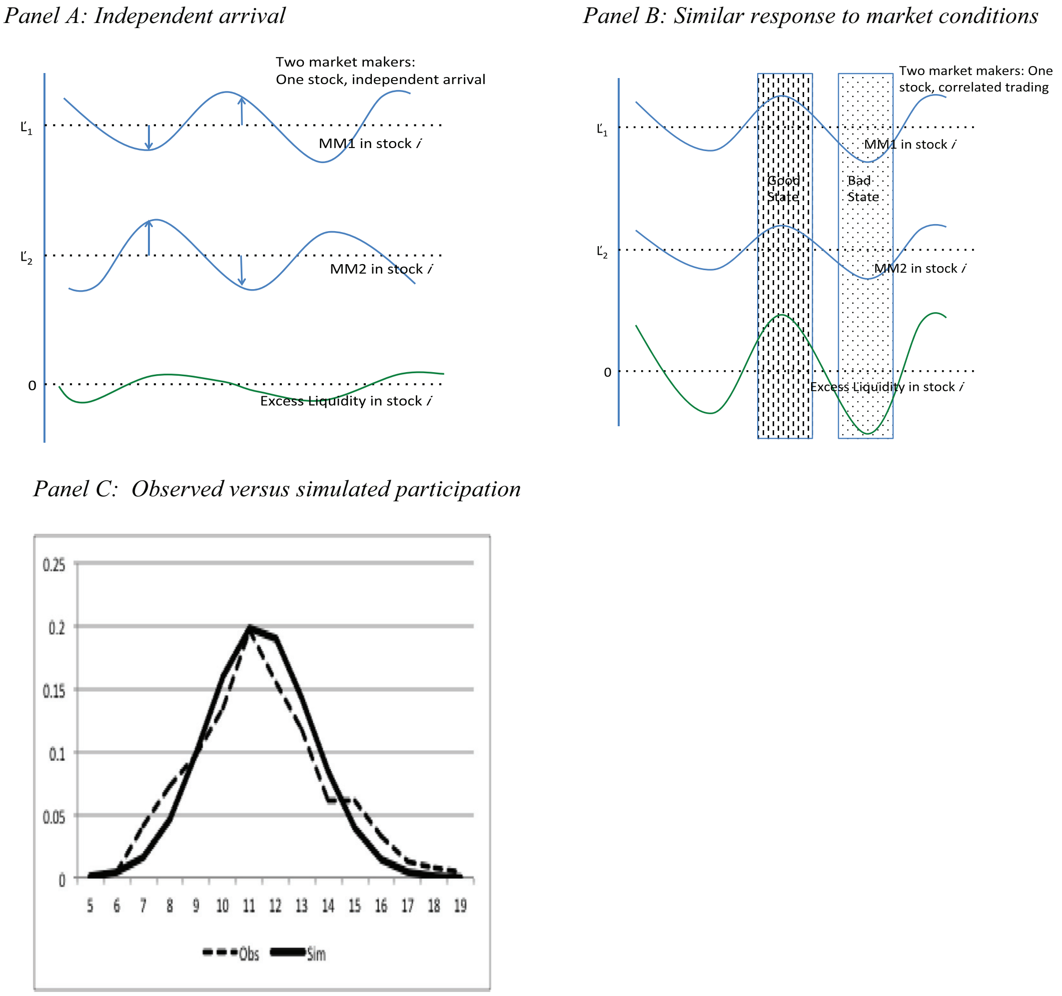


Fig. 1. Framework for correlated trading by endogenous liquidity providers (ELPs). Panel A illustrates the scenario when two ELPs participate for idiosyncratic reasons. Panel B illustrates the scenario in which the two ELPs respond in a similar manner to market conditions, which leads to correlated participation. Panel C plots the observed versus simulated distribution of the daily number of ELPs participating in a trade for Barrick Gold Corporation (ticker: ABX).

circumstances under which a market maker supplies liquidity:

$$\overline{MMPct}_s = \left(\frac{1}{T}\right)\sum_{t=1}^{T} MMPct_{s,t} = \left(\frac{1}{T}\right)\sum_{t=1}^{T}\frac{D_{s,t}}{\sum_{s=1}^{S} D_{s,t}}$$
$$MM = DMM \text{ or } ELP, \quad (2)$$

where $D_{s,t}$ is an indicator variable, which equals one if market maker s participates on day t and equals zero otherwise, and S represents the number of market makers in the stock. $MMD_{s,t}$ equals one when market maker s is the sole participant, equals zero when market maker s does not participate and takes a value between zero and one when multiple market makers participate on day t. When ELPs scale back under unfavorable conditions, the DMM plays an important role as market maker, resulting in a high score for *DMMPct*. We use *DMMPct* as a summary measure of the DMM's importance as a market maker on a stock-day.[15]

3.3. Commonality in ELP participation

Our framework describing correlated trading among market makers is related to the important literature on commonality in liquidity (see CRS, 2000; Hasbrouck and Seppi, 2001). The literature shows that liquidity metrics, such as quoted spreads and effective spreads, exhibit comovement across stocks and that liquidity commonality is an important source of systematic risk (see Pastor and Stambaugh, 2003). Can covariation in market maker

[15] Across ELPs in all stocks, observed $\overline{ELPPct}$ is smaller than simulated $\overline{ELPPct}$, suggesting that an ELP participates more often on trading days when other ELPs participate. In contrast, observed $\overline{DMMPct}$ is larger than simulated $\overline{DMMPct}$, suggesting that DMMs participate more often when ELPs do not participate.

Table 3
Analysis of commonality in participation by endogenous liquidity providers (ELPs).

This table presents analysis of commonality in ELP participation. Panel A presents tests of commonality in an ELP's participation in a stock on a day with other ELPs' participation in the stock on the day. Participation is measured based on the Fragility Score. For each individual ELP, we regress the daily change in individual ELP's fragility score in a stock on the concurrent change in the stock's fragility score. The individual ELP being assessed in the regression is excluded from the calculation of the stock's fragility score. Explanatory variables are one lead and one lag of the change in the stock's fragility score, stock fixed effects, the concurrent, lead, and lagged market return, and contemporaneous stock squared return. Panel B uses a similar specification to test for commonality in an ELP's participation in a stock on a day with the same ELP's participation in all other stocks on the day. Panel C tests for the commonality in aggregate ELP participation in a stock on a day with the aggregate ELP participation in all other stocks on the day. We report the cross-sectional average concurrent coefficient, the percentage of coefficients that are positive, and the percentage that are statistically significant. We also report cross-sectional average and median of the combined concurrent, lead, and lag coefficients, labeled Sum. *p*-values for medians are based on the sign test.*,** and*** indicate statistical significance of test of difference at the 10%, 5%, and 1% level, respectively.

Commonality in liquidity supply		Market capitalization quintile				
	All stocks	1 (small)	2	3	4	5 (large)
Panel A: Commonality - individual ELP with other ELPs within a stock over time						
Number of ELPs	140	106	121	126	137	140
Concurrent	0.18***	0.17***	0.10***	0.13***	0.11***	0.23***
Percent positive	95%	75%	75%	83%	78%	92%
Percent + significant	75%	41%	36%	44%	45%	61%
Sum	0.23***	0.20***	0.12***	0.19***	0.16***	0.30***
Median	0.18***	0.13***	0.07***	0.14***	0.12***	0.22***
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Commonality - individual ELP in a stock with same ELP in other stocks						
Number of ELPs	140	106	121	126	137	140
Concurrent	0.28***	0.21***	0.15***	0.18***	0.21***	0.35***
Percent positive	88%	75%	74%	75%	79%	84%
Percent + significant	74%	25%	28%	36%	46%	67%
Sum	0.34***	0.30***	0.17***	0.15***	0.21***	0.43***
Median	0.34***	0.21***	0.15***	0.13***	0.21***	0.39***
Panel C: Commonality - Overall stock participation versus *the Market participation*						
Number of stocks	923	162	176	189	193	203
Concurrent	0.74***	0.40*	0.27***	0.40***	0.62***	1.84***
Percent positive	66%	59%	64%	63%	67%	75%
Percent + significant	12%	4%	6%	12%	10%	25%
Sum	0.84***	0.71*	0.13	0.48***	0.65***	2.09***
Median	0.22***	0.11	0.12*	0.12**	0.27***	0.99***

participation lead to supply-side driven commonality in liquidity? We analyze co-variation from three perspectives: individual ELP's participation and aggregate ELP participation within a stock, individual ELP's participation across stocks on the same day, and a stock's ELP participation and market wide ELP participation. Participation is measured based on Fragility Score, and all three analyses use the methodology established in CRS (2000).

We begin by examining the covariation between individual ELP participation and the aggregate ELP participation over time within a stock. For each ELP, we regress the daily change in ELP's Fragility Score in a stock on the concurrent change in the stock's Fragility Score, estimated using Eq. (1).[16] The individual ELP being assessed in the regression and the stock's DMM are excluded from the calculation of the stock's Fragility Score. Following the commonality literature, we include one lead and one lag of the change in the stock's fragility score to account for any lagged adjustment in commonality. In all the regressions, we also include stock fixed effects; the concurrent, lead and lagged market return; and contemporaneous stock squared return as control variables. In Table 3, we report the cross-sectional average Concurrent coefficient, the percentage of coefficients that are positive, and the percentage that are positive and statistically significant. We also report cross-sectional average and median of the combined concurrent, lead, and lag coefficients, labeled Sum.

The results in Table 3, Panel A, support commonality in ELP participation within a stock. Across 140 ELPs, the average Concurrent coefficient is 0.18 and statistically significant. We find that 95% of the individual ELP coefficients are positive and that 75% are positive and exceed the 5% one-tailed critical value. The average Sum variable is 0.23, the median is 0.18, and both mean and median are highly significant. These results provide strong empirical support for regulatory concerns that ELPs participate in unison over time within a stock. We stratify the sample into firm size quintiles and report results for each quintile. The highest slope Sum coefficients are observed for Quintile 5 (large cap) stocks. Thus, an individual ELP has stronger co-movement in participation with other ELPs in large stocks, although large stocks have higher participation rates from ELPs.

