High-Frequency Market Making to Large Institutional Trades*

Robert A. Korajczyk†
Northwestern University

Dermot Murphy‡
University of Illinois at Chicago

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Abstract

We characterize high-frequency trader (HFT) and designated market maker (DMM) behavior in the presence of large, directional institutional trade packages in Canadian equity markets. HFT liquidity provision is significantly reduced for "stressful" trades. HFT average stock-day profitability is under $300, mostly from liquidity rebates. HFTs reduce liquidity provision after losses. The average effective spread for large non-stressful (stressful) institutional trades is 12 (42) basis points and is significantly affected by HFT choice of liquidity provision. Over the life of a large trade, HFTs initially accommodate the order, but quickly switch to competing with the order.

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†Kellogg School of Management, Northwestern University, 2001 Sheridan Road, Evanston, IL, 60208-2001; tel: (847) 491-8336; e-mail: r-korajczyk@kellogg.northwestern.edu.

‡University of Illinois at Chicago, College of Business, Department of Finance, 601 South Morgan Street, Chicago, IL, 60607-7121; tel: (312) 355-4372; e-mail: murphyd@uic.edu.

1 Introduction

An increased prevalence of high-frequency trading is often associated with improvements in market quality in the form of reduced quoted 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. High-frequency market makers reap a profit by turning over shares quickly—they do not want to be exposed to the risk of adverse price movements during their brief holding period. If high-frequency market makers believe that adverse price movements are more likely, they will adjust the price and quantity at which they are willing to buy or sell shares or even withdraw from the market altogether, since they have no strict obligation to make markets when they are not designated market makers (DMMs).

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.[2] It is particularly important to examine larger-sized institutional orders because they 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 a sample of over 150,000 large institutional trading packages, or parent orders (which we will typically call "large trades"),

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

[2] See, for example, an article by the *Financial Post* entitled "Pressure grows for crackdown on high-frequency trading" from October 2012.

on Canadian equities exchanges and compare HFT behavior with that of designated market makers (DMMs) on the Toronto Stock Exchange. According to the TMX web site, DMMs have the responsibility, among other things, to provide quotes on both sides of the market, contribute to the depth of the market, and maintain market activity (see Davies (2003)). 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.

The 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 from January 2012 to June 2013. For each message, we are provided with a broker ID and a client ID, so 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, so 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 large trade packages than do DMMs. Within high-volume stocks, HFTs provide 22.19 percent of liquidity to the aggressive component (the marketable order component) of large trades, while DMMs provide 0.88 percent. In lower-volume stocks, HFTs provide less liquidity (14.96 percent), and DMMs' liquidity provision is about the same (0.93 percent). This is consistent with other studies which find that HFTs provide more liquidity in more frequently traded stocks.[3]

However, liquidity provision substantially changes when the large trade is considered "stressful," i.e., the trading volume of that large trade, as a percentage of all trading volume in that stock–day, is in the upper quartile of all large trades. For high-volume firms, HFTs provide 15.07 percent of liquidity to the aggressive component of the large stressful trade, which represents a percentage reduction of 32.1 percent. DMMs, in contrast, continue to provide approximately the same percentage of liquidity. HFTs also reduce 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 stock's price is particularly volatile (in the top 10 percent of absolute open-to-close return days for that stock).

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

We estimate HFT profitability and find that, on average, HFTs make \$519 per stock–day in high-volume stocks on days with no stressful trades. Most of this profit comes from liquidity rebates (\$634); trading profits, on average, are negative (-\$116).[4] On days with stressful trades, the average HFT profit is \$315 per stock–day within high-volume stocks. This reduction in profitability is mostly due to the reduction in liquidity rebates (\$394), which is likely due to the reduction in HFT liquidity provision to stressful trades. When HFTs have particularly poor profitability in the previous week, we find that average HFT liquidity provision to large trades is 5.16 percentage points lower.

The cost of executing an institutional-sized parent trade is significantly influenced by HFT behavior. We estimate the effective spread (ES) for large trade packages, which represents the additional cost of a large trade due to price impact. ES averages 12 basis points for large non-stressful trades and 42 basis points for large stressful trades. ES is significantly negatively related to HFT liquidity provision. If HFTs provide 10 percentage points less liquidity to the aggressive component of a large trade, then ES is 3.9 basis points higher.

