Are Market Makers Incentivized to Provide Liquidity? Evidence from the Nasdaq

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Abstract

We explore the effectiveness of Nasdaq's Qualified Market Maker (QMM) program, an incentive scheme meant to encourage liquidity provision, focusing on the requirement that participants submit a quota of non-anonymous quotes attributed to their market participant identification number (MPID). Using a panel dataset aggregated from high-frequency trade and quote data that contains information on MPIDs, we explore both the determinants of MPID revelation, along with their implications for market quality. We find that, while market makers are incentivized to provide "patient" liquidity through their MPID-attributed orders, these orders typically reflect momentum (rather than contrarian) strategies. Secondly, while MPID-attributed orders from market makers tend to attract counterparties, there is little evidence that they lead to improved market quality. Therefore, by requiring market makers to expose themselves to higher adverse selection through identity revelation, this incentive program may be counterproductive to the goal of stabilizing markets.

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1 Introduction

While equity market makers were traditionally agents appointed by exchanges to maintain orderly markets , recent years have seen the rise of so-called "endogenous liquidity providers" (ELPs), who are not appointed by exchanges but arise as liquidity providers on their own accounts. This shift has led many U.S. equity trading platforms to implement programs to properly incentivize and obligate this new type of market maker to maintain orderly markets and provide liquidity, though questions remain as to their success.[1] Recent literature has focused much attention on "market fragility": Without the presence of exchange-mandated obligations, ELPs tend to withdraw liquidity provision in unison once conditions become suboptimal, as in times of high price uncertainty and order imbalances when liquidity would be most needed (see, e.g., Bessembinder et al., 2015; Anand and Venkataraman, 2016).[2] Raman et al. (2014) argues that market fragility can become particularly severe given the anonymity of modern electronic markets, as market makers can no longer use reputation and long-term relationships to identify and credibly discipline those who trade on private information (Battalio et al., 2007).[3]

Within this context, this paper explores the effectiveness of Nasdaq's Qualified Market Maker (QMM) program in incentivizing liquidity provision in highly anonymous markets. We focus in particular on the requirement that, to register as a qualified market maker under this program, participants are required submit a certain amount of non-anonymous quotes attributed to their market participant identification number

[1]Examples of liquidity provider incentive programs in the United States include the Qualified Market Maker Program on Nasdaq and the Designated Market Market Program on the NYSE in the United States, and in Europe the Deutsche Börse's Xetra Liquidity Provider Program, explored in Clapham et al. (2017).

[2]In a speech before the Economics Club of New York, Securities and Exchange Commission (SEC) chairman Mary L. Shapiro expressed concern "whether the firms that effectively act as market makers during normal times should have any obligation to support the market in reasonable ways in tough times." (see "Strengthening Our Equity Market Structure", 7 September 2010, available at https://www.sec.gov/news/speech/2010/spch090710mls.htm). In a report written in response to the May 2010 Flash Crash, a joint committee of the SEC and Commodity Futures Trading Commission (CFTC) emphasizes that "...there remain legitimate concerns over the absence of present incentives for market participants to provide liquidity in the present market structure." (see "Recommendations Regarding Regarding Regulatory Responses to the Market Events of May 6, 2010", 18 Februrary 2011, available at http://www.cftc.gov/idc/groups/public/@aboutcftc/documents/file/jacreport_021811.pdf).

[3]The tendency of liquidity to disappear when it is needed most by long-term investors is also refered to as "ghost" and "phantom" liquidity by regulators and in the literature. See, for example, van Kervel (2015); Korajczyk and Murphy (2017).

(MPID). Specifically, the program stipulates that a QMM must, on a daily basis, post displayed quotes at the national best bid and offer (NBBO) during at least 25% of trading hours in at least 1,000 securities.[4] In return, market makers receive additional rebates on liquidity provision, along with other privileges. However, given their fulfillment of this quota of MPID-attributed orders, the choice of when and under what circumstances to reveal their presence is still at the discretion of the individual market maker. This has put modern market makers at a crossroads in terms of avoiding adverse selection and exposure in highly anonymous markets, against fulfilling their role as liquidity providers.

At the same time, it is not necessarily straightforward what the role of a proper liquidity provider should be. According to more classical definitions of market makers, the goal of liquidity provision should simply be the "patient" provision of limit orders, to meet demand from and help smooth out the non-synchronous arrival of "impatient" buyers and sellers (see, e.g., Grossman and Miller, 1988). On the other hand, more recent authors have begun to argue that the definition of liquidity provision should be generalized to describe the use of contrarian trading to actively correct and stabilize prices that deviate from fundamental values (see, e.g., Hendershott and Menkveld, 2014; Van Kervel and Menkveld, 2018). Biais et al. (2016) argue that the latter type of liquidity provision is less likely to contribute to market fragility, as such liquidity providers tend to stay in the market when price uncertainty increases.

Accordingly, we explore the determinants of non-anonymous intervention by market makers on the Nasdaq, and the implications that this may have for market quality. Specifically, this paper asks: Are MPID-attributed orders submitted by market makers in line with their obligations to provide liquidity? To what extent do they respond to market conditions in which they must intervene as "patient counterparties," and to what extent do they act as "contrarian traders," according to the two definitions of liquidity provision? Secondly, how does the market react to non-anonymous orders posted by market makers? In order to address these questions, we use a unique dataset that reconstructs the limit order book for several Nasdaq-traded stocks. Our dataset contains information on whether or not a limit order is submitted anonymously, and, given non-anonymity, the market participant identifier number (MPID) of the submitter. This allows us to identify the non-anonymous orders submitted by market makers. In answering these questions, we aim to contribute insights into whether liquidity provision

[4]See http://Nasdaq.cchwallstreet.com/Nasdaq/main/Nasdaq-equityrules/chp_1_1/chp_1_1_4/chp_1_1_4_6/chp_1_1_4_6_5/chp_1_1_4_6_5_4/default.asp.

incentive schemes put into place by modern exchanges indeed properly incentivize market makers to maintain orderly markets and provide liquidity when it is needed.

In a first step, to determine what drives the MPID revelation decision, we perform a fixed effects panel regression of MPID submission intensities on lagged market characteristics, in which MPID submissions intensities are defined as the ratio of MPID-attributed submissions to total submissions. Additional robustness checks consider results from time series regressions on a stock-by-stock basis, and also the behavior of an individual market maker (the largest market maker in our sample, Timber Hill, LLC) to minimize possible noise from market makers following different strategies. In a second step, to measure the market's reaction to MPID-attributed orders, we perform panel regressions of market quality measures on lagged measures of MPID submission intensities. As submission intensities and market quality can be co-determined, we address this endogeneity first by using a two-stage least square (2SLS) panel regression in which we instrument for MPID-attributed submission intensities. Following Comerton-Forde and Putnis (2015) and others, for a given stock we use the average MPID-attributed submission intensities in other sample stocks, as the level of MPID submissions in other stocks is correlated with that of a particular stock (the average correlation coefficient across stocks is 12.5%) but unlikely to be driven by the characteristics of the particular stock. As an alternative to 2SLS, we also perform the Heckman (1979) correction procedure, which includes into the regression a "correction" term to control for the potential endogeneity problems introduced by self-selection.

Our main results can be summarized as follows. In terms of the determinants of market maker MPID attribution, the results are consistent with the hypothesis that the market makers submit MPID-attributed orders in their capacity to provide liquidity when the supply of limit orders is low. A one-standard deviation decrease in submission volumes leads to a relative increase in MPID-attributed submissions by market makers of 2-4%, and a one-standard deviation decrease in depth increases MPID-attributed submissions by about 1-2%. MPID-attributed order submissions by market makers are also higher following intervals of high volatility and high relative bid-ask spreads, reflecting a response to illiquid conditions on the limit order book. However, market makers are not shown to respond with MPID-attributed orders to intervals of high pricing errors, nor are they shown to submit orders that would act against movements in prices. In fact, submission strategies are more consistent with momentum than with contrarian trading: market makers are 55% more likely to submit attributed orders in the same direction as price movements. Therefore, Nasdaq's incentive program seems to encourage visible interventions by market makers in the sense of a more classical definition of liquidity provision, but does not necessarily encourage them to intervene to correct and stabilize prices.

As for the market's reaction to MPID-attributed submissions by market makers, the results indeed show that MPID-attributed orders by market makers succeed at increasing the number of executions. A one-standard-deviation increase in the intensity of MPID-attributed submissions increases same-side execution volumes by 8-14%. However, this increased rate of market participation does not seem to translate into an improvement in market quality. There is little evidence that MPID-attributed orders are followed by lower relative bid-ask spreads or volatility. Same-side submissions decrease in response to higher MPID submission intensities, leading to an overall deterioration in depth.

Taken together, these results show that, while liquidity provision incentive programs on Nasdaq indeed encourage market makers to submit patient limit orders to meet liquidity demand, there are little incentives for them to respond to correct destabilized prices. In fact, the requirement that they reveal their MPID, thereby exposing themselves to adverse selection, may strongly reduce their incentives to intervene in response to pricing errors. Since little improvement in market quality is found absent this incentive, the "contrarian trader" role of liquidity provision may be crucial in transferring the incentives to provide liquidity into real benefits for modern markets.

Our paper is most closely related to that of Comerton-Forde et al. (2011), who examine the determinants and impact of anonymous trading on the Toronto Stock Exchange, using trading book data from 1 May to 31 July 2004. These authors find that traders use anonymity when submitting informed orders, and that anonymity can reduce the executions costs of orders that are large and aggressive. However, it should be noted that the properties of their dataset hint that TSX at this period of time had a very different trading landscape than that of the present study. While 2.86% of orders in our sample are submitted non-anonymously, in the dataset of Comerton-Forde et al. (2011) about 94% are submitted non-anonymously. Furthermore, TSX stocks each have a designated market maker firm who is compensated directly by the issuer for maintaining an orderly market in that stock; such contracts are currently prohibited in the U.S. under FINRA Rule 5250.[5] In addition, our paper is related to two working papers. Both Ben-

[5]See FINRA Rule 5250, Payments for Market Making: "No member or person associated with a member

hami (2006) and Karam (2012) examine the value of the choice of (non-) anonymity for Nasdaq traders; however, both papers use datasets that pre-date the implementation of Regulation National Market System (Reg NMS), after which most trading shifted onto ECNs that more easily facilitate anonymous trading.

The remainder of this paper is organized as follows. Section 2 describes the economic foundations to our paper and lays out our hypotheses regarding the determinants of and market reactions to non-anonymous market maker intervention. Details on our unique dataset, along with descriptions of the MPID data and our measure of MPID submission intensity, are provided Section 3. Section 4 describes the methodology and empirical results for our question on the determinants of market maker intervention, while Section 5 does the same addressing our question regarding market reactions to market makers' non-anonymous interventions. Finally, Section 6 concludes.

2 Economic Foundations

The first aim of our paper is to address the question: Do market makers submit non-anonymous orders according to their obligations to provide liquidity? In order to examine this question, it is first necessary to clarify what the purpose and function of a market maker as a provider of liquidity should be.

A more classic definition of liquidity provision focuses on liquidity providers as "patient" traders, who submit limit orders to meet liquidity demand from market-order-submitting "impatient" traders. Demsetz (1968) identifies the non-synchronous arrival of buyers and sellers into a market as one of the key frictions in financial markets. However, he proposes that this problem can be alleviated by market makers who bridge the gaps between these non-synchronous arrivals. In subsequent papers, Garbade and Silber (1979) and Grossman and Miller (1988) show that market makers help to mitigate order imbalances and lower execution risk for other market participants. According to this "patient-counterparty" definition, the main role of market makers should be to serve as counterparties to impatient traders when no others are available.

shall accept any payment or other consideration, directly or indirectly, from an issuer of a security, or any affiliate or promoter thereof, for publishing a quotation, acting as market maker in a security, or submitting an application in connection therewith." Available at http://finra.complinet.com/en/display/display_main.html?rbid=2403&element_id=8626.

Guided by this intuition, if liquidity providers are indeed properly incentivized and/or obligated to act as market makers according to this definition, then submitted quotes that are attributed to a market maker MPID should reflect this role. We would expect to see a higher rate of MPID-attributed quotes when limits orders are insufficient to meet liquidity demand, i.e., when available depth is relatively low, order submissions are relatively low, and order executions are relatively high.[6] We might also see a higher rate of MPID-attributed quotes when depth on the books is low, as this represents a low supply of limit orders.

On the other hand, with the rise of modern electronic market structures and changing incentives for traders, some have argued that the definition of what it means to supply liquidity requires a further update. Specifically, liquidity providers should be seen as "contrarian" traders who prevent large pricing fluctuations by trading against error-driven price movements, and in this sense can supply liquidity even through aggressive or marketable orders.[7] Using a state-space model, Hendershott and Menkveld (2014) show that specialists on the NYSE respond to price pressures and seek to revert pricing errors by trading against them, thus showing the tendency of liquidity providers to trade against transitory price movements. Other recent papers that explore the provision of contra-side trades can be found, for example, in the literature on liquidity provision by institutional investors (Franzoni and Plazzi, 2015), liquidity provision in dark pools (Boni et al., 2013), and liquidity provision by proprietary traders (Biais et al., 2016). This "contrarian-trader" definition tells us that the role of the market maker should be to stabilize markets in the face of price uncertainty.

In this case, we would also expect to see a higher rate of MPID-attributed quotes when price uncertainty is high. Uncertainty in this case refers to an occasion in which asset prices deviate significantly from fundamental underlying values. This is typically measured using asset volatility (see, e.g., Chung and Chuwonganant, 2014). Furthermore, higher uncertainty is also associated with higher illiquidity as measured by the relative bid-ask spread, as (1) illiquidity prevents information from being quickly incorporated into prices (see, e.g., Chordia et al., 2008), and (2) uncertainty about prices exposes traders to higher adverse selection as in the classic "lemons problem" of Akerlof

[6]In an alternative hypothesis, market makers may also submit limit orders when executions are low, if they expect that their orders will attract executions by "reactive traders" in the spirit of Harris (1997).

[7]Note that our dataset does not allow for the identification of MPID-attributed market orders. Therefore, price aggressiveness (the distance of a limit order to the midquote) serves as a proxy for the "marketability" of an MPID-attributed order.

(1995), and higher adverse selection in turn leads to higher spreads (see, e.g., Kyle, 1985; Huang and Stoll, 1997). Following this definition of liquidity provision as contrarian trading, we might also expect to see higher rate of MPID-attributed errors following significant directional changes in prices.

Note that these roles are not mutually exclusive, and difficult to entangle empirically. As an example, if market makers are shown to increase buy-side MPID-attributed orders following periods of low buy-side depth, this could be because they are responding to a low supply of limit orders, and/or because they are responding to price pressures by sell market orders that are "eating up" depth on the buy side side of the book. If market makers use MPID-attributed according to this second definition, then we might expect to see a higher MPID submission following large price changes, or following an increase in pricing "noise" (as measured using, e.g., the Hasbrouck (1993) definition of pricing errors). This brings us to the following hypotheses:

Hypothesis 1: If the MPID-attributed orders are submitted by market makers in their capacity as liquidity providers, then we should see an increase in MPID submission in response to: (a) lower submission volume and higher execution volume; (b) lower depth; (c) higher volatility; and (d) higher bid-ask spreads.

Hypothesis 1a: If MPID-attributed orders are submitted by market makers in the capacity as "contrarian traders", then we should see an increase in MPID submission in response to: (e) large prices changes; and (f) an increase in pricing errors.