Coughenour and Saad (2004) posit that the degree of liquidity covariation is explained by shocks to common

[16] CRS (2000) observe that the change specification helps avoid econometric problems (e.g., non-stationarity) that are associated with a level specification of commonality.

resources of the NYSE specialists, such as shared capital and information. In the spirit of Coughenour and Saad (2004), we next examine whether individual ELPs (i.e., market makers other than DMMs) exhibit a common component in liquidity provision across stocks. For each ELP, we regress the daily change in ELP's fragility score in a stock on the concurrent change in the same ELP's average fragility score across other stocks. In Table 3, Panel B, the average slope Sum coefficient is 0.34 and highly significant, indicating that participation by an individual ELP co-varies across stocks. Large stocks have a larger slope coefficient, suggesting that participation in large stocks exhibits stronger co-movement with ELP's portfolio behavior.

The results on commonality in ELP participation observed within a stock (Panel A) and within an ELP (Panel B) should translate into commonality in ELP participation across stocks. We explicitly test for such a relation in Table 3, Panel C. We regress the daily change in a stock's fragility score on the concurrent, lead, and lagged change in average fragility score across other stocks. The average Sum coefficient for the full sample is 0.84, suggesting that ELP participation exhibits significant co-movement across stocks. Further, participation in large stocks is more strongly associated with market wide participation than those in small stocks.[17] The extant literature on DMM obligations has focused on small and illiquid stocks. However, the stronger results that we document for large stocks indicate that periodic illiquidity resulting from synchronous withdrawal by ELPs is a more likely outcome in large stocks.

CRS (2000) show that effective spreads of large firms have greater response to market-wide changes in effective spreads, although large firms have smaller average effective spreads. They posit a liquidity demand- based explanation that greater prevalence of institutional trading in large firms could drive the pattern. Our results are consistent with a large firm effect shown in CRS (2000). While demand-side effects are likely, our results point to a supply-side explanation that is driven by inventory risk management. Market makers have the ability to enter and exit a position at low cost and easily manage inventory in large stocks. The lower frictions facilitate more frequent entry and exit by ELPs in unison, which contributes to higher commonality in liquidity supply in large stocks.

4. Market conditions and market maker participation

We hypothesize that synchronous participation by ELPs is explained by market conditions that influence the economics of market making. In this section, we analyze the influence of market conditions on ELPs' participation within a stock. We begin our analysis by examining market conditions on days when ELPs do not participate versus when they do. The analysis is based on a sample of stock-days when the DMM participates in the stock. We report plots for the logarithm of trading volume in Panel A of Fig. 2 and the absolute value of order imbalance in Panel B. When trading interest among investors is low, or when order flow is one-sided, market makers face higher risk of managing inventory. Consistent with this expectation, trading activity is lower and order imbalance is higher on days when ELPs do not participate versus when they do. Even in large stocks, in which ELPs participate on a high percentage of the stock-days, ELPs scale back on participation when trading activity declines.

In Panel C, we plot the quoted bid-ask spreads for days with and without ELP participation. Higher quoted spreads lead to greater revenues for market makers but also reflect more difficult market conditions. Consistent with the latter, we find that ELP participation is significantly lower on days with higher quoted spreads. Since higher stock volatility increases inventory risk, regulators have expressed concern that ELPs scale back on participation when volatility is high. Contrary to regulatory concerns, Panel D indicates that intraday stock volatility is higher on days when ELPs participate versus when they do not. Along similar lines, we find in an unreported analysis that Fragility Score is lower on trading days when intraday stock volatility exceeds the 95th percentile for the stock.

4.1. Volatility and market maker participation

Because the intraday volatility results appear inconsistent with the regulatory view, we scrutinize these results in more detail in this subsection. One possibility is that, while we treat intraday volatility as exogenous, the causality goes in the opposite direction; i.e., ELP participation contributes, not responds, to higher volatility. To address reverse-causality, we examine earnings announcements, an exogenous event in which pending corporate news is the source of information flow, or volatility. In Table 4, Panel A, we compare ELP participation on the day before earnings announcements (Day [−1]) with control days (Day [−10,−30]) for the same stock. The sample consists of 592 stocks with a total of 1,532 announcements, ranging from 61 for small stocks to 653 for large stocks. Results indicate that Fragility Score is lower (i.e., ELP participation is higher) on the day before an earnings announcement (Day [-1]) relative to control days. Using standard errors clustered at stock and day level, the decline in fragility score is statistically significant for the full sample but not for the sub samples.

We further examine whether the intraday volatility result holds in different market conditions. Intraday stock volatility could be attractive to ELPs when market-wide volatility is low, but not when market-wide volatility is high. Accordingly, in Table 4, Panel B, we examine Fragility Scores based on independent double-sorts of trading days into stock and market volatility quintiles. We use US VIX as an instrument for (exogenous) TSX volatility that is not influenced by the participation from TSX market makers. We find that high intraday stock volatility is associated with significantly lower fragility scores. Even when VIX is high, the fragility score is negative when intraday stock volatility is high. The positive association between ELP

[17] In unreported analysis, we find that stock liquidity co-varies with market liquidity for our sample of stocks, where percentage effective spreads serves as the liquidity proxy.

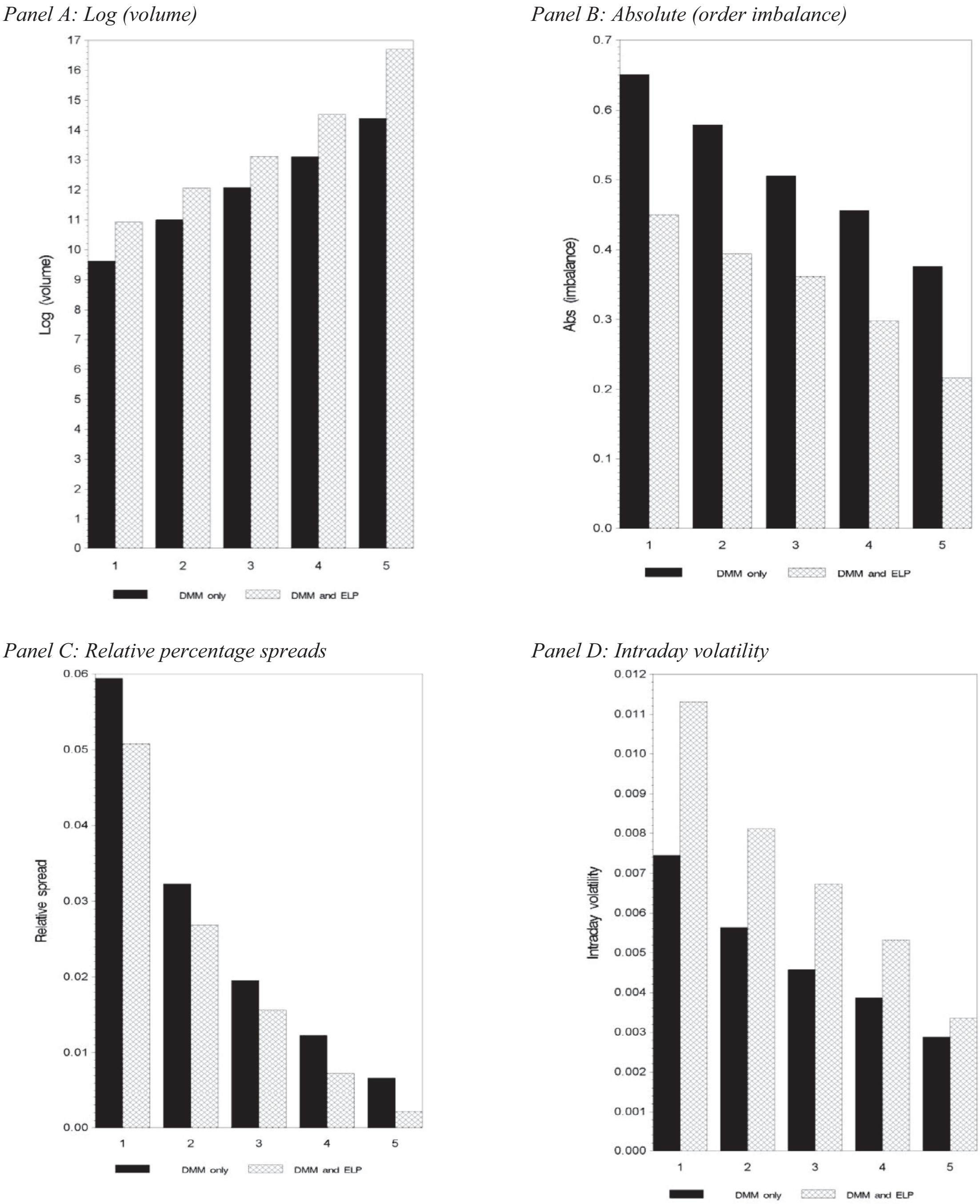


Fig 2. Impact of market conditions on market maker participation. Panel A presents log (volume), Panel B presents the percentage bid-ask spreads, Panel C presents buy-sell imbalance, and Panel D presents intraday volatility. Within market cap quintiles, the plots present averages based on stock days when both the designated market maker (DMM) and endogenous liquidity providers (ELPs) participate (DMM and ELP) and stocks days when the DMM participates but ELPs as a group do not participate (DMM only).

participation and volatility supports Handa and Schwartz's (1996) theoretical prediction that the market making strategy of posting buy and sell limit orders simultaneously is profitable when intraday volatility is high. In a subsequent analysis, we find that trading profits are positively associated with stock volatility, which provides an economic rationale for the decision to voluntarily supply liquidity on high volatility days.[18]

[18] In unreported analysis, we find similar results when we double-sort by directional volatility and intraday volatility. Directional volatility is measured by the absolute value of autocorrelation in 15-minute returns

Table 4
Market conditions and participation by endogenous liquidity providers (ELPs).