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 exceeding 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, according to which DMMs would now receive a discount of 70 percent on fees charged to traders by the exchange, with these fees typically based on the proportion of message traffic originating from that trader.[5] 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.

We also examine HFT liquidity provision when there are multiple, same-direction stressful trades. For example, if a stock-day has three stressful buys and one stressful sell, then we consider there to be two net stressful trades on that day. According to our regression analysis, in this case we find that HFT liquidity provision is 2.84 percentage points lower.

[4]Unless otherwise stated, all dollar figures quoted in this paper are in Canadian dollars.

[5]This regulation also stipulated that fees would now be charged for all market messages and not just trades as before. 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 introduction of this regulation.

That is, when there are multiple concurrent stressful trades in the same direction, HFT liquidity provision is slightly lower.

Finally, we examine HFT liquidity provision over the course of large stressful trades by dividing these trades into time deciles. HFTs are net sellers (buyers) during large stressful buys (sells) during the first time decile. However, in later time deciles, this reverses—HFTs tend to be net buyers (sellers) during large stressful buys (sells) in terms of both passive and active trading activity. Relative to large non-stressful trades, HFT activity is lower both in terms of trades and orders submitted. There is no discernable difference between HFT buying and selling activity for non-stressful trades, although a significant difference is observed for the stressful trades.

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 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. Hagströmer 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.

Several papers are related to ours. Anand and Venkataraman (2013) 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 large-price-movement days and high-volatility days. Our primary focus is on large institutional trades, 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.

Tong (2014) 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 we detail the trading characteristics of all market-making HFTs and DMMs individually.

Van Kervel and Menkveld (2015) study the effects of HFT trading on a set of 6,000 institutional trades in Swedish stocks. Their estimated effective spread (which they call implementation shortfall) is similar is magnitude to our estimates. As we do, they also find that HFT choice of accommodating or competing with the institutional trade is a significant determinant of its effective spread. The HFTs in our sample change from accommodating (trading on the opposite side) to competing with (trading on the same side) of the institutional much sooner than in their sample.

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 with DMMs. Section 6 identifies and characterizes the large institutional trades in our sample, including the effective spread for the total trade package. Section 7 examines the determinants of HFT and DMM liquidity provision. Section 8 examines several exogenous events that affect HFT liquidity provision: (1) an event in which DMMs across several stocks were replaced by an HFT; (2) HFT profitability in the past week, particularly at times of low profitability; (3) days with several same-direction concurrent stressful trades; and (4) stock–days with extreme price movements. Section 9 examines HFT activity over the course of large trades. Section 10 examines the determinants of the cost of executing a large trade package. In particular, we study the effect that HFT liquidity provision has on the effective spread of large institutional trades. Finally, Section 11 concludes.

2 Data and Canadian 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.[6]

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 from 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 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 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.
- User ID: this is the masked identification for the trader submitting the order. In the case of trades, the User IDs for both the buyer and seller are provided.
- Event: this field 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 nonempty.

[6] This information and additional details can be found at `www.iiroc.ca/about`.

- Active and passive indicators for trades: these determine 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: this is useful for determining the designated market makers in our database, as they are the only traders that have autofill privileges (these will be discussed shortly).

We make extensive use of this rich data set, first to classify high-frequency traders that act as market makers on Canadian markets, and 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.[7] The dollar turnover of shares in 2013 for shares traded with the TMX exchanges is about $1.3 trillion USD, and for 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. 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 from late 1999 to late 2014. Given that Canada and the U.S. are strong trading partners with close geographical proximity, this high correlation is unsurprising.

Finally, we make note of a few specifics of the Canadian market structure. As mentioned

[7] 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.

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 inferiorly 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 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 (henceforth, HFTs). Our methodology for identifying HFTs in a given stock is as follows. First, we define a trader as an HFT for a given stock–day if the following four conditions hold:

1. The trader is in the highest quintile of the 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 traded at least 50 times during that stock–day.
3. The trader has a net daily trading position, as a percentage of its volume of shares traded, for that stock–day of 10 percent or less.

4. The trader has an order-to-trade ratio that is greater than 5 and an order-to-cancel ratio that is less than 2.

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), (2), and (3). Requirement (4) ensures that we only include traders that have high order-to-trade ratios and low order-to-cancel ratios, both of which are common features for HFTs.

