High Frequency Market Making to Large Institutional Trades*

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Abstract

We utilize a unique data set that provides all orders and trades, with (masked) trader identity known, for all equities traded on Canadian exchanges. We identify and characterize designated market makers (DMMs) and high frequency traders that act as market makers (HFTs). We also identify large institutional trade packages and characterize how HFTs and DMMs provide liquidity to these trades. Both HFTs and DMMs provide liquidity to large institutional trades, with HFTs providing substantially more. In high volume stocks, HFTs reduce liquidity provision for "stressful" trades by 42 percent while DMM liquidity provision remains mostly unchanged. Implementation shortfall (price) of large trades is significantly affected by HFT (and to a lesser extent DMM) choice of liquidity provision during the trade.

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1 Introduction

An increased prevalence of high-frequency trading is often associated with improvements in market quality in the form of reduced quoted and effective bid-ask spreads and greater efficiency in the price discovery process.[1] High-frequency traders, in particular those that have largely taken on a market-making role but without the obligations of a traditional market-maker, compete with one another to turn over shares quickly, which naturally results in a lower equilibrium bid-ask spread. On the surface, it appears that high-frequency traders greatly contribute to a more liquid market.

This argument, however, is more difficult to justify during times of market stress. A high-frequency market maker reaps a profit by turning over shares quickly - he does not want to be exposed to the risk of adverse price movements during his brief holding period. If a high-frequency market maker believes that adverse price movements are more likely, then he will adjust the price and quantity at which he is willing to buy or sell shares or even withdraw from the market altogether, as he has no strict obligation to make markets.

Large orders placed by portfolio managers are often split throughout the day to avoid detection by other market participants; otherwise, the portfolio managers will receive inferior prices for their total orders. While markets may appear liquid, a concern is that high-frequency market makers, with the ability to eventually detect such a large order, will modify their standing limit orders or withdraw their liquidity altogether to avoid the potential adverse price movements. Therefore, while markets might appear liquid, portfolio managers sometimes think of this as "phantom liquidity," due to its tendency to disappear when needed. Indeed, portfolio managers are increasingly making their voices heard regarding the potentially detrimental effects of unchecked high-frequency market making on market quality for larger-sized orders.

The ultimate goal of finance is to facilitate the efficient allocation of capital. Larger-sized institutional orders are particularly important to examine because these orders often originate from pension funds, mutual funds, and hedge funds, all of which represent a significant cross-section of global investors.

We study liquidity provision of HFTs during execution of large institutional trading packages on Canadian equities exchanges and compare HFT behavior to that of designated market makers (DMMs) on the Toronto Stock Exchange. According to the TMX website, DMMs have the responsibility to, among other things, provide quotes on both sides of the market, contribute to depth of the market, and maintain market activity. DMMs are usually not HFTs over our sample period, but we exploit a change of DMM for 24 stocks in which the new DMM is an HFT.

[1] See, for example, Jovanovic and Menkveld (2011), Menkveld (2013), Hagstromer and Norden (2013), and Brogaard, Hendershott, and Riordan (2014).

Investment Industry Regulatory Organization of Canada (IIROC) provides us with access to order-level data, which will be described in more detail below, for all Canadian equities for the period January 2012 to June 2013. For each message, we are provided with a broker ID and a client ID, meaning we can track the order and trade activity for any client ID across time and across stocks. A drawback of this information is that if a client uses multiple brokers, the client ID will be different across brokers, meaning we can only accurately track trading activity for a specific client ID within the same broker.

We find that HFTs generally provide substantially more liquidity to larger trades than do DMMs. Within high volume firms, HFTs provide 27.42 percent of liquidity to the aggressive component (the market order component) of large trades, while DMMs provide 1.24 percent. In lower volume firms, HFTs provide less liquidity (12.82 percent) and DMMs provide slightly more (1.47 percent). This is consistent with other studies finding that HFTs provide more liquidity in more frequently traded stocks.[2]

However, liquidity provision substantially changes when the large trade is considered "stressful," in which the trading volume of that large trade, as a percentage of all trading volume in that stock-day, is in the upper quintile of all large trades. For high volume firms, HFTs provide 15.93 percent of liquidity to the aggressive component of the large stressful trade, which represents a percentage reduction of 41.9 percent. DMMs, in contrast, continue to provide approximately the same percentage of liquidity. HFTs also have reduced liquidity provision for stressful trades in lower volume firms, while DMM liquidity provision slightly increases. We also find that HFTs reduce liquidity provision on days in which the stocks price is particularly volatile (in the top 10 percent of absolute open-to-close return days for that stock).

On November 26, 2012 one HFT became the DMM for 24 stocks. In some of these stocks, the orders submitted by the DMM increased by a factor of over 1,000. We suspect that this HFT was motivated to take on a DMM role because of the "Integrated Fee Model" regulation that was introduced by IIROC on April 1, 2012, in which DMMs would now receive a discount of 70 percent on fees charged to traders by the exchange, where these fees are typically based on the proportion of message traffic originating from that trader.[3] After the HFT takes on the DMM roles in these 24 stocks, we find that combined DMM and HFT liquidity provision significantly improves for high volume stocks while there is a slight reduction for other stocks. Much of the improvement for high volume stocks disappears for stressful trades - in fact, combined liquidity provision is now 1 percentage point lower for these trades.

We estimate the implementation shortfall (IS) for large trades, which represents the additional cost

[2] See Anand and Venkataraman (2013) and Tong (2014).

[3] Malinova, Park, and Riordan (2013) focus on this regulatory change and find that trades, quotes, and cancellations fell while bid-ask spreads increased following the regulation.

of a large trade due to price impact. IS averages 12 basis points for large trades (dollar volume of at least \$1 million but less than \$10 million) and 21 basis points for extra-large trades (dollar volume of at least \$10 million). IS is negatively related to HFT and DMM liquidity provision and positively related to HFT and DMM liquidity demanding trades. If an HFT provides 10 percentage points less liquidity to the aggressive component of large trades, then IS is 2.7 basis points higher. For extra-large trades, it is 4.4 basis points higher.

Finally, we predict HFT liquidity provision using an indicator variable for stressful trades, among other control variables, and examine the effect of this predicted liquidity provision on the IS of large trades. If a large trade is stressful and within a high volume stock, HFT liquidity provision is 11.8 percentage points lower. This lowered liquidity provision results in a 13 basis point increase in implementation shortfall. This amounts to a considerable reduction in HFT liquidity - supposing there are 100,000 large trades in our year-and-a-half sample at an average trade size of \$3 million, and that 20 percent of these trades are considered stressful, implies a total reduction of (\$3 million $\times$ $100,000 \times 20$ percent) $\times 13$ basis points = \$78 million, relative to if those trades were not considered stressful.

There is considerable interest in the effect of high frequency traders (HFTs) on the price efficiency of markets and on the trading costs of other market participants. For example, Hirschey (2013) finds evidence consistent with HFTs trading in anticipation of future order flow by non-HFTs. Brogaard, Hendershott, and Riordan (2014) find that HFTs trade in the direction of permanent price movements and in the opposite direction of transitory pricing errors using aggressive orders. Carrion (2013) finds that spreads are higher when HFTs supply more liquidity and narrower when HFTs demand more liquidity, and also finds that price efficiency is higher when HFT participation is higher. Breckenfelder (2013) finds that when HFTs compete for trades, liquidity deteriorates and short-term volatility rises. Hagstromer and Norden (2013) use a tick size change on NASDAQ OMX Sweden to show that HFT market makers mitigate short-term volatility. Finally, Kirilenko, Kyle, Samadi, and Tuzun (2014) find that while HFTs were not responsible for the "Flash Crash" of May 2010, they did exacerbate market volatility.

On the theoretical side, Hoffman (2013) finds that fast traders extract rents from other traders, which triggers a costly arms race that reduces social welfare. Budish, Cramton, and Shim (2014) show that a continuous time market structure creates frequent technical arbitrage opportunities that are available to the fastest traders, triggering a costly trading speed arms race and leading to wider spreads and thinner markets. Biais, Foucault, and Moinas (2013) show that fragmented markets allow fast traders to observe market information before slow traders, leading to adverse selection and negative externalities.

Algorithmic trading, which encompasses but is not exclusive to high-frequency trading, is generally viewed favorably. Hendershott, Jones, and Menkveld (2011) show that market quality increases after NYSE automated quote dissemination in 2003, which is used as an exogenous instrument that affects algorithmic trading without affecting market quality. Riordan and Storkenmaier (2012) find that spreads and the price discovery process improve following an upgrade to the Deutsche Bourse trading system in 2007 that allowed for lower latency trading. Similarly, Easley, Hendershott, and Ramadorai (2014) find improved market quality following an upgrade to the NYSE trading system in 1980 that also allowed for lower latency trading. Hasbrouck and Saar (2013) find that increased lower-latency activity is associated with improved market quality measures, both during normal times and times of heightened economic uncertainty. Boehmer, Fong, and Wu (2014) analyze 39 global stock exchanges and find increased algorithmic trading increases information efficiency and liquidity, but also increases volatility.

A paper that is related to ours is by Anand and Venkataraman (2013), which examines whether stock exchanges should impose market maker obligations. Using a similar transaction level data set with masked trader identity from the TSX for the year 2006, they find that "endogenous liquidity providers" provide different levels of liquidity based on their trading profits, inventory risks, and capital commitments and based on different market conditions such as high price movement days and high volatility days. Our primary focus is large institutional trades and how HFTs and DMMs interact with them, and what this ultimately means for the costs of these large trades, which is arguably where market quality is most important. Another paper that is related to ours is Tong (2014), which examines aggregated HFT trading activity on a sample of NASDAQ stocks and how this relates to execution price for large institutional trades. In our paper, we are able to directly examine HFT liquidity provision to large trades and compare HFT and DMM liquidity provision when these large trades are particularly stressful to the market, in addition to detailing the trading characteristics of all HFTs and DMMs individually.

The rest of this paper is organized as follows. Section 2 provides a description of the data set used in this study and details about Canadian markets and market structure. Sections 3 and 4 provide the methodologies for classifying HFTs and DMMs, while Section 5 compares HFTs to DMMs. Section 6 identifies and characterizes the large institutional trades in our sample. Section 7 examines the determinants of HFT and DMM liquidity provision. Section 8 analyzes an event in which DMMs across several stocks were replaced by an HFT and examines how liquidity was affected by this exogenous HFT event. Section 9 examines the effect of extreme stock price movements on HFT liquidity provision. Section 10 examines the effect that HFT liquidity provision has on the implementation shortfall (price) of large institutional trades. Finally, Section 11 concludes.

2 Data and Canada Market Structure

For this study, we are provided with access to detailed order-level data by the Investment Industry Regulatory Organization of Canada (IIROC), a Canadian national self-regulatory organization that regulates securities dealers in Canada's equity markets. IIROC carries out its regulatory responsibilities through setting and enforcing rules regarding the proficiency, business and financial conduct of dealer firms and their registered employees, and through setting and enforcing market integrity rules regarding trading activity on Canadian equity marketplaces.[4]

Through the monitoring of the Canadian equities markets, IIROC collects detailed records on all orders submitted to Canadian exchanges. IIROC provides us with access to a data set that contains all trades, orders, order cancellations, and order amendments for the period January 1, 2012 to June 30, 2013. Each record contains a masked identification for the trader submitting that order. In the case of trades, we are given masked identification for both the buyer and the seller, in addition to the party that is submitting the market or marketable limit order (henceforth, we will use "marketable limit order" to denote a marketable limit order or market order). Altogether, the data set comprises approximately 60 billion observations for a total of approximately 6 terabytes of information. For each observation, there are 47 data fields.