Panels A and B present robustness tests of the impact of intraday volatility on ELP participation. Intraday volatility is the standard deviation of 15-minute returns based on quote midpoints. Panel A reports participation on the trading day before an earnings announcement (Day [-1]) benchmarked against control days (Days [-10,-30]) for the same firm. Earnings announcements date is obtained from the Institutional Brokers Estimate System (I/B/E/S) database. I/B/E/S data are matched to Toronto Stock Exchange (TSX) data by ticker. The sample consists of 592 stocks with a total of 1,532 announcements, ranging from 61 for small stocks and 653 for large 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 announcement day. Panel B reports the interplay between stock volatility, market volatility and participation. US stock market based VIX (Chicago Board Option Exchange Volatility Index) serves as an instrument for TSX-wide volatility that is exogenous to ELP participation. The intraday quintile assignments are made separately for each stock. Measures are reported for overall sample, small cap quintile and large cap quintile. Trade participation rates are unconditional (fill in a zero for days with no trading). ***, ** and * indicate that the measures differ between pre-earnings announcement days and control days in Panel A, and differ between low and high intraday quintiles in Panel B, at the 1%, 5%, and 10% level, respectively, based on double-clustered standard errors at stock and day level. Panels C and D present the regression coefficients of a multivariate analysis of stock characteristics and market conditions on the stock's fragility score. We estimate a stock fixed effects specification in which the dependent variable is the stock's fragility score on the stock-day. The explanatory variables are daily stock- and market-level conditions such as the stock volume, intraday volatility, percentage quoted spread, 1/price, absolute value of the order imbalance, a dummy variable that equals one if the stock-day is a pre-earnings announcement day, downstock (equals one if the rolling 30-day stock return is negative), downmarket (equals one if the rolling 30-day market return is negative), the US market VIX, and the share volume of all securities traded in the TSX on the day. Panel D includes interactions with the large stock dummy that equals one for the largest cap quintile of stocks and the active ELP dummy that equals one if ELP's participation based on the number of days is above the average for all active ELPs in the stock. Fragility scores for the more and less active ELPs are calculated separately for each stock. The regressions include stock fixed effects, and *p*-values are calculated based on double clustered standard errors at stock and day level.

Panel A: ELP participation before earnings announcements

Variables	All stocks	Small cap stocks	Large cap stocks
Day [-1] before earnings announcements			
Percent of stock days with ELP participation	51.17%	16.39%	81.47%
Fragility Score	−0.063	−0.060	−0.106
Participation rate of trades	2.81%	1.89%	4.72%
Control days [-10,-30] before earnings announcement			
Percent of stock days with ELP participation	48.68% *	13.35%	81.36%
Fragility score	0.016 **	-0.005	-0.003
Participation rate of trades	2.69%	1.59%	4.80%

Panel B: Stock volatility, market volatility, and ELP participation

	Intraday stock volatility quintile					
Variables	Low volatility	2	3	4	High volatility	*P*-value: test q1 = q5
Lowest VIX quintile days						
Stock days	9892	9696	9114	8682	8094	
Percent of stock days	36.90%	37.00%	37.20%	37.50%	39.80%**	0.04
Fragility score	0.15	0.01	−0.06	−0.15	−0.33***	0.00
Participation rate of trades	2.10%	2.00%	2.10%	2.00%	2.20%	0.22
Highest VIX quintile days						
Stock days	6931	7100	7608	8420	9971	
Percent of stock days	21.50%	28.90%	33.10%	36.50%	43.30%***	0.00
Fragility Score	0.21	0.16	0.10	0.03	−0.17***	0.00
Participation rate of trades	1.50%	1.90%	2.10%	2.20%	2.60%***	0.00

Panel C: Determinants of Fragility Score on the stock day

Variables	(1)	*p*-value (2)	(3)	*p*-value (4)	(5)	*p*-value (6)	(7)	*p*-value (8)	Economic significance (one σ shock) (9)
Stock variables									
Log (stock volume)	−0.133	0.00	−0.126	0.00			−0.122	0.00	0.17
Volatility (intraday)	−0.155	0.00	−0.146	0.00			−0.148	0.00	0.13
Quoted spread (percent)	0.002	0.19	0.002	0.16			0.002	0.33	0.04
Price (inverse)	−0.018	0.03	−0.016	0.02			−0.016	0.02	0.01
Abs(Imbalance)	0.043	0.00	0.043	0.00			0.041	0.00	0.03
Earn_Pre			−0.057	0.06			−0.055	0.07	0.04
Downstock			−0.007	0.44			−0.010	0.24	0.01
Market variables									
Log (market volume)					-0.239	0.00	−0.107	0.00	0.01
Downmarket					−0.023	0.02	−0.018	0.04	0.02
VIX					0.002	0.45	0.003	0.23	0.02
Stock fixed effects	Yes		Yes		Yes		Yes		
Adjusted R^2	4.2%		3.9%		0.3%		4.0%		
N. obs.	190,265		186,222		187,773		186,222		

(continued on next page)

Table 4
(*continued*)

Panel D: Fragility Score on the stock day

	Dummy =1 for Large Cap stock		Dummy=1 for Active ELP		Fragility Score based on member firm participation		Economic significance (one σ shock)
Variables	(1)	*p*-value (2)	(3)	*p*-value (4)	(5)	*p*-value (6)	(7)
Stock variables							
Log (stock volume)	−0.086	0.00	−0.023	0.00	−0.098	0.00	0.165
Log (stock volume) ∗ Dummy	−0.235	0.00	−0.076	0.00			
volatility (intraday)	−0.113	0.00	−0.031	0.00	−0.120	0.00	0.123
volatility ∗ Dummy	−1.481	0.00	−0.088	0.00			
quoted spread (percent)	0.005	0.00	−0.001	0.00	0.002	0.13	0.039
quoted spread ∗ Dummy	0.204	0.02	0.004	0.02			
price (inverse)	−0.014	0.04	0.001	0.86	−0.013	0.02	0.015
price (inverse) ∗ Dummy	7.850	0.00	−0.017	0.01			
absolute value of order imbalance	0.038	0.00	0.001	0.77	0.049	0.00	0.036
abs(Imbalance) ∗ Dummy	0.198	0.00	0.041	0.00			
Earn_Pre	−0.038	0.05	−0.016	0.09	−0.030	0.16	−0.027
Earn_Pre ∗ Dummy	−0.010	0.87	−0.023	0.36			
Downstock	0.015	0.02	0.004	0.02	−0.001	0.85	−0.011
DownStock∗Dummy	−0.099	0.00	−0.018	0.03			
Market variables							
Log (market volume)	−0.055	0.00	0.007	0.08	−0.064	0.00	0.004
Log (market volume) ∗ Dummy	0.006	0.92	−0.120	0.00			
Downmarket	0.008	0.13	0.001	0.61	−0.010	0.11	0.014
Downmarket ∗ Dummy	−0.053	0.07	−0.021	0.02			
VIX	0.003	0.06	0.001	0.12	0.005	0.01	0.024
VIX ∗ Dummy	0.014	0.10	0.002	0.46			
Stock fixed effects	Yes		Yes		Yes		
Adjusted R^2	7.9%		2.8%		4.3%		
N. obs.	186,222		358,703		186,222		

4.2. Multivariate analysis of market maker participation

Volatility, bid-ask spreads, and order imbalances tend to be positively correlated (see Stoll, 2000). While the plots in Fig. 2 suggest that order imbalance and stock volatility have an opposite impact on Fragility Score, stock volume and stock volatility have a similar impact on Fragility Score. In Table 4, Panel C, we employ a multivariate, stock fixed effects, regression framework that accounts for the correlation among explanatory variables and identifies the marginal impact of each explanatory variable on ELP participation. The fixed effects specification controls for omitted stock attributes and examines within stock variation in participation. Statistical inference is based on standard errors that are double clustered at stock and day level.

Following the framework in Section 3, the dependent variable is the stock's fragility score based on ELP participation on the stock-day, and the regression specification is:

$$ELP_{FS_{i,t}} = \sum_i \alpha_i + \beta_1.stockVol_{i,t} + \beta_2.\log(stockvolume_{i,t}) + \beta_3.relspread_{i,t} + \beta_4.\left(\frac{1}{Price_{i,t}}\right) + \beta_5.abs(imbal_{i,t}) + \beta_6.Earn\_Pre_{i,t} + \beta_7.DownStock_{i,t} + \epsilon_{i,t}, \quad (3)$$

where *stockvolume* is the daily dollar volume in the stock; *stockVol* is the standard deviation of 15-minute returns based on quote midpoints; *relspread* is the time-weighted quoted percentage spread on the stock-day; *Price* is the midpoint of the stock's closing bid-ask quote; *imbal* is the absolute value of buy-sell trade imbalance normalized by trading volume; and α_i is the stock fixed effect. DMMs participate on all trading days included in the regressions, but DMMs are not included in the calculation of Fragility Score.

We report the regression coefficients in Column 1 of Table 4, Panel C. The coefficients suggest that Fragility Score is negatively associated with trading volume and intraday volatility and positively associated with order imbalance. Thus, market makers increase participation in response to higher trading activity or higher stock volatility and decrease participation in response to higher order imbalance. The latter finding is consistent with the Bessembinder, Hao and Zheng (2015) prediction that market maker participation declines when information asymmetry is high. Fragility Score is negatively associated with stock price but not associated with the quoted spread. In Column 3, we include two indicator variables: *Earn_Pre* equals one on the day prior to earnings announcement and equals zero otherwise, and *Downstock* equals one when cumulative stock return over the previous 30 days (not including the stock-day) is negative and equals zero otherwise. Consistent with Panel A results, *Earn_pre* has a negative coefficient indicating that Fragility Score declines before an earnings announcement while the *Downstock* coefficient is not statistically significant.

on the day. ELP fragility score declines with higher intraday volatility even when the absolute value of return autocorrelation is high.