Traders are identified as HFTs for a given stock–day if they meet these four requirements. We define traders as HFTs for a given stock if they additionally satisfy the following two requirements:

1. The traders are identified as HFTs for at least 75 percent of stock–days in which they trade at least once.

2. The traders are identified as HFTs for at least 20 active stock–days.

Altogether, this classification methodology yields 19 distinct HFTs. Panel A of Table 1 contains information about each of these 19 HFTs. In Panel B, we partition these HFTs into three groups: (1) Super HFTs, which are identified as HFTs in at least 50 stocks; (2) Major HFTs, which are identified as HFTs in at least 10 stocks and less than 50 stocks; and (3) Minor HFTs, which are identified as HFTs in less than 10 stocks. There are 3 Super HFTs, 8 Major HFTs, and 8 Minor HFTs. According to Panel B, on average, a Super HFT is classified as an HFT in 132 stocks, is involved in 11.74 percent of all trades, has an order-to-trade ratio of 22.99, and 26.04 percent of its share volume is executed via marketable limit orders (and thus, 73.96 percent of its share volume is executed via passive limit orders). Super HFTs tend to close the day with an absolute inventory position, as a percentage of share volume, of 4.00 percent. Finally, they are classified as HFTs on 88.2 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 22 stocks and 4 stocks, respectively. Relative to the Super HFTs, the fraction of trades in which they are involved is lower (7.87 and 5.25 percent), their order-to-trade ratios are comparable (21.71 and 25.99), the percentage of share volume executed via marketable limit orders is lower (17.67 percent and 12.38 percent), and their closing net trading positions are similar (3.32 percent and 3.38

percent). Finally, Major and Minor HFTs are classified as HFTs on 86.9 and 80.1 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) web site (also see Davies (2003)), the responsibilities of the Market Maker include the following:

- Call a two-sided market providing market continuity within a prespecified 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. 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.

Assuming the responsibilities of a DMM is associated with several benefits. First, an Optional Registered Participation feature allows DMMs to trade passively at the TSX best bid and offer (BBO) without requiring an order at the top of the limit order book, in order to manage their inventory positions. Second, DMMs receive preferential trading fees and are eligible for a monthly symbol credit in each stock of responsibility.[8]

[8]Information regarding DMM responsibilities and benefits can be found at `http://www.tsx.com/trading/toronto-stock-exchange/order-types-and-features/market-maker-system`.

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 executed by the DMM 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 nonempty "Registered Trader Autofill" field (for its 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 with DMMs

There are 190 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 $78.3 million in dollar volume, 10,467 trades, and 207,655 orders per day. A medium-volume stock has $13.9 million in dollar volume, 3,566 trades, and 72,362 orders per day. Finally, a low-volume stock has $3.4 million in dollar volume, 1,970 trades, and 26,003 orders per day. The highest-volume stock in our sample on average has $242.8 million in dollar volume, 20,284 trades, and 334,079 orders per day. Volume information can be found in Panel C of Table 2.

Our next step is to compare HFT activity with DMM activity within each volume tercile. This information can be found in Panels A and B of Table 2. Within the highest-volume tercile, an average of 2.79 HFTs are trading on any stock–day. In addition, the HFTs together submit 20.6 percent of all orders, provide liquidity to 15.2 percent of all dollar volume, and actively take liquidity for 3.3 percent of all dollar volume.[9] On average, 16.3 percent of HFT

[9]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.

dollar volume is due to aggressive orders, while the remaining 83.7 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 0.9 percent of all orders, provide liquidity to 2.3 percent of all dollar volume, and actively take liquidity for 1.3 percent of all dollar volume. On average, DMMs actively take liquidity for 25.2 percent of all DMM dollar volume, which is higher than HFTs (16.3 percent). The average size of a single trade is also smaller for a DMM compared to an HFT ($3,331 per trade versus $5,285 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 1.44 and 0.98 HFTs present on any stock–day, respectively, which is much lower than the HFT presence in the high-volume stocks (2.79). HFTs provide slightly less passive liquidity within these terciles than for high-volume stocks (11.8 percent and 14.3 percent), in contrast to DMMs, which provide slightly more passive liquidity (2.9 percent and 2.2 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 we denote Stock 1, has an average of 5.84 active HFTs on any stock–day, and together these HFTs submit 35.8 percent of all orders, passively provide liquidity to 30.5 percent of all dollar volume, and actively take liquidity for 9.1 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 approximately $30.5\% \times \$242.8$ million = $74.05 million of all aggressive volume per day. For DMMs, however, the liquidity statistics are 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 2.