The second aim of our paper is to answer the question: How does the market react to non-anonymous orders posted by market makers? By submitting an MPID-attributed order, a market maker essentially reveals two important signals, to which the market can react. The first signal can be tied to the nature of the order as non-anonymous. Numerous papers on trader anonymity have shown that informed traders prefer to submit their orders anonymously, to prevent other traders from discovering their information or trading strategies (see, e.g., Grammig et al., 2001; Barclay et al., 2003; Comerton-Forde et al., 2011). As the submission of an non-anonymous orders by market makers is mandated by Nasdaq, this potentially exposes market makers to increased adverse selection, depending on the types of traders that are attracted to trade against their orders. Following Harris (1997), order exposure may on the one hand encourage market participation from so-called defensive, "reactive" traders, who wait to be presented with valuable trading opportunities. Increased market participation from this type of trader, whose orders may provide as well as take liquidity, may improve liquidity conditions and thus the overall market quality of the limit order book. On the other hand, if MPID-attributed orders are seen by the market as containing some amount of information (e.g., information about trading strategies or inventories), order exposure could also potentially encourage reactions by so-called "parasitic" traders, who trade in order to take advantage of the information they glean from exposed orders. Harris (1997) argues that these types of traders do not improve or can even deteriorate market quality, as these orders take, rather than supply, liquidity, and furthermore make no contributions to price efficiency. In either case, we would expect to see market participation rates rise following MPID-attributed orders; however, whether the increase in market participation leads to an improvement in market quality may depend on the types of traders that are attracted.

The second signal stems from the fact that, since the MPID reveals the full identity of the submitter, MPID attribution also reveals that the order is submitted by a market maker. Given regulatory concern over low investor confidence in liquidity providers since the 2010 Flash Crash, the revealed presence of a reliable liquidity provider may serve to boost investor confidence and stabilize uncertain markets (see, e.g., Watanabe, 2015; Anand and Venkataraman, 2016). As a result, we might see lower volatility in response to an MPID-attributed order. Particularly if the market can observe market makers acting to smooth out pricing errors, MPID-attributed order may be viewed as "anchoring" the price on the side of the book (buy or sell) to which it is submitted. Therefore, we might also see a drop in pricing errors. This leads to the following hypotheses:

> **Hypothesis 2**: If the MPID-attributed orders are submitted by market markers in their capacity as liquidity providers, then in response to higher rates of MPID submission we should see: (a) higher execution and submission volume (b) higher depth; (c) lower bid-ask spreads; and (d) lower volatility.
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> **Hypothesis 2a**: If MPID-attributed orders are submitted by market makers in the capacity as "contrarian traders", then in response to higher rates of MPID submission we should see a (e) decrease in pricing errors.

Overall, if market makers are indeed properly incentivized and/or obligated to use their MPID-attributed orders to encourage market participation and to stabilize markets, then these incentives should be reflected in the MPID's strategic choice of when to submit a non-anonymous order, as well as reflected in the market's reaction to an MPID-attributed order. Deviations from Hypotheses 1 and 2 should reflect an alternative motivation for the market maker's submission of MPID-attributed orders, and thus a deviation from the principal goals of exchange-mandated market maker incentive programs.

3 Data

Data is obtained from LOBSTER[8] Academic Data, an online data tool that reconstructs the limit order book for the universe of Nasdaq stocks using the Nasdaq TotalView-ITCH direct data feed. The dataset includes order book data on prevailing bid and ask quotes and depths at up to 200 price levels, as well as message files that contain updates to the limit order book. This includes information on the type of event (submissions, partial or total cancellations, and executions of visible or hidden orders), the number of shares, price, direction (buy or sell), and time stamp (to the nanosecond) of the order that the event concerns, as well as a unique order reference number that allows us to track the submission and eventual execution or cancellation of the order. In addition, our data sample uniquely contains information on the Market Participant Identification Number (MPID). This will be described in more detail in Section 3.2.

The main sample in this analysis is composed of eight Nasdaq-listed firms, mostly in the high-tech industry. These firms include: Apple, Inc. (AAPL); Cisco Systems, Inc. (CSCO); eBay, Inc. (EBAY); Facebook, Inc. (FB); Google, Inc. (GOOG); Intel Corporation (INTC); Microsoft Corporation (MSFT), and Yahoo! Inc. (YHOO). The sample time period includes 14 trading days in November 2013, from 4 November to 22 November 2013.[9] Summary statistics for the stock prices, returns, and order flow for these firms is presented in Table 1. From the summary statistics we can see, first, a wide dispersion in share prices between the sample stocks. The two highest-priced stocks (GOOG, at $1025.43; and AAPL, at $521.25) are particularly distinct from the other stocks, as they have stocks prices that are an order of magnitude higher than the next highest-priced stock (EBAY, at $51.94). Furthermore, these stocks also differ widely in terms of order flow. While GOOG has just over 5,000 average daily trades, FB has nearly eleven times as mainly, at nearly 55,000 average daily trades. Lastly, five out of the eight stocks experience, on average, negative daily returns, implying that this time period may be in one in which the market is in particular need of stable liquidity

[8]See `https://lobsterdata.com/`.
[9]It was necessary to exclude 11 November 2013 due to corrupt data files.

provision by market makers. Also reported for each firms are the percentages of total order submissions that are attributed to an MPID. MPID-attribution rates range from a low of 1.61% for MSFT, to a high of 6.80% for FB.

3.1 Nasdaq's Qualified Market Maker Program

The Nasdaq Qualified Market Maker Program, introduced in November 2012, designated a market participant as a Qualified Market Maker (QMM) if they maintained quotes at the national best bid or offer (NBBO) during at least 25% of trading hours in at least 1,000 securities.[10] During our sample period (November 2013), as an incentive for participating, QMMs received a $0.0002-0.0005 credit per submitted MPID-attributed order, along with an additional $0.0001 credit for executions and reduced liquidity take fees.[11]

QMM qualifications were assessed on a monthly basis, meaning that a market maker had discretion over how to distribute their MPID-attributed orders across stocks and over time within a given month. In order to qualify as a QMM, a market participant need not have been a *registered market maker*, an additional Nasdaq designation that required participants to consistently maintain two-sided quotations within a single stock. Therefore, this incentive program did not strictly incentivize traditional market making in the sense of a consistent provision of "patient" limit orders. In fact, a SEC report described the QMM incentive program as a departure from traditional market making requirements, "designed to attract liquidity both from traditional market makers and from other firms that are willing to commit capital to support liquidity at the NBBO."[12] Given that it was designed to respond to a more modern reality of market making, the Nasdaq QMM Program is thus a particularly interesting incentive program in which to explore how market makers are incentivized absent obligations and the implications that this has for market quality.

[10] An additional qualification required the participant to not have been charged any "Excess Order Fees," assessed against members deemed to have submitted an excessive number of inefficient orders.

[11] See SEC Release No. 34-70361, 10 September 2013, available at https://www.sec.gov/rules/sro/nasdaq/2013/34-70361.pdf.

[12] Ibid.

Table 1: Sample Stocks Descriptive Statistics

	Mean	**Median**	**Std. Dev.**	**Min.**	**Max.**
(1) AAPL					
Average Stock Price (USD)	521.25	520.43	3.66	512.38	529.27
Daily Return (bp)	-0.10	-0.21	1.00	-1.61	1.57
Number of Daily Orders	138,681	137,088	23,008	96,796	186,736
Number of Daily Trades	16,368	15,555	2,500	13,614	21,515
% MPID	1.96%				
(2) CSCO					
Average Stock Price (USD)	22.11	21.47	1.03	20.77	24.00
Intradaily Return Volatility (bp)	0.0022	0.0015	0.0028	0.0013	0.0121
Daily Return (bp)	-0.34	0.70	3.31	-10.84	2.13
Number of Daily Orders	249,443	244,267	90,655	152,238	536,612
Number of Daily Trades	22,544	19,668	13,670	12,247	67,736
% MPID	2.14				
(3) EBAY					
Average Stock Price (USD)	51.94	52.15	1.07	49.87	53.85
Daily Return (bp)	-0.15	-0.30	1.68	-3.34	4.31
Number of Daily Orders	310,645	286,657	113,001	164,888	597,135
Number of Daily Trades	20,620	17,564	7,797	13,560	40,018
% MPID	3.84%				
(4) FB					
Average Stock Price (USD)	47.89	47.89	1.13	45.73	50.45
Daily Return (bp)	-0.29	0.04	2.84	-6.49	4.51
Number of Daily Orders	638,182	649,744	162,879	369,426	852,392
Number of Daily Trades	54,356	59,540	13,418	32,768	78,343
% MPID	6.80%				
(5) GOOG					
Average Stock Price (USD)	1025.43	1025.80	9.58	1005.00	1048.80
Daily Return (bp)	0.05	-0.15	0.88	-1.48	2.05
Number of Daily Orders	75,042	76,744	19,323	49,241	114,180
Number of Daily Trades	5,187	4,710	1,395	3,531	7,935
% MPID	1.81%				
(6) INTC					
Average Stock Price (USD)	24.36	24.34	0.33	23.77	25.28
Daily Return (bp)	-0.11	0.29	1.88	-5.35	2.69
Number of Daily Orders	190,832	172,346	49,940	138,646	326,237
Number of Daily Trades	14,174	12,548	5,644	9,398	31,298
% MPID	1.89%				
(7) MSFT					
Average Stock Price (USD)	37.34	37.45	0.55	35.55	38.22
Daily Return (bp)	0.35	0.43	1.71	-1.77	4.18
Number of Daily Orders	444,870	426,755	105,221	269,153	640,988
Number of Daily Trades	29,026	27,207	10,764	16,448	57,101
% MPID	1.61%				
(8) YHOO					
Average Stock Price (USD)	34.56	34.85	1.32	32.07	36.66
Daily Return (bp)	0.75	0.52	1.94	-2.40	3.15
Number of Daily Orders	378,733	358,077	124,213	208,150	552,838
Number of Daily Trades	21,726	22,149	5,121	15,623	34,732
% MPID	2.85%				

This table shows the average stock price, daily return (using closing transaction prices), daily number of orders (i.e., submitted limit orders), and the number of daily trades (i.e., executed orders or submitted market orders), for eight Nasdaq-traded stocks for 4-22 November 2013. Reported are the mean, median, standard deviation, minimum, and maximum of these variables for each firm. Also reported for each firm are the percentages of order submissions that are attributed to an MPID.

3.2 Market Maker Identifier Data

LOBSTER Academic Data records data directly from the Nasdaq TotalView-ITCH direct data feed. When a market participant submits a limit order to Nasdaq, the information on a number of characteristics of the order, including the order reference number, limit price and size, will be recorded as a submission message. If the market participants has chosen to display their identity to other market participants, than the message will additionally contain their Market Participant Identification (MPID), which is uniquely assigned to each market participant registered on the exchange.

Along with the firm name of the market participant and other identifying information, Nasdaq additionally provides information on the market participant type (i.e., Market Maker, Order Entry Firm, Electronic Crossing Network (ECN), general Nasdaq Market Participant, etc.).[13] This allows us to identify which market participants are registered as market makers. Table 2 shows the list of the Nasdaq MPIDs that are revealed within our sample, along with the corresponding market participant type. Also reported in Column (4) is the relative contribution of each MPID to the total MPID-attributed submission volume. The table confirms that a vast majority (99.89%) of MPID revelation is done by firms that identify as market makers. To remain consistent with our hypotheses on the behavior of market makers, those MPIDs which are not attributed to the market maker MPID type are removed.[14]

Table 3 decomposes the contribution of each market participant to the submission volume of individual stocks. From the table, it becomes clear that only three market makers maintain a presence in all stocks: Citigroup Global Markets LLC (SBSH), Timber Hill LLC (TMBR), and UBS Securities LLC (UBSS). Also reported are the Herfindahl-Hirschman Index (HHI) scores for each stock, calculated as the sum of squares of the market shares (i.e., relative contribution to MPID-attributed submission volume) of each market making firm active within a stock. This measure should capture the degree of competition between liquidity providers in each stock, and ranges from a low of 3973 for GOOG (most competitive), to a high of 8943 for EBAY (least competitive).

[13] For more information on MPID types, see http://www.Nasdaqtrader.com/trader.aspx?id=symboldirdefs and ftp://ftp.Nasdaqtrader.com/symboldirectory/mpidlist.txt.

[14] Note that the MPID "WEMM", formerly belonging to Wells Fargo, Inc., has since been de-listed as an MPID, and thus its MPID type cannot be verified. Therefore, this (relatively small) sample is also removed.

Table 2: Market Participant Identifiers, Types and Relative Submission Contribution

MPID	**Firm Name**	**MPID Type**	**%Sub.**
ATDF	Automated Trading Desk Financial Services, LLC	Market Maker	0.05%
BARD	Robert W. Baird & Co. Incorporated	Market Maker	< 0.01%
DADA	D.A. Davidson & Co.	Market Maker	< 0.01%
FBCO	Credit Suisse Securities (USA) LLC	Market Maker	0.28%
GSCO	Goldman, Sachs & Co.	Market Maker	1.55%
RHCO	Suntrust Robinson Humphrey, Inc.	Market Maker	< 0.01%
SBSH	Citigroup Global Markets Inc.	Market Maker	17.21%
TMBR	Timber Hill LLC	Market Maker	76.36%
UBSS	UBS Securities LLC	Market Maker	4.44%
WCHV	Wells Fargo Securities, LLC.	Market Maker	< 0.01%
		Total Market Maker	**99.89%**
BOOK	Bloomberg Tradebook LLC	ECN	0.03%
LEHM	Barclays Capital Inc./Le	Nasdaq Participant	0.01%
NITE	Knight Capital Americas LLC	Nasdaq Participant	0.03%
WEMM	Wells Fargo Securities, LLC.	Nasdaq Participant	0.04%
		Total Other	**0.11%**

This table shows the list of Nasdaq market participant identifiers (MPIDs) identified from a sample of eight Nasdaq-traded stocks for 4-22 November 2013. Reported are the MPIDs, the firm name of the market participant, the MPID type, and the percentage of total MPID-attributed submission volume contributed by that particular MPID. The market participants are split according to whether or not Nasdaq registers the market participant as a market maker or not; see ftp://ftp.Nasdaqtrader.com/symboldirectory/mpidlist.txt.

Table 3: Relative Contribution of Market Participants to Submission Volume, By Stock

	(1) AAPL	(2) CSCO	(3) EBAY	(4) FB	(5) GOOG	(6) INTC	(7) MSFT	(8) YHOO
ATDF	0.21%	0.24%	0.02%	0.02%	0.16%	0.15%	0.07%	0.04%
BARD	–	–	< 0.01%	–	–	–	0.01%	–
BOOK	0.03%	0.11%	0.09%	< 0.01%	0.17%	0.15%	0.02%	0.01%
DADA	–	0.01%	–	–	–	–	–	–
FBCO	0.35%	2.08%	0.05%	0.06%	0.10%	2.13%	0.08%	0.04%
GSCO	–	5.57%	–	–	–	7.52%	10.81%	–
LEHM	–	–	–	–	–	0.11%	0.05%	–
NITE	0.05%	0.07%	–	0.02%	0.96%	0.03%	0.02%	0.01%
RHCO	< 0.01%	–	–	–	–	–	–	–
SBSH	3.72%	18.90%	4.65%	24.11%	51.56%	4.89%	0.87%	16.49%
TMBR	68.08%	57.89%	94.45%	73.06%	33.73%	72.15%	84.95%	81.78%
UBSS	27.23%	14.98%	0.73%	2.71%	13.26%	12.77%	3.09%	1.61%
WCHV	0.01%	–	–	–	–	–	–	–
WEMM	0.32%	0.16%	0.01%	0.02%	0.06%	0.11%	0.03%	0.02%
Herfindahl-Hirschman Index	5390.47	3968.31	8942.97	5926.41	3972.96	5453.76	7343.68	6962.48

This table shows the list of Nasdaq market participant identifiers (MPIDs) from a sample of eight Nasdaq-traded stocks for 4-22 November 2013. Reported are the MPIDs and their relative contribution (in percentage terms) to the total submission volume for each stock. Also reported are each stock's Herfindahl-Hirschman Index (HHI), to capture the each stock's level of competition between liquidity providers.

3.3 Measure of MPID Submission Intensity

As a measure of MPID submission intensity, we treat the decision to attribute an order to an MPID as a binary decision variable and consider the number of orders submitted that are attributed to an MPID, divided by the total number of submitted orders. Specifically, the MPID submission intensity $MPID_t^i$ is calculated for each stock i over the interval $[t, t+1]$, as:

$$MPID_t^i = \frac{\sum_{s=t-1}^{t} \mathbb{I}_s^{MPID.SUB,i}}{\sum_{s=t-1}^{t} \mathbb{I}_s^{SUB,i}}, \tag{1}$$

where $\mathbb{I}_t^{SUB,i}$ is a dummy variable equal to one if the order book message at time t describes the submission of a limit order, and $\mathbb{I}_t^{MPID.SUB,i}$ if the order book message at time t shows the submission of a limit order with an attributed MPID. Likewise, measures of buy-side and sell-side MPID submission intensities ($MPID.BUY_t^i$ and $MPID.SELL_t^i$) are calculated, respectively, as the ratio of buy- (sell-) side MPID-attributed submissions to the total number of buy- (sell-) side submissions over the interval $[t, t+1]$.