The commonality in liquidity literature posits that market-wide conditions exert a common influence on liquidity supply across stocks. In Columns 5 and 7, we examine whether market-wide conditions influence ELP participation over time within a stock. We include the log of market-wide trading volume as an explanatory variable because trading activity is an important measure of inventory risk. The coefficient on market volume is negative and highly significant, suggesting that Fragility Score is higher when market wide trading activity is lower. The negative coefficient on *Downmarket* is unexpected, indicating that markets are less fragile when the cumulative market return over the previous 30 days is negative. Theoretical models (e.g., Acharya and Viswanathan, 2011) predict that market-wide uncertainty increases asset correlations and affect margin limits on portfolio positions. Although the VIX coefficient is positive, indicating that Fragility Score is high when market volatility is high, the coefficient is not statistically significant. Thus, we do not find support for regulatory concerns, but we note that our sample period does not include extreme market volatility events, along the lines of a flash crash event. Most exchanges, including the TSX, rely on trading halts to stabilize markets during extreme events because it might not be economically feasible for a DMM to stabilize highly stressed markets.

Column 9 in Panel C reports the economic significance of explanatory variables based on the standardized regression coefficients. One important finding is that stock-specific market conditions play a more important role than market-wide conditions in influencing stock fragility. Among stock-specific variables, the stock's trading volume and stock volatility have the largest impact on the Fragility Score. A decrease of one standard deviation in stock volume (volatility) is associated with an increase of 0.17 (0.13) standard deviation in Fragility Score. The economic significance of other variables is relative small. One standard deviation increase in order imbalance is associated with 0.03 standard deviation increase in the Fragility Score, and the Fragility Score on the day before earnings news is lower by 0.04 standard deviations. Among market-wide variables, the standardized regression coefficient on market volume is 0.01 and the coefficient on *Downmarket* variable is 0.02.

4.3. Cross-sectional variation in sensitivity to market conditions

Popular press articles report that HFTs participate more actively in large stocks. In Column 1 of Table 4, Panel D, we examine whether ELPs are more sensitive to market conditions when participating in large stocks relative to other stocks. We estimate a separate slope coefficient for large firms by interacting each market condition variable with a *Large* indicator variable, which equals one for stocks in the largest capitalization quintile and equals zero otherwise. Results suggest that market conditions affect participation in large stocks in the same direction, but the sensitivity is three to ten times larger than other stocks. Among stock-specific variables, the interaction coefficient on volume and volatility is negative and the interaction term on imbalance is positive. Higher market volume or VIX has no differential impact for large stocks. Our results are consistent with the higher covariation in liquidity supply shown for large stocks in Table 3. The stronger commonality results for large stocks indicate that periodic illiquidity created by synchronous ELP withdrawal is not limited to the smaller segment of the market and that the regular market presence of a DMM can mitigate fragility in both large and small stocks.

Which ELPs are more sensitive to changes in market conditions? An exit by marginal ELPs is less of a concern because they play a less important role in facilitating trading. In Column 3 of Table 4, Panel D, we examine differences in sensitivity of more and less active ELPs. For this analysis, we retain the 25 most active ELPs in the stock and define an *Active* indicator variable that equals one when an ELP's stock participation (based on number of days) exceeds the stock's median ELP participation and zero otherwise. The regression analysis is based on daily Fragility Scores, estimated separately for active and less active groups of ELPs, on a stock-day. We estimate a separate slope coefficient for active ELPs by interacting each market condition variable with *Active*. The slope coefficients on interaction terms suggest that while some market conditions, such as order imbalance or pre-earnings day, affect active and less active ELPs in a similar manner, active ELPs exhibit higher sensitivity to stock volume, stock volatility, and market volume. Thus, the more active ELPs show a higher propensity to enter and exit a stock in a synchronous manner when market conditions are unfavorable.

We next examine whether lower participation in response to adverse conditions reduces the number of brokerage firms active in the stock. To the extent that capital is supplied at the brokerage firm level, an exit by an ELP is less of a concern if another ELP from the same broker continues to participate using firm capital. In Column 5 of Table 4, Panel D, we report regression coefficients using daily Fragility Score based on member firm participation on a stock-day; that is, following Eq. (2), we aggregate the excess liquidity supply across all member firms j in stock i on day t. The regression coefficients indicate that market conditions influence ELP Fragility Score more than member firm Fragility Score but in the same direction. In the adjacent column 7, we report standardized regression coefficients based on member firm Fragility Score. We find that one standard deviation shock to market conditions has an economically similar impact on Fragility Score of ELPs and member firms. Thus, adverse market conditions result in synchronized withdrawal among not only ELPs but also brokerage firms, implying that aggregate capital available for market making is lower in stressful periods.

5. Trading profits and inventory risk of market makers

We hypothesize that market conditions influence Fragility Scores via their impact on profit opportunities and inventory risk. Are risk-adjusted profits lower on days when ELPs withdraw from the market? One of the advantages of the TSX market structure is that ELPs and DMMs co-exist. The participation decision by DMMs helps identify market conditions when market making is feasible and provides measures of trading profit and risk when ELPs enter versus exit the market.[19]

We examine account-level transaction data to present univariate statistics on trading profits and risk. Results are equally weighted averages across stock-days in the respective sample. Panel A of Table 5 presents the statistics for ELP accounts and Panel B presents the statistics for DMM accounts. Tests of differences across groups are based on double clustered standard errors at the stock and day level. For each stock-day for an account, we calculate trading profits by marking the day's transactions to the closing quote midpoint and aggregating the dollar profit or loss over all positions for the day.[20] 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 the bid-ask spread. Some studies on HFTs conclude that co-location arrangements and HFTs' investments in speed contributes to large positioning profits (e.g., Hirschey (2013)) while other studies attribute positioning profits to private information on fundamentals [see Hu, Pan, and Wang (2013); and Chordia, Green, and Kottimukkalur (2015)].

Our primary measure of market maker's capital commitment (i.e., inventory) is the absolute value of average intraday inventory. Because microstructure theory suggests that inventory risk is a function of stock volatility, we also estimate a volatility-adjusted inventory measure, in which average absolute inventory is multiplied by the stock's intraday volatility on the day, to account for differences in risk across positions. Signed closing inventory accounts for daily change in inventory positions relative to daily stock return. The measure is positive when a market maker is a net buyer (seller) on negative (positive) return days. Inventory measures are normalized by the stock's monthly trading volume. We also report the number of times the intraday inventory crosses zero. More zero crossings indicate lower inventory risk.

Based on Table 5, Panel A, we conclude that ELPs, on average, earn positive trading profits. The majority of profits are attributed to passive trades, which is consistent with market making, but ELPs also earn positive positioning profits. Results support the Grossman and Miller (1988) prediction that large stocks are more attractive for market makers. Based on an aggregate profit analysis across all ELP accounts, Fig. 3, Panel A, shows that ELPs earn almost 90% of profits from large stocks and, in particular, from the highest 5th percentile (T5) on market capitalization. Fig. 3, Panel B, shows that ELPs earn large positioning profits in large stocks, particularly T5 stocks, but make losses in small stocks. Overall, more than 40% of ELP profits come from positioning profits. Results also show that market making is less risky in large stocks. In Table 5, Panel A, the daily number of inventory crosses for large stocks is 9.0 versus 0.60 for small stocks, and the absolute average inventory is 0.02% for large stocks versus 0.86% for small stocks. Trading profits per unit of risk are higher for large stocks than small stocks. Consistent with these results, ELPs participate on four out of five trading days (79%) in large stocks but only one out of eight trading days (12%) in small stocks.

The analysis in Table 5, Panel A, presents an incomplete picture as the results are based on stock-days when ELPs choose to participate. We therefore present a conditional analysis of DMM profits and risk on trading days when ELPs participate as a group versus when they do not. Days without ELP participation are associated with high Fragility Score because ELPs choose to withdraw in unison. Trading profits are almost 60% lower on days when ELPs withdraw than on days when ELPs participate. Based on the plot of DMMs' profit distribution in Fig. 4, Panel A, we conclude that ELPs scale back in unison when DMM profits are close to zero but increase participation when DMM profits are either positive or negative. Thus, ELPs appear to be active when profit potential is large but scale back when profit potential is small. Across market cap quintiles, the statistical tests show that inventory risk is higher on days when ELPs do not participate (see Fig. 4, Panel B). Under these conditions, DMMs fulfill their obligations by participating in undesirable trades, particularly in small stocks. Chordia and Subrahmanyam (2004) show that daily returns are correlated with daily order imbalances. The higher signed inventory suggests that DMMs trade against the imbalance by buying stocks when daily return is negative, and vice versa.

The combined profitability and inventory risk results from Table 5, Panel B, are consistent with market conditions affecting ELP Fragility Scores via their impact on the economics of market making. The results do not support a reverse-causality explanation as lower competition when ELPs do not participate as a group is not associated with higher DMM profits. The results point to two types of cross-subsidies in market making. First, the DMMs' risk-adjusted profits are higher in large stocks than small stocks, implying a cross-subsidy from large to small stocks. Second, higher profits under normal conditions compensate for the inventory risk under stressful conditions. Panayides (2007) finds similar evidence of cross-subsidies in the old NYSE-specialist structure. However, one difference is noteworthy: The primary source of NYSE-specialist's income is positioning profits, which reflects the information advantages enjoyed by the NYSE-specialist. In contrast, as seen in Fig. 3, Panel B, the TSX DMMs do not earn positioning profits. The primary source of TSX DMMs' profits is the spread earned on passive, liquidity-supplying trades. Thus, our study describes the economics of market

[19] Some contemporaneous papers examine the trades of market makers in exchanges without DMM adoption (e.g., Kirilenko, Kyle, Samadi and Tuzun, 2011; Clarke-Joseph, 2012; Brogaard, Hendershott and Riordan, 2014; Baron, Brogaard and Kirilenko, 2012; Raman, Robe and Yadav, 2014; IIROC, 2012). The analysis leaves unresolved to what extent market making with obligations is viable when ELPs scale back on participation.

[20] We also estimate two alternative profit measures based on Hasbrouck and Sofianos (1993) and Menkveld (2013): 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. We close out the open inventory positions at the closing price for both cash flow and mark-to-market profits. All three profit measures yield identical measures for the profitability analysis.

Table 5
Trading profits and inventory risk of market makers.