For the purposes of our study, we make extensive use of the following data fields:

- Security ID, date, time of order (reported to the one-thousandth of a second), price of order, share quantity of order;
- Buyer and Seller User ID: masked identification for the trader submitting the order. In the case of trades, the User ID for both the buyer and seller are provided.
- Event: specifies whether an observation is a trade, order, order cancellation, order amendment, trade cancellation (typically due to data error), or off-market trade, among other event types;
- Bid price and ask price: we can determine whether a submitted order originates from a buyer or seller, depending on which of these data fields is non-empty;
- Active and passive indicators for trades: determines which side of the trade submits the marketable limit order (thus making trade direction inference algorithms, such as the Lee and Ready (1991) algorithm, unnecessary);
- Registered trader autofill field: useful for determining the designated market makers in our database, as these are the only traders to have autofill privileges (these will be discussed shortly);

[4]This information and additional details can be found in the "About IIROC" section at www.iiroc.ca.

- Short-marking exempt indicator: useful for potentially determining high-frequency traders, as a trader can be relieved from having to mark their order as a short-sale if they indicate that their account is "short-marking exempt" and the trader exhibits trading behaviors that are consistent with a high-frequency trader (among other specific trader types, such as cross-market arbitrageurs). IIROC separately monitors traders with short-marking exempt status.

We make extensive use of this rich data set, first to classify high-frequency traders that act as market makers on Canadian markets, then to classify designated market makers. Our ultimate goal is to determine how high-frequency traders and designated market makers change their behavior during periods of market stress, and how this influences market quality.

According to the World Federation of Exchanges, as of 2013, the total market capitalization of stocks listed with the TMX group (which operates the two national exchanges of Canada – the Toronto Stock Exchange (TSX), which serves the senior equity market, and the TSX Venture Exchange (TSX-V), which serves the public venture equity market) is equal to about $2 trillion USD, while the total market capitalization of stocks listed with the New York Stock Exchange (NYSE) or NASDAQ is equal to about $24 trillion USD. This makes the TMX group the seventh-largest exchange in the world by total market capitalization.[5] The dollar turnover of shares in 2013 for shares traded with the TMX exchanges is about $1.3 trillion USD and with the NYSE and NASDAQ it is about $21.5 trillion USD. In 2013, TMX had 3,810 stocks listed domestically while NYSE and NASDAQ together had 4,180. The Canadian dollar and U.S. dollar were typically close to parity in 2012 and 2013, which makes their respective dollar values comparable (all dollar values reported in this paper hereafter are in Canadian dollars). The monthly returns of an index fund representing the S&P/TSX 60 (a stock market index of 60 large companies listed on the TSX) and the monthly returns of an index fund representing the S&P 500 have a correlation of 0.79, which is based on the period late-1999 to late-2014. Given that Canada and U.S. are strong trading partners with close geographical proximity, this high correlation is unsurprising.

Finally, a few notes on Canadian market structure. As mentioned above, the two national stock exchanges of Canada are the TSX and TSX-V, which are both completely electronic stock exchanges in which orders are submitted to their respective limit order books. Both are owned and operated by the TMX Group. In addition, the TMX Group operates the TMX Information Processor, which provides a central source of consolidated Canadian equity market data that meets standards approved by regulators. Also, in 2011, the Canadian Securities Administrators (CSA) implemented the "Order Protection Rule," which is designed to ensure that all accessible, visible, better-priced limit orders are executed before inferior priced limit orders. The Order Protection Rule differs from Regulation NMS in the United States in that it protects the full depth of the visible limit order

[5] The six largest exchanges by market capitalization in 2013, from largest to smallest, are NYSE, NASDAQ OMX, Japan Exchange Group, Euronext, Hong Kong Exchanges, and Shanghai SE.

book as opposed to just the top of the limit order book. For example, if Marketplace 1 has two standing sell limit orders with different prices and Marketplace 2 has one standing sell limit order with a price that is inferior to both limit orders from Marketplace 1, then the Order Protection Rule ensures that a large buy will first execute against both limit orders from Marketplace 1. This is unlike Regulation NMS, which would ensure that a large order first executes against the best immediate quotes in both marketplaces, resulting in a total execution price that is inferior to that under the Order Protection Rule. Altogether, there are 13 distinct stock exchanges identified in our sample – like the traders, these exchanges also have masked identification.

3 Classifying HFTs

The first step in our analysis is to classify high-frequency traders that act as market makers (which we will henceforth refer to as HFTs). Our methodology for identifying HFTs in particular stocks is as follows. First, we define a trader as an HFT for a given stock-day if:

1. The trader is in the highest quintile of number of trades as a percentage of all trades on that stock-day relative to all other traders within that stock-day.
2. The trader has a net daily trading position, as a percentage of his volume of shares traded, for that stock-day of 10 percent or less.
3. The trader has an order-to-trade ratio that is greater than 1. It is possible to have an order-to-trade ratio that is less than 1 – for example, if the trader places a large marketable limit order that executes against 10 different orders, this is recorded as a single order and 10 trades.
4. The volume of shares traded actively (that is, via marketable limit orders) as a percentage of all shares traded is less than 80 percent.

HFTs tend to trade much more than other traders and close the day with close-to-zero net trading positions, which motivates our requirements (1) and (2). Requirement (3) removes traders that take on very large inventory positions via large marketable limit orders throughout the day, but yet still satisfy requirements (1) and (2). Requirement (4), which overlaps with requirement (3), removes traders that primarily trade using marketable limit orders. Essentially, our goal is to keep HFTs that frequently trade, have close-to-zero positions at the end of the day, submit many orders relative to the trades they actually make, and do not trade primarily via marketable limit orders.

A trader is identified as an HFT for a given stock-day if he meets these four requirements. We define a trader as an HFT for a given stock if he then satisfies the following two requirements:

1. The trader has been identified as an HFT for at least 75 percent of stock-days in which he trades at least once.

2. The trader has been identified as an HFT for at least 20 active stock-days.

Altogether, this classification methodology yields 28 distinct HFTs. Table 1 contains information about each of these 28 HFTs. In addition, we partition the HFTs into three groups: (1) Super HFTs, who are identified as HFTs in at least 100 stocks; (2) Major HFTs, who are identified as HFTs in at least 10 stocks and less than 100 stocks; and (3) Minor HFTs, who are identified as HFTS in less than 10 stocks. There are 4 Super HFTs, 11 Major HFTs, and 13 Minor HFTs. Information about these HFT groups can be found in Table 2.

According to Table 2, on average, a Super HFT is classified as an HFT in 196 stocks, is involved in 17.85 percent of all trades, has an order-to-trade ratio of 14.11, and 21.46 percent of her share volume is executed via marketable limit orders (and thus, 78.54 percent of her share volume is executed via passive limit orders). She tends to close the day with an absolute inventory position, as a percentage of share volume, of 3.95 percent. Only one of the four Super HFTs has "short-marking exempt" designation – the purpose of this designation is to relieve the trading account from having to mark an order as "short" (IIROC then monitors these accounts separately). Accounts essentially are allowed this designation if they exhibit trading behaviors consistent with HFTs (for arbitrage or market making purposes) or have designated market maker status in that stock. Finally, Super HFTs are classified as HFTs on 87 percent of all stock-days in which they are active, which substantially clears the 75 percent hurdle that we set in the requirements above.

On average, Major HFTs and Minor HFTs are classified as HFTs in 43 stocks and 3 stocks, respectively. Relative to the Super HFTs, the fraction of trades in which they are involved is about 10 percentage points lower (7.53 and 6.86 percent), their order-to-trade ratios are slightly higher (19.99 and 18.11), the percentage of share volume executed via marketable limit orders is lower (14.27 percent and 13.52 percent), and their closing net trading positions are similar (3.56 percent and 3.70 percent). Major and Minor HFTs also more often have "short-marking exempt" designation. Finally, Major and Minor HFTs are classified as HFTs on 87.7 and 83.8 percent of all active stock-days, respectively, which also substantially clears the 75 percent hurdle set in the HFT classification requirements.

4 Classifying DMMs

A trader is designated as a Market Maker for a particular stock by the Toronto Stock Exchange (TSX), which is the primary stock market in Canada. According to the TMX (which owns and operates the TSX) website, the responsibilities of the Market Maker include the following:

- Call a two-sided market providing market continuity within a pre-specified range;
- Contribute to market liquidity and depth;
- Maintain activity in the market;
- Fulfill the needs of retail-sized order flow through guaranteed minimums (minimum guaranteed fills, or MGFs);
- Service odd lots (typically, orders for less than 100 shares).

In addition, TSX continuously monitors the performance of Market Makers to ensure that they maintain a reasonable bid-ask spread, continually participate in their stock of responsibility, and line the limit order book with reasonable depth. According to the TMX Group, the Market Maker system is designed to maximize market efficiency and remove the interfering influence of a traditional specialist. As of November 3, 2014, there were 16 firms that acted as TSX Market Makers. For our purposes, we will classify a TSX Market Maker as a "Designated Market Maker" or DMM for short.

DMMs are not explicitly identified in the IIROC database, but they can be easily inferred. We make use of a data field called "Registered Trader Autofill." This field identifies trades that are automatically generated by the market to fulfill market making obligations for that trader. These trades are primarily used to service odd lot orders and satisfy minimum guaranteed fill requirements (DMMs are required to fill retail-sized aggressive orders when the limit order book contains insufficient liquidity). As such, any trader that has at least one trade with a non-empty "Registered Trader Autofill" field (for their side of the trade) is classified as a DMM for that stock-day. For the vast majority of cases, this yields a single DMM for each stock-day, although it can occasionally yield two DMMs, due to the fact that a primary DMM can have a secondary DMM as backup for when it is unavailable.

5 Comparing HFTs to DMMs

There are 251 stocks with an active DMM and at least one active HFT in our sample - because our ultimate goal is to analyze DMM and HFT activity around stressful events, we will focus exclusively on these stocks. We also partition these stocks into average daily dollar volume terciles over the sample period. On average, a high volume stock has \$63.4 million in dollar volume, 8,701 trades, and 180,709 orders per day. A medium volume stock has \$9.8 million in dollar volume, 2,735 trades, and 47,241 orders per day. Finally, a low volume stock has \$2.5 million in dollar volume, 1,561 trades, and 20,973 orders per day. The highest volume stock in our sample is Stock 1, which on average has \$242.8 million in dollar volume, 20,284 trades, and 334,095 orders per day. Volume information can be found in Panel C of Table 3.

Our next step is to compare HFT activity to DMM activity within each volume tercile. This information can be found in Panels A and B of Table 3. Within the highest volume tercile, an average of 3.76 HFTs are trading on any stock-day. In addition, the HFTs together submit 24.7 percent of all orders, provide liquidity to 19.6 percent of all dollar volume, and actively take liquidity for 3.9 percent of all dollar volume.[6] On average, 15.0 percent of HFT dollar volume is due to aggressive orders, while the remaining 85.0 percent is due to passive orders that are counterparty to other traders' aggressive trades. These HFTs are clearly taking on a market-making role via passive liquidity provision, but they do also trade using aggressive orders.