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 its trade, either in full or in part. Institutional traders typically engage in large trades (parent trades) that are executed over the course of hours or even days (through smaller child trades), as opposed to retail traders, which 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:

- For high-volume stocks, an aggregate dollar volume of at least $1 million that comes from a single account;
- For stocks that are not in the high-volume tercile, an aggregate dollar volume of at least $500,000 that comes from a single account;
- The aggregate dollar volume must consist of either 100 percent buys or 100 percent sells.

We allow large trades to span multiple days in our sample. When a client trades the same asset in the same direction on consecutive days, we treat this as a single parent trade package if there are child trades in both the last half hour of the first day and the first half hour of the following day. Otherwise, these are treated as separate parent trades.

A large trade is defined as a "stressful trade" if its total dollar volume, as a percentage of total volume within that stock, is in the upper quartile relative to other large trades; otherwise, the large trade is considered "non-stressful."

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 of its order executed using aggressive trades—we are interested in examining liquidity provision to large trades, so we require a reasonable number of aggressive orders to be contained in these large trades. Second, we require large parent trades to be executed via a sequence of smaller child trades; hence, we do not include any large trades that are executed using fewer than 20 child trades or in less than 30 minutes. Altogether, 151,855 parent trades will be used in our analyses.

Table 3 provides details about the large non-stressful and stressful trades identified in our database. There are 114,075 large non-stressful trades in our sample of 190 stocks. On average, a large non-stressful trade is for \$2.35 million and comprises 2.8 percent of trading volume in that stock. On average a parent trade is executed using 375 child trades, with 559 child orders submitted. About 60.1 percent of the total trade is executed via marketable limit orders, and 39.9 percent of the total trade is executed via passive limit orders. The average large trade takes about 5.5 hours to completely execute.

There are 37,780 large stressful trades in our sample of 190 stocks. On average, a large stressful trade is for \$3.31 million. It is executed using 648 child trades, with 838 orders submitted. On average, 62.0 percent of the total trade is executed via marketable limit orders, and 38.0 percent of the total trade is executed via passive limit orders. The average large stressful trade takes about 5.8 hours to completely execute. Additional information regarding medians and quantile cutoffs for large non-stressful and stressful trades can also be found in Table 3.

We also compute the effective spread (ES) for every large trade. Effective spread is measured as the total cost of a trade relative to what the cost would have been if the trade had executed at the initial bid–ask midpoint. For example, suppose there is 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, at the initiation of this trade, the bid–ask midpoint was equal to \$10. If there was no price impact, then ideally the trader would have paid $\$10 \times 100,000 = \$1.0$ million for its 100,000 share purchase. However, because of price impact, the trader ends up paying \$1.02 million $-$ \$1.0 million $= \$20,000$ more for its trade. Therefore, its effective spread equals $\$20,000/\$1.0$ million $= 2$ percent.

Specifically, suppose that a large trade t in stock i for X_{it} total shares is executed using N smaller trades, where $p_{n,it}$ and $x_{n,it}$ denote the price and share volume, respectively, of the n-th trade within large trade t for shares in stock i. Also denote $m_{1,it}$ as the bid–ask midpoint at the initiation of the large trade. The effective spread for large trade t is calculated as:

$$ES_{it} = \frac{\sum_{n=1}^{N} p_{n,it} x_{n,it} - m_{1,it} X_{it}}{m_{1,it} X_{it}} \text{ for large buys, and}$$

$$ES_{it} = \frac{m_{1,it} X_{it} - \sum_{n=1}^{N} p_{n,it} x_{n,it}}{m_{1,it} X_{it}} \text{ for large sells.}$$

Note that it is possible for the effective spread to be negative—a negative ES would be good for the trader making the large trade. For example, if the effective spread for a large buy order is negative one percent, this means that the large trader paid one percent less than it would have paid if it had bought all shares at the initial bid–ask midpoint.

Table 3 also provides statistics regarding the effective spread for large trades. The mean ES for a large non-stressful trade is 12 basis points. Large non-stressful trades at the ES tenth percentile have an ES of -81 basis points, while those at the ES ninetieth percentile have an ES of 107 basis points. 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. We adjust for contemporaneous market movements in our analysis of ES later in the paper. Large stressful trades generally have a higher ES: the mean, tenth percentile, and ninetieth percentile are 42, -61, and 164 basis points, respectively.