The table presents trading profit and inventory risk of market makers. Panel A presents results for endogenous liquidity providers (ELPs); Panel B, for designated market makers (DMMs). We report results for the full sample and by market cap quintiles. ST-ELP refers to the subset of ELP accounts that serve as DMM in some stocks. 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 instead of traded prices. Proxies for inventory risk are the average absolute value of intraday inventory, a volatility-adjusted inventory in which the previous measure is multiplied by the stock's volatility during the day, and the signed closing inventory position, all normalized by monthly stock trading volume. We also report the number of times the inventory switches between long and short positions. Profit ratios are calculated by dividing trading profits by normalized intraday average inventory and volatility-adjusted inventory. The profit ratios are divided by 10^6. "Percentage of stock days" represents the proportion of days with ELP participation. The statistics are equally weighted averages across stock-days in the respective sample. Results are reported for large cap (quintile 5), mid cap (quintile 3), and small cap (quintile 1) stocks. Panel B presents trading profits and inventory for the sample of DMMs on stock-days when the DMM and ELPs participate (DMM with ELP) and stock-days when the DMM participates but ELPs do not participate as a group (DMM w/o ELPs). "DMM w/o ELPs" refers to trading days with a high Fragility Score. Results are reported for the full sample of stocks, large cap stocks, mid cap stocks, and small cap stocks. "Percentage of stock days" for 'All stocks: DMM' reports the proportion of trading days in which DMM participates in a stock. Conditional on DMM participation, "Percentage of stock days" reports the proportion of trading days for 'DMM with ELP' and 'DMM w/o ELP' categories. ***, ** and * indicate statistical significance of test of difference at the 1%, 5%, and 10% level, respectively. p-values are calculated based on double clustered standard errors at stock and day level.

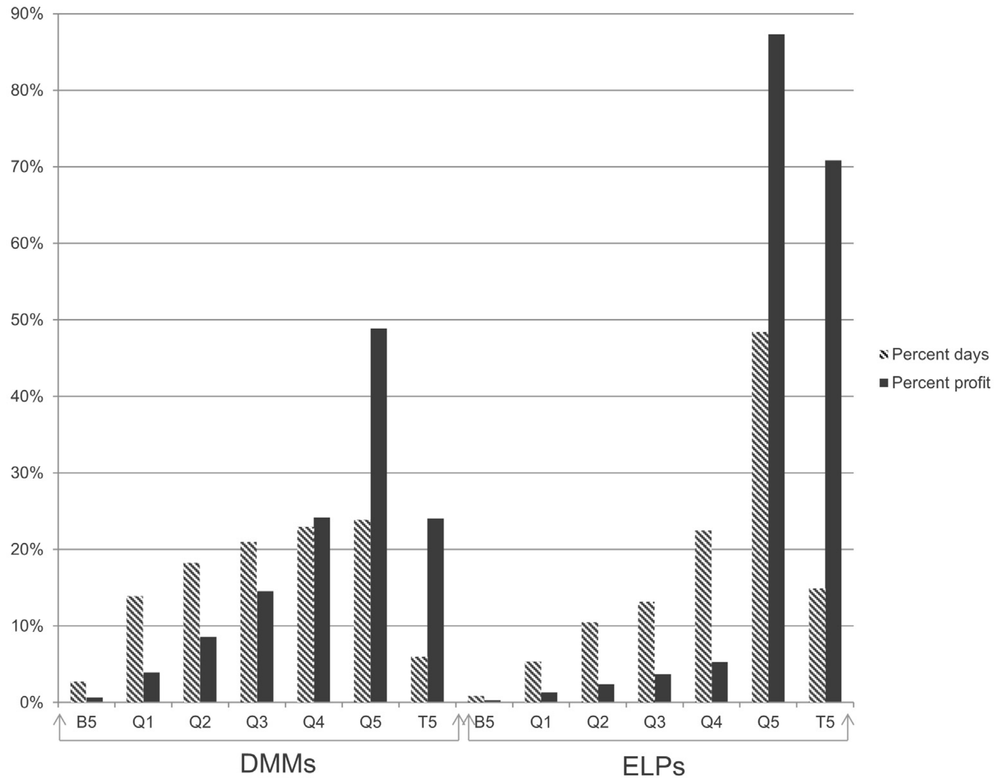
Panel A: Trading profits and inventory risk of endogenous liquidity providers (ELPs)

		Trading profits						Inventory		Trading profits / inventory	
Sample	Percentage of stock-days	Profit (1)	Passive (2)	Active (3)	Positioning (4)	Zero crossing (5)	Signed inventory (6)	Intraday average (7)	Average * Volatility (8)	Average inventory (1)/(7)	Average * Volatility (1)/(8)
All stocks											
ELP	35.9	68.9	119.2	62.7	13.2	4.9	0.00%	0.14%	0.5	1.6	91.0
ST-ELP		122.3	150.3	92.9	67.5	3.1	0.01%	0.10%	0.4	2.5	150.8
Q1 (Small)											
ELP	12.0	61.7	136.6	51.5	−22.0	0.6	0.04%	0.76%	3.3	0.0	0.4
ST-ELP		63.8	151.9	44.3	−42.7	0.7	0.05%	0.67%	2.8	0.0	0.5
Q3 (Mid)											
ELP	22.7	55.1	99.3	61.1	16.1	0.7	−0.03%	0.20%	0.6	0.1	2.3
ST-ELP		86.6	142.2	60.9	5.8	1.0	0.02%	0.14%	0.4	0.2	5.4
Q5 (Large)											
ELP	79.4	92.3	137.8	66.1	21.7	9.0	0.00%	0.02%	0.0	3.1	182.6
ST-ELP		152.2	152.3	116.8	119.0	4.7	0.00%	0.01%	0.0	4.2	261.2

Panel B: Trading profits and inventory risk of designated market makers (DMMs)

		Trading profits						Inventory		Trading profits / inventory	
	Percentage of stock-days	Profit (1)	Passive (2)	Active (3)	Positioning (4)	Zero crossing (5)	Signed inventory (6)	Intraday average (7)	Average * Volatility (8)	Average inventory (1)/(7)	Average * Volatility (1)/(8)
All stocks: DMM	91.9	150.9	255.8	103.6	0.1	3.6	0.08%	0.26%	0.7	1.6	98.0
DMM = ELP		0.00	0.00	0.00	0.22	0.00	0.00	0.00	0.00	0.81	0.40
Trading Days with DMM participation:											
All stocks											
DMM w/o ELP	61.4	92.6	137.6	45.1	1.3	1.2	0.12%	0.37%	1.0	0.2	10.5
DMM with ELP	38.6	243.6***	441.1***	195.4***	−1.8	7.4***	0.03%***	0.09%***	0.3***	3.9***	236.9***
Quintile 1 (small)											
DMM w/o ELP	86.4	41.4	59.6	18.7	1.4	0.4	0.24%	0.73%	2.6	0.0	0.6
DMM with ELP	13.6	52.7*	93.0***	29.2***	−10.5**	0.9***	0.15%***	0.37%***	1.7***	0.1***	1.0***
Quintile 3 (mid-cap)											
DMM w/o ELP	75.9	93.5	132.0	41.8	4.0	1.1	0.10%	0.29%	0.5	0.1	5.3
DMM with ELP	24.1	142.7**	242.5***	80.1***	−19.5	2.2***	0.04%***	0.13%***	0.4***	0.3***	9.3***
Quintile 5 (large)											
DMM w/o ELP	20.4	200.0	330.5	108.3	−21.8	3.2	0.05%	0.12%	0.2	0.8	61.1
DMM with ELP	79.6	333.3***	630.2***	297.7***	1.1	12.3***	0.01%***	0.03%***	0.1***	7.3***	462.3***

Panel A: Participation and profits, by market cap



Panel B: Positioning profits as proportion of total

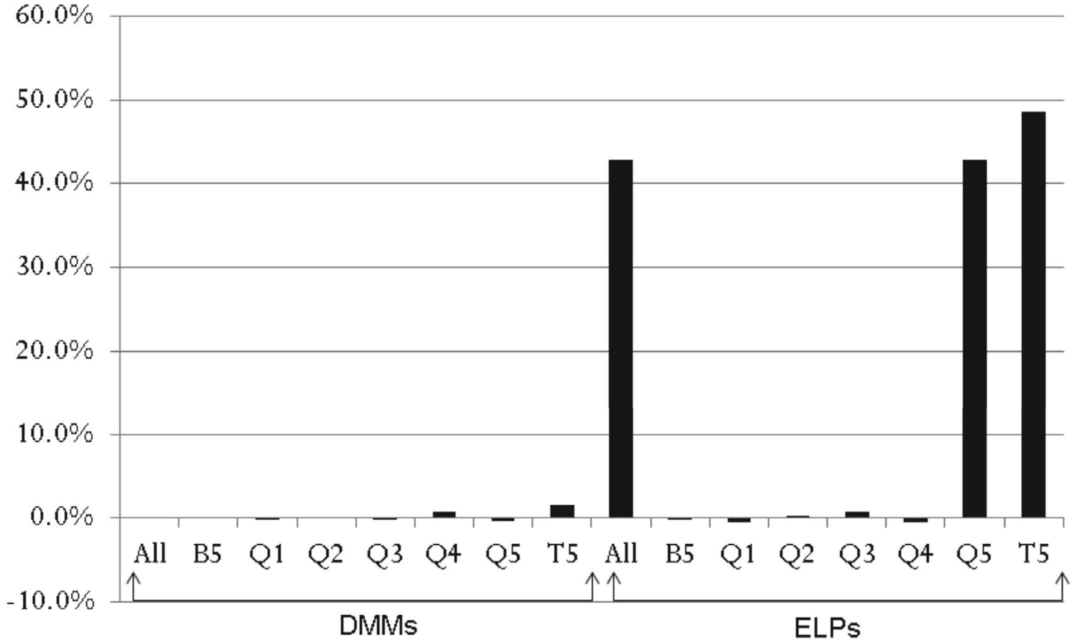
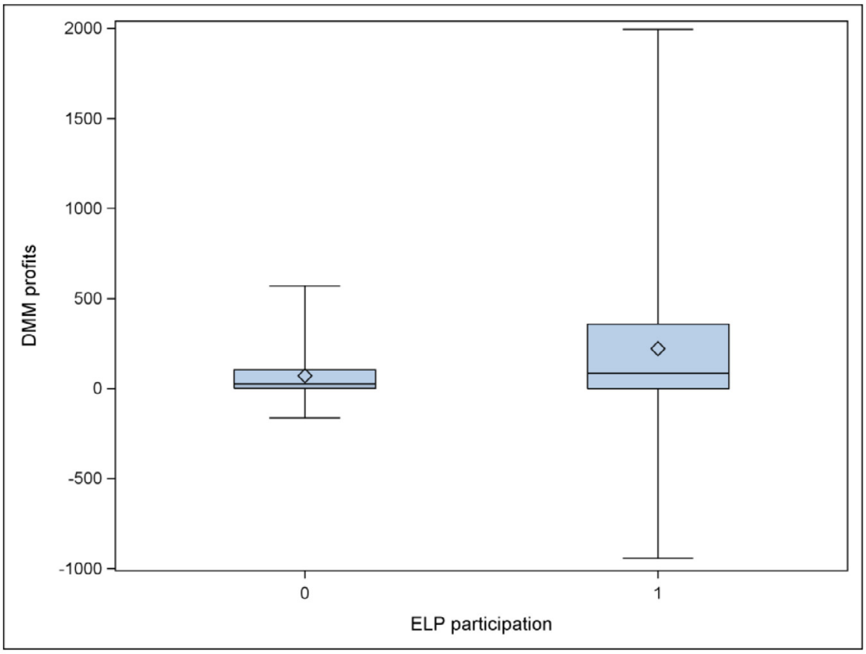