Compared to HFTs, DMMs take on a relatively minor role. Within the highest volume tercile, DMMs submit 1.7 percent of all orders, provide liquidity to 2.5 percent of all dollar volume, and actively take liquidity for 2.2 percent of all dollar volume. On average, DMMs actively take liquidity for 26.8 percent of all DMM dollar volume, which is higher than HFTs (15.0 percent). The average size of a single trade is also smaller for a DMM compared to an HFT ($3,527 per trade versus $4,853 per trade) – this is likely due to the fact that DMMs execute a large proportion of odd-lot trades for fewer than 100 shares.

Within the medium-volume and low-volume stocks, there is an average of 1.70 and 1.28 HFTs present on any stock-day, respectively, which is much lower than the HFT presence in the high-volume stocks (3.76). HFTs provide slightly less passive liquidity within these terciles than for high volume stocks (13.7 percent and 18.1 percent), in contrast to DMMs which provide slightly more passive liquidity (3.2 percent and 2.6 percent).

We also include information for the five highest-volume securities, where it is apparent that the HFTs are especially active. The highest volume stock, which again we denote Stock 1, has an average of 8.65 active HFTs on any stock-day and together these HFTs submit 43.5 percent of all orders, passively provide liquidity to 39.4 percent of all dollar volume, and actively take liquidity for 9.2 percent of all dollar volume. To put the HFT passive liquidity provision into context, Stock 1 has an average daily dollar volume of $242.8 million, meaning that HFTs provide liquidity to $39.4\% \times \$242.8$ million = $95.66 million of all aggressive volume per day. For DMMs, however, the liquidity statistics are remarkably similar across stocks, regardless of the volume tercile or highest-volume stock. Information on the remaining four highest-volume securities (Stocks 2 to 5) can also be found in all three panels of Table 3.

[6] To "provide liquidity" or "passively trade" means to execute against marketable limit orders using passive limit orders that are standing on the limit order book. To "actively take liquidity" or "aggressively trade" means to submit a marketable limit order that executes against passive standing limit orders.

6 Examining Large Trades

A major issue raised by many institutional traders regards the concept of "phantom liquidity," in which displayed liquidity tends to disappear when an institutional trader attempts to execute his trade, either in full or in part. Institutional traders typically engage in large trades that are executed over the course of hours of even the full day, as opposed to retail traders who typically engage in much smaller transactions. To examine "phantom liquidity" and how it might affect the cost of a large trade, we must first identify these large trades. Fortunately, the IIROC database allows us to track any trader (whose identification is masked) over time, meaning we can identify large trades that are executed via many smaller trades over the course of the day.

We define a "large trade" as follows:

- The aggregate dollar volume that comes from a single account within a single stock-day, where this aggregate dollar volume is at least \$1 million;
- This aggregate dollar volume must consist of either 100 percent buys or 100 percent sells;
- The large trade is considered "extra-large" if its aggregate dollar volume is at least \$10 million.

Table 4 provides details about the large trades and extra-large trades identified in our database. There are 179,036 large trades in our sample of 251 stocks. On average, a large trade is for \$2.34 million. It is executed using 317 trades, with 452 orders submitted. About 56.2 percent of the total trade is executed via marketable limit orders, meaning 43.8 percent of the total trade is executed via passive limit orders. The average large trade takes about 3 hours and 15 minutes to completely execute.

There are 4,932 extra-large trades in our sample of 251 stocks. On average, an extra-large trade is for \$17.44 million. It is executed using 1,110 trades, with 1,232 orders submitted. About 58.2 percent of the total trade is executed via marketable limit orders, meaning 41.8 percent of the total trade is executed via passive limit orders. The average extra-large trade takes about 3 hours and 30 minutes to completely execute. Additional information regarding medians and quantile cutoffs for large trades and extra-large trades can also be found in Table 4.

We also compute the implementation shortfall (IS) for every large trade. Implementation shortfall is measured as the total cost of a trade relative to what the cost would have been if the trader executed the entire trade at the initial price. For example, suppose there was a large buy for 100,000 shares executed throughout the course of the day and this buyer ended up paying \$1.02 million for these shares. Suppose also that the first small trade within this 100,000 share transaction was executed at a price of \$10. If there was no price impact, then ideally the trader would have paid $\$10 \times 100,000 = \$1.0$ million for his 100,000 share purchase. However, because of price impact, he ended up paying \$1.02 million − \$1.0 million = \$20,000 more for his trade. Therefore, his implementation shortfall equals \$20,000/\$1.0 million = 2 percent.

Specifically, suppose that a large trade t for X_t total shares is executed using N smaller trades, where $p_{n,t}$ and $x_{n,t}$ denote the price and share volume, respectively, of the n-th trade within large trade t. Implementation Shortfall for large trade t is calculated as:

$$IS_t = \frac{\sum_{n=1}^{N} p_{n,t}x_{n,t} - p_{1,t}X_t}{p_{1,t}X_t} \text{ for large buys, and}$$

$$IS_t = \frac{p_{1,t}X_t - \sum_{n=1}^{N} p_{n,t}x_{n,t}}{p_{1,t}X_t} \text{ for large sells.}$$

Note that it is possible for implementation shortfall to be negative - a negative IS would be good for the trader making the large trade. For example, if the implementation shortfall for a large buy order is negative one percent, this means that the large trader paid one percent less than he would have paid if he bought all his shares at the initial price.

Table 4 also provides statistics regarding implementation shortfall. The mean IS for a large trade is 12 basis points. Large trades at the IS tenth percentile have an IS of negative 49 basis points while those at the IS ninetieth percentile have an IS of 82 basis points. Clearly, some large trades that are buys (sells) will occasionally benefit from contemporaneous downward (upward) market movements while others will be more costly due to contemporaneous upward (downward) market movements.

7 HFT and DMM Liquidity Provision

Our first goal is to determine what influences HFT and DMM liquidity provision for large trades. Earlier, we discussed the concept of "phantom liquidity" – the concept that traders, particularly HFTs, might withdraw liquidity if they anticipate that prices will move against them when holding a position in a stock. Large trades, for example, tend to move prices, so it would be rational for an HFT to withdraw liquidity and either re-offer it at a costlier price or not re-offer it at all to the large trader. One possible explanation is that the HFT adjusts prices as compensation for the adverse selection detected in the large trade. Another possible explanation is that the HFT prefers to avoid all large trades, including those that are liquidity-motivated (and hence no adverse selection concerns), because of the possibility of permanent price impact from an information based large trade or a transitory price impact from a liquidity-motivated trade that persists for longer than the HFT is willing to hold that stock position.

Our dependent variables of interest are HFT and DMM liquidity provision for the aggressive component of large trades. For example, suppose there is a large buy in a particular stock for \$10 million and that 50 percent of this order is executed using aggressive orders. If HFTs together provide liquidity to \$2 million of the \$5 million aggressive order, then they are said to provide 40 percent of liquidity to the aggressive component of the large trade. If the DMM provides liquidity to an additional \$1 million of the order, then they are said to provide 20 percent of liquidity to the aggressive component of the large trade. Specifically, we define our dependent variables as follows:

$$
\begin{aligned}
HFTLIQ_t &= \frac{\text{HFT Passive Dollar Volume}_t}{\text{Aggressive Dollar Volume}_t} \\
DMMLIQ_t &= \frac{\text{DMM Passive Dollar Volume}_t}{\text{Aggressive Dollar Volume}_t}.
\end{aligned}
$$

We apply several filters to the large trades we want to include in our analysis. First, a large trade needs to have at least 10 percent and at most 90 percent of its order executed using aggressive trades – we are interested in examining liquidity provision to large trades, meaning we require a reasonable number of aggressive orders to be contained in these large trades. Second, we require that large trades are executed via a sequence of smaller trades, hence we do not include any large trades that are executed using less than 20 smaller trades. This reduces the sample of 183,968 large trades reported in Table 4 (the sum of large trades and extra-large trades) to 117,897.

We are interested in the determinants of HFT and DMM liquidity provision to large trades. In particular, our goal is to measure the extent to which HFTs in particular might reduce their liquidity provision to large trades when those trades exert more "stress" on the marketplace. We identify a large trade as "stressful" (the stress indicator variable will equal one) if it is in the highest quintile of large trade dollar volume as a percentage of total dollar volume for that stock-day (the stress indicator variable equals zero otherwise).

HFTs should be more active in high-volume stocks because of the ability to turn over shares quickly. Indeed, according to Table 3, we see that HFTs provide more liquidity in these stocks. We are particularly interested in the extent to which HFTs might reduce their liquidity provision within these stocks when a stressful event occurs, as there is potential for bigger losses if prices move against their positions. Therefore, we will also interact the "stress" indicator variable with an indicator variable that equals one if the large trade is in a high volume stock and zero otherwise.

Finally, we include control variables that could also plausibly affect HFT and DMM liquidity provision. We include the percentage of dollar volume for the large trade that is executed using aggressive orders (AGG), the number of hours it takes to fully execute the trade ($TIME$), the dollar volume of the large trade ($DVOL$, in millions of dollars), and the squared dollar volume of the large trade ($DVOL2$) to account for potential non-linearities in the price impact of the trade.

That is, to examine the determinants of HFT and DMM liquidity provision, we run the following regressions:

$$
\begin{aligned}
HFTLIQ_t = \alpha + \gamma_d &+ \beta_1 \cdot STRESS_t + \beta_2 \cdot HIGHVOL_t \\
&+ \beta_3 \cdot (STRESS_t \times HIGHVOL_t) + \gamma' X_t + \varepsilon_t \\
DMMLIQ_t = \alpha + \gamma_d &+ \beta_1 \cdot STRESS_t + \beta_2 \cdot HIGHVOL_t \\
&+ \beta_3 \cdot (STRESS_t \times HIGHVOL_t) + \gamma' X_t + \varepsilon_t.
\end{aligned}
$$

In these regressions, γ_d represents date fixed effect controls and X_t is a vector of control variables that includes AGG_t, $TIME_t$, $DVOL_t$, and $DVOL2_t$.

The regression results for HFT liquidity provision are reported in Table 5. According to regression (3), HFTs provide liquidity to 12.82 percent of the aggressive component of large trades and provide 1.74 percentage points less if the trade is considered stressful. More importantly, if the large trade is within a high-volume stock, then HFTs provide an additional 14.60 percentage points of liquidity to the aggressive component of large trades but 9.75 percentage points less (relative to the 1.74 percentage points less from before) if the trade is considered stressful.

That is, within high-volume firms, HFTs provide liquidity to 27.42 percent (12.82 percent plus 14.60 percent) of the aggressive component of large, non-stressful trades. When that trade is considered stressful, HFTs provide liquidity to only 15.93 percent of the aggressive component of the large trade, for a difference of 11.49 percentage points (9.75 percent plus 1.74 percent) or a percentage difference of negative 41.9 percent ((11.49 minus 27.42)/27.42). Figure 1 summarizes these results graphically.