We define MPID submission intensities in this way for two reasons. First, defining MPID submission intensities in terms of the *number* of MPID-attributed submissions (as opposed to, e.g., volumes), isolates the decision to trade non-anonymously from other order choices (i.e., the size and price of the order). In all specifications, we control for the average MPID order size and price (aggressiveness) separately since these decisions are made simultaneously with the MPID revelation decision.

Secondly, defining MPID submission intensities in terms of a *ratio*, rather than the absolute number of MPID-attributed order submissions, allows us to control for general trading strategies and order flow trends. For example, limit order submissions in general tend to be high early in the trading day, such that observing a high absolute number of MPID orders during this time may reflect a general trend in order submission strategies. However, observing a higher *ratio* of MPID order submissions entails that there are additional incentives for traders to reveal their presence early in the trading day.

To construct the ratios in (1), the trading day is segmented into a 30-second grid, and MPID submission intensities are calculated for each 30-second interval. We aggregate the data into intervals rather than using the full time series because, first, aggregating the data across an equally-spaced grid allows us to use panel models and thus take advantage of more sample variation and more degrees of freedom. Secondly, it is likely that market participants respond to cumulative or persistent characteristics (i.e., an interval of high market maker activity), rather than isolated observations. The interval length of 30 seconds is chosen to ensure a sufficient number of observed submissions within each interval (the average time between submissions for GOOG, the least liquid stock in our sample, is 0.33 seconds). However, in unreported analyses we confirm that results are robust to longer (60-second) and shorter (10-second) intervals.

Table 4 shows summary statistics for the MPID submission intensities $MPID_t^i$, $MPID.BUY_t^i$ and $MPID.SELL_t^i$, for the individual stocks in our sample, along with on an aggregate level. The aggregate mean MPID submission intensity is about 0.03. FB has the highest MPID order submission intensities, with a mean of about 0.07, while all other firms have average MPID order submission intensities that range from 0.01 to 0.05. GOOG has the highest standard deviation in its MPID submission intensities; this is perhaps not surprising, as from Table 1 it is the least liquid firm in our sample. Furthermore, MPID submission intensities tend to be right-skewed, reflecting the presence of occasional very high values. This is especially true for GOOG, who sees maximum MPID submission intensities equal to 1.

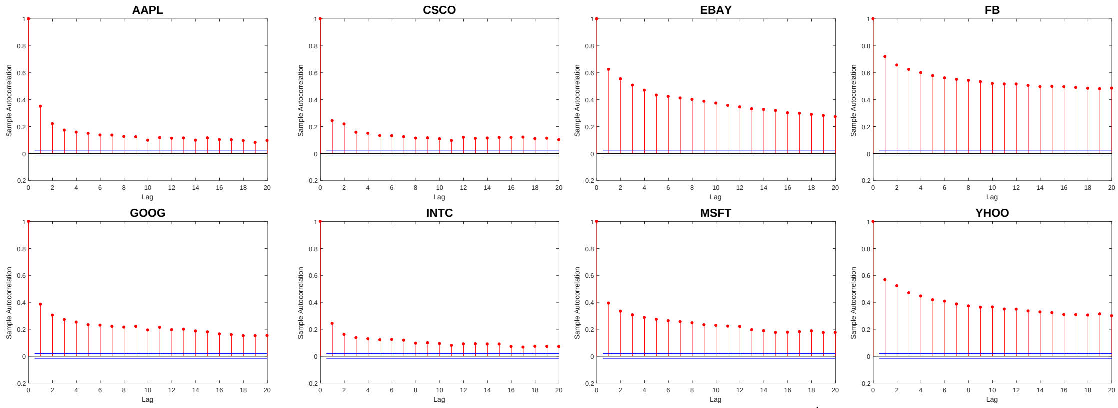
Autocorrelograms for $MPID_t^i$ for each stock are presented in Figure 1, and show high persistence in MPID submission intensities, as autocorrelation remains highly significant even after 20 lags. This reveals a necessity for controlling for this high degree of autocorrelation. Figure 2 plots, respectively, the $MPID_t^i$ for each individual firm, as well as stock-averages of the total MPID submission intensity $MPID_t^i$, buy-side MPID submission intensity, $MPID.BUY_t^i$, and sell-side MPID submission intensity, $MPID.SELL_t^i$, averaged across each interval in the trading day. From these Figures, it becomes clear that MPID submission variables peak at opening and gradual decreasing over the course of the trading day. Our regressions will additionally include a dummy variable capturing the first thirty minutes of each trading day.

Table 4: MPID Submission Intensities Descriptive Statistics

	Mean	Median	Std. Dev.	Min.	Max.	Skew
			(A) All MPID Submissions			
AAPL	0.022	0.010	0.032	0.000	0.344	2.859
CSCO	0.022	0.020	0.017	0.000	0.304	2.119
EBAY	0.043	0.039	0.029	0.000	0.324	1.887
FB	0.069	0.064	0.030	0.000	0.294	1.054
GOOG	0.019	0.000	0.042	0.000	1.000	4.959
INTC	0.019	0.017	0.017	0.000	0.214	1.815
MSFT	0.015	0.014	0.011	0.000	0.125	1.725
YHOO	0.030	0.027	0.022	0.000	0.368	2.311
			(B) Buy-Side MPID Submissions			
AAPL	0.019	0.000	0.039	0.000	0.526	3.896
CSCO	0.024	0.019	0.027	0.000	0.397	2.764
EBAY	0.046	0.040	0.036	0.000	0.563	2.209
FB	0.072	0.067	0.036	0.000	0.375	1.066
GOOG	0.025	0.000	0.063	0.000	1.000	4.516
INTC	0.020	0.014	0.025	0.000	0.333	2.491
MSFT	0.016	0.014	0.015	0.000	0.200	2.471
YHOO	0.033	0.027	0.029	0.000	0.556	2.933
			(C) Sell-Side MPID Submissions			
AAPL	0.027	0.000	0.051	0.000	0.519	3.193
CSCO	0.023	0.019	0.025	0.000	0.333	2.411
EBAY	0.044	0.039	0.036	0.000	0.435	1.877
FB	0.069	0.063	0.036	0.000	0.364	1.182
GOOG	0.014	0.000	0.049	0.000	1.000	6.110
INTC	0.022	0.016	0.027	0.000	0.394	2.719
MSFT	0.016	0.014	0.016	0.000	0.200	2.515
YHOO	0.033	0.027	0.029	0.000	0.313	2.386
			(D) All Stocks			
All	0.030	0.021	0.031	0.000	1.000	2.666
Buy-Side	0.032	0.020	0.040	0.000	1.000	3.383
Sell-Side	0.031	0.020	0.039	0.000	1.000	3.094
			(E) TMBR Submissions, All Stocks			
All	0.022	0.015	0.026	0	1	2.856
Buy-Side	0.023	0.012	0.032	0	1	3.469
Sell-Side	0.023	0.013	0.033	0	0.692	3.29

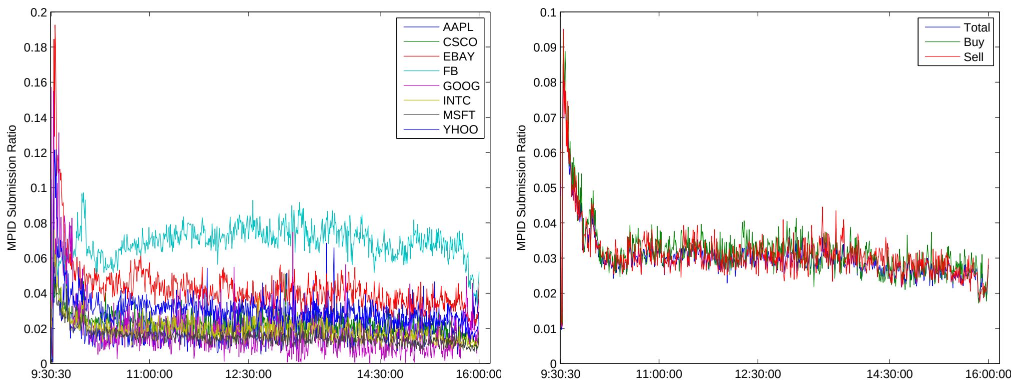
This table shows summary statistics for the measures of MPID submission intensities described in Section 3.2. Shown are the mean, median, standard deviation, minimum, maximum, and skewness of MPID submission intensities including all orders (Panel A), only buy orders (Panel B), and only sell orders (Panel C), for each stock individually. Panel D shows the aggregate summary statistics across all firms. Panel E shows the summary statistics for only TMBR-attributed orders.

Figure 1: Autocorrelograms for MPID submission intensities



These figures show the autocorrelograms for MPID submission intensities $MPID_t^i$ for each stock in our sample. Autocorrelations are measured up to twenty lags. Blue lines correspond to 95% confidence bounds.

Figure 2: Average Daily MPID submission intensities, by Firm



The figure on the left plots the MPID submission intensities $MPID_t^i$ for each individual firm, averaged across each interval in the trading day. The figure on the right plots the stock-averages of the total MPID submission intensity $MPID_t^i$, buy-side MPID submission intensity, $MPID.BUY_t^i$, and sell-side MPID submission intensity, $MPID.SELL_t^i$, averaged across each interval in the trading day.

4 Determinants of MPID Order Submissions

4.1 Methodology

In the first step of our analysis, we explore whether market makers submit MPID-attributed orders in their capacity as liquidity providers, in order to meet liquidity demand and/or stabilize uncertain markets. Therefore, our focus is on the marginal contribution that various market characteristics have on the rate at which MPID-attributed orders are submitted. To achieve this, we perform a fixed effects panel regression of the MPID-attributed submission intensities on lagged market conditions hypothesized to influence the decision to submit MPID-attributed orders as described in Section 2. We aggregate our measures into panel data because, first, it allows for us to more easily control for time-varying characteristics that might otherwise be unobservable or difficult to measure (such as sentiment). Secondly, we are able to take advantage of more degrees of freedom, which should improve the efficiency of our estimates.

We estimate the following fixed effects panel regression for $t = 1, ..., T$ and $i = 1, ..., N$:

$$MPID_t^i = \alpha_0^i + \theta' \sum_{p=1}^{20} MPID_{t-p}^i + \beta' \mathbf{x}_t^i + \gamma' \mathbf{m}_{t-1}^i + \delta' DAY_t + \varepsilon_t^i, \tag{2}$$

where $MPID_t^i$ is our measure of MPID submission intensity over the interval $[t, t+1]$ (as described in Section 3.3), $\mathbf{x}_t^i$ is a vector containing the average order characteristics of MPID-attributed orders submitted over the interval $[t, t+1]$ and $\mathbf{m}_{t-1}^i$ is a vector containing various market conditions averaged over the interval $[t-1, t]$ that are hypothesized to influence the decision to submit MPID-attributed orders, such as volatility and the bid-ask spread. DAY_t is a vector of dummy variables controlling for daily fixed effects and firm fixed effects are captured by α_0^i; for robustness results excluding daily and firm fixed effects are also reported. In different specifications, $MPID_t^i$ is defined as the buy- and sell-side MPID submission intensities, as well as the total MPID submission intensity.

To account for the high autocorrelation of MPID submissions, first, $p = 20$ lags of the dependent variable, $MPID^i_{t-p}$, are included as additional regressors. Table 9 in the Appendix shows that this choice of lags is sufficient to ensure that the null of no serial correlation in the errors is not rejected according to Ljung-Box tests when estimated on a stock-by-stock basis. The addition of lags implies that we have a *dynamic panel regression*, which potentially introduces bias into the estimates, which can be corrected using, e.g., the GMM procedure of Arellano and Bond (1991). However, this bias converges to zero as as $T \to \infty$. As we have a long time series ($T = 10,920$ intervals) and rather short cross-section ($n = 8$), our estimates should still be consistent (see, e.g., Baltagi, 2008, p. 135). Secondly, we include fixed effects and cluster errors at the stock-time level, which is recommended by Petersen (2009) to deal with serial dependence in panel data.

The vector of order characteristics, $\mathbf{x}^i_t$, contains two variables, to control for the possibility that a higher intensity of MPID orders may be driven by, e.g., order-splitting strategies or by "hiding" attributed orders deep in the book:

1. **Aggressiveness** ($AGGR.MPID^i_t$): The average aggressiveness of MPID-attributed orders over the interval $[t, t+1]$, where aggressiveness is defined as the signed distance of a submitted order to the best available quote. A larger value corresponds to a more aggressive order: i.e., $AGGR.MPID^i_t > 0$ implies that the order improves upon the best (bid or ask) quote, while $AGGR.MPID^i_t < 0$ implies that the order is placed deeper within the limit order book.
2. **Order Size** ($ORSZ.MPID^i_t$): The average order size (in dollar volume) of MPID-attributed submissions over the interval $[t, t+1]$.

The vector $\mathbf{m}^i_{t-1}$, contains ten lagged variables meant to capture market conditions that are hypothesized in Section 2 to influence market makers' decision to submit MPID-attributed orders:

1. **Relative Quoted Bid-Ask Spreads** ($RELSPR^i_{t-1}$): The average difference between the observed bid and ask quotes during the interval $[t, t+1]$, standardized by the average midquote. This measure approximates the cost of a round-trip trade relative to the stock price.

2. **Volatility** (VOL^i_{t-1}): The sum of squared midquote returns over five equally-spaced sub-intervals within a given interval $[t-1,t]$ (e.g., for 30-second intervals, this corresponds to 6-second returns), also referred to as realized variance. In order to increase the efficiency of this measure, it is sub-sampled by taking the average of all realized variance estimators sampled over 10-second grids starting at earlier observations (see, .e.g, Hautsch, 2011).

3. **Submissions** (SUB^i_{t-1}): The total volume of limit order submissions (in dollar volume) during the interval $[t-1,t]$.

4. **Executions** (EXE^i_{t-1}): The total volume of limit order executions (in dollar volume) during the interval $[t-1,t]$. In the following a, e.g., "buy-side execution" refers to the execution of a buy limit order.

5. **Depth** ($DEPTH^i_{t-1}$): The average total depth (in dollar volume) available at the prevailing best bid and ask quote during the interval $[t-1,t]$. This measure captures the best-priced liquidity available for impatient traders.

6. **Price Change** ($RELDPR^i_{t-1}$): The (unsigned) percentage change in the midquote over the interval $[t-1,t]$. This measure captures the magnitude of price movements.

7. **Negative Dummy** (NEG^i_{t-1}): A dummy variable equal to one if the unsigned price change is negative (i.e., if $RELDPR^i_{t-1} < 0$). This measure captures the sign of price movements.

8. **Negative Price Change** ($RELDPR^i_{t-1} \times NEG^i_{t-1}$): The interaction between these variables to capture the effects of large, negative changes in prices

9. **Pricing Errors** ($PR.ERR^i_{t-1}$): The Hasbrouck (1993) measure of pricing errors, which uses a VAR approach to measure pricing errors as the stationary component of prices after separating out the random walk component. Similarly to in Rösch et al. (2017), these pricing errors are taken as the maximum measure over the interval $[t-1,t]$.

10. **Open Dummy** ($OPEN_t$): A dummy variable equal to one if the interval $[t,t+1]$ is within the first thirty minutes of the trading day.

An alternative specification replaces NEG^i_{t-1} with POS^i_{t-1}, a dummy variable equal to one if the unsigned price change is positive ($RELDPR^i_{t-1} > 0$), to determine if market makers respond symmetrically to negative and positive price changes. Further alternative specifications explore whether market makers respond differently to buy and sell order flow by replacing SUB^i_{t-1}, EXE^i_{t-1}, and $DEPTH^i_{t-1}$ with their values on the buy side ($SUB.BUY^i_{t-1}$, $EXE.BUY^i_{t-1}$, and $DEPTH.BUY^i_{t-1}$) or sell side ($SUB.SELL^i_{t-1}$, $EXE.SELL^i_{t-1}$, and $DEPTH.SELL^i_{t-1}$) of the book.