Fig 3. Participation and profits of designated market maker (DMM) and endogenous liquidity provider (ELP). Panel A plots the statistics on participation and profits by market cap quintile and Panel B plots the contribution of positioning profits to total profits. Q1 refers to the quintile of small cap stocks and Q5 refers to the quintile of large cap stocks. B5 and T5 refer to the bottom and top 5th percentiles of market capitalization.

Panel A: DMM profits, by ELP participation



Panel B: Average abs (inventory), by ELP participation

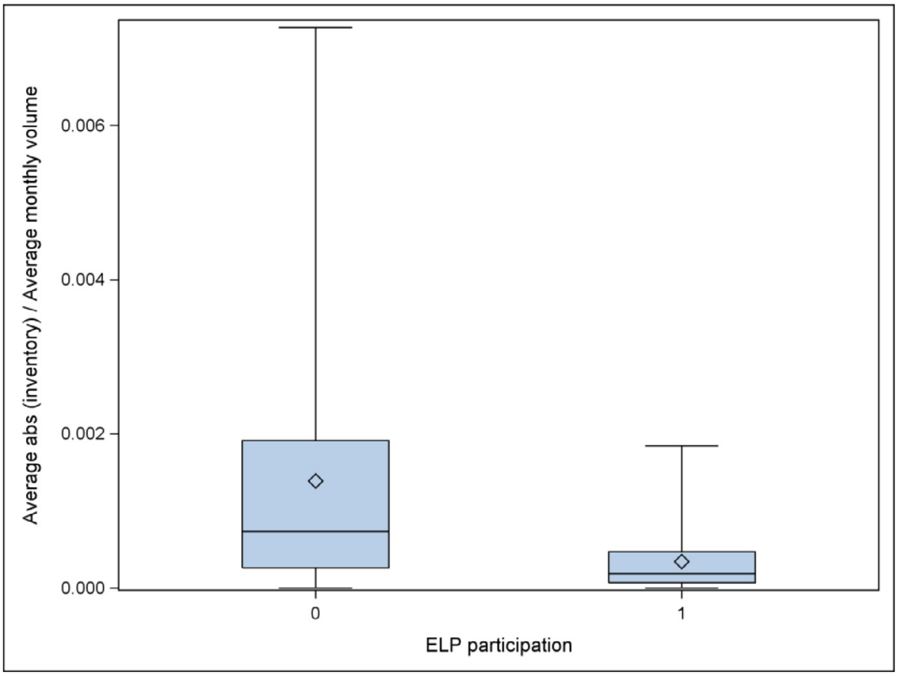


Fig 4. Designated market maker (DMM) profits and inventory risk. A box-and-whiskers plot of the DMM's trading profits (dollars per account per stock-day) is presented in Panel A and the average absolute intraday inventory position is presented in Panel B. The plots use stock-days when ELPs participate in principal trades (code = 1) and stock-days when ELPs as a group do not participate (code = 0). For representative tractability, the plots are trimmed at 5th and 95th percentile.

making when exchanges do not confer an informational advantage on the DMM.

The profitability analysis in Table 5 does not take the TSX fee structure into account because the database does not report the fees associated with each trade. In an unreported analysis, we calculate DMM and ELP profits after incorporating publicly available information on fees obtained from TSX notices to member firms. The primary fee differentiation between DMMs and ELPs exists in terms of trading fees charged by the exchange. The TSX offered two fee structures in 2006: a make-take structure and a structure that charged a fee on a member's active trades. Regardless of the fee structure in place, DMMs typically enjoy a fee advantage, directly because of lower fees and indirectly because they trade more often on the passive side than ELPs (which lowers their net fees in a make-take structure). Thus, incorporating fees results in the difference between DMM and ELP profits being larger with the fee adjustment than without the fee adjustment. Therefore, we find that the conclusions based on Table 5 are robust to the inclusion of fees.

5.1. Time series variation in trading profits and risk

To further understand the economics of market making, Table 6, Panel A, presents the regression coefficients of a stock fixed effects analysis of DMM's daily trading profits (Columns 1 and 3) and trading profits per unit of inventory (Columns 5 and 7), defined as daily profits divided by daily absolute average inventory, on variables that capture market conditions on the stock-day:

$$\begin{aligned}
&\text{Trading Profits}_{i,t}\\
&= \textstyle\sum_i \alpha_i + \beta_1.\mathit{StockVol}_{i,t} + \beta_2.\log\left(\mathit{Stockvolume}_{i,t}\right)\\
&\quad + \beta_3.\mathit{relspread}_{i,t} + \beta_4.\left(\frac{1}{\mathit{Price}_{i,t}}\right) + \beta_5.\mathit{abs}(\mathit{imbal}_{i,t})\\
&\quad + \beta_6.\mathit{Earn_Pre}_{i,t} + \beta_7.\mathit{DownStock}_{i,t}\\
&\quad + \beta_8.\log\left(\mathit{Mktvolume}_{i,t}\right) + \beta_9.\mathit{Downmarket}_{i,t}\\
&\quad + \beta_{10}.\mathit{VIX}_{i,t} + \epsilon_{i,t} \qquad (4)
\end{aligned}$$

where the explanatory variables are defined in Section 4. The analysis is based on trading profits and inventory of DMM accounts because ELPs do not participate on many stock-days, particularly in small stocks. We interpret trading profits per unit of inventory as a proxy of return on capital but acknowledge that assessing the risk of market making is complex and beyond the scope of this paper.[21]

The regression coefficients based on daily trading profits (Column 1) indicate higher profits on trading days when stock volatility is high and stock volume is high. These results are consistent with results in Table 4 that ELP participation is higher on trading days with high stock volume and high stock volatility. In Column 3, we obtain a positive coefficient on market volume, implying that market makers earn more profits when market-wide trading activity is high. The *VIX* coefficient is positive, indicating that higher market volatility is associated with higher profits. Regression coefficients based on trading profits per unit of inventory offer similar insights. Collectively, the results in Tables 4, 5, and 6 describe the economics of market making by showing that market conditions that cause ELPs to scale back in unison are associated with smaller trading profits and higher capital commitment.

We also examine the value of a DMM by modeling the time series variation in *DMMPct*, which measures the importance of DMM as a market maker on a stock-day. Intuitively, the DMM plays a crucial role as a liquidity supplier when ELPs do not participate (*DMMPct* = 1) but plays a less important role when many ELPs are active on a stock-day, which leads *DMMPct* to be small. Columns 9 and 11 report regression coefficients based on stock fixed effects model, in which the dependent variable is the daily *DMMPct* and the explanatory variables are the market conditions on the stock-day. One striking result observed in Table 6, Panel A, is that the regression coefficients in Columns 3 and 11 have the opposite sign, implying that DMM plays a more important role as a market maker when market conditions reduce trading profits on a stock-day. As shown in Table 4, these market conditions are associated with lower ELP participation. Collectively, these results describe the mechanism by which DMMs lower the covariation in liquidity supply across stocks, thereby lowering liquidity risk.

5.2. Analysis of market makers who serve as both DMMs and ELPs

In Table 5, we report significant differences in trading profits, positioning profits, and inventory risk of DMMs and ELPs. Because ELP identification relies on a propensity score model, one concern is that traders identified by the model as ELPs have different skills than traders assigned as DMMs. In this sub-section, we rely on a model-free identification of ELPs by examining the sub-sample of traders who have obligations in assigned stocks (DMM) but also trade other stocks without obligations (*ST-ELP*). The regression specification is a trader fixed effects model that includes market conditions and an indicator variable *ST-ELP* that equals one for trades in an unassigned stock and equals zero for trades in the assigned stock with obligations. The analysis is based on large capitalization stocks because ELPs' trading profits and risk are well populated for this sample.

In Panel B of Table 6, we report the regression coefficients, which broadly provide support for the univariate results in Table 5. We conclude based on the negative coefficient on *ST-ELP* in Column 1 that market makers earn higher profits as DMMs than as ELPs. Higher profits can be attributed to passive, liquidity-supplying trades, as evidenced by the statistically significant negative *ST-ELP* coefficient in the passive profits regression. The TSX market structure allows the DMM the option to participate in a trade ahead of other orders with time priority in the book and also to execute all odd-lot trades. The higher passive profits suggest that trading privileges serve as a mechanism to compensate DMMs.

[21] In a robustness analysis, we find similar results when trading profits are defined as daily aggregate profits for all market makers (both DMM and ELPs) on the stock-day.

Table 6
Regression analysis of the determinants of trading profits and the importance of the designated market maker (DMM).