The coefficients for the control variables are as expected. HFTs provide less liquidity to more aggressive large trades, as the aggressiveness of the trade implies more price impact, which is what market makers generally prefer to avoid when taking a position in a stock. HFTs provide more liquidity to trades that take a longer time to fully execute, suggesting that HFTs are less able to infer the information content contained in an order that executes more slowly, or that they infer a smaller adverse selection problem from those trades. The control variable results also indicate that HFTs provide more liquidity to larger trades, and the negative coefficient on the squared dollar trade size term indicates that this liquidity provision is non-linear and decreasing in trades that are especially large.

As mentioned before, DMMs are responsible for maintaining a reasonable bid-ask spread and lining the limit order book with reasonable depth. As such, we do not expect stressful trades to significantly affect DMM liquidity provision, unlike HFTs who do not have DMM responsibilities. In fact, because HFTs provide less liquidity for stressful trades, it is possible that DMMs will provide more liquidity in their place.

The regression results for DMM liquidity provision are reported in Table 6. According to regression (3), DMMs provide liquidity to 1.47 percent of the aggressive component of large trades and provide an additional 0.23 percentage points if the trade is considered stressful. If the large trade is within a high volume stock, the DMM provides 0.23 percentage points less liquidity and, if the large trade is considered stressful, they provide 0.07 percentage points less, though this last number is not statistically different from zero. Figure 2 summarizes these results graphically.

From the DMM regressions, it is apparent that DMMs provide less liquidity in high-volume stocks, which is likely due to the fact that more HFTs are competing to provide the same liquidity. It is also apparent that DMMs provide more liquidity for stressful trades, particularly in the non-high volume stocks, possibly because HFTs provide less liquidity for these stressful trades and DMMs pick up some of the slack. The evidence suggests that DMMs continue to fulfill their assigned market making responsibilities.

8 When DMMs Become HFT-DMMs

The evidence presented so far regarding HFT and DMM liquidity provision is correlative. HFTs provide less liquidity for stressful trades, particularly those in high-volume stocks, but it is possible that there is an omitted variable that causes both the stressful trade to occur and the HFT liquidity provision to be lower. Therefore, our next goal is to examine potential exogenous instruments that affect HFT liquidity provision to large trades and are independent of determinants of stressful trades.

We first examine an interesting event that increased HFT presence in 24 stocks in our sample. Prior to November 26, 2012, a variety of DMMs were assigned to 24 specific stocks. The behavior of these DMMs is typical - few orders per day and many trades relative to those orders. DMMs have the right to execute against odd lot orders without placing any orders of their own, which is why we observe a low number of DMM orders relative to their trades. Interestingly, starting on November 26, 2012, these 24 stocks were all assigned the same, new DMM. This new DMM clearly exhibits behaviors of an HFT - in particular, this DMM submits many more orders (in some stocks, more than 1,000 times the number of orders than before) and trades, its order-to-trade ratio is very high, and the dollar volume originating with this DMM is also much higher.

Table 7 provides additional details. Many of these 24 stocks have high dollar volume and market capitalization and in this table we report four of the highest-volume stocks which, in the interest of confidentiality, we will name Stock A, Stock B, Stock C, and Stock D. The DMM for Stock A, for example, submits an average of 10 orders per day in the five days before November 26, 2012 and approximately 18,000 orders per day in the five days starting on November 26, 2012, indicating an approximate 181,000 percent increase. Average daily trades increased from approximately 600 to 2,900 and average daily dollar volume increased from approximately $1.9 million to $19 million. Similarly large relative increases in orders, trades, and dollar volume are also observed for the remaining 20 stocks.

We have a conjecture for why this event occurred. Effective April 1, 2012, IIROC implemented its "Integrated Fee Model," in which designated market makers would now receive a 70 percent discount on marketplace fees. These fees are typically based on the proportion of message traffic (orders and trades) originating from that trader. HFTs taking on a non-designated market-making role, however, do not qualify for this 70 percent discount. Given that HFTs constitute a significant portion of submitted orders and trades, a 70 percent discount would be highly beneficial, which is why we are not surprised to see an HFT take on the DMM role for several high-volume stocks.

However, the date on which the DMMs in those 24 stocks all become the single HFT-DMM is November 26, 2012, which is approximately 8 months after the implementation of the Integrated Fee Model. While it is clear that some HFTs would now have incentive to take on a DMM role, we do not believe that HFTs would instantaneously become DMMs following the new regulation – the application process and approval process by the TSX Allocation Committee for DMMs assumedly takes time, and 8 months seems like a reasonable time frame.

Therefore, we have identified an event in which HFT presence in these particular stocks has increased, via the DMM channel, and is independent of the arrival of stressful trades. To examine how this exogenous event might influence liquidity provision to large trades, we first define a new variable indicating liquidity provision to large trades by HFTs and the DMM combined:

$$HDLIQ_t = HFTLIQ_t + DMMLIQ_t.$$

Henceforth, HD liquidity provision will denote the liquidity provision provided to large trades by HFTs and the DMM combined.

As in the previous section, we will examine the potential determinants of this liquidity provision using the same independent variables as regression (1). However, we will now also include an indicator variable that equals one ($NEWDMM = 1$) when the large trade is executed on a day in which the HFT is assigned as a DMM in one of the 24 stocks discussed above. This indicator variable will be interacted with the stress indicator, the high volume stock indicator, and the cross product of the stress and high volume stock indicators.

Specifically, we run the following regression:

$$\begin{aligned} HDLIQ_t = \alpha + \gamma_d \quad &+ \quad \beta_1 \cdot STRESS_t + \beta_2 \cdot HIGHVOL_t + \beta_3 \cdot (STRESS_t \times HIGHVOL_t) + \\ &+ \quad \beta_4 \cdot NEWDMM_t + \beta_5 \cdot (NEWDMM_t \times STRESS_t) \\ &+ \quad \beta_6 \cdot (NEWDMM_t \times HIGHVOL_t) \\ &+ \quad \beta_7 \cdot (NEWDMM_t \times STRESS_t \times HIGHVOL_t) + \gamma' X_t + \varepsilon_t. \end{aligned}$$

If HFTs have an increased presence within a stock, then we expect to observe higher liquidity provision for non-stressful trades. However, it is unclear whether we will observe higher or lower liquidity provision to the stressful trades. On the one hand, additional HFTs should generally improve liquidity provision, even in the stressful trades, due to increased competition to provide liquidity. On the other hand, if a traditional DMM, who is obligated to provide liquidity at all times, is replaced by an HFT, then it is possible that total liquidity provision could even be lower, based on our previous observation that HFTs provide less liquidity to stressful trades.

The regression results are reported in Table 8. According to regression (3), HD liquidity provision is equal to 27.95 percent for large trades. When that trade is stressful, HD liquidity provision is equal to 17.42 percent, which represents a reduction of 10.53 percentage points.

More importantly, within high-volume firms, HD liquidity provision is 5.64 percentage points higher when the DMM is replaced by an HFT within the sample of 24 stocks discussed earlier. However, if the trade is stressful during the period when the DMM is replaced by an HFT, this liquidity provision is reduced by 6.64 percentage points. That is, HD liquidity provision is actually lower for stressful trades (negative 1.00 percentage points) when the traditional DMM is replaced by an HFT. For ease of interpretation, Figure 3 summarizes these results graphically.

9 HFT Liquidity Provision and Extreme Returns

Occasionally, a stock experiences an unusually large price movement in a single day. This movement could be attributed to an idiosyncratic event within that stock or a large price change in the stock market as a whole. Before, we had the potential problem that HFT liquidity provision to stressful trades is correlative. That is, an omitted third variable was influencing both HFT liquidity provision and the stressful trade. Here, we argue that large return movements, either on the day of the large trade or the day previous to the large trade, are exogenous to the large trade decision. Because it is possible that the large trade itself could cause the contemporaneous extreme return, we include lagged extreme returns. This way, we can identify a clear causal relation between a stressful period and an HFT's decision to provide less liquidity.

First, we must define a "stressful" return day. We calculate the open-to-close return for each stock-day in our sample. Any absolute return that is in the upper decile of all absolute returns within that stock is identified as a stressful return day. That is, we create an indicator variable called $STRESSRET$ that equals 1 if the large trade takes place on a stressful return day. We also examine HFT liquidity provision if the stressful return was on the previous day, as it is possible that HFTs adjust their liquidity provision after the fact.

Specifically, we run the following regression:

$$\begin{aligned} HDLIQ_t = \alpha + \gamma_d &+ \beta_1 \cdot STRESSRET_t + \beta_2 \cdot HIGHVOL_t \\ &+ \beta_3 \cdot (STRESSRET_t \times HIGHVOL_t) + \\ &+ \beta_4 \cdot STRESS_t + \beta_5 \cdot (STRESS_t \times HIGHVOL_t) + \gamma' X_t + \varepsilon_t. \end{aligned}$$

As a reminder, $STRESS_t$ indicates whether the large trade itself is stressful, $HIGHVOL_t$ indicates whether the large trade takes place within a high volume firm, and X_t is a vector of control variables that includes AGG_t, $TIME_t$, $TSIZE_t$, and $TSIZE2_t$.

Table 9 reports the results from this regression. Regressions (1) and (2) use the contemporaneous $STRESSRET$ variable while regressions (3) and (4) use the lagged $STRESSRET$ variable. According to regression (1), HFTs provide 1.12 percentage points less liquidity to large trades if that day is also a stressful return day. If the large trade takes place within a high volume firm, then HFTs provide 2.93 percentage points less liquidity (1.12 percent plus 1.71 percent). This reduction would be added to the existing 11.60 percentage point reduction in liquidity (1.83 percent plus 9.77 percent) if the trade itself is stressful and within a high volume firm. It should also be noted that, when including date fixed effects, the effect of stressful returns on HFT liquidity provision is only significant within the high volume firms.

Regressions (3) and (4) report the results when we use the lagged value of the $STRESSRET$ indicator instead of the contemporaneous value. We use the lagged value as well because it is possible that a contemporaneous stressful return day could potentially experience most of it price movements after a large trade on that day has already occurred, and because the stressful trade could cause the contemporaneous return. The results are similar to regression (1), though the effects are slightly less significant. According to regression (3), if the previous stock day had a stressful return, then HFT liquidity provision is 0.82 percentage points lower. If the lagged stressful return is within a high volume stock, then HFT liquidity provision is 2.69 percentage points lower (0.82 percent plus 1.87 percent). This would be added to the 11.91 percentage point reduction if the large trade was also considered stressful and within a high volume stock.

10 HFT Liquidity Provision and the Cost of a Large Trade

So far, we have provided evidence that HFTs provide less liquidity to a large trade when it is considered stressful, and that when HFT presence in a stock is higher, there is even less liquidity provided to a large trade, in addition to the lower liquidity provision when the stock is experiencing large price movements. When there is less liquidity provided to a large trade, the effective depth of the limit order book across the day is lower, meaning that large trades will get inferior prices – large buys will cost more and large sells will receive lower proceeds.

In this section, we examine the relationship between the cost of a trade and HFT liquidity provision to that trade. Recall that we calculated the implementation shortfall (IS) for each large trade in our sample – this represents the cost of a trade due to price impact. For example, if IS equals 20 basis points for a large buy order, this means that the buyer paid 20 basis points more than he would have paid had there been unlimited liquidity at the initial price in this large buy order. If the buyer was interesting in purchasing \$10 million worth of shares, he would have paid \$10.02 million due to price impact.