Similarly to the calculation of $MPID^i_t$ as described in Section 3.3, all regressors are calculated across 30-second intervals, giving us a time series of length $T = 10,920$ (i.e., 780 intervals per day over 14 trading days). Descriptive statistics of the order and market characteristics are presented in Panel (A) of Table 5. In order to see if MPID-attributed orders differ in terms of their characteristics, the average aggressiveness and order size of all anonymous orders are also presented. The summary statistics reveal some interesting characteristics of MPID-attributed orders. Negative mean and median MPID-attributed order aggressiveness reveals that market makers tend to submit MPID-attributed orders deeper than the first level of the limit order book, and comparing them with anonymous orders reveals that they may be less aggressive and larger on average. The highly positive skew on MPID-attributed order sizes perhaps reveals the presence of a few very large MPID-attributed order submissions. Panel (B) of Table 5 shows the correlation coefficients between the main regressors, averaged across stocks. The table reveals a high correlation (67%) between total executions and submissions, implying potential multicollinearity between these two variables. Therefore we will also consider our baseline model excluding either executions of submissions.

Before performing the panel regression, all variables (excluding the dummies) in the stock-level regressions and in the panel regression in (2) are standardized by the stock-level standard deviation, in order to control for differences in regressor magnitudes across stocks and ease interpretation of the coefficients.

4.2 Empirical Results

This section presents results from the panel regression as described in Section 4.1, which examines the marginal impact that various market conditions have on the decisions by market makers to submit MPID-attributed orders. As laid out in Hypothesis 1, if MPID-attributed orders are indeed submitted by market makers in their capacity as liquidity providers, then we should see an increase in MPID submission in response to an

Table 5: Summary Statistics for Market Condition and Order Characteristic Variables

(A) Descriptive Statistics

	Mean	Median	Std. Dev.	Min.	Max.	Skew
RELSPR	0.035	0.032	0.013	0.003	0.226	1.396
VOL	0.218	0.071	0.588	0.000	31.985	13.897
AGGR.MPID	-0.078	-0.068	0.057	-0.804	0.079	-1.262
AGGR.ANON	-0.041	-0.037	0.018	-0.188	0.021	-1.221
ORSZ.MPID	0.025	0.007	0.065	0.000	2.970	15.504
ORSZ.ANON	0.011	0.030	0.001	0.359	2.931	
SUB.ALL	5.874	3.483	7.531	0.000	374.183	5.100
EXE.ALL	0.519	0.197	1.100	0.000	67.423	12.872
SUB.BUY	2.996	1.653	4.110	0.000	107.886	4.278
EXE.BUY	0.253	0.074	0.555	0.000	20.012	8.122
SUB.SELL	2.877	1.612	4.105	0.000	366.986	11.945
EXE.SELL	0.266	0.072	0.705	0.000	63.447	20.900
DEPTH.TOTAL	0.402	0.235	0.447	0.004	22.704	7.341
DEPTH.BUY	0.200	0.111	0.236	0.001	6.949	5.286
DEPTH.SELL	0.202	0.112	0.288	0.001	22.465	18.798
RELDPR	0.000	0.000	0.047	-0.801	0.749	0.144
PR.ERR	0.312	0.126	0.832	-4.435	48.357	15.542

(B) Cross-Correlations in Regressors

	RELSPR	VOL	AGGR. MPID	ORSZ. MPID	SUB. ALL	EXE. ALL	DEPTH. ALL	RELDPR	PR.ERR
RELSPR	1.000								
VOL	0.381	1.000							
AGGR.MPID	-0.232	-0.212	1.000						
ORSZ.MPID	0.028	0.009	-0.093	1.000					
SUB.ALL	0.353	0.429	-0.19	0.034	1.000				
EXE.ALL	0.228	0.422	-0.164	0.039	0.670	1.000			
DEPTH.ALL	-0.074	-0.093	0.039	0.088	0.159	0.231	1.000		
RELDPR	0.363	0.617	-0.248	0.014	0.427	0.410	-0.079	1.000	
PR.ERR	0.145	0.197	-0.108	0.025	0.302	0.478	0.133	0.215	1.000

Panel (A) shows summary statistics for the order characteristic and market condition variables. Relative bid-ask spreads (RELSPR), relative price changes (RELDPR), aggressiveness of MPID-attributed orders (AGGR.MPID), and pricing errors (PR.ERR) are scaled by 10^3. Volatility (VOL) is scaled by 10^6. Total, buy-side, and sell-side submission and execution volumes and depth, as well as MPID-attributed order sizes (ORSZ.MPID), are expressed as dollar volumes and scaled by 10^{-6}. Panel (B) shows cross-correlations among the main regressors in our regression, averaged across each stock.

imbalance between submission and execution volumes, lower depth, higher volatility, and higher bid-ask spreads. Furthermore, if MPID-attributed orders are submitted by market makers in their capacity as "contrarian traders," in order to reduce price uncertainty and correct pricing errors, then we might see a higher MPID-attributed order submission intensity following large price movements, as well as in response to higher pricing errors as measured by the Hasbrouck (1993) measure.

Table 6 shows results from the panel regression estimation in (2). Columns 1-3 show results in which the dependent variable is defined as the total MPID submission intensity, $MPID_t^i$. Columns 4-5 show results from specifications in which the dependent variable is defined as buy-side MPID submission intensity, regressed on either buy-side (Column 4) or sell-side (Column 5) submission volumes, execution volumes, and depth. Columns 6-7 are similarly specified for sell-side MPID submission intensities.

The results broadly support Hypothesis 1, in that market makers indeed submit MPID-attributed orders within the capacity of a liquidity provider. However, the results are more consistent with the idea that market makers submit MPID-attributed orders in order to meet demand according to the "patient counterparties" hypothesis, rather than to stabilize pricing errors according to the "contrarian trader" hypothesis.

First, the results show that market makers tend to intervene using MPID-attributed orders following periods of high volatility and high relative bid-ask spreads. Positive and significant coefficients (significance level $< 1\%$) on lagged relative quote bid-ask spreads, $RELSPR_{t-1}^i$, reflect that MPID submission intensities tend to be higher following intervals of high spreads: a one-standard-deviation increase in spreads leads to a marginal increase in MPID submissions in the next interval of about 1.5 basis points (a relative increase of about 3.5-5%).[15] Likewise, coefficients on lagged volatility, VOL_{t-1}^i, are also positive and significant (significance level $< 1\%$), reflecting a 2.5-4% (relative) marginal increase in MPID submission intensities following periods of high volatility. Particularly in terms of magnitude, one of the most important drivers of MPID submission intensities seems to be time-of-day effects. The coefficient on the open dummy, $OPEN_t^i$, reflects that MPID order submission intensities tend to be ceteris paribus 12-18% higher during

[15]Note from Table 4 that the standard deviation of $MPID_t^i$ is between 0.031 and 0.040, depending on whether it is defined according to the buy-side, sell-side, or both sides of the book. Since we standardize variables by dividing by the standard deviation, regression coefficients can be interpreted as the marginal increase in standard deviation units of the dependent variable associated with a one-standard deviation increase in the regressor.

Table 6: Determinants of MPID Submissions, Panel Regression Results

Dep.Var	(1) MPID.SUB	(2) MPID.SUB	(3) MPID.SUB	(4) MPID.BUY	(5) MPID.BUY	(6) MPID.SELL	(7) MPID.SELL
L.RELSPR	0.0463***	0.0485***	0.0486***	0.0377***	0.0379***	0.0283***	0.0286***
	(9.517)	(9.797)	(9.792)	(7.769)	(7.753)	(6.008)	(6.102)
L.VOL	0.0323***	0.0303***	0.0302***	0.0322***	0.0310***	0.0204***	0.0219***
	(4.901)	(4.606)	(4.607)	(5.337)	(5.211)	(3.649)	(3.911)
L.PR.ERR	-0.000548	-0.00118	-0.00108	0.000822	-0.00227	0.00666*	0.00697*
	(-0.138)	(-0.297)	(-0.272)	(0.237)	(-0.679)	(1.764)	(1.819)
L.AGGR.MPID	0.0119***	0.0146***	0.0146***	-0.00282	-0.00232	0.0120***	0.0117***
	(3.600)	(4.345)	(4.349)	(-0.819)	(-0.676)	(3.585)	(3.500)
L.ORSZ.MPID	-0.0176***	-0.0175***	-0.0176***	-0.0132***	-0.0131***	-0.0143***	-0.0150***
	(-5.892)	(-5.835)	(-5.850)	(-4.602)	(-4.586)	(-4.829)	(-5.114)
L.RELDPR	-0.0236***	-0.0240***	-0.0257***	-0.0173***	-0.0325***	-0.0405***	-0.0306***
	(-4.689)	(-4.782)	(-4.961)	(-3.297)	(-6.295)	(-7.986)	(-5.897)
L.NEG	0.0129	0.0127		0.00692		0.0124	
	(1.488)	(1.467)		(0.789)		(1.369)	
L.RELDPR*NEG	-0.144	-0.160		-0.280		0.438**	
	(-0.870)	(-0.968)		(-1.607)		(2.499)	
L.SUB	-0.0324***	-0.0288***	-0.0286***				
	(-6.533)	(-5.836)	(-5.805)				
L.EXE	0.0326***	0.0306***	0.0305***				
	(4.575)	(4.296)	(4.282)				
L.DEPTH	-0.0114***	-0.0125***	-0.0125***				
	(-3.712)	(-4.026)	(-4.009)				
OPEN	0.122***	0.133***	0.133***	0.139***	0.135***	0.138***	0.142***
	(7.736)	(8.369)	(8.366)	(8.827)	(8.610)	(8.424)	(8.600)
L.POS			0.0123		0.0147		0.00848
			(1.402)		(1.602)		(0.947)
L.RELDPR*POS			-0.0666		0.418**		-0.0499
			(-0.392)		(2.413)		(-0.279)
L.SUB.BUY				-0.0221***		-0.0161***	
				(-5.739)		(-3.812)	
L.EXE.BUY				0.00288		0.0199***	
				(0.622)		(3.469)	
L.DEPTH.BUY				-0.00552		-0.0173***	
				(-1.476)		(-5.877)	
L.SUB.SELL					-0.0235***		-0.0137***
					(-5.967)		(-3.483)
L.EXE.SELL					0.0140***		0.0144**
					(3.130)		(2.482)
L.DEPTH.SELL					-0.00877***		-0.00641**
					(-3.256)		(-1.987)
Constant	0.0492*	0.0231	0.0226	0.0564**	0.0561**	0.0983***	0.0808***
	(1.883)	(0.823)	(0.805)	(1.999)	(2.010)	(3.518)	(2.922)
Observations	87,200	87,200	87,200	87,200	87,200	87,200	87,200
Stock FE	YES	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES	YES
Lagged Dep. Var	YES	YES	YES	YES	YES	YES	YES
#Lags	20	20	20	20	20	20	20
Within R2	0.282	0.283	0.283	0.215	0.216	0.205	0.205
Between R2	0.979	0.977	0.977	0.973	0.974	0.984	0.983
Overall R2	0.431	0.431	0.431	0.351	0.352	0.339	0.339
Avg. Ljung-Box-Stat	207.1	191.5	191.7	136.5	139	169.8	172.5

This table shows results from a panel regression of the MPID submission intensities on a number of market and order characteristics. The dependent variable in Columns 1-3 is the total number of MPID-attributed orders divided by the total number of submissions; in Columns 4-5 it is the total number of buy-side MPID-attributed orders divided by the total number of by-side submissions; and in Columns 6-7 it is the total number of sell-side MPID-attributed orders divided by the total number of sell-side submissions. The MPID submissions ratios are calculated within 30-second intervals over a period of 14 trading days from 4-22 November 2013. Errors are clustered at the stock-time level. Also reported are the Ljung-Box statistics, averaged across each time series in the panel. Robust t-statistics are in parentheses, where *** p<0.01, ** p<0.05, * p<0.1.

the first thirty minutes of the trading day. This reflects that market makers are active in supplying limit orders early in the trading day as limit order books are being filled, and when uncertainty is high as information revealed through after-hours trading is compounded into prices (see, e.g., Foster and Viswanathan, 1993; Gerety and Mulherin, 1994).

Secondly, the negative and significant coefficients on submission volume and depth across all specifications (significance level $< 1\%$) show that MPID submission intensities tend to be higher following periods of low submission volume and low depth, on both sides of the book. In terms of magnitude, a one-standard-deviation decrease in submission volume is followed by up to a 3% relative increase in the total MPID submission intensity, while a one-standard-deviation decrease in total depth is followed by a $1-2\%$ relative increase in the total MPID submission intensity. Coefficients on total execution volume are positive and significant across most specifications, reflecting a tendency of market makers to meet demand from impatient traders. The coefficients imply that a one-standard-deviation increase in total execution volume is followed by up to a 3% relative increase MPID submissions.

Lastly, the coefficient on relative price changes $RELDPR^i_{t-1}$ is negative and significant across all specifications. Taken along with the results for volatility, the implication is the market makers respond with MPID-attributed orders following intervals of high variations in price, but actually *reduce* their MPID exposure by $2-5\%$ following large directional price changes. The coefficient on the interaction term between $RELDPR^i_{t-1}$ and the dummy variables capturing the directions of prices changes further show that market makers are more likely to follow momentum strategies with their MPID-attributed orders. Market makers are 54% more like to submit a buy order following an interval of positive price changes, and 55% more likely to submit a sell order following an interval of negative price changes. No significance is found for the coefficient on pricing errors, $PR.ERR^i_{t-1}$. This provides evidence that market makers do not necessarily take on the role of "contrarian traders," at least with their MPID-attributed limit orders.

In order to see if our main results are robust at the individual stock level, time-series regressions are separately run for each individual stock i. These regressions include the same explanatory and control variables as described in Section 4.1. The regressions are similarly specified to include daily dummies, DAY_t, and for simplicity only the results from regressions specifying the dependent variables as total MPID submission intensities are presented. Results largely confirm the main results from the panel regressions and are presented in Table 9 in Appendix C. Another robustness check considers that different market makers may have different strategies in terms of MPID attribution. Therefore, to decrease the potential noise created by aggregating all market makers into one analysis, the panel regression in (2) is run, in which the dependent variable is redefined as the MPID-attributed order submission intensity of Timber Hill, LLC, $TMBR_t^i$, a market maker that accounts for around 76% of total MPID submission volume across stocks in our sample (see Table 2). Results from this panel regression are presented in Table 10 in Appendix C, and are largely with the results using the entire sample of MPID-attributed orders

Overall, the findings that MPID-attributed order submissions are higher following intervals of high volatility, high relative bid-ask spreads, low submission volumes, and low depth are rather robust across various specifications, and support the hypothesis that market makers submit MPID-attributed orders within their capacity to provide liquidity. However, the lack of evidence that MPID-attributed orders respond to pricing errors, and the finding that they even trade in the same direction as price changes, both point to the idea that these markets makers are following a role of "bridging the gap" between buyers and sellers, rather than working to correct pricing errors. The next section explores the extent to which market makers may succeed in generating order flow or stabilizing prices, by exploring whether and how the market reacts to MPID-attributed orders.

5 Market Reactions to MPID Order Submissions

5.1 Empirical Methodology

In this section, we aim to explore the market's reaction to MPID-attributed orders posted by market makers, and the implications that this has for market quality. We consider a panel regression of ex post market quality measures (i.e., measures of market conditions following the submissions of limit orders) on lagged MPID submission intensities, $MPID_{t-1}^i$, $t = 1, ..., T$ and $i = 1, ..., N$, in which estimated coefficient on $MPID_{t-1}^i$ measures the marginal effect that the submission of an MPID-attributed order has on market quality and market conditions:

$$q_t^i = \alpha_0^i + \alpha_1 MPID_{t-1}^i + \theta' \sum_{p=1}^{20} q_{t-p}^i + \beta' \mathbf{x}_{t-1}^i + \gamma' \mathbf{m}_{t-1}^i + \mu' DAY_t + \varepsilon_{t^i}, \tag{3}$$

where q_t^i represents a measure of ex post market quality measured over the interval $[t+1, t]$, $\mathbf{x}_{t-1}^i$ is a vector controlling for the average order characteristics of MPID-attributed orders submitted over the interval $[t-1, t]$, and $\mathbf{m}_{t-1}^i$ is a vector controlling for various market conditions averaged over the interval $[t-1, t]$, α_0^i are stock fixed effects and DAY_t is a vector of day fixed effects. Since measure of market quality tend to also exhibit high degrees of autocorrelation, the regression in (3) also includes $p = 20$ dependent variable lags.[16] The key coefficient of interest is on lagged MPID order submission intensity, α_1, which should give the effect of an increase in MPID submission intensity on market quality.[17] To address remaining autocorrelation and heteroskedasticity, errors are clustered at the stock-time level.