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 "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 reoffer it at a costlier price or not reoffer 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 with 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 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 it provides 20 percent of liquidity to the aggressive component of the large trade. Specifically, we define our dependent variables as follows:

$$\begin{aligned} HFTLIQ_{it} &= \frac{\text{HFT Passive Dollar Volume}_{it}}{\text{Large Trade Aggressive Dollar Volume}_{it}} \\ DMMLIQ_{it} &= \frac{\text{DMM Passive Dollar Volume}_{it}}{\text{Large Trade Aggressive Dollar Volume}_{it}}. \end{aligned}$$

We are interested in the determinants of HFT and DMM liquidity provision to large trades. Specifically, 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. As previously mentioned, we identify a large trade as “stressful” if it is in the highest quartile of large-trade dollar volume, as a percentage of total dollar volume for that stock–day (the stress indicator variable equals one in this case and zero otherwise).

HFTs should be more active in high-volume stocks because of the ability to turn over shares more quickly. Indeed, according to Table 2, 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 ($TSIZE$, in millions of dollars), and the squared dollar volume of the large trade ($TSIZE2$) to account for potential nonlinearities in the price impact of the trade. For convenience, a list and definitions of all variables used in this paper are contained in an Internet appendix.

To examine the determinants of HFT and DMM liquidity provision, we run the following regressions:

$$\begin{aligned} HFTLIQ_{it} = \alpha + \gamma_d &+ \beta_1 \cdot STRESS_{it} + \beta_2 \cdot HIGHVOL_i \\ &+ \beta_3 \cdot (STRESS_{it} \times HIGHVOL_i) + \gamma' X_{it} + \varepsilon_{it}, \\ DMMLIQ_{it} = \alpha + \gamma_d &+ \beta_1 \cdot STRESS_{it} + \beta_2 \cdot HIGHVOL_i \\ &+ \beta_3 \cdot (STRESS_{it} \times HIGHVOL_i) + \gamma' X_{it} + \varepsilon_{it}. \end{aligned}$$

In these regressions, γ_d represents date fixed effect controls and X_{it} is a vector of control variables that includes AGG_{it}, $TIME_{it}$, $TSIZE_{it}$, and $TSIZE2_{it}$. Standard errors are clustered at the firm level.

The regression results for HFT liquidity provision are reported in Table 4. According to the regression in the column labeled (3), HFTs provide liquidity to 14.96 percent of the aggressive component of large trades and provide 1.46 percentage points less if the trade is considered stressful (t-statistic = -2.74). More importantly, if the large trade is within a high-volume stock, then HFTs provide an additional 7.23 percentage points of liquidity to the aggressive component of large trades but 5.65 percentage points less (relative to the 1.46 percentage points less from before) if the trade is considered stressful (t-statistic = -3.52). [10]

That is, within high-volume firms, HFTs provide liquidity to 22.19 percent (14.96 percent

[10] Because HFT liquidity provision in bounded below by zero and above by one, we also run an alternative regression where we apply logistic transformation to the HFT liquidity provision variable. We get similarly significant results (in this regression and subsequent regressions using HFT and DMM liquidity provision) if we use this logistic transformation. To ease interpretation of the coefficients, we report the results of the linear probability model.

plus 7.23 percent) of the aggressive component of large, non-stressful trades. When that trade is considered stressful, HFTs provide liquidity to only 15.07 percent of the aggressive component of the large trade, for a difference of 7.12 percentage points or a percentage difference of negative 32.1 percent ((15.07 - 22.19)/22.19). Figure 1 summarizes these results graphically.

The coefficients for the control variables are as expected. HFTs provide less liquidity to more aggressive large trades, since 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 slightly less liquidity to trades that take a longer time to fully execute, suggesting that HFTs have more time to infer information content contained in these 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 nonlinear 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, which generally 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 5. According to the regression in the column labeled (3), DMMs provide liquidity to 0.93 percent of the aggressive component of large trades and provide an additional 0.08 percentage points if the trade is considered stressful, although the latter number is not statistically significant. Within high-volume stocks, there is also no significant change in DMM liquidity provision. Figure 2 summarizes these results graphically.