This table presents the regression coefficients of a multivariate analysis of stock characteristics and market conditions on trading profits and DMM importance. Panel A presents the results of a stock fixed effects specification in which the dependent variables are DMM's daily profits on the stock-day, the DMM's risk-adjusted profits defined as daily profits divided by the absolute value of average inventory (normalized by trading volume in the stock), and the relative importance of the DMM on the stock-day measured by *DMMPct* as defined in Eq. (2). The explanatory variables are stock- and market-level conditions, including the stock volume, intraday volatility, percentage quoted spread, 1/price, absolute value of the order imbalance, a dummy variable that equals one if the stock-day is a pre-earnings announcement day, downstock (equals one if the rolling 30-day stock return is negative), downmarket (equals one if the rolling 30-day market return is negative), the US market VIX (Chicago Board Option Exchange Volatility Index) and the share volume of all securities traded on Toronto Stock Exchange (TSX) on the day. *p*-values are based on standard errors clustered at the stock level. Panel B presents the results of a multivariate analysis of the impact of stock characteristics and market conditions on trading profits and capital commitment for large stocks. Only user accounts who serve as both DMMs and endogenous liquidity providers (ELPs) are included in the analysis. ST-ELP is an indicator variable that equals one when the user account trades as an ELP and equals zero when the user account trades as the DMM in the stock. The specification includes user account fixed effects. Capital commitment is the average absolute value of intraday inventory (normalized by trading volume in the stock). We present results for overall trading profits, passive profits, and positioning profits. *p*-values are based on standard errors clustered at the stock level.

Panel A: Dependent Variables are trading profits, profits per capital and the importance of DMM on a stock-day

	Trading profits				Trading profits per unit of capital				DMM importance			
Variables	(1)	*p*-value (2)	(3)	*p*-value (4)	(5)	*p*-value (6)	(7)	*p*-value (8)	(9)	*p*-value (10)	(11)	*p*-value (12)
Stock variables												
Log (stock volume)	31.13	0.00	28.31	0.00	0.22	0.00	0.20	0.00	−0.03	0.00	−0.03	0.00
Volatility (intraday)	50.24	0.00	48.62	0.00	0.18	0.00	0.15	0.00	−0.04	0.00	−0.04	0.00
Quoted spread (percent)	14.96	0.00	14.92	0.00	0.04	0.00	0.04	0.00	0.00	0.00	0.00	0.00
Price (inverse)	−7.48	0.00	−6.29	0.00	0.00	0.94	0.02	0.15	−0.01	0.00	0.00	0.02
Abs(Imbalance)	−31.68	0.27	−31.48	0.26	−0.08	0.29	−0.08	0.29	0.02	0.00	0.02	0.00
Earn_Pre	58.59	0.34	56.36	0.37	0.89	0.03	0.88	0.03	−0.01	0.02	−0.01	0.02
Downstock	8.83	0.57	6.93	0.61	0.07	0.44	0.02	0.87	0.00	0.00	0.00	0.28
Market variables												
Log (market volume)			109.35	0.00			1.02	0.00			−0.01	0.00
Downmarket			16.36	0.17			0.22	0.00			0.00	0.23
VIX			3.85	0.03			0.06	0.06			0.00	0.00
Stock fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Adj. R^2	1.6%		1.60%		29.0%		29.1%		69.2%		69.3%	
N	186,232		186,232		186,232		186,232		186,232		186,232	

Panel B: Dependent Variable: Trading Profits and Capital Commitment in Large Stocks

	Trading profits		Passive profits		Positioning profits		Capital commitment	
Variables	(1)	*p*-value (2)	(3)	*p*-value (4)	(5)	*p*-value (6)	(7)	*p*-value (8)
ST-ELP Dummy	−193.23	0.00	−489.42	0.00	118.22	0.06	−0.0001	0.03
Stock variables								
Log (stock volume)	33.16	0.00	104.49	0.00	−9.91	0.52	−0.0001	0.00
Volatility (intraday)	19.61	0.69	36.88	0.47	43.00	0.40	0.0000	0.45
Quoted spread (percent)	184.80	0.01	336.29	0.00	−35.87	0.39	0.0011	0.06
Price (inverse)	0.27	0.37	0.83	0.08	−0.43	0.00	−0.1078	0.00
Abs(Imbalance)	−167.97	0.00	−57.44	0.03	−148.04	0.00	0.0003	0.00
Earn_Pre	−0.56	0.99	−0.47	0.97	1.72	0.96	0.0000	0.55
Downstock	2.49	0.80	−1.45	0.86	8.67	0.28	0.0000	0.13
Log (market cap)	24.83	0.12	0.82	0.97	14.20	0.26	0.0001	0.03
Market variables								
Log (market volume)	162.40	0.00	24.61	0.12	148.59	0.00	0.0001	0.02
Downmarket	13.75	0.42	3.58	0.62	21.25	0.22	0.0000	0.95
VIX	8.62	0.00	5.27	0.04	7.91	0.01	0.0000	0.46
Stock fixed effects	Yes		Yes		Yes		Yes	
Adj. R^2	6.0%		35.2%		7.4%		20.8%	
N	68,176		67,035		67,035		68,176	

The positive coefficient for *ST-ELP* obtained in the positioning profits regression indicates that, after controlling for trader-specific attributes including trading skill, TSX obligations restrict the DMM′s ability to participate opportunistically in a designated stock. As an example, the obligation could restrain the ability to use market orders to enter and exit positions. In Column 7, the negative coefficient on the *ST-ELP* coefficient in average intraday inventory regression suggests that traders commit more capital in an assigned stock. Thus, traders earn higher profits but commit more capital in assigned stocks.

5.3. Auto-participation and market conditions

The mechanism to compensate DMMs is critical to the viability of the DMM model. On TSX, compensation in the form of auto-participation violates time priority and runs counter to the principal of a fair market by favoring DMMs at the expense of other liquidity providers. Therefore, it is important to understand the scenarios under which DMMs use this compensation mechanism. There are two possibilities: Auto-participation allows DMMs to earn extra profits in favorable periods, which subsidizes market making in stressful periods. Alternately, auto-participation

Table 7
Regression analysis of the designated market maker's (DMM) auto-participation decision on market conditions.
This table presents results of the stock fixed effects regressions of the decision to auto-participate in a stock on market conditions. The dependent variable in Columns 1–6 is the proportion of DMM's daily trading volume that is executed using the auto-participation mechanism. The dependent variables are Fragility Score, DMMPct, and a number of variables that proxy for stock and market conditions. In Columns 7–12, the dependent variable is the difference between the proportion of trading volume that is executed using the auto-participation flag and the proportion of trading volume that is executed without the auto-participation flag (normal trades). Normal trades exclude trades occurring due to auto-participation, odd-lot trades, and guaranteed fill trades. *p*-values are calculated based on double clustered standard errors at stock and day level.

	Percentage of DMM's daily trading volume executed using auto-participation flag						Difference in percentage volume executed with autoparticipation versus normal trades					
		p-value		*p*-value		*p*-value		*p*-value		*p*-value		*p*-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Fragility Score	0.002	0.03					0.001	0.00				
DMMPct			0.001	0.00					0.054	0.00		
Stock variables												
Log (stock volume)					−0.003	0.00					−0.047	0.00
Volatility (intraday)					−0.037	0.00					−0.102	0.00
Quoted spread (percent)					−0.011	0.00					−0.027	0.00
Price (inverse)					−0.001	0.87					0.013	0.02
Abs(Imbalance)					0.014	0.00					0.075	0.00
Earn_Pre					0.001	0.91					−0.004	0.74
Downstock					−0.003	0.14					−0.011	0.00
Market variables												
Log (market volume)					0.016	0.00					0.004	0.57
Downmarket					−0.003	0.09					−0.013	0.00
VIX					0.001	0.01					-0.001	0.79
Stock fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Adj. R^2	24.0%		24.0%		25.3%		24.0%		24.0%		28.0%	
N	189,163		191,735		183,635		189,163		191,735		183,635	

makes market making easier on days when conditions are stressful and allows DMMs to facilitate trading when the economics of market making are otherwise unfavorable.[22] In Table 7, we report stock fixed effects regressions in which the dependent variable is the percentage of DMM's daily trading volume executed using the auto-participation flag. We examine the daily association between the stock's auto-participation rate and the Fragility Score (Column 1) and *DMMPct* (Column 3), which serve as a comprehensive proxy for market conditions. We obtain a positive regression coefficient in both columns, indicating that auto-participation plays an important role for the DMM on trading days when ELPs scale back on participation and the DMM steps in to fulfill obligations. The results in Column 5 support this interpretation. That is, the DMM executes more volume with auto-participation on trading days when stock volume is low, stock volatility is low, and order imbalance is high. Results in Table 6 indicate that these market conditions are associated with lower profits and higher inventory risk. In Columns 7, 9 and 11, we present results based on the difference between the proportion executed through auto-participation and normal trading on a day. Normal trades exclude trades occurring due to auto-participation, odd-lot trades, and guaranteed fill trades, and they serve as a control for omitted market conditions that affect DMM participation. Results based on the difference specification yield similar insights.

In unreported analysis, we estimate the trading profits per share and the five-minute price impact for DMM's trades executed with auto-participation versus normal trades. Using paired differences on the same stock-day, we find that auto-participation trades earn higher profits per share (*P*-value of difference = 0.00), which can be attributed almost entirely to the smaller price impact of trades (*P*-value = 0.00).

Overall, the results support the following interpretation: Auto-participation by DMMs is observed more often under market conditions that are unfavorable for market making. Under these unfavorable conditions, the ability to auto-participate allows DMM to selectively participate in trades with lower adverse selection risk, which yields higher profits but potentially allows the market to stay open. The results do not support that trading privileges are used to earn higher profits on proprietary trades in favorable periods, possibly due to significant quoting responsibilities and monitoring by the exchange.

6. Conclusions

Improvements in technology and increased competition among trading venues have vastly expanded the pool of proprietary trading desks playing the role of market makers. These participants have no obligations to facilitate trading but choose to supply liquidity when it is profitable. At the same time, the role of market makers with exchange-assigned obligations, such as the NYSE specialist, has declined in recent years. Subsequent to the 2010 Flash Crash, regulators have expressed concern that a market structure that relies on ELPs for liquidity provision is inherently fragile.