However, in performing this regression, we must take into account that market makers still have discretion over the timing of their non-anonymous orders, and their selection of when to reveal likely depends on the expected costs of doing so. By submitting an MPID-attributed order, for example, when they expect execution volumes to increase, market makers reduce their own exposure to execution risk. Therefore, it would be difficult for an observer to determine whether executions increase as a result of the market maker's submission, or the submission was a result of an expected increase in executions. This introduces a likely endogeneity problem between the market maker's submission decision, and ex-post market conditions. For robustness, we use two difference methods to correct for this potential endogeneity problem: two-stage least squares (2SLS) and the Heckman correction model.

5.1.1 Two-Stage Least Squares (2SLS)

The first method we use to address the potential endogeneity problem is a two-stage least squares (2SLS) instrumental variable panel regression. 2SLS estimation addresses endo-

[16]Table 11 in the Appendix shows that this choice of lags is sufficient to ensure that the null of no serial correlation fails to be rejected according to Ljung-Box tests for a majority of variables and stocks.

[17]In alternative specifications we also control for changes in the denominator of $MPID_t^i$, i.e., the total number of submissions $SUB.NUM_t^i$, to control for the possibility that the denominator and not the numerator drives the significance of the coefficient. The results are similar and available upon request.

geneity by extracting the variation in the endogenous regressor(s) that is uncorrelated with the regression model errors, by regressing them on instruments that are assumed to be uncorrelated with the errors in a first step. In our case, the endogenous variable $MPID_t^i$ is regressed on the controls and a set of one or more instrumental variables $\mathbf{z}_t^i$:

$$MPID_t^i = \alpha_0^i + \pi'\mathbf{z}_t^i + \theta' \sum_{p=0}^{19} q_{t-p}^i + \beta'\mathbf{x}_t^i + \gamma'\mathbf{m}_t^i + \mu' DAY_t + \varepsilon_t^i.$$

In a second step, fitted values $\overline{MPID}_t^i$ are obtained from the above panel regressions and replace the regressor $MPID_t^i$ in (3):

$$q_t^i = \alpha_0^i + \alpha_1 \overline{MPID}_{t-1}^i + \theta' \sum_{p=1}^{20} q_{t-p}^i + \beta'\mathbf{x}_{t-1}^i + \gamma'\mathbf{m}_{t-1}^i + \mu' DAY_t + \varepsilon_t^i, \tag{4}$$

For the instruments $\mathbf{z}_t^i$ to be valid, they must be correlated with $MPID_t^i$ but exogenous to the dependent variable q_t^i. Following similar techniques in Comerton-Forde and Putnis (2015), Hasbrouck and Saar (2013), and Buti et al. (2011), we instrument for stock-level MPID order submission intensities by using the average MPID order submission intensities from the other stocks in our sample. These instruments are valid if, first, MPID-attributed order submissions are correlated across stocks due to, e.g., trading capacities or constraints of market makers, and secondly if MPID-attributed orders submissions in other stocks are likely not driven by the market characteristics in a given stock.

First, Panel A of Table 7 shows the correlation coefficient between the (total) MPID submission intensities in each stock. The average correlation coefficient is 12.5%, although there is a high amount of variation between stocks. The highest correlations are around 30-45%, shown between EBAY, MSFT and YHOO. The lowest correlations are shown for AAPL, which displays very low (or even slightly negative) correlations with the remaining stocks. Panel B of Table 7 shows the correlation coefficients between the MPID submission intensities in each stock with the average MPID submission intensities in the other sample stocks. Correlation coefficients between $MPID_t^i$ and $MPID_t^{-i}$ are also relatively high for six of the stocks, ranging from 0.13-0.447. However, there is nearly zero correlation for AAPL. Therefore, our 2SLS estimates will exclude AAPL, as an F-test confirms that the instrument is weak for this stock.

Table 7: Correlation Coefficients

(A) Correlation Coefficients between Stock MPID Submissions

	AAPL	CSCO	EBAY	FB	GOOG	INTC	MSFT	YHOO
AAPL	1.000							
CSCO	0.023	1.000						
EBAY	0.012	0.185	1.000					
FB	-0.06	0.01	0.089	1.000				
GOOG	0.041	0.04	0.193	0.084	1.000			
INTC	0.065	0.142	0.193	-0.01	0.075	1.000		
MSFT	-0.006	0.194	0.378	0.086	0.141	0.201	1.000	
YHOO	-0.008	0.135	0.432	0.21	0.173	0.139	0.326	1.000

(B) Correlation Coefficients between Submissions and Instruments

	AAPL	CSCO	EBAY	FB	GOOG	INTC	MSFT	YHOO
MPID	0.018	0.206	0.447	0.113	0.211	0.229	0.392	0.421
MPID.BUY	0.053	0.125	0.366	0.158	0.154	0.139	0.291	0.356
MPID.SELL	0.006	0.167	0.313	0.073	0.145	0.180	0.280	0.288

Panel A shows the correlation coefficient between the (total) MPID submission intensities in each stock. Panel B of shows the correlation coefficient between the (resp. total, buy-side, and sell-side) MPID submission intensities in each stock with that of the equal-weighted average (resp. total, buy-side, and sell-side) MPID submission intensities in the other sample stocks.

Secondly, the assumption that MPID-attributed orders submissions to a particular stock are not driven by the order characteristics of other stocks requires the assumptions that market makers treat each stock independently in making their order exposure decisions. We believe that this is plausible in our case, as the market makers in our sample are also registered market makers and are thus mandated to submit quotes to the particular stock in which they are registered (in other words, substituting order submissions between stocks would not be plausible). However, recall from Section 3.1 that the Nasdaq QMM rules only require a minimum number of quoted stocks. Therefore, if a market maker is registered in multiple stocks (which we unfortunately cannot observe), this could allow market makers to strategically shift their order exposures between stocks. For example, market makers may shift their order exposures away from stocks with less favorable conditions and towards stocks with more favorable conditions. Given this potential violation of the validity of our instrument, for robustness we use a second methodology to address potential endogeneity, as described in the next section.

5.1.2 Heckman Correction

A further robustness check considers an alternative way to correct for potential endogeneity problems. Specifically, we perform the Heckman correction model in the vein of Comerton-Forde et al. (2011) and O'Hara and Ye (2011), which uses a two-step procedure to include a "correction" term to account for endogeneity problems related to self-selection.

The first stage consists of performing a panel probit model:

$$y_t^i = \alpha_0^i + \beta' \mathbf{x}_t^i + \gamma' \mathbf{m}_t^i + \mu' DAY_t + \varepsilon_t^i$$

$$MPID.DUM_t^i = \begin{cases} 1 & \text{if} \quad y_t^i > 0 \\ 0 & \text{otherwise,} \end{cases}$$

in which the dummy variable $MPID.DUM_t^i$ equal to one if the MPID submission intensity $MPID_t^i$ is in the upper quartile of the stock-day distribution. y_t^i can be thought of as an unobservable latent variable that is only observed through the binary observable variable $MPID_t^i$. From this probit model we obtain fitted values $\hat{y}_t^i$, which are used to calculate the inverse Mills ratio, or the *Heckman selectivity correction term*:

$$\lambda_t^i = \frac{\phi(-\hat{y}_t^i)}{1 - \Phi(-\hat{y}_t^i)}.$$

where ϕ and Φ are, respectively, the standard normal density and cumulative distribution functions. The inverse Mills ratio can be thought of as the probability of observing a positive outcome of y_t^i, divided by the cumulative decision probability. The second step controls for this probability λ_t^i in the following variation of the regression from (3):

$$q_t^i = \alpha_0^i + \alpha_1 MPID.DUM_{t-1}^i + \alpha_2 \lambda_{t-1}^i + \theta' \sum_{p=1}^{20} q_{t-p}^i + \beta' \mathbf{x}_{t-1}^i + \gamma' \mathbf{m}_{t-1}^i + \mu' DAY_t + \varepsilon_{it}. \quad (5)$$

More details regarding the Heckman selection procedure are described in Appendix B.

5.2 Empirical Results

In this section we describe the results from panel regressions of ex post market conditions on lagged MPID submission intensities. According to Hypothesis 2, if the MPID-attributed orders are submitted by market markers in their capacity as liquidity providers, then in response to higher rates of MPID submission we should see higher market participation levels in the form of higher execution and submission volumes. If MPID-attributed orders are submitted by market makers in the capacity as "contrarian traders" such that their orders are seen by the market as anchoring prices, then in response to higher rates of MPID submission we should see a decrease in pricing errors.

Results are presented in Table 8.[18] Column 1 shows results from the 2SLS estimation described in Section 5.1.1, in which the main independent variable of interest is the lagged total MPID submission intensity, $MPID_{t-1}^i$. Columns 2 and 3 replace $MPID_{t-1}^i$ with $MPID.BUY_{t-1}^i$ and $MPID.SELL_{t-1}^i$, respectively. In order to see if the raw number of MPID-attributed submissions drives ex post market conditions, Column 4 shows results where the regressor of interest is defined as the total *number* of MPID submissions $MPID.NUM_{t-1}^i$, as opposed to the ratio of MPID submissions. Lastly, Column 5 shows the results from the second-stage Heckman correction regressio described in Section 5.1.2, in which the main regressor of interest is the dummy variable $MPID.DUM_{t-1}^i$, equal to one if the total MPID submission intensity is within the stock-day upper quartile.

Overall, the results show little support for Hypothesis 2. MPID-attributed orders are shown to attract more executions on the same side of the book, but the number of same-side submissions decreases, leading to a deterioration in same-side depth. Furthermore, there is no evidence that spreads, volatility, or pricing errors decrease following MPID-

[18]Coefficients on the control variables and lagged dependent variables are suppressed for reasons of space, but full results are available upon request.

Table 8: Market Reaction to MPID Submissions, Panel Regression

	(1) MPID	(2) MPID.BUY	(3) MPID.SELL	(4) MPID.NUM	(5) MPID.DUM
DepVar: RELSPR	0.146	0.112	0.219**	0.149***	0.00595**
	(1.546)	(1.325)	(2.017)	(3.112)	(2.142)
F-test	10.79	18.89	19.66	10.85	
pval	0.0134	0.00337	0.00303	0.0132	
Wu-Hausman	4.897	2.863	2.658	5.111	
pval	0.0269	0.0906	0.103	0.0238	
Avg. Ljung-Box	344.4	325.8	321.1	386.3	218
DepVar: VOL	0.112	0.155	0.112	0.360***	-0.181
	(0.932)	(1.253)	(1.122)	(2.737)	(-1.090)
F-test	10.54	18.69	10.28	32.56	
pval	0.0141	0.00346	0.0149	0.000731	
Wu-Hausman	1.724	2.086	2.260	0.00265	
pval	0.189	0.149	0.133	0.959	
Avg. Ljung-Box	245.9	252.4	247.6	476.4	325.9
Dep.Var: PR.ERR	0.00926	0.0203	-0.0606	0.260***	0.00494
	(0.213)	(0.331)	(-0.760)	(5.679)	(1.509)
F-test	10.86	18.82	10.62	27.61	
pval	0.0132	0.00340	0.0139	0.00118	
Wu-Hausman	0.0235	0.0925	0.673	2.432	
pval	0.878	0.761	0.412	0.119	
Avg. Ljung-Box	106	112.1	103.4	131	99.96
Dep.Var: RELDPR	0.316**	0.292***	0.360**	0.677***	0.0101***
	(2.251)	(2.705)	(2.407)	(4.335)	(3.023)
F-test	10.27	17.89	10.28	19.64	
pval	0.0150	0.00389	0.0150	0.00304	
Wu-Hausman	5.630	5.204	5.713	3.740	
pval	0.0177	0.0225	0.0168	0.0531	
Avg. Ljung-Box	130.4	92.76	165	682.8	56.74
Dep.Var: SUB.BUY	0.181**	-0.00902	0.336***	0.649**	-0.0105***
	(2.044)	(-0.139)	(2.764)	(5.550)	(-3.704)
F-test	11.12	19.41	10.72	22.06	
pval	0.0125	0.00313	0.0136	0.00222	
Wu-Hausman	6.704	0.928	6.702	3.911	
pval	0.00962	0.335	0.00963	0.0480	
Avg. Ljung-Box	186.8	91.59	517	2494	107.3
Dep.Var: EXE.BUY	0.316***	0.513***	-0.398***	-0.000932	
	(0.0358)	(3.256)	(4.296)	(-2.678)	(-0.303)
F-test	10.24	18.86	10.18	24.26	
pval	0.0151	0.00339	0.0153	0.00170	
Wu-Hausman	0.148	5.621	5.807	1.926	
pval	0.701	0.0177	0.0160	0.165	
Avg. Ljung-Box	92.98	169.9	259.6	453.2	91.92

Table 8: Market Reaction to MPID Submissions, Panel Regression (Cont.)

	(1) MPID	(2) MPID.BUY	(3) MPID.SELL	(4) MPID.NUM	(5) MPID.DUM
Dep.Var:DEPTH.BUY	-0.213***	-0.289***	-0.0786	0.0206	-0.00772***
	(-3.238)	(-4.973)	(-0.929)	(0.944)	(-2.862)
F-test	11.12	19.84	10.52	29.08	
pval	0.0125	0.00296	0.0142	0.00102	
Wu-Hausman	6.913	6.604	1.299	0.00212	
pval	0.00856	0.0102	0.254	0.963	
Avg. Ljung-Box	695.8	742.1	730.1	747.3	672.3
Dep.Var: SUB.SELL	0.117	0.265***	-0.128**	0.614***	0.330**
	(1.554)	(2.929)	(-2.286)	(6.336)	(-4.458)
F-test	11.17	19.21	10.84	25.62	
pval	0.0124	0.00322	0.0133	0.00146	
Wu-Hausman	4.189	5.395	1.137	3.915	
pval	0.0407	0.0202	0.286	0.0479	
Avg. Ljung-Box	96.96	110	106.7	860.2	131.4
Dep.Var: EXE.SELL	0.0841	-0.247**	0.364***	0.509***	-0.00489*
	(1.624)	(-2.520)	(2.692)	(4.546)	(-1.658)
F-test	10.06	18.23	10.23	24.79	
pval	0.0157	0.00370	0.0151	0.00160	
Wu-Hausman	2.049	3.798	5.868	2.949	
pval	0.152	0.0513	0.0154	0.0860	
Avg. Ljung-Box	128.1	124.6	359.3	491	116.9
Dep.Var: DEPTH.SELL	-0.197***	-0.0331	-0.341***	0.00519	-0.00536*
	(-3.157)	(-0.986)	(-4.108)	(0.365)	(-1.960)
F-test	10.58	17.32	10.59	28.38	
pval	0.0140	0.00424	0.0140	0.00109	
Wu-Hausman	6.801	1.242	6.646	0.197	
pval	0.00911	0.265	0.00994	0.657	
Avg. Ljung-Box	1047	1206	944.1	1144	1184
Observations	87,200	87,200	87,200	87,200	87,200
Stock FE	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES
Lagged Dep. Var	YES	YES	YES	YES	YES
#Lags	20	20	20	20	20

Columns 1-4 shows the coefficients of the main regressor of interest from a 2SLS panel regression of ex post market characteristics on MPID submission intensities. For each stock, MPID submission intensities are instrumented using the average MPID submission intensities from the remaining stocks in the sample. Column 1 defines the regressor of interest as the ratio of total MPID-attributed submissions to the total number of submissions, $MPID_t^i$. Columns 2 and 3 define the regressor of interest as, respectively, the ratio of buy-side MPID-attributed submissions ($MPID.BUY_t^i$) and the ratio of sell-side MPID-attributed submissions ($MPID.SELL_t^i$). Column 4 defines the regressor of interest as the raw number of MPID submissions ($MPID.NUM_t^i$). Column 5 shows results from a panel regression of ex-post market conditions on dummy variable ($MPID.DUM_t^i$) equal to one if $MPID_t^i$ is in the upper stock-day quartile, and includes the Heckman correction term for endogeneity. Errors are clustered at the stock-time level. Robust z-statistics are in parentheses, where *** p<0.01, ** p<0.05, * p<0.1.

attributed orders. Therefore, there is not much support that MPID-attributed orders are acting to stabilize markets.