Therefore, our dependent variable of interest in this section is implementation shortfall. We will examine how this variable relates to both HFT and DMM liquidity provision, as defined previously. In addition, we will examine the percentage of passive volume in the large trade that is aggressively executed by the HFT and DMM. For example, suppose there is a large trade for \$10 million and 50 percent of that trade is fulfilled via passive orders. If an HFT is the active trader to \$2 million of that passive volume, then the HFT executes against 40 percent of the large trade passive volume.

Specifically, we define the percentage of passive liquidity in the large trade executed by aggressive HFT and DMM orders, respectively, as follows:

$$\begin{aligned} HFTAGG_t &= \frac{\text{HFT Active Dollar Volume}_t}{\text{Passive Dollar Volume}_t} \\ DMMAGG_t &= \frac{\text{DMM Active Dollar Volume}_t}{\text{Passive Dollar Volume}_t}. \end{aligned}$$

Finally, we include the same control variables used in the regressions in the previous sections: AGG, $TIME$, $DVOL$, and $DVOL2$. In these control variables, we now also include indicator variables for large trades that execute in high-volume stocks and medium-volume stocks. The vector of control variables is denotes by Y.

That is, to examine the determinants of the implementation shortfall in large trades, we run the following regression:

$$
\begin{aligned}
IS_t = \alpha + \xi_d \quad &+ \quad \beta_1 \cdot HFTLIQ_t + \beta_2 \cdot DMMLIQ_t \\
&+ \quad \beta_3 \cdot HFTAGG_t + \beta_4 \cdot DMMAGG_t + \xi' Y_t + u_t.
\end{aligned}
$$

Altogether, we run seven regressions: for all large trades, only extra-large trades, only large trades that are not extra-large, and large trades within a particular quartile of stress as defined by its percentage of dollar volume for that stock-day (these quartiles of stress are denoted high, medium-high, medium-low, and low).

The regression results are reported in Table 10. According to regression (1), if HFTs provides 10 percentage points more liquidity to the active component of a large trade, the IS of the trade is 2.7 basis points lower. Conversely, if HFTs provide 10 percentage points less liquidity, then the IS of the trade is 2.7 basis points higher. If a DMM provides 10 percentage points less liquidity to the active component of a large trade, then the IS of the trade is 1.5 basis points higher. However, it should be noted that, according to the previous section, HFTs tend to provide less liquidity to stressful trades, but this is not apparent for DMMs.

We also observe a positive relationship between HFT aggressive execution and IS. If HFTs are actively taking liquidity for 10 percent more of the executed passive volume within a large trade, then the IS of the large trade is 1.5 basis points higher. That is, the HFT perceives the standing limit order from the large trader as a profitable opportunity and aggressively executes against this order, meaning that the large trader got an inferior price for that trade, which is reflected in a higher implementation shortfall. A similar result holds for DMMs.

The coefficients on the control variables in this regression are as expected. Large trades that are executed with more aggressive orders have a higher IS. If a large trade takes a longer time to execute, then the IS is lower, likely because the large trade is more successful in hiding the information content contained in the total order. IS is increasing in its total trade size, but decreasing in total trade size squared, indicating a concave relationship. Finally, IS is lower in medium volume stocks and even lower in high volume stocks, likely because there is more liquidity provided within these stocks.

Regressions (2) and (3) differentiate large trades and extra-large trades (not greater than \$10 million and at least \$10 million, respectively). The main observation here is that the sensitivity of IS to passive HFT and DMM liquidity provision has increased – for example, if an HFT provides 10 percentage points less liquidity to the active component of an extra-large trade, then IS is 4.4 basis points higher, in contrast to large trades, in which IS is 2.7 basis points higher.

Regressions (4) to (7) separate large trades by stress quartiles. Again, for HFTs, we find a similar result to regressions (2) and (3): when a trade is more stressful, IS is more sensitive to HFT liquidity provision. For example, when HFTs provide 10 percent less liquidity to the aggressive component of a large trade, then the IS is 1.7 basis points higher for a low stress trade, but 3.4 basis points higher for a high stress trade. The increase in IS sensitivity to HFT liquidity provision is likely because the information content contained in a stressful or very large trade has more potential for permanent price impact.

So far, we have shown that HFTs provide less liquidity to stressful trades. We have also shown that the cost of a large trade is higher when HFTs provide less liquidity to large trades. We combine these results by running the following two-stage least-squares regression:

$$\begin{aligned}\text{First Stage: } HFTLIQ_t &= \alpha + \gamma_d + \beta_1 \cdot STRESS_t + \beta_2 \cdot HIGHVOL_t \\ &\quad + \beta_3 \cdot (STRESS_t \times HIGHVOL_t) + \gamma' X_t + \varepsilon_t \\ \text{Second Stage: } IS_t &= \alpha + \xi_d + \beta_1 \cdot HF\hat{T}LIQ_t + \xi' Y_t + u_t.\end{aligned}$$

That is, we run the first-stage regression to obtain predicted values of HFT liquidity provision to large trades and then run the second-stage regression to determine the effect of predicted liquidity provision on implementation shortfall.

The results are reported in Table 11. As before, in the first-stage regression, HFT liquidity provision is lower for stressful trades. The first-stage regression indicates that implementation shortfall is higher when predicted HFT liquidity provision from the first-stage regression is lower. For example, suppose a trade is denoted as stressful. This implies that HFT liquidity provision is 11.8 percentage points lower (2.5 percent plus 9.3 percent). If HFT liquidity provision is predicted to be 11.8 percentage points lower, then implementation shortfall for this large trade increases by 13 basis points (11.8 percentage points multiplied by 0.011). For a trade totaling \$20 million, this implies an additional cost equal to \$20 million $\times$ 0.0013 = $\$26,000$.

A back-of-the-envelope calculation: suppose there are 100,000 large trades in our sample, averaging \$3 million per trade. Suppose also that 20 percent of these trades are considered stressful - this implies a total stressful dollar volume of \$60 billion. If IS is 13 basis points higher, this implies a reduction in liquidity provision of \$78 million to all stressful trades, relative to if those trades were not considered stressful, during our year and a half sample.

11 Conclusion

We utilize a data set provided by the Investment Industry Regulatory Organization of Canada (IIROC) which allows us to identify large trading packages in Canadian equities over the period

January 2012 to June 2013. We define a large trading package as a group of (at least 20) smaller trades by the same customer (potentially using multiple brokers) in the same direction (buy or sell) in the same stock that totals a minimum of \$1 million.

We also identify high frequency traders (HFTs) and designated market makers (DMMs) for Canadian equities and study the manner in which these traders accommodate large customer trades. Both HFTs and DMMs provide a significant amount of liquidity to large trades in the sense that the large trader executes marketable orders against passive limit orders by HFTs and DMMs. In the aggregate, HFTs provide substantially more liquidity than DMMs, particularly in stocks that typically have high volume.

We define trading packages as stressful if they are particularly large for a given stock-day combination. HFTs provide less liquidity to stressful trades than non-stressful trades, while DMMs provide more liquidity to stressful trades. The increase is DMMs liquidity provision is small relative to the decline in HFT liquidity provision, so it must be the case that other traders supply that liquidity.

We also study a subsample of 24 equities for which the DMM switched from a low-frequency trader to a high-frequency trader. Total liquidity provided by HFTs and DMMs significantly increases for high volume stocks and insignificantly declines for non-high volume stocks. For stressful trades, total liquidity provided by HFTs and DMMs slightly decreases.

Implementation shortfall (IS) averages 12 basis points for large trades (at least \$1 million and less than \$10 million) and 21 basis points for extra-large trades (at least \$10 million). IS is negatively related to HFT and DMM liquidity provision and positively related to HFT and DMM liquidity demanding trades. IS is also increasing in the fraction of the order that is filled with liquidity demanding trades and is negatively related to the time taken to execute the trade. The IS of stressful trades is larger than the IS for non-stressful trades by 13 basis points, on average. Incidentally, stressful trades are also associated with significant reductions in HFT liquidity provision, especially in high volume firms.

Our results show that endogenous choice of liquidity provision by HFTs and DMMs to larger trades and their reaction to stressful larger trades has significant impact on the cost of implementing a large trade. The data do not allow us, however, to comment on the counterfactual of what trading costs would be in the complete absence of HFTs.

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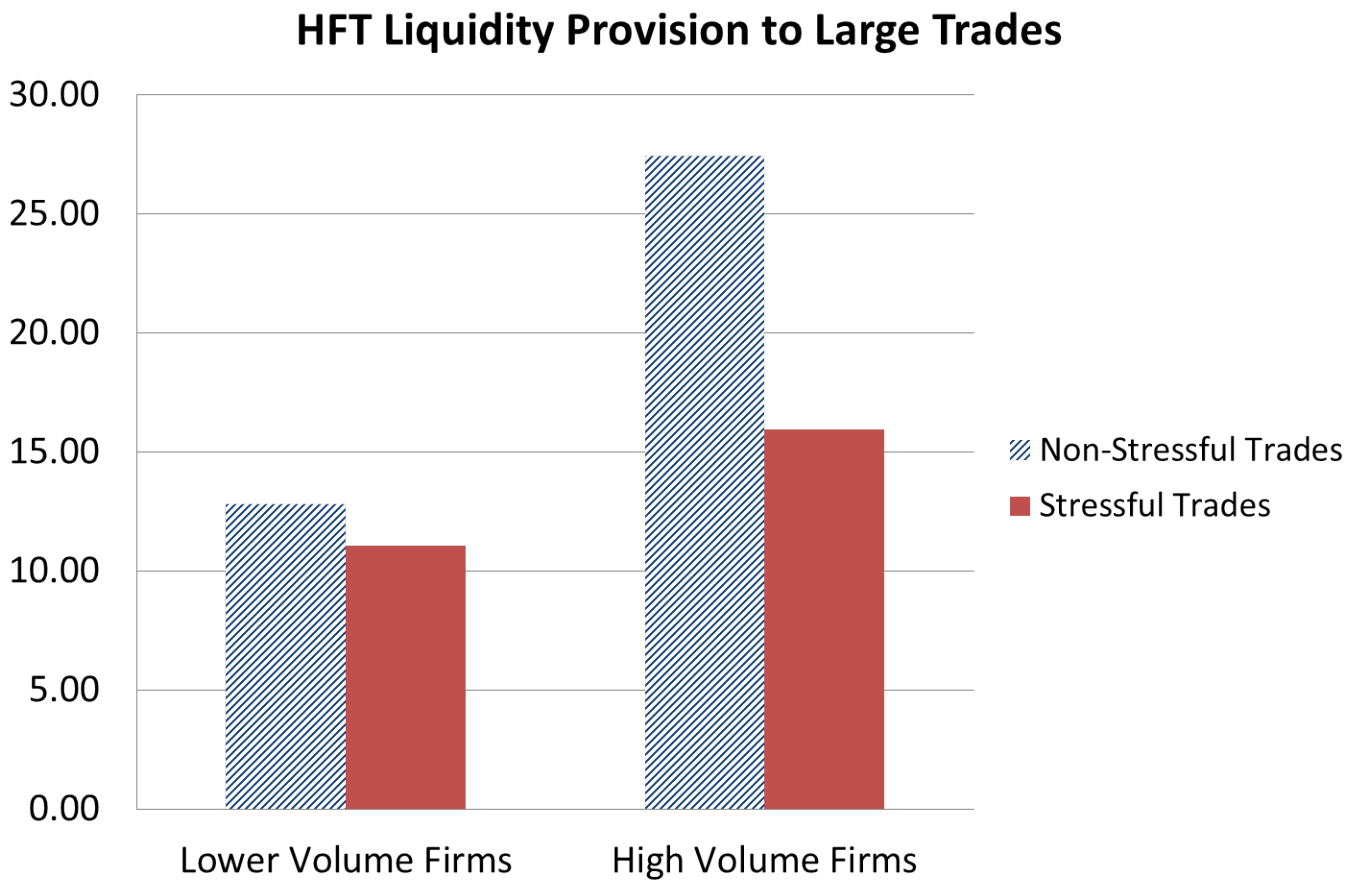

Figure 1. HFT Liquidity Provision for Stressful and Non-Stressful Trades. This graph plots HFT liquidity provision (as a percentage of total liquidity provision to the aggressive component of the large trade) for large trades that are stressful and large trades that are non-stressful, within both high volume firms and lower volume firms. A trade is stressful if its total dollar volume, as a percentage of total dollar volume for that stock-day, is in the upper quartile relative to all large trades. A firm is high-volume if it is in the upper tercile of average daily dollar volume. Otherwise, it is a lower-volume firm. Numbers are based on the coefficients from the HFT liquidity provision regression from Table 5.