8 HFT Events

HFTs provide less liquidity for stressful trades, particularly those in high-volume stocks. However, 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.

8.1 When DMMs Become HFT-DMMs

We first examine an interesting event that increased HFT presence in 24 stocks in our sample. Prior to November 26, 2012, a variety of non-HFT 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 and executes many more trades (in some stocks, more than 1,000 times the number of orders than before), has a high order-to-trade ratio, and also has much higher dollar volume.

Table 6 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 based on the proportion of message traffic (orders and trades) originating from that trader, although before the Integrated Fee Model (IFM) was implemented, the fees were only based on the proportion of message traffic due to trades and not orders. HFTs that are not DMMs 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, particularly because fees under the

Integrated Fee Model are charged based on order activity.

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 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 presumably take 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:

$$HDLIQ_{it} = HFTLIQ_{it} + DMMLIQ_{it}.$$

Henceforth, HDLIQ 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 the previous regressions. 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:

$$\begin{aligned} HDLIQ_{it} &= \alpha + \gamma_d + \beta_1 \cdot STRESS_{it} + \beta_2 \cdot HIGHVOL_i \\ &+ \beta_3 \cdot (STRESS_{it} \times HIGHVOL_i) + \beta_4 \cdot NEWDMM_{it} \\ &+ \beta_5 \cdot (NEWDMM_{it} \times STRESS_{it}) + \beta_6 \cdot (NEWDMM_{it} \times HIGHVOL_i) \\ &+ \beta_7 \cdot (NEWDMM_{it} \times STRESS_{it} \times HIGHVOL_i) + \gamma' X_{it} + \varepsilon_{it}. \end{aligned}$$

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, while an HFT-DMM would still have to fulfill the obligations of a DMM, it may be more sophisticated in its ability to vary its liquidity provision, meaning that liquidity provision to stressful trades in particular could potentially be lower.

The regression results are reported in Table 7. According to the regression reported in the column labeled (3), HD liquidity provision is equal to 22.81 percent for large trades. When that trade is stressful, HD liquidity provision is equal to 16.09 percent, which represents a reduction of 6.72 percentage points.

More importantly, within high-volume firms, HD liquidity provision is 3.74 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 4.03 percentage points. That is, HD liquidity provision is actually lower for stressful trades (negative 0.29 percentage points) when the traditional DMM is replaced by an HFT. For ease of interpretation, Figure 3 summarizes these results graphically.

8.2 HFT Profitability and Liquidity Provision

In this section, we estimate HFT profitability and its components. We also examine HFT liquidity provision after HFTs had a particularly bad week in a stock. Specifically, we examine the average profit per share (PPS) of HFTs over the previous five business days within each stock. Past HFT profitability is likely exogenous to a large trade decision by an institutional investor, allowing us to provide insight on variation in HFT liquidity provision to large trades.

We calculate stock–day HFT trade profitability as the value of shares sold minus the value of shares bought and marking to market any inventory held at the end of the day. We also account for liquidity taking-fees and liquidity-providing rebates by crediting \$0.0031 per share for each share passively supplied by the HFT and subtracting \$0.0035 per share for each share actively demanded by the HFT via marketable limit orders.[11] Specifically, for HFT h on day t and stock i, we calculate the following profitability measures:

$$\begin{aligned}
\text{Trade Profit}_{hit} &= -\sum_{n=1}^{N} p_{n,hit} x_{n,hit} + p_{T,hit} \sum_{n=1}^{N} x_{n,hit}, \\
\text{Rebate Profit}_{hit} &= \sum_{n=1}^{N^P} |x^P_{n,hit}| \times 0.0031 - \sum_{n=1}^{N^A} |x^A_{n,hit}| \times 0.0035, \\
\text{Total Profit}_{hit} &= \text{Trade Profit}_{hit} + \text{Rebate Profit}_{hit},
\end{aligned}$$

where x_n is the number of shares bought in trade n (if x_n is negative, this indicates shares sold), p_n is the price for trade n, and p_T is the closing price at which any HFT nonzero inventory is marked to market. Passive trades (P) and active trades (A) by the HFT are indicated with a superscript on x, which is used to calculated liquidity rebate profits. Finally, total profit per share (PPS) is calculated as:

$$PPS = \frac{\text{Total Profit}_{hit}}{\max\{X^B_{hit}, X^S_{hit}\}},$$

where X^B represents total shares bought and X^S represents total shares sold. This measure of profit per share is similar to the day-trader daily return measure used in Linnainmaa (2011).