First, there is little evidence that MPID submissions have an effect of decreasing relative bid-ask spreads and volatility. If anything, the opposite is true: if the coefficient on MPID submission intensity is significant, it tends to be *positive*. From Column 4, a one-standard-deviation increase in MPID submissions increases spreads by about two basis points (5.5%) and volatility by 13%. Likewise, there is no evidence that MPID submissions serve to decrease pricing errors, as the coefficients on $MPID^i_{t-1}$ are either insignificant or positive. Overall, this shows that the revelation of a market maker's presence does not necessarily succeed at "anchoring" the price and reducing price uncertainty.

Secondly, the results for order flow variables show that MPID submissions attract executions while repelling submissions on the same side of the book. The results for $MPID.BUY^i_t$ show that executions of buy orders increase by 14% (and executions of sell orders decrease by 8%) following intervals of high buy-side MPID submission intensities. Likewise, sell-side executions increase by 12% and buy-side executions decrease by 14% when $MPID.SELL^i_t$ is high. This implies that MPID-attributed orders may indeed be successful at attracting counterparties. However, the results from submission volumes shows that patient traders react to the increase in executions by flocking away from these executions. Specifically, the results show that submissions tend to decrease on the *same* side of the book as the MPID-attributed orders, and flock to the *opposite* side of the book. Submissions on the opposite side of the book increase by 18-24%. The resulting impact on depth is shown to be negative across most specifications. These results go along Harris (1997), who argues that order exposure potentially attracts participation by "parasitic traders," which increases the pick-off risk for other traders. These results could also reflect the market makers' own adjustments of their non-anonymous quotes, as they update them in anticipation of further executions by fast traders.[19] Table 11 in Appendix C shows the coefficients from the 2SLS regression estimated on a stock-by-stock basis, and while the results are slightly noisier, they again mostly confirm the results from the panel regressions.

[19]This activity is also explored in van Kervel (2015), who shows that, following executions, market makers tend to cancel submissions on the same side of the book and increase their submissions on the opposite side in anticipation of further executions, as their limit orders are adversely selected against the inflow of marketable orders by fast traders.

From the results examining market reactions to MPID-attributed orders, MPID-attributed orders appear to encourage market participation, but this increased participation does not seem to bring about an improvement in market quality. Rather than encouraging participation by reactive traders, who wish to trade for exogenous reasons but wait for reliable trading opportunities to appear before acting upon trading intentions, order exposure by market makers may encourage participation from "parasitic traders," whose trading strategies profit off of information gleaned from MPID-attributed orders. For example, a parasitic traders may view and MPID-attributed order as containing some information about the market maker's inventory, and may attempt to exploit this information by front-running the MPID-attributed order. As orders by parasitic traders do not provide liquidity or generate information of their own, encouraging trading by such market participants does not necessarily lead to improvements in market quality in terms of lower volatility or spreads or an increased price efficiency.

In their paper on pricing errors, Hendershott and Menkveld (2014) shows that specialists who act to correct pricing errors at the same time expose themselves to significant levels of adverse selection. As MPID-attributed orders are already exposed to a high degree of adverse selection through the revelation of trading intentions, market makers may not be willing to go the extra step with their MPID-attributed orders to actively trade against pricing errors. Instead of "anchoring" the price and encouraging reactive traders, who might help improve market quality by providing their own contra-side liquidity and may contain exogenous information that could improve price efficiency, MPID-attributed orders may encourage the "wrong" types of traders, who exploit information revealed through MPIDs, without contributing liquidity or information of their own. Therefore, while achieving the classic goal of increased market participation, the requirement that market makers expose a portion of their limit orders may not translate into an overall improvement in market quality.

6 Conclusion

Since the mid-2000s, technological advances and regulatory changes have largely pushed out the role of traditional market makers, mandated to maintain orderly markets, and led to the rise of endogenous liquidity providers, who provide liquidity on their own accounts without direct obligations. To ensure a smooth and continuous provision of liquidity, Nasdaq and other exchanges have implemented a number of programs, to encourage market participants who register as market makers to fulfill the roles that make market makers invaluable to financial markets: namely, to step in as counterparties when they are scarce, and to stabilize markets when uncertainty is high. On the other hand, such incentive programs mandate that market makers disclose their identities for a certain quota of submissions throughout the trading day. This leaves market makers at a crossroads between fulfilling their obligations as liquidity providers, and avoiding the adverse selection that comes along with order disclosure within highly anonymized electronic markets. Thus, with this paper, we aim to explore whether MPID-attributed orders by market makers are indeed aligned with incentives to act according to these obligations, and the potential implications that this has for market quality in modern-day equity markets.

Using a unique dataset that contains information on the identities of the market makers who submit orders, our results show that market makers for the most part respond to market conditions in which liquidity provision is needed. They tend to submit higher intensities of MPID-attributed limit orders when relative bid-ask spreads and volatility are high, and when depth and submission volumes are low. However, there is little evidence that market makers submit non-anonymous contrarian orders in order to correct pricing errors and stabilize markets. Further results show the implications that this has for market quality. MPID-attributed orders, while shown to increase market participation levels in the form of higher executions, do not seem to lead to improvements in overall market quality. There is no evidence that these orders lead to reduced bid-ask spreads, lower volatility, or lower pricing errors, while same-side submissions and depth tend to decrease.

Hendershott and Menkveld (2014) suggest that one way to encourage liquidity provision is by reducing the risk exposure of liquidity providers, as such allowing them to better act to use their inventory positions to correct pricing errors. By requiring market makers to expose themselves to a *higher* level of adverse selection by exposing their identities in highly anonymous markets, the market maker incentive program may thus be counterproductive to this goal. While MPID-attributed order achieve one goal of increasing order executions, these executions may stem from the attraction of “parasitic traders,” and thus lead to an overall lack of improvement in market quality.

References

Akerlof, G. (1995). The market for lemons: Quality uncertainty and the market mechanism. In *Essential Readings in Economics*, pages 175–188. Springer.

Anand, A. and Venkataraman, K. (2016). Market conditions, fragility and the economics of market making. *Journal of Financial Economics (JFE), Forthcoming.*

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The review of economic studies*, 58(2):277–297.

Baltagi, B. (2008). *Econometric analysis of panel data.* John Wiley & Sons.

Barclay, M. J., Hendershott, T., and McCormick, D. T. (2003). Competition among trading venues: Information and trading on electronic communications networks. *The Journal of Finance*, 58(6):2637–2666.

Battalio, R., Ellul, A., and Jennings, R. (2007). Reputation effects in trading on the new york stock exchange. *The Journal of Finance*, 62(3):1243–1271.

Benhami, K. (2006). Liquidity providers valuation of anonymity: The nasdaq market makers evidence. Technical report, Working Paper, University of Toulouse.

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

Biais, B., Declerck, F., and Moinas, S. (2016). Who supplies liquidity, how and when? Working Paper.

Boehmer, E. and Wu, J. J. (2013). Short selling and the price discovery process. *The Review of Financial Studies*, 26(2):287.

Boni, L., Brown, D. C., and Leach, J. C. (2013). Dark pool exclusivity matters. Working Paper.

Buti, S., Rindi, B., and Werner, I. M. (2011). Diving into dark pools. Working Paper.

Chordia, T., Roll, R., and Subrahmanyam, A. (2008). Liquidity and market efficiency. *Journal of Financial Economics*, 87(2):249–268.

Chung, K. H. and Chuwonganant, C. (2014). Uncertainty, market structure, and liquidity. *Journal of Financial Economics*, 113(3):476–499.

Clapham, B., Gomber, P., Lausen, J., and Panz, S. (2017). Liquidity provider incentives in fragmented securities markets. Working Paper.

Comerton-Forde, C., Putnins, T. J., and Tang, K. M. (2011). Why do traders choose to trade anonymously? *Journal of Financial and Quantitative Analysis*, 46(04):1025–1049.

Comerton-Forde, C. and Putnis, T. J. (2015). Dark trading and price discovery. *Journal of Financial Economics*, 118(1):70 – 92.

Demsetz, H. (1968). The cost of transacting. *The quarterly journal of economics*, pages 33–53.

Foster, F. D. and Viswanathan, S. (1993). Variations in trading volume, return volatility, and trading costs: Evidence on recent price formation models. *The Journal of Finance*, 48(1):187–211.

Franzoni, F. A. and Plazzi, A. (2015). What constrains liquidity provision? evidence from hedge fund trades. Working Paper.

Garbade, K. D. and Silber, W. L. (1979). Structural organization of secondary markets: Clearing frequency, dealer activity and liquidity risk. *The Journal of Finance*, 34(3):577–593.

Gerety, M. S. and Mulherin, J. H. (1994). Price formation on stock exchanges: The evolution of trading within the day. *Review of Financial Studies*, 7(3):609–629.

Grammig, J., Schiereck, D., and Theissen, E. (2001). Knowing me, knowing you:: Trader anonymity and informed trading in parallel markets. *Journal of Financial Markets*, 4(4):385–412.

Grossman, S. J. and Miller, M. H. (1988). Liquidity and market structure. *the Journal of Finance*, 43(3):617–633.

Harris, L. (1997). Order exposure and parasitic traders. *University of Southern California working paper*.

Hasbrouck, J. (1993). Assessing the quality of a security market: A new approach to transaction-cost measurement. *Review of Financial Studies*, 6(1):191–212.

Hasbrouck, J. and Saar, G. (2013). Low-latency trading. *Journal of Financial Markets*, 16(4):646 – 679. High-Frequency Trading.

Hautsch, N. (2011). *Econometrics of financial high-frequency data*. Springer Science & Business Media.

Heckman, J. (1979). Sample specification bias as a selection error. *Econometrica*, 47(1):153–162.

Hendershott, T. and Menkveld, A. J. (2014). Price pressures. *Journal of Financial Economics*, 114(3):405 – 423.

Huang, R. D. and Stoll, H. R. (1997). The components of the bid-ask spread: A general approach. *Review of Financial Studies*, 10(4):995–1034.

Karam, A. (2012). The value of non-anonymity on the nasdaq. *Working Paper*.

Korajczyk, R. and Murphy, D. (2017). High frequency market making to large institutional trades. Working Paper.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, pages 1315–1335.

O'Hara, M. and Ye, M. (2011). Is market fragmentation harming market quality? *Journal of Financial Economics*, 100(3):459–474.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, 22(1):435–480.

Raman, V., Robe, M. A., and Yadav, P. K. (2014). Electronic market makers, trader anonymity and market fragility. *Trader Anonymity and Market Fragility (May 29, 2014)*.

Rösch, D. M., Subrahmanyam, A., and Van Dijk, M. A. (2017). The dynamics of market efficiency. *The Review of Financial Studies*, 30(4):1151–1187.

van Kervel, V. (2015). Competition for order flow with fast and slow traders. *The Review of Financial Studies*, 28(7):2094–2127.

Van Kervel, V. and Menkveld, A. J. (2018). High-frequency trading around large institutional orders. *The Review of Financial Studies, Forthcoming*.

Watanabe, M. (2015). Supply ambiguity and market fragility. *Working Paper*.

A Measures of Market Conditions and Order Characteristics

- **Relative Quoted Bid-Ask Spread**: $RELSPR_t^i$, the average difference between the observed bid and ask quotes during the interval $[t-1,t]$, standardized by the average midquote (i.e., the average of the bid and ask price) during the respective interval; for stock i for an order submission at time t, denoting by $\#[\cdot]$ the number of quotes during that interval:

$$RELSPR_t^i = \frac{\sum_{s=t-1}^{t}(ask_s^i - bid_s^i)/\frac{1}{2}(ask_s^i + bid_s^i)}{\#[t-1,t]} \tag{6}$$

- **Volatility**: VOL_t^i, for a given order, is defined as the sum of squared midquote returns over five equally-spaced sub-intervals within a given interval $[t-1,t]$, calculated using sub-sampling over 10-second grids. This definition follows that of Hautsch (2011). A more detailed description of the calculation steps is given below.

  In a first step, log midquotes are calculated as the average bid and ask price; for firm i at time t this is given by:

$$m_t^i := \log\left(\frac{1}{2}(ask_t^i + bid_t^i)\right). \tag{7}$$

  The interval of interest is an x-second interval, denoted by $[t-x,t]$. For simplicity, in the following notation the interval is normalized to $[0,t]$. Midquote returns of length $\Delta_n = t/n$ are then calculated. The realized variance is then calculated as the sum of the n squared returns during the x-second interval:

$$RV_{0:t,n}^i := \sum_{s=1}^{n}(m_{s\Delta_n}^i - m_{(s-1)\Delta_n}^i)^2 =: \sum_{s=1}^{n}(r_{j,n}^i)^2$$

  Next, consider K sub-intervals of midquotes given by:

$$\begin{gathered}\{m_{1\Delta_n}, m_{(K+1)\Delta_n}, m_{(2K+1)\Delta_n}, ..., m_{(n_1K+1)\Delta_n}\}\\ \{m_{2\Delta_n}, m_{(K+2)\Delta_n}, m_{(2K+2)\Delta_n}, ..., m_{(n_2K+2)\Delta_n}\}\\ \vdots\\ \{m_{K\Delta_n}, m_{2K\Delta_n}, m_{3K\Delta_n}, ..., m_{(n_k+1)K\Delta_n}\}\end{gathered}$$

The realized variance specific to each sub-interval is thus given by (for $k = 1, ..., K$):

$$RV^i_{0:t,n_k} := \sum_{s=1}^{n_k} (m^i_{(sK+k)\Delta_n} - m^i_{((s-1)K+k)\Delta_n})^2 =: \sum_{s=1}^{n_k} (r^i_{j,n_k})^2$$

The volatility measure is then calculated as the average realized variances over the sub-intervals. In this study, to ensure an equally-spaced grid the interval of interest is the 30-second interval prior to a given order submission, with returns calculated over interval length 6 seconds such that $\Delta_n = 1/5$. For the sub-sampling, $K = 10$ intervals are chosen over a 10-second grid. Therefore, for stock i and order submission time t, this is given by:

$$VOL^i_t := \frac{1}{10} \sum_{k=1}^{10} RV^i_{t-1:t,n_k}$$

- **Submission Volume**: SUB^i_t, the dollar volume of submissions during the interval $[t-1, t]$ preceding a given submission; denoting by $\mathbb{I}^{SUB,i}_t$ an indicator variable equal to 1 if the order book message for stock i at time t represents an order submission and 0 otherwise and by v^i_t the dollar volume of an order, for stock i for an order submission at time t the measure is equal to:

$$SUB^i_t = \sum_{s=t-1}^{t} \mathbb{I}^{SUB,i}_s \cdot v^i_s$$

- **Execution Volume**: EXE^i_t, the dollar volume of executions during the interval $[t-1, t]$ preceding a given submission; $\mathbb{I}^{EXE}_t$ be an indicator variable equal to 1 if the order book message at for stock i at time t is represents an order execution and 0 otherwise and by v^i_t the dollar volume of an order, for stock i for an order submission at time t the measure is equal to:

$$EXE^i_t = \sum_{s=t-1}^{t} \mathbb{I}^{EXE,i}_s \cdot v^i_s$$

- **Depth**: $DEPTH^i_t$, the average total depth available on both sides of the book during the interval $[t-1, t]$. Denoting by bid^i_t the prevailing best bid quote, $qbid^i_t$ the quantity of shares available at the prevailing best bid quote, ask^i_t the prevailing best ask quote, and $qask^i_t$ the quantity of shares available at the prevailing best ask quote; for stock i for an order submission at time t, denoting by $\#[\cdot]$ the number of quotes during that interval:

$$DEPTH_t^i := \frac{\sum_{s=t-1}^{t} bid_s^i \times qbid_s^i + ask_s^i \times qask_s^i}{\#[t-1,t]}$$