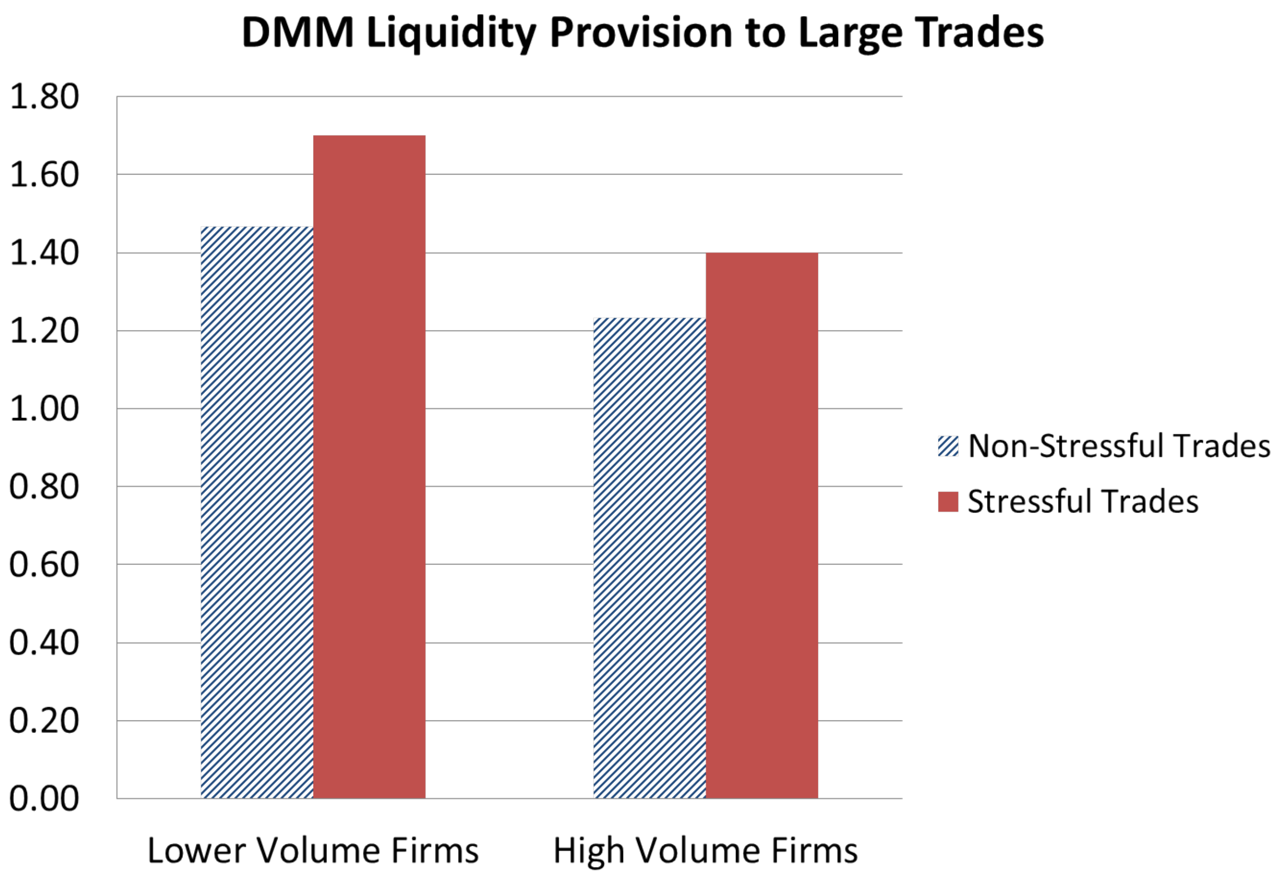

Figure 2. DMM Liquidity Provision for Stressful and Non-Stressful Trades. This graph plots DMM liquidity provision (as a percentage of total liquidity provision to the aggressive component of the large trade) for large trades that are stressful and large trades that are non-stressful, within both high volume firms and lower volume firms. A trade is stressful if its total dollar volume, as a percentage of total dollar volume for that stock-day, is in the upper quartile relative to all large trades. A firm is high-volume if it is in the upper tercile of average daily dollar volume. Otherwise, it is a lower-volume firm. Numbers are based on the coefficients from the DMM liquidity provision regression from Table 6.

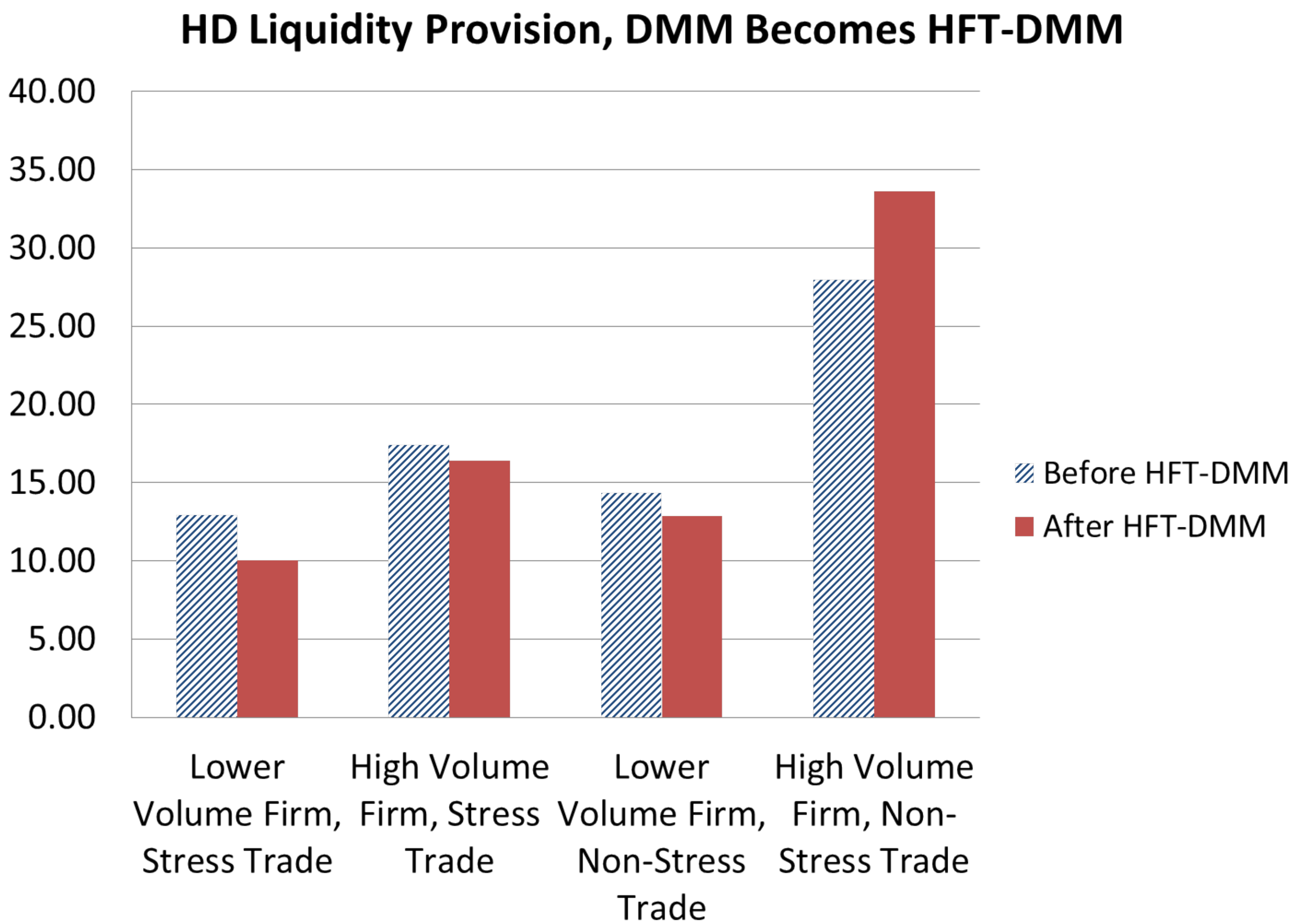

Figure 3. HD Liquidity Provision Before and After DMM Becomes HFT-DMM. This graph plots HFT and DMM combined liquidity provision (as a percentage of total liquidity provision to the aggressive component of the large trade) for 24 stocks in which each DMM became the same HFT-DMM on November 26, 2012. We examine HFT and DMM combined liquidity provision before and after this date, for stressful trades and non-stressful trades, and within high-volume a lower-volume firms. Numbers are based on the coefficients from the HD liquidity provision regression from Table 8.

Table 1. Summary of Individual HFTs. Using our HFT identification methodology, 28 HFTs have been identified in our sample. Stocks represents the number of stocks in which each HFT is involved. % Trades is the average percentage of trades the HFT is involved in across all stock-days in which the HFT is active in that stock. OTR is the average order-to-trade ratio (the within-stock average number of daily orders divided by number of daily trades, then averaged across stocks). AGG is the percentage of dollar volume that is executed via marketable limit orders. ENDPOS is the HFT average net end-of-day inventory for that stock-day divided by share volume for that stock day. SME is the percentage of trades in which those trades are identified a short-marking exempt. HFT Days is the percentage of active stock-days in which the HFT meets the criteria to be identified as an HFT. Table 2 averages across HFTs within each of the three HFT subroups: Super HFTs, Major HFTs, and Minor HFTs. All columns are reported in percentage points except for HFT, Stocks, and OTR.