[22] Auto-participation increases the execution probability of a limit order and makes it easier to manage position risk without paying the bid-ask spread. In addition, auto-participation allows trading without displaying the depth to the market.

In this study, we present the first direct empirical evidence in support of regulatory concerns that ELPs enter and exit the stock in a correlated manner. We implement the methodology used in the analysis of liquidity commonality in Chordia, Roll, and Subrahmanyam (2000) to show that ELPs exhibit statistically significant positive covariation in liquidity supply, both within a stock and across stocks. Based on multivariate, stock fixed effects regression, we identify market conditions that lower ELPs' aggregate participation. In addition, we relate market conditions to the trading profits and inventory risk of market makers, thus establishing the link between the participation decision and the economics of market making. Contrary to a popular view, high stock volatility is related to greater profit potential and higher ELP participation. We identify trading volume as an important determinant of liquidity supply and further show that fragility concerns apply to large stocks and to the active ELPs in a stock.

The recent theoretical work by Bessembinder, Hao, and Zheng (2015) shows that a DMM contract with an obligation to narrow bid-ask spreads prevents market failure and improves social welfare when information asymmetry is heightened. The extant empirical literature on DMMs as well as many regulatory initiatives has offered affirmative obligations as a solution to improve liquidity supply in small stocks. For example, Nasdaq has introduced quoting and trading obligations on registered market makers in newly launched ETFs under its market quality program. While our study concludes that DMMs lower execution uncertainty for small stocks, the synchronized withdrawal by ELPs when market conditions are unfavorable has the potential to create periodic illiquidity in large stocks as well. Our results indicate that market maker obligations that require continuous participation and impose limits on maximum spreads serve as a mechanism to mitigate failure under adverse conditions in both large and small stocks.

Our study identifies circumstances in which obligations become binding and highlights the related but largely neglected issue of compensating market makers with obligations. Saar (2011) provides an excellent review of compensation structures observed in electronic markets today. In many global stock markets, such as Amsterdam, Brussels, Frankfurt, Oslo, Paris and Stockholm, the listed firm compensates the DMM via an annual fee based on a liquidity agreement. Prior studies find that DMM compensation is explained by the contractual obligations described in liquidity agreements [see Anand, Tanggaard, and Weaver (2009)] and the potential for earning lucrative investment banking business in the future [see Skjeltorp and Odegaard (2015)]. However, as per Financial Industry Regulatory Authority (FINRA) rule 5250, this type of arrangement in which an issuer directly compensates a market maker is prohibited in the US. In this paper, we study an alternative compensation mechanism that can be considered for US stocks – the ability to auto-participate ahead of limit orders with time priority in the queue, which is being used by TSX and the larger US options exchanges. We find that DMMs more often exercise the option to auto-participate under unfavorable market conditions, suggesting that the mechanism helps DMMs to facilitate trading on difficult days.

We conclude that a DMM contract that balances trading privileges with both stringent affirmative obligations and exchange monitoring offers a possible mechanism to reduce market fragility. As noted in the joint SEC-CFTC report, a fragmented market structure makes it difficult for an individual exchange to provide market makers with sufficient incentives to accept meaningful quoting and trading obligations. Therefore, US and European regulators need to solve the coordination problem by implementing, through incentives or regulation, a uniform system of market maker obligations and compensation for all the exchanges that trade the security.

Appendix. Description of the TSX data

We identify 94 member firms in the TSX database of which 22 firms have user IDs associated with DMMs. All retail and institutional orders are routed through a user ID (trader) at a member firm.[23] The trader can internalize the order; that is, execute the order against the firm's capital as a proprietary trade or execute against another client's order. As per IIROC rules, internalized orders must offer price improvement, which results in most client orders being routed to the limit order book. When brokers submit anonymous orders, information on Broker ID is not displayed to market participants but is reported in the database.[24] Member firms offer direct market access (DMA) to larger clients (e.g., hedge funds). Therefore, similar to IIROC (2012), we do not exclude client (CL) accounts from our analysis but the selection criteria yields only a small number of client accounts as ELPs. The results are similar when these accounts are excluded from the sample.

We examine transactions of common stocks that occur during regular trading hours (9:30 a.m. – 4:00 p.m.). We 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. Information on corporate events and shares outstanding are obtained from the monthly *Toronto Stock Exchange Review* publications. 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 indexes). Activity is dramatically lower on days when US 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 in which the difference between the bid and ask quotes is greater than $5.

[23] Investment Industry Regulatory Organization of Canada (IIROC), the self-regulatory organization that oversees Canadian debt and equity markets, classifies member firms into retail, institutional, proprietary, integrated, and "other" category composed of managed accounts and corporate finance.

[24] Once placed on the book, a broker can violate time priority and trade with the client's order if the broker's ID is displayed at the inside bid or ask quote to market participants. For this reason, large brokers with considerable client volume use anonymous orders less frequently.

References

Acharya, V., Viswanathan, S., 2011. Leverage, moral hazard, and liquidity. Journal of Finance 66, 99–138.

Aitken, M., Cumming, D., Zhan, F., 2015. High frequency trading and end-of-day price dislocation. Journal of Banking and Finance 59, 330–349.

Anand, A., Hua, J., McCormick, T., 2015. Make-take structure and market quality: evidence from the US options markets. Management Science, forthcoming.

Anand, A., Tanggaard, C., Weaver, D., 2009. Paying for market quality. Journal of Financial and Quantitative Analysis 44, 1427–1457.

Baron, M., Brogaard, J., Kirilenko, A., 2012. The trading profits of high--frequency trades Unpublished working paper. Princeton University, Princeton, NJ.

Bessembinder, H., Hao, J., Zheng, K., 2015. Market making contracts, firm value, and the IPO decision. Journal of Finance 70 (5), 1997–2028.

Brogaard, J., Hendershott, T., Riordan, R., 2014. High-frequency trading and price discovery. Review of Financial Studies 27, 2267–2306.

Chordia, T., Green, T., Kottimukkalur, B., 2015. Do high-frequency traders need to be regulated? Evidence from algorithmic trading on macro news Unpublished working paper. Emory University, Druid Hills, GA.

Chordia, T., Subrahmanyam, A., 2004. Order imbalance and individual stock returns: theory and evidence. Journal of Financial Economics 72, 485–518.

Chordia, T., Roll, R., Subrahmanyam, A., 2000. Commonality in liquidity. Journal of Financial Economics 56, 3–28.

Coughenour, J., Saad, M., 2004. Common market makers and commonality in liquidity. Journal of Financial Economics 73, 37–69.

Clark-Joseph, A., 2012. Exploratory trading Unpublished working paper. University of Illinois, Urbana-Champaign, IL.

Glosten, L., 1994. Is the electronic open limit order book inevitable? Journal of Finance 49, 1127–1161.

Grossman, S., Miller, M., 1988. Liquidity and market structure. Journal of Finance 43, 617–633.

Handa, P., Schwartz, R., 1996. Limit order trading. Journal of Finance 51, 1835–1861.

Hasbrouck, J., Saar, G., 2013. Low-latency trading. Journal of Financial Markets 16, 646–679.

Hasbrouck, J., Seppi, D., 2001. Common factors in prices, order flows, and liquidity. Journal of Financial Economics 59, 383–411.

Hasbrouck, J., Sofianos, G., 1993. The trades of market makers: an analysis of NYSE specialists. Journal of Finance 48, 1565–1594.

Hendershott, T., Jones, C., Menkveld, A., 2011. Does algorithmic trading improve liquidity? Journal of Finance 66, 568–604.

Hendershott, T., Riordan, R., 2013. Algorithmic trading and the market for liquidity. Journal of Financial and Quantitative Analysis 48, 1001–1024.

Hirschey, N., 2013. Do high-frequency traders anticipate buying and selling pressure? Unpublished working paper. London Business School, London, UK.

Hu, G., Pan, J., Wang, J., 2013. Earl peek advantage? Unpublished working paper. Massachusetts Institute of Technology, Cambridge, MA.

IIROC, 2012. The HOT Study, Phases I and II of IIROC's Study of High-Frequency Trading Activity on Canadian Equity Marketplaces. Investment Industry Regulatory Organization of Canada, Toronto, Ontario, Canada.

Kennedy, P., 2003. A Guide to Econometrics. MIT Press, Cambridge, MA.

Kirilenko, A., Kyle, A., Samadi, M., Tuzun, T., 2011. The flash crash: the impact of high-frequency trading on an electronic market Unpublished working paper. Massachusetts Institute of Technology, Cambridge, MA.

Menkveld, A., 2013. High-frequency trading and the new market makers. Journal of Financial Markets 16, 712–740.

Menkveld, A., Wang, T., 2013. How do designated market makers create value for small-caps? Journal of Financial Markets 16, 571–603.

Nimalendran, M., Petrella, G., 2003. Do 'thinly-traded' stocks benefit from specialist intervention? Journal of Banking and Finance 27, 1823–1854.

Panayides, M., 2007. Affirmative obligations and market making with inventory. Journal of Financial Economics 86, 513–542.

Pastor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Perotti, P., Rindi, B., 2010. Market makers as information providers: the natural experiment of star. Journal of Empirical Finance 17, 895–917.

Raman, V., Robe, M., Yadav, P., 2014. Electronic market makers, trader anonymity, and market fragility Unpublished working paper. University of Warwick, Coventry, UK.

Saar, G., 2011. Specialist markets. In: Cont, R. (Ed.), Encyclopedia of Quantitative Finance. John Wiley & Sons, Chichester, West Sussex, UK.

Securities and Exchange Commission, 2010. Concept Release on Equity Market Structure. Release no. 34-61358. US Government Printing Office, Washington, DC.

Skjeltorp, J., Odegaard, B., 2015. When do listed firms pay for market making in their own stock? Financial Management 44, 241–266.

Stoll, H., 2000. Friction. Journal of Finance 55, 1479–1514.

Venkataraman, K., Waisburd, A., 2007. The value of a designated market maker. Journal of Financial and Quantitative Analysis 42, 735–758.