- **Unsigned Price Changes**: $RELDPR_t^i$, the (unsigned) relative change in the prices over during the interval $[t-1,t]$ preceding an order submission. The absolute value is taken such this variable captures the magnitude but not the direction of the change. Denoting by p_t^i the price at time t, for stock i for an order submission at time t this is equal to:

$$RELDPR_t^i = |(p_t - p_{t-1})/p_{t-1}| \tag{8}$$

- **Aggressiveness**: $AGGR_t^i$, the aggressiveness of an order submission is defined as the distance of an submitted order's price to the best same-side quote divided by the midquote. Denoting by p_t^i the price of the submitted order and d_t^i the direction of the order (where $d_t^i = 1$ represents a buy order and $d_t^i = -1$ represents a sell order), the aggressiveness $AGGR_t^i$ of a submitted buy order for stock i at submission time t is thus given by:

$$AGGR_t^i = \begin{cases} \frac{p_t^i - bid_t^i}{m_t^i} & \text{if } d_t^i = 1 \\ \frac{ask_t^i - p_t^i}{m_t^i} & \text{if } d_t^i = -1. \end{cases}$$

- **Order Size**: $ORSZ_t^i$, the size of an order submitted at time t in terms of U.S. dollars. Denote by p_t^i and s_t^i, respectively, the price and size (in terms of number of shares) of an order submitted at time t; for stock i for an order submission at time t the measure is equal to:

$$ORSZ_t^i = p_t^i \cdot s_t^i$$

- **Hasbrouck (1993) Pricing Errors**: $PR.ERR_t^i$, measures pricing errors as the stationary component of prices from decomposing log transaction prices p_t into a random walk component (the efficient price, m_t) and a stationary component (the pricing error, s_t), such that $p_t = m_t + s_t$. To estimate this measure, Hasbrouck (1993) proposes the following vector autoregressive (VAR) system of differences in log prices ($r_t = \Delta p_t$) and trade-related characteristics x_t:[20]

$$\begin{aligned} r_t &= \sum_{j=1}^{p} a_j r_{t-j} + \sum_{j=1}^{p} (b_j)' \mathbf{x}_{t-j} + v_{1,t} \\ \mathbf{x}_t &= \sum_{j=1}^{p} c_j r_{t-j} + \sum_{j=1}^{p} (d_j)' \mathbf{x}_{t-j} + v_{2,t}. \end{aligned} \tag{9}$$

The column vector of trade variables $\mathbf{x}_t$ includes: (1) a sign indicator reflecting the direction of the trade, (2) signed trading volume, and (3) the signed square root of trading volume. This VAR system can be rewritten in terms of a vector moving average (VMA) representation as:

$$\begin{aligned} r_t &= \sum_{j=0}^{\infty} a_j^* v_{1,t-j} + \sum_{j=0}^{\infty} b_j^* v_{2,t-j} \\ \mathbf{x}_t &= \sum_{j=0}^{\infty} c_j^* v_{1,t-j} + \sum_{j=0}^{\infty} d_j^* v_{2,t-j}. \end{aligned} \tag{10}$$

The first equation in (10) is used to calculate pricing errors as:

$$s_t = \sum_{j=0}^{\infty} \alpha_j v_{1,t-j} + \sum_{j=0}^{\infty} \beta_j v_{2,t-j}, \text{ where} \tag{11}$$

$$\begin{aligned} \alpha_j &= -\sum_{k=j+1}^{\infty} a_k^* \\ \beta_j &= -\sum_{k=j+1}^{\infty} a_k^* \end{aligned} \tag{12}$$

Harris (1997) then suggest using the (daily) variance of the pricing error, σ_s^2 as

[20] This summary follows and uses the notation of Boehmer and Wu (2013). In the estimation we use $p = 5$ lags.

an inverse measure of price efficiency. Following Rösch et al. (2017), we measure pricing errors as the maximum absolute realization of s_t in (11) for the interval $[t, t+1]$, $PR.ERR_t = \max s_t$. This is because we are interested in the magnitude of the pricing error rather than in its intraday variation.

B Methodology: Heckman Correction Regression

In order to correct for the potential endogeneity problem between market makers' submission decisions and ex post market conditions, the Heckman correction methodology is used in the vein of Comerton-Forde et al. (2011) and O'Hara and Ye (2011). The idea behind the use of this methodology is that order characteristics (such as MPID attribution) and market conditions are endogenously determined, and thus this procedure includes a "correction" term to account for this endogeneity. The exact procedure can be described as follows.

Consider the following model:

$$q_t^i = \alpha^i + \beta^i \mathbf{V}_{t-1}^i + u_t^i, \tag{13}$$

$$y_{t-1}^i = \alpha^i + \gamma^i \mathbf{X}_{t-1}^i + \varepsilon_{t-1}^i \tag{14}$$

$$MPID.DUM_t^i = \begin{cases} 1 & \text{if} \quad y_t^i > 0 \\ 0 & \text{otherwise,} \end{cases} \tag{15}$$

where in our case q_t^i in (13) represents a set of ex post market conditions during the $[t, t+1]$ interval following an order submission at time t, and for simplicity $\mathbf{V}_{t-1}^i = ((\mathbf{x}_{t-1}^i)', (\mathbf{m}_{t-1}^i)', q_{t-1}^i, ..., q_{t-5}^i, DAY_t)'$ and $\mathbf{X}_{t-1}^i = ((\mathbf{x}_{t-1}^i)', (\mathbf{m}_{t-1}^i)', DAY_t)$ represent the explanatory variables. $MPID.DUM_t^i$ is a dummy variable equal to one if $MPID_t^i$ (our measure of MPID submission intensities, described in Section 3.3) is in the upper quartile of observations per stock per day, and Y_t^i is an unobserved latent variable. The model is defined according to a *probit* specification, in which the error terms are assumed to follow the standard normal distribution, $\varepsilon_t^i \sim N(0, 1)$. More specifically, the Heckman correction procedure relies on the assumption that the error terms u_t^i, ε_t^i have the *bivariate normal distribution*:

$$\begin{bmatrix} u_t^i \\ \varepsilon_{t-1}^i \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix}\right)$$

Then, the condition expectation of q_t^i given a positive value of y_{t-1}^i follows from the properties of the conditional expectation of truncated normal distribution:

$$\begin{aligned} E[q_t^i|\mathbf{V}_{t-1}^i, y_{t-1}^i > 0] &= \beta^i \mathbf{V}_{t-1}^i + E[u_t^i|\varepsilon_{t-1}^i > -\gamma^i \mathbf{X}_{t-1}^i] \\ &= \beta^i \mathbf{V}_{t-1}^i + \frac{\sigma_{12}}{\sigma_2} \cdot \frac{\phi(-\gamma^i \mathbf{X}_{t-1}^i)}{1 - \Phi(-\gamma^i \mathbf{X}_{t-1}^i)} \end{aligned}$$

where ϕ and Φ are, respectively, the standard normal density and cumulative distribution functions. The second term in the above equation is also known as the inverse Mills ratio. Heckman (1979) thus considers the selection problem as the case of an "omitted variable" problem, with the inverse Mills ratio acting as the omitted variable. Therefore, his procedure consists of two steps. In the first step, a probit model as represented by (14) and (15) is estimated, and the predicted values $\hat{y}_t^i = \hat{\gamma}^i \mathbf{X}_{t-1}^i$ are obtained using the estimated parameters $\hat{\gamma}^i$. Then, the inverse Mills ratio, or the *Heckman selectivity correction term* is obtained as:

$$\lambda_t^i = \frac{\phi(-\hat{y}_t^i)}{1 - \Phi(-\hat{y}_t^i)} \tag{16}$$

In the second step, these terms are then included in an OLS regression of market conditions and order characteristics, including MPID attribution and the Heckman selectivity correction term as above. In this way, the relationship between MPID revelation and ex post market quality can be explored, while controlling for the endogeneity of these market quality variables in the decision to reveal. The second-stage regression thus takes the following form:

$$q_t^i = \alpha^i + \beta^i \mathbf{V}_{t-1}^i + \delta^i \lambda_{t-1}^i + u_t^i, \tag{17}$$

Similarly to in Section 4.1, to ease the comparison of coefficients obtained from the regression in (17) across stocks, for each stock i, all variables except binary dummy variables are standardized by dividing by the stock time-series standard deviation.

C Tables and Figures

Table 9: Determinants of MPID Submissions, Individual Stock Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AAPL	CSCO	EBAY	FB	GOOG	INTC	MSFT	YHOO
Dep.VAR	MPID.SUB	MPID.SUB	MPID.SUB	MPID.SUB	MPID.SUB	MPID.SUB	MPID.SUB	MPID.SUB
L.RELSPR	0.00808	0.0733***	0.104***	0.0355***	0.00910	0.0365***	0.0712***	0.112***
	(0.595)	(5.046)	(6.321)	(4.054)	(0.737)	(2.900)	(5.632)	(4.654)
L.VOL	0.0235**	0.00578	0.0277*	0.0332***	0.0124	0.0505***	0.0423	0.0935***
	(1.980)	(0.442)	(1.709)	(2.961)	(0.678)	(2.935)	(1.517)	(3.332)
L.PR.ERR	-0.00531	0.0192	0.00477	0.00190	-0.00792	-0.0175*	-0.000948	0.0130
	(-0.521)	(1.222)	(0.335)	(0.236)	(-0.730)	(-1.864)	(-0.0969)	(1.393)
L.AGGR.MPID	0.0376***	0.0219**	0.0303***	0.000468	-0.00208	0.0124	0.0304***	0.0244***
	(4.266)	(2.168)	(3.043)	(0.0625)	(-0.157)	(1.095)	(3.437)	(2.733)
L.ORSZ.MPID	0.0135*	-0.0247***	-0.0309**	-0.0227***	-0.00200	-0.00468	-0.0147**	-0.0265***
	(1.867)	(-2.779)	(-2.292)	(-3.029)	(-0.233)	(-0.554)	(-2.014)	(-3.422)
L.RELDPR	-0.0459***	-0.0239	0.0220	-0.0165	-0.0529***	-0.0244	-0.0270	-0.0232
	(-3.616)	(-1.566)	(1.337)	(-1.519)	(-3.077)	(-1.641)	(-1.328)	(-1.460)
L.NEG	0.00309	0.0133	0.0155	-0.0233	-0.0198	-0.00364	0.0330	0.0371
	(0.134)	(0.338)	(0.730)	(-1.294)	(-0.902)	(-0.0665)	(1.082)	(1.380)
L.RELDPR*NEG	0.407	-0.0370	-1.197**	0.335	1.890**	0.00284	-0.496	-0.844*
	(0.602)	(-0.0629)	(-2.308)	(1.345)	(2.035)	(0.00259)	(-0.660)	(-1.930)
L.SUB	-0.0324*	-0.0260*	-0.0269**	-0.0132	0.00506	-0.0416**	-0.0414**	-0.0459***
	(-1.868)	(-1.646)	(-2.202)	(-1.100)	(0.464)	(-2.435)	(-2.537)	(-3.534)
L.EXE	0.0721***	-0.000305	0.00585	-0.0158	0.0578***	0.0270**	0.0276**	-0.0185
	(3.205)	(-0.0156)	(0.379)	(-1.081)	(2.853)	(2.423)	(2.201)	(-1.252)
L.DEPTH	0.000733	-0.0496***	-0.0347***	-0.0150*	0.0382***	-0.0234***	-0.0277***	-0.0109
	(0.0491)	(-4.647)	(-4.345)	(-1.749)	(3.665)	(-2.732)	(-2.748)	(-1.520)
OPEN	0.207***	0.257***	0.137**	0.00136	0.394***	0.351***	0.391***	0.124**
	(4.007)	(5.546)	(2.220)	(0.0368)	(6.007)	(6.047)	(5.837)	(1.961)
Constant	0.421***	0.170*	0.0943	-0.0374	0.0381	0.421***	0.0391	-0.145
	(8.237)	(1.749)	(1.520)	(-0.422)	(0.875)	(3.981)	(0.502)	(-1.137)
Observations	10,900	10,900	10,900	10,900	10,900	10,900	10,900	10,900
R2	0.169	0.137	0.475	0.601	0.238	0.111	0.261	0.445
Day FE	YES	YES	YES	YES	YES	YES	YES	YES
Lagged Dep. Var	YES	YES	YES	YES	YES	YES	YES	YES
#Lags	20	20	20	20	20	20	20	20
Ljung-Box	1.087	1.596	19.28	7.333	1.965	3.947	3.247	20.43
pval	1	1	0.504	0.995	1	1	1	0.431

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This table shows results from a regression of the MPID submission intensities on a number of market and order characteristics. The regression is performed separately for each of the eight stocks in our sample. The dependent variable in each regression is the total number of MPID-attributed orders, divided by the total number of submissions, within each 30-second interval over a period of 14 trading days from 4-22 November 2013. Standard errors are calculated using the Newey-West estimator with $T^{1/4}$ lags. *t*-statistics are in parentheses, with *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Determinants of TMBR Submissions, Panel Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep.Var	TMBR.SUB	TMBR.SUB	TMBR.SUB	TMBR.BUY	TMBR.BUY	TMBR.SELL	TMBR.SELL
L.RELSPR	0.0567***	0.0561***	0.0564***	0.0430***	0.0428***	0.0379***	0.0385***
	(11.27)	(11.00)	(11.03)	(8.559)	(8.458)	(7.953)	(8.055)
L.VOL	0.0432***	0.0416***	0.0414***	0.0387***	0.0396***	0.0275***	0.0278***
	(6.151)	(5.943)	(5.932)	(5.966)	(6.202)	(4.629)	(4.673)
L.PR.ERR	0.00707*	0.00552	0.00560	0.00211	-0.00130	0.00758**	0.00599*
	(1.941)	(1.520)	(1.537)	(0.614)	(-0.382)	(2.112)	(1.701)
L.AGGR.TMBR	0.0142***	0.0136***	0.0135***	0.00359	0.00389	0.0103***	0.00962***
	(3.977)	(3.776)	(3.767)	(0.939)	(1.018)	(2.798)	(2.602)
L.ORSZ.TMBR	0.0192***	0.0178***	0.0179***	0.0226***	0.0224***	0.0222***	0.0207***
	(4.219)	(3.804)	(3.850)	(5.703)	(5.646)	(5.610)	(5.271)
L.RELDPR	-0.0169***	-0.0180***	-0.0206***	-0.00880	-0.0411***	-0.0361***	-0.0134**
	(-3.211)	(-3.423)	(-3.841)	(-1.594)	(-7.659)	(-7.009)	(-2.567)
L.NEG	0.0189**	0.0194**		0.00254		0.0268***	
	(2.104)	(2.160)		(0.281)		(2.868)	
L.RELDPR*NEG	-0.178	-0.183		-0.793***		0.588***	
	(-1.008)	(-1.038)		(-4.244)		(3.173)	
L.SUB	-0.0390***	-0.0405***	-0.0403***				
	(-8.176)	(-8.347)	(-8.327)				
L.EXE	-0.00682	-0.00626	-0.00631				
	(-1.481)	(-1.351)	(-1.364)				
L.DEPTH	-0.0184***	-0.0167***	-0.0167***				
	(-5.654)	(-5.178)	(-5.173)				
OPEN	0.166***	0.181***	0.181***	0.200***	0.198***	0.173***	0.174***
	(9.476)	(10.17)	(10.15)	(11.26)	(11.17)	(9.926)	(9.971)
L.POS			0.0138		0.0260***		-0.00130
			(1.521)		(2.714)		(-0.141)
L.RELDPR*POS			0.000382		0.789***		-0.486***
			(0.00212)		(4.253)		(-2.608)
L.SUB.BUY				-0.0322***		-0.0295***	
				(-7.857)		(-7.414)	
L.EXE.BUY				-0.0131***		-0.00473	
				(-3.283)		(-1.200)	
L.DEPTH.BUY				-0.0112***		-0.0205***	
				(-3.031)		(-7.153)	
L.SUB.SELL					-0.0370***		-0.0288***
					(-7.691)		(-6.467)
L.EXE.SELL					-0.00555		-0.00888**
					(-1.582)		(-2.267)
L.DEPTH.SELL					-0.0107***		-0.00998***
					(-3.726)		(-3.114)
Constant	-0.00615	-0.00181	-0.00268	0.0405	0.0346	0.0537*	0.0409
	(-0.229)	(-0.0615)	(-0.0913)	(1.348)	(1.165)	(1.838)	(1.405)
Observations	87,200	87,200	87,200	87,200	87,200	87,200	87,200
Stock FE	YES	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES	YES
Lagged Dep. Var	YES	YES	YES	YES	YES	YES	YES
#Lags	20	20	20	20	20	20	20
Within R2	0.266	0.267	0.267	0.199	0.199	0.191	0.190
Between R2	0.978	0.978	0.977	0.975	0.976	0.978	0.976
Overall R2	0.487	0.487	0.487	0.375	0.376	0.368	0.367
Avg. Ljung-Box-Stat	131	125.5	125.6	121.1	119.6	111.4	114