	HFT	Stocks	% Trades	OTR	AGG	ENDPOS	SME	HFT Days
Super HFTs	1	311	17.97	30.72	7.53	2.25	100.0	92.4
	2	208	20.93	2.67	23.38	0.80	0.0	88.5
	3	141	22.24	3.11	25.45	5.21	0.0	85.2
	4	124	10.25	19.93	29.50	7.54	0.0	82.1
Major HFTs	5	88	10.02	28.80	1.34	6.26	100.0	81.0
	6	56	8.40	16.35	29.36	3.74	84.8	90.1
	7	55	7.77	14.13	14.08	5.97	100.0	87.3
	8	47	6.44	21.28	12.74	0.03	100.0	95.2
	9	42	7.08	14.72	18.19	4.56	100.0	90.0
	10	40	8.52	11.86	33.23	3.48	100.0	87.4
	11	40	17.28	41.01	6.41	8.53	100.0	78.1
	12	39	8.53	29.70	10.79	0.00	100.0	95.8
	13	25	2.67	16.08	3.63	3.03	0.0	88.8
	14	19	3.61	14.91	23.38	1.26	100.0	87.0
	15	18	2.56	10.99	3.86	2.33	94.8	84.2
Minor HFTs	16	8	1.43	33.69	0.03	5.54	98.2	80.5
	17	6	7.82	21.65	5.55	7.52	100.0	77.0
	18	5	9.89	71.09	22.43	1.64	100.0	82.8
	19	5	4.76	26.91	50.30	1.10	0.0	90.1
	20	3	3.34	6.38	5.85	1.32	100.0	80.6
	21	3	18.94	3.88	34.99	6.79	0.0	77.2
	22	2	7.10	2.46	4.62	7.76	0.0	80.0
	23	2	4.94	18.97	7.92	3.93	100.0	83.1
	24	2	2.45	10.35	4.28	1.68		77.0
	25	1	1.91	11.56	0.01	6.04	87.4	88.4
	26	1	18.23	5.06	30.24	0.52	0.0	100.0
	27	1	5.78	15.11	8.46	0.00		86.1
	28	1	2.62	8.25	1.13	4.30		86.4

Table 2. Summary of HFTs by HFT Subgroup. Averages taken within three HFT categories (Super HFT, Major HFT, Minor HFT) and across all HFTs. Same variable definitions as Table 1.

	HFT	Stocks	% Trades	OTR	AGG	ENDPOS	SME	HFT Days
Super HFTs	1-4	196	17.85	14.11	21.46	3.95	25.0	87.0
Major HFTs	5-15	43	7.53	19.99	14.27	3.56	89.1	87.7
Minor HFTs	16-28	3	6.86	18.11	13.52	3.70	58.6	83.8
All HFTs	1-28	46	8.70	18.27	14.95	3.68	66.6	85.8

Table 3. Statistics for HFTs and DMMs. PVOL and AVOL represent the average stock-day passive volume and active volume, as a percentage of total daily volume, for the HFT group and DMM. Orders is the average stock-day number of orders as a percentage of all orders for that stock-day. Buys and Sells represent the average stock-day number of buys and sells, respectively, as a percentage of the number of trades for that stock-day. OTR, ENDPOS, and AGG are defined as in Table 1. N(HFT) is the average daily number of HFTs active in the stock. N(DMM) is the average daily number of DMMs active in the stock. All columns are reported in percentage points except for OTR, SIZE (which is reported in dollar value), N(HFT), and N(DMM).

Panel A: HFT Statistics

	PVOL	AVOL	Orders	Buys	Sells	OTR	ENDPOS	AGG	SIZE	N(HFT)
Stock 1	39.4	9.2	43.5	28.8	29.1	12.2	0.7	18.8	9070	8.65
Stock 2	34.5	9.8	32.4	26.4	26.3	11.1	0.6	21.5	5447	6.77
Stock 3	25.9	3.6	33.6	17.3	17.6	19.0	1.7	12.2	9963	4.86
Stock 4	40.5	7.1	57.4	29.2	29.5	15.2	0.5	14.4	7360	8.78
Stock 5	10.0	1.1	12.4	10.9	10.9	23.3	0.8	9.2	17148	1.93
Highvol Stocks	19.6	3.9	24.7	14.9	15.1	28.1	1.4	15.0	4853	3.76
Midvol Stocks	13.7	1.8	19.0	10.1	10.1	29.1	2.2	11.4	2924	1.70
Lowvol Stocks	18.1	1.6	24.2	13.6	13.6	16.8	2.8	8.4	942	1.28

Panel B: DMM Statistics

	PVOL	AVOL	Orders	Buys	Sells	OTR	ENDPOS	AGG	SIZE	N(DMM)
Stock 1	2.5	1.6	2.6	3.8	3.7	3.8	7.1	28.3	4705	1.07
Stock 2	0.8	0.7	0.0	1.6	1.5	0.0	0.8	19.5	2670	1.01
Stock 3	3.5	1.8	2.4	4.2	4.6	4.5	7.4	27.1	6531	1.04
Stock 4	2.3	1.4	0.0	2.8	3.3	0.1	0.9	31.2	5098	1.01
Stock 5	2.8	2.1	3.0	3.7	3.9	21.5	52.0	33.2	22654	1.00
Highvol Stocks	2.5	2.2	1.7	3.5	3.4	10.7	10.3	26.8	3527	1.03
Midvol Stocks	3.2	2.2	1.3	3.7	3.8	11.0	15.6	26.4	2146	1.02
Lowvol Stocks	2.6	1.9	0.5	2.7	2.8	2.4	26.3	23.8	711	1.01

Panel C: Volume Statistics

	Daily Volume ($M)	Daily Trades	Daily Orders
Stock 1	242.8	20,284	334,095
Stock 2	209.2	27,290	491,759
Stock 3	202.5	14,327	287,629
Stock 4	190.2	17,149	268,812
Stock 5	184.9	4,416	167,184
Highvol Stocks	63.4	8,701	180,708
Midvol Stocks	9.8	2,735	47,241
Lowvol Stocks	2.5	1,561	20,973

Table 4. Summary of Large Trades. Panel A reports statistics for large trades, which are trades for at least \$1 million but less than \$10 million. Panel B reports statistics for extra-large trades, which are trades for at least \$10 million. Value of Trade is the total dollar value of the trade. Number of Trades is the number of recorded trades that are used to execute the total trade. Number of Orders is the total number of orders submitted while executing the trade. Liquidity Demanded is the percentage volume of the trade executed via marketable limit orders. Time to Completion is the number of hours it takes to execute the trade. Implementation Shortfall, measured in basis points, is the price of the trade relative to the price if all shares were executed at the initial price in the trade.

Panel A: Large Trades [\$1M, \$10M) (N=179,036)						
	Mean	P10	P25	P50	P75	P90
Value of Trade (\$M)	2.34	1.09	1.27	1.74	2.77	4.46
Number of Trades	317	35	123	236	413	673
Number of Orders	452	7	51	201	513	997
% Liquidity Demanded	56.2%	8.8%	29.1%	58.7%	85.1%	99.9%
Time to Completion (hours)	3.26	0.07	0.71	3.25	5.87	6.42
Implementation Shortfall (bps)	12	-49	-9	5	33	82

Panel B: Extra-Large Trades (at least \$10M) (N=4,932)						
	Mean	P10	P25	P50	P75	P90
Value of Trade (\$M)	17.44	10.51	11.48	14.06	18.44	26.35
Number of Trades	1,110	5	56	980	1,649	2,452
Number of Orders	1,232	1	7	579	1,630	3,055
% Liquidity Demanded	58.2%	18.4%	36.2%	59.5%	81.4%	97.5%
Time to Completion (hours)	3.57	0.00	0.46	4.27	6.15	6.48
Implementation Shortfall (bps)	21	-37	-1	2	42	98

Table 5. HFT Liquidity Provision For Stressful Trades. The dependent variable in these regressions is HFTLIQ, which is the percentage of liquidity provided by HFTs to the active component of large trades. STRESS is an indicator variable that equals one if the dollar value of the large trade as a percentage of dollar volume for that stock-day is in the highest quintile of all large trades. HIGHVOL is an indicator variable that is equal to one if the stock is in the highest tercile of average daily dollar volume. AGG represents the percentage of the large trade that is executed using aggressive orders. TIME is the number of hours is takes to execute the large trade. TSIZE is the dollar value of the large trade and TSIZE2 is the dollar value squared. t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	28.45	14.03	12.82	17.97	4.35	3.22
	(451.64)	(48.17)	(38.65)	(18.14)	(4.28)	(3.16)
STRESS	-11.66	-1.09	-1.74	-11.92	-1.84	-2.51
	(-92.50)	(-3.28)	(-5.24)	(-95.44)	(-5.58)	(-7.65)
HIGHVOL		15.11	14.60		14.53	13.91
		(50.71)	(49.18)		(49.13)	(47.23)
STRESS x HIGHVOL		-8.16	-9.75		-7.63	-9.30
		(-22.14)	(-26.47)		(-20.93)	(-25.54)
AGG			-0.032			-0.035
			(-13.27)			(-15.02)
TIME			0.46			0.43
			(19.28)			(17.97)
TSIZE			0.75			0.80
			(30.46)			(32.80)
TSIZE2			-0.0064			-0.0066
			(-13.92)			(-14.70)
Day Fixed Effects	No	No	No	Yes	Yes	Yes
Adj. R-Squared	0.068	0.095	0.108	0.098	0.124	0.138
N	117897	117897	117897	117897	117897	117897

Table 6. DMM Liquidity Provision For Stressful Trades. The dependent variable in these regressions is DMMLIQ, which is the percentage of liquidity provided by the designated market maker to the active component of large trades. STRESS is an indicator variable that equals one if the dollar value of the large trade as a percentage of dollar volume for that stock-day is in the highest quintile of all large trades. HIGHVOL is an indicator variable that is equal to one if the stock is in the highest tercile of average daily dollar volume. AGG represents the percentage of the large trade that is executed using aggressive orders. TIME is the number of hours is takes to execute the large trade. TSIZE is the dollar value of the large trade and TSIZE2 is the dollar value squared. t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	1.14	1.43	1.47	1.19	1.49	1.57
	(92.77)	(24.73)	(22.15)	(6.09)	(7.33)	(7.64)
STRESS	0.32	0.26	0.23	0.31	0.25	0.23
	(12.80)	(3.97)	(3.52)	(12.72)	(3.78)	(3.41)
HIGHVOL		-0.30	-0.23		-0.33	-0.26
		(-5.06)	(-3.95)		(-5.49)	(-4.33)
STRESS x HIGHVOL		-0.12	-0.07		-0.12	-0.07
		(-1.63)	(-0.89)		(-1.66)	(-0.99)
AGG			-0.0038			-0.0039
			(-7.97)			(-8.27)
TIME			0.060			0.059
			(12.45)			(12.16)
TSIZE			-0.044			-0.042
			(-8.89)			(-8.51)
TSIZE2			0.00037			0.00036
			(4.02)			(3.99)
Day Fixed Effects	No	No	No	Yes	Yes	Yes
Adj. R-Squared	0.001	0.002	0.005	0.012	0.013	0.015
N	117897	117897	117897	117897	117897	117897

Table 7. DMM Activity Around November 26, 2012. This table reports DMM activity around November 26, 2012 for four large capitalization stocks. These four stocks, along with twenty other stocks in our sample of 251, all had a change in DMM on November 26, 2012. As a result, all 24 stocks now had the same new DMM, whereas these stocks did not necessarily have the same DMM before this date. The behavior of this new DMM is consistent with that of an HFT. Orders and Trades represent the number of orders and trades, respectively, submitted by the DMM. DVOL represents the dollar volume traded by the DMM in that stock.