This table shows results from a panel regression of the TMBR submission intensities on a number of market and order characteristics. The dependent variable in Columns 1-3 is the total number of TMBR-attributed orders divided by the total number of submissions; in Columns 4-5 it is the total number of buy-side TMBR-attributed orders divided by the total number of by-side submissions; and in Columns 6-7 it is the total number of sell-side TMBR-attributed orders divided by the total number of sell-side submissions. The TMBR submissions ratios are calculated within 30-second intervals over a period of 14 trading days from 4-22 November 2013. Errors are clustered at the stock-time level. Also reported are the Ljung-Box statistics, averaged across each time series in the panel. Robust t-statistics are in parentheses, where *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 11: Market Reaction to MPID Submissions, Individual Stock Regressions

	(1) AAPL	(2) CSCO	(3) EBAY	(4) FB	(5) GOOG	(6) INTC	(7) MSFT	(8) YHOO
				(A) Ind.Var: MPID				
Dep.Var: RELSPR	2.144	0.173**	0.0665	0.307**	0.452**	0.0539	0.147***	0.0312
	(1.428)	(2.163)	(0.877)	(2.061)	(2.395)	(0.937)	(2.663)	(0.439)
F-test	2.396	119.3	114.2	21.14	12.61	115.5	131.4	151.1
pval	0.122	0	0	4.32e-06	0.000386	0	0	0
Wu-Hausman	29.89	13.23	3.900	5.199	9.012	8.558	17.71	3.560
pval	4.56e-08	0.000276	0.0483	0.0226	0.00268	0.00344	2.57e-05	0.0592
Ljung-Box	1235	4.107	51.84	426.9	198.8	2.887	9.187	23.15
pval	0	1	0.000120	0	0	1	0.981	0.281
Dep.Var: VOL	2.895	-0.0474	-0.0563	0.502***	0.448	0.0860	-0.0264	0.0430
	(1.140)	(-0.392)	(-0.727)	(2.883)	(1.214)	(0.881)	(-0.351)	(0.438)
F-test	1.501	122.1	106.7	39.75	14.48	106.9	123.5	154.1
pval	0.221	0	0	2.99e-10	0.000142	0	0	0
Wu-Hausman	9.130	0.0337	1.98e-05	15.94	1.254	1.421	0.527	0.657
pval	0.00252	0.854	0.996	6.55e-05	0.263	0.233	0.468	0.418
Ljung-Box	1256	22.77	36.50	1199	71.86	12.57	3.962	11.24
pval	0	0.300	0.0134	0	9.02e-08	0.895	1	0.940
Dep.Var: PR.ERR	0.0172	0.0252	-0.00754	0.0397	-0.0739	0.220*	0.0610	0.0329
	(0.0416)	(0.268)	(-0.118)	(0.338)	(-0.462)	(1.896)	(1.335)	(0.547)
F-test	2.967	122.6	110.6	27.06	15.43	122.3	132.9	152.9
pval	0.0850	0	0	2.01e-07	8.63e-05	0	0	0
Wu-Hausman	0.000672	0.129	0.0457	0.750	0.359	3.841	0.0865	0.289
pval	0.979	0.720	0.831	0.386	0.549	0.0500	0.769	0.591
Ljung-Box	2.601	5.688	2.360	5.598	1.592	7.503	0.821	4.998
pval	1	0.999	1	0.999	1	0.995	1	1
Dep.Var: RELDPR	2.960	0.252***	0.0746	0.762***	0.374	0.222***	0.105	0.163***
	(1.427)	(3.054)	(1.403)	(3.742)	(1.626)	(2.892)	(1.421)	(2.844)
F-test	2.332	120	111.6	33.26	14.18	110.4	128	146.4
pval	0.127	0	0	8.28e-09	0.000167	0	0	0
Wu-Hausman	21.72	8.770	3.789	27.13	1.919	9.555	0.172	8.142
pval	3.15e-06	0.00306	0.0516	1.90e-07	0.166	0.00199	0.679	0.00433
Ljung-Box	1233	3.251	21.08	2137	26.11	3.294	3.180	4.629
pval	0	1	0.393	0	0.162	1	1	1

Table 11: Market Reaction to MPID Submissions, Individual Stock Regressions (Cont.)

	(1) AAPL	(2) CSCO	(3) EBAY	(4) FB	(5) GOOG	(6) INTC	(7) MSFT	(8) YHOO
				(B) Ind.Var: MPID.BUY				
Dep.Var: SUB.BUY	0.157	-0.217**	-0.0932**	0.178**	0.516	-0.0812	0.0157	-0.0402
	(0.645)	(-2.302)	(-2.190)	(2.506)	(1.263)	(-0.813)	(0.280)	(-0.803)
F-test	5.212	75.53	117	82.76	11.05	67.59	158.9	148.9
pval	0.0224	0	0	0	0.000891	0	0	0
Wu-Hausman	0.564	1.905	4.320	12.35	1.498	0.00923	2.437	2.817
pval	0.453	0.167	0.0377	0.000441	0.221	0.923	0.119	0.0933
Ljung-Box	29.59	8.640	12.92	31.43	70.94	7.446	10.69	8.485
pval	0.0768	0.987	0.881	0.0498	1.28e-07	0.995	0.954	0.988
Dep.Var: EXE.BUY	1.038**	0.0899	0.0901*	0.381***	1.180***	0.249**	0.269***	0.221***
	(1.988)	(0.955)	(1.734)	(4.019)	(2.760)	(2.525)	(4.582)	(4.158)
F-test	5.374	76.69	126.2	79.72	9.838	65.37	149.8	147.5
pval	0.0205	0	0	0	0.00171	0	0	0
Wu-Hausman	10.50	0.852	1.673	20.53	24.07	5.589	9.613	12.86
pval	0.00120	0.356	0.196	5.87e-06	9.27e-07	0.0181	0.00193	0.000335
Ljung-Box	903.8	8.138	14.11	160.9	801.6	5.778	3.840	5.511
pval	0	0.991	0.825	0	0	0.999	1	0.999
Dep.Var: DEPTH.BUY	0.241	-0.433***	-0.198***	-0.0570	-0.197	-0.368***	-0.236***	-0.163***
	(0.823)	(-5.635)	(-4.776)	(-0.624)	(-1.043)	(-4.898)	(-6.077)	(-4.140)
F-test	5.374	76.69	126.2	79.72	9.838	65.37	149.8	147.5
pval	0.0205	0	0	0	0.00171	0	0	0
Wu-Hausman	10.50	0.852	1.673	20.53	24.07	5.589	9.613	12.86
pval	0.00120	0.356	0.196	5.87e-06	9.27e-07	0.0181	0.00193	0.000335
Ljung-Box	903.8	8.138	14.11	160.9	801.6	5.778	3.840	5.511
pval	0	0.991	0.825	0	0	0.999	1	0.999
Dep.Var: SUB.SELL	0.770*	0.123	0.0562	0.200*	1.257***	0.209**	0.228***	0.147***
	(1.773)	(1.245)	(1.265)	(1.724)	(2.925)	(2.165)	(4.094)	(2.846)
F-test	4.952	75.64	114.9	72.56	11.11	64.56	152.7	144.7
pval	0.0261	0	0	0	0.000863	0	0	0
Wu-Hausman	11.02	1.844	2.662	3.851	26.40	5.116	8.986	6.643
pval	0.000899	0.175	0.103	0.0497	2.77e-07	0.0237	0.00272	0.00995
Ljung-Box	635.2	18.60	20.14	11.09	730.9	9.827	4.183	7.561
pval	0	0.548	0.449	0.944	0	0.971	1	0.994
Dep.Var: EXE.SELL	-1.249*	-0.246***	-0.0494	-0.100	-0.747**	-0.00175	-0.104**	-0.0445
	(-1.682)	(-2.778)	(-1.133)	(-1.011)	(-2.565)	(-0.0203)	(-1.966)	(-0.795)
F=test	5.316	73.73	114	80.80	11.04	66.99	140.5	144.1
pval	0.0211	0	0	0	0.000893	0	0	0
Wu-Hausman	7.593	3.429	0.913	0.0744	17.17	0.259	2.719	0.641
pval	0.00586	0.0641	0.339	0.785	3.41e-05	0.611	0.0992	0.424
Ljung-Box	1003	3.494	14.57	4.181	264.9	1.064	3.366	6.863
pval	0	1	0.800	1	0	1	1	0.997
Dep.Var: DEPTH.SELL	-0.542	-0.0476	-0.0154	-0.0672	-0.0964	0.0316	0.0366	-0.00304
	(-1.126)	(-0.688)	(-0.386)	(-0.586)	(-0.523)	(0.550)	(1.362)	(-0.0679)
hline F-test	5.688	68.99	121.8	73.88	10.95	65.42	149.1	142.2
pval	0.0171	0	0	0	0.000937	0	0	0
Wu-Hausman	1.563	0.363	0.350	0.00711	0.332	0.546	0.509	0.760
pval	0.211	0.547	0.554	0.933	0.565	0.460	0.475	0.383
Ljung-Box	98.34	2.151	0.605	2.469	0.353	2.988	8.961	10.26
pval	0	1	1	1	1	1	0.983	0.963

Table 11: Market Reaction to MPID Submissions, Individual Stock Regressions (Cont.)

	(1) AAPL	(2) CSCO	(3) EBAY	(4) FB	(5) GOOG	(6) INTC	(7) MSFT	(8) YHOO
(C) Ind.Var: MPID.SELL								
Dep.Var: SUB.BUY	1.482**	0.296***	0.0758	0.337***	0.350	0.318***	0.171***	0.146***
	(1.990)	(2.968)	(1.622)	(3.021)	(1.398)	(3.183)	(2.882)	(2.901)
F-test	4.766	90.57	125.2	29.48	8.789	45.41	142.3	163.5
pval	0.0290	0	0	5.76e-08	0.00304	0	0	0
Wu-Hausman	22.26	8.632	3.537	13.51	2.907	12.32	3.710	3.357
pval	2.38e-06	0.00330	0.0600	0.000237	0.0882	0.000448	0.0541	0.0669
Ljung-Box	1141	12.95	9.804	438	22.15	13.95	5.930	8.055
pval	0	0.879	0.972	0	0.332	0.833	0.999	0.991
Dep.Var: EXE.BUY	-1.619**	-0.120*	-0.108**	-0.355**	-1.085***	-0.306***	-0.158***	-0.211***
	(-2.028)	(-1.687)	(-2.329)	(-2.385)	(-2.962)	(-3.419)	(-2.906)	(-3.882)
F-test	5.046	98.34	134.9	30	9.589	48.11	133.1	166.3
pval	0.0247	0	0	4.43e-08	0.00196	0	0	0
Wu-Hausman	17.89	0.812	0.0779	2.270	29.36	11.55	4.295	4.388
pval	2.34e-05	0.367	0.780	0.132	6.01e-08	0.000678	0.0382	0.0362
Ljung-Box	1155	5.313	11.95	80.02	638.3	11.53	6.315	5.559
pval	0	1	0.918	3.90e-09	0	0.931	0.998	0.999
Dep.Var: DEPTH.BUY	-0.532	-0.0167	0.0144	-0.479***	-0.208	0.0799	0.0562	-0.0313
	(-1.158)	(-0.246)	(0.300)	(-3.789)	(-1.022)	(1.230)	(1.508)	(-0.673)
F-test	5.850	89.65	127.1	26.59	8.505	46.96	121.3	168.2
pval	0.0156	0	0	2.56e-07	0.00355	0	0	0
Wu-Hausman	1.771	0.00755	0.00756	21.30	1.265	2.967	0.513	4.525
pval	0.183	0.931	0.931	3.93e-06	0.261	0.0850	0.474	0.0334
Ljung-Box	80.46	24.03	4.511	300.3	8.138	14.93	2.735	11.81
pval	3.28e-09	0.241	1	0	0.991	0.781	1	0.922
Dep.Var: SUB.SELL	0.227	-0.0767	-0.0290	-0.157	0.0906	-0.167**	-0.163***	-0.153***
	(0.623)	(-0.816)	(-0.587)	(-1.060)	(0.447)	(-1.974)	(-2.935)	(-3.235)
F-test	5.295	90.82	126.4	32.94	8.474	47.65	137.9	160.9
pval	0.0214	0	0	9.75e-09	0.00361	0	0	0
Wu-Hausman	0.437	0.00319	5.104	0.350	0.245	1.536	2.674	1.769
pval	0.509	0.955	0.0239	0.554	0.620	0.215	0.102	0.184
Ljung-Box	25.78	10.11	18.63	18.66	4.508	20.53	5.883	11.31
pval	0.173	0.966	0.546	0.544	1	0.425	0.999	0.938
Dep.Var: EXE.SELL	1.508*	0.279***	0.114**	0.295**	1.247***	0.455***	0.131**	0.213***
	(1.858)	(2.729)	(2.367)	(2.254)	(2.844)	(3.989)	(2.083)	(3.466)
F-test	4.510	91.04	133.1	29.53	8.790	58.03	146.6	170.5
pval	0.0337	0	0	5.61e-08	0.00303	0	0	0
Wu-Hausman	13.06	7.041	3.816	6.092	36.06	15.86	1.234	5.586
pval	0.000302	0.00797	0.0508	0.0136	1.92e-09	6.80e-05	0.267	0.0181
Ljung-Box	907.4	11.38	7.224	113	1118	126.5	3.054	18.25
pval	0	0.936	0.996	0	0	0	1	0.571
Dep.Var: DEPTH.SELL	-0.257	-0.418***	-0.202***	-0.190	-0.300	-0.387***	-0.128***	-0.246***
	(-0.957)	(-5.438)	(-4.481)	(-1.617)	(-1.541)	(-3.445)	(-4.998)	(-5.489)
F-test	6.681	88.76	126.1	27.76	9.349	45.21	126.4	150.4
pval	0.00976	0	0	1.40e-07	0.00224	0	0	0
Wu-Hausman	2.719	43.45	8.655	2.803	5.410	16.29	32.16	19.96
pval	0.0991	0	0.00326	0.0941	0.0200	5.43e-05	1.42e-08	7.89e-06
Ljung-Box	13.77	64.09	25.31	23.09	17.72	47.17	17.06	21.28
pval	0.842	1.63e-06	0.190	0.285	0.606	0.000556	0.649	0.381
Observations	10,900	10,900	10,900	10,900	10,900	10,900	10,900	10,900
Day FE	YES	YES	YES	YES	YES	YES	YES	
Lagged Dep. Var.	YES	YES	YES	YES	YES	YES	YES	
# Lags	20	20	20	20	20	20	20	20

This table shows the coefficients on the main regressor of interest from the 2SLS regression of ex post market characteristic, estimated on a stock-by-stock basis. For each stock, MPID submission intensities are instrumented using the average MPID submission intensities from the remaining stocks in the sample. The main regressor of interest is total MPID submission intensities $MPID_t^i$ (Panel A), buy-side MPID submission intensities $MPID.BUY_t^i$ (Panel B), or sell-side MPID submission intensities $MPID.SELL_t^i$ (Panel C). Robust z-statistics are in parentheses, where *** p<0.01, ** p<0.05, * p<0.1.