Stock A				**Stock B**			
Date	Orders	Trades	DVOL	Date	Orders	Trades	DVOL
11/19/2012	9	517	$1,527,098	11/19/2012	136	747	$4,563,382
11/20/2012	9	662	$2,137,486	11/20/2012	151	689	$3,592,483
11/21/2012	8	638	$1,761,786	11/21/2012	143	726	$3,981,145
11/22/2012	14	582	$2,198,969	11/22/2012	325	1015	$11,386,931
11/23/2012	10	675	$2,090,191	11/23/2012	261	897	$8,410,121
11/26/2012	13743	2604	$16,658,721	11/26/2012	61579	1920	$14,963,364
11/27/2012	14901	2587	$16,443,534	11/27/2012	17940	2272	$19,844,678
11/28/2012	13860	2219	$14,833,054	11/28/2012	18212	1658	$12,820,071
11/29/2012	30716	4170	$29,203,356	11/29/2012	20080	4272	$41,967,859
11/30/2012	17333	2792	$18,637,773	11/30/2012	23207	2494	$20,815,559

Stock C				**Stock D**			
Date	Orders	Trades	DVOL	Date	Orders	Trades	DVOL
11/19/2012	16	237	$681,213	11/19/2012	17	208	$402,912
11/20/2012	11	238	$602,872	11/20/2012	33	258	$649,643
11/21/2012	8	192	$412,844	11/21/2012	33	305	$861,744
11/22/2012	70	285	$1,611,610	11/22/2012	3	153	$235,719
11/23/2012	19	297	$874,819	11/23/2012	9	227	$389,226
11/26/2012	18998	2491	$11,546,836	11/26/2012	6564	1321	$4,710,680
11/27/2012	21410	2508	$11,684,627	11/27/2012	17188	2012	$7,946,701
11/28/2012	28037	2743	$12,617,069	11/28/2012	15745	1620	$6,410,117
11/29/2012	32049	3638	$16,548,740	11/29/2012	19319	2709	$10,035,004
11/30/2012	27224	2600	$11,593,508	11/30/2012	13813	1714	$6,441,608

Table 8. Liquidity Provision to Large Trades After DMM Becomes HFT-DMM. The dependent variable in these regressions is HDLIQ, which is the percentage of liquidity provided by the HFTs and designated market maker combined to the active component of large trades. NEWDMM is an indicator that equals one if the large trade takes place on a stock-day in which the DMM is now an HFT-DMM. All other variables are defined as before.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	15.46	15.58	14.34	5.84	6.46	5.35
	(52.88)	(51.03)	(41.74)	(5.73)	(6.33)	(5.23)
STRESS	-0.83	-0.71	-1.40	-1.59	-1.47	-2.17
	(-2.49)	(-2.05)	(-4.02)	(-4.80)	(-4.25)	(-6.29)
HIGHVOL	14.81	14.01	13.61	14.20	13.39	12.89
	(49.52)	(44.80)	(43.72)	(47.81)	(43.12)	(41.72)
STRESS x HIGHVOL	-8.27	-7.65	-9.14	-7.75	-7.13	-8.72
	(-22.38)	(-19.82)	(-23.70)	(-21.17)	(-18.65)	(-22.84)
NEWDMM		-1.35	-1.48		-2.30	-2.43
		(-1.33)	(-1.46)		(-2.28)	(-2.43)
NEWDMM x STRESS		-1.39	-1.43		-1.24	-1.32
		(-1.19)	(-1.23)		(-1.07)	(-1.15)
NEWDMM x HIGHVOL		7.14	7.11		7.40	7.31
		(6.89)	(6.92)		(7.22)	(7.19)
NEWDMM x STRESS x HIGHVOL		-5.18	-5.21		-5.27	-5.23
		(-4.00)	(-4.05)		(-4.10)	(-4.11)
AGG			-0.035			-0.038
			(-14.54)			(-16.35)
TIME			0.55			0.51
			(22.70)			(21.25)
TSIZE			0.68			0.73
			(27.33)			(29.79)
TSIZE2			-0.0057			-0.0060
			(-12.40)			(-13.21)
Day Fixed Effects	No	No	No	Yes	Yes	Yes
Adj. R-Squared	0.090	0.097	0.110	0.118	0.123	0.137
N	117897	117897	117897	117897	117897	117897

Table 9. HFT Liquidity Provision on Stressful Return Days. The dependent variable in these regressions is HFTLIQ, which is the percentage of liquidity provided by HFTs to the active component of large trades. STRESSRET is equal to one if the stock-day on which the large trade takes place has an absolute return that is in the highest decile of all absolute return days in that stock. LAGSTRESSRET is equal to one if the previous stock-day has an absolute return that is in the highest decile of all absolute return days in that stock. All other variables are defined as before.

	(1)	(2)	(3)	(4)
Intercept	13.04	3.93	12.89	3.24
	(4.00)	(3.84)	(37.7)	(3.17)
STRESSRET	-1.12	-0.82		
	(-2.75)	(-2.04)		
LAGSTRESSRET			-0.32	-0.26
			(-0.77)	(-0.63)
HIGHVOL	14.73	14.10	14.73	14.03
	(47.67)	(46.00)	(47.64)	(45.76)
STRESSRET x HIGHVOL	-1.71	-1.87		
	(-3.87)	(-4.26)		
LAGSTRESSRET x HIGHVOL			-1.28	-1.16
			(-2.83)	(-2.60)
STRESS	-1.83	-2.57	-1.77	-2.53
	(-5.51)	(-7.78)	(-5.30)	(-7.66)
STRESS x HIGHVOL	-9.77	-9.34	-9.77	-9.32
	(-26.43)	(-25.56)	(-26.41)	(-25.47)
AGG	-0.031	-0.035	-0.032	-0.035
	(-13.24)	(-14.97)	(-13.39)	(-15.08)
TIME	0.46	0.42	0.46	0.43
	(11.00)	(17.86)	(19.28)	(18.00)
TSIZE	0.77	0.81	0.76	0.81
	(30.99)	(33.23)	(30.67)	(32.96)
TSIZE2	-0.0064	-0.0066	-0.0064	-0.0067
	(-14.02)	(-14.75)	(-14.03)	(-14.78)
Day Fixed Effects	No	Yes	No	Yes
Adj. R-Squared	0.110	0.140	0.109	0.139
N	117897	117897	117897	117897

Table 10. Trade Price and Market Maker Liquidity Provision. The dependent variable in this regression is Implementation Shortfall (IS), which is the total price of a large trade relative to the price if all of the shares were executed at the initial price and measured in percentage points. Regression (1) uses all large trades. Regressions (2) and (3) use only large trades and extra-large trades, respectively. Regressions (4) to (7) use large trades in the following respective "stress" quartiles: high, medium-high, medium low, and low. A large trade is placed in a stress quartile based on its total dollar volume relative to all dollar volume within that stock-day. HFTAGG and DMMAGG are the HFT and DMM active dollar volume within a large trade, respectively, as a percentage of all passive volume within that large trade. HIGHVOL equals one if a large trade executes within a stock that is in the upper tercile of average daily dollar volume. MIDVOL equals one if a large trade executes within a stock that is in the middle tercile of average daily dollar volume. All other variables are defined as before. t-statistics are reported in parentheses.

	TRADE SIZE			STRESS OF TRADE			
	All	Large	X-Large	High	Med-High	Med-Low	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.67	0.61	1.53	0.23	0.91	0.78	0.47
	(13.45)	(12.09)	(3.52)	(1.77)	(7.36)	(4.40)	(2.12)
HFTLIQ	-0.0027	-0.0027	-0.0044	-0.0034	-0.0021	-0.0022	-0.0017
	(-19.09)	(-18.84)	(-4.19)	(-7.86)	(-6.78)	(-8.41)	(-8.05)
DMMLIQ	-0.0015	-0.0013	-0.0044	-0.0020	-0.0003	-0.0018	-0.0009
	(-2.24)	(-1.99)	(-0.68)	(-1.24)	(-0.18)	(-1.44)	(-0.92)
HFTAGG	0.0015	0.0014	0.0067	0.0063	0.0023	0.0019	0.0015
	(5.04)	(4.64)	(2.97)	(5.89)	(3.33)	(3.78)	(4.08)
DMMAGG	0.0017	0.0019	-0.0019	0.0000	0.0018	0.0012	0.0039
	(2.60)	(2.88)	(-0.45)	(0.02)	(1.18)	(0.81)	(3.45)
AGG	0.0018	0.0018	0.00159	0.00403	0.0021	0.0009	-0.0002
	(16.76)	(16.37)	(2.14)	(14.93)	(9.48)	(4.59)	(-1.27)
TIME	-0.004	-0.005	0.024	0.013	0.001	-0.021	-0.019
	(-3.43)	(-4.30)	(2.78)	(3.97)	(0.33)	(-11.07)	(-11.71)
TSIZE	0.018	0.054	0.000	0.007	0.007	0.021	0.022
	(17.07)	(10.48)	(-0.01)	(3.78)	(2.08)	(4.87)	(1.89)
TSIZE2	-0.0001	-0.0037	0.0001	0.0000	0.0000	-0.0010	-0.0001
	(12.00)	(-6.13)	(1.93)	(-0.10)	(-0.01)	(-3.07)	(-0.05)
HIGHVOL	-0.55	-0.56	-1.02	-0.40	-0.70	-0.41	-0.33
	(-25.30)	(-25.69)	(-2.73)	(-13.76)	(-8.38)	(-2.64)	(-1.52)
MIDVOL	-0.36	-0.36	-0.78	-0.33	-0.51	-0.36	-0.11
	(-16.26)	(-16.38)	(-1.97)	(-11.32)	(-6.01)	(-2.28)	(-0.52)
Adj. R-Squared	2.6%	2.6%	15.3%	3.8%	3.2%	2.5%	2.6%
N	117897	114891	3006	29474	29475	29474	29474
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11. Two-Stage Least Squares Regression. The first-stage regression examines the relationship between HFT liquidity provision to large trades on a stress indicator and other control variables, all of which are as defined before. The second-stage regression examines the relationship between implementation shortfall and the predicted HFT liquidity provision that results from the first-stage regression, along with other control variables, all of which are defined as before. t-statistics are reported in parentheses.

FIRST STAGE REGRESSION Dependent Variable: HFTLIQ		SECOND STAGE REGRESSION Dependent Variable: IS	
Intercept	3.22	Intercept	0.70
	(3.16)		(14.07)
Stress Trade	-2.51	Predicted HFTLIQ	-0.011
	(-7.65)		(-16.61)
High Volume Firm	13.91	Aggressiveness	0.001
	(47.23)		(13.30)
Stress x Highvol	-9.30	Time to Completion	-0.003
	(-25.54)		(-2.47)
Aggressiveness	-0.04	Trade Size	0.021
	(-15.02)		(19.17)
Time to Completion	0.43	Trade Size Squared	-0.0001
	(17.97)		(-5.82)
Trade Size	0.80	High Volume Firm	-0.42
	(32.80)		(-17.85)
Trade Size Squared	-0.007	Medium Volume Firm	-0.35
	(-14.70)		(-15.86)
Day Fixed Effects	Yes	Day Fixed Effects	Yes
Adjusted R-Squared	13.8%	Adjusted R-Squared	2.5%
N	117897	N	117897