Summary statistics for HFT profitability are reported in Table 8. According to Panel A, in which we examine HFT profitability on days without stressful trades, an HFT loses about \$100 per stock–day from trading and this is similar across volume subgroups. However, HFTs more than make up for this via liquidity rebates. On average, an HFT makes \$380 per stock–day in liquidity rebates (net of liquidity-taking fees). This number is highest in the high-volume stocks, which is expected, since the HFTs are turning over more shares

[11] This is the rebate schedule for stocks that trade above one dollar on the TSX and TSX-V. Because a very large portion of volume is traded on these exchanges, we use this rebate schedule to approximate rebate profits. Other exchanges with a large proportion of volume have similar, but slightly lower, rebates and charges.

in these stocks. Specifically, HFTs make \$634 per stock–day in rebates within high-volume stocks and make \$182 per stock–day in low-volume stocks. On average, HFT profit per share traded is \$0.0023, and this is higher in the high-volume stocks (\$0.0027). Standard deviation in profit per share is also highest in the high-volume stocks.[12]

In Panel B, we examine HFT profitability on stock–days in which there was at least one stressful trade. We find that trade profits are similarly negative, while rebate profits are generally lower (with the exception of the low volume subgroup), which is consistent with our findings that HFTs provide less liquidity during times of stress. Profit per share statistics are also similar, which means that HFTs must be trading fewer shares since total profit statistics are comparable to those reported in Panel A.

We also report DMM profitability in Panels C and D, which are calculated in a similar way to HFT profits. Interestingly, DMM profits are higher for stressful trade days than they are for non-stressful trade days, and this holds across all trading volume subgroups. The higher DMM profits on stressful trade days seem to primarily due to trading profits, possibly because HFT liquidity withdrawal during stressful periods allows DMMs to step in and provide a higher percentage of liquidity to incoming trades.

We use PPS to determine HFT performance in the previous week. Specifically, for each stock–day, we calculate the average PPS over the past 5 days and then place this performance into performance deciles. If an HFT is currently in the lowest performance decile, then we expect to observe significant changes in HFT liquidity to large trades. To examine the relation between past HFT performance and HFT liquidity provision to large trades, we run the following regression:

$$
\begin{aligned}
HFTLIQ_{it} = \alpha + \gamma_d \quad &+ \quad \beta_1 \cdot BADWEEK_{it} + \beta_2 \cdot HIGHVOL_i \\
&+ \quad \beta_3 \cdot (BADWEEK_{it} \times HIGHVOL_i) + \\
&+ \quad \beta_4 \cdot STRESS_{it} + \beta_5 \cdot (STRESS_{it} \times HIGHVOL_i) + \gamma' X_{it} + \varepsilon_{it},
\end{aligned}
$$

where $BADWEEK_{it}$ is an indicator that equals 1 if the HFT average profit per share in

[12] The result that average trading profits are negative while average net liquidity rebates are positive and greater in magnitude is consistent with Battalio, Corwin, and Jennings (2015), which states that a broker cannot maximize both execution quality and liquidity rebates (that is, they cannot “have it all”).

the five days prior to large trade t in stock i is in the lowest decile. All other variables are defined as before.

The results are presented in Table 9. According to the regression in the column labeled (3), HFTs provide 5.08 percentage points less liquidity to the active component of large trades when they had poor performance (in terms of profit per share) in the previous week. We do not see any significant difference when we interact the $BADWEEK$ indicator with an indicator for high-volume firms, indicating that HFTs provide less liquidity conditional on poor performance, but unconditional on volume type. We also include the previous indicator for "stressful" trades and find that the results for those trades are similar to before. Our evidence indicates that when HFTs have a particularly bad week, they provide less liquidity to the large trades.

8.3 Multiple Concurrent Stressful Trades and HFT Liquidity Provision

We have shown that HFT liquidity provision is lower when a large trade is considered stressful, especially in high-volume stocks, where HFTs are particularly active. However, there is also the possibility that two stressful trades, in opposing directions, may cancel each other out, which means that an HFT might not necessarily provide less liquidity in the presence of these offsetting trades. In this subsection, we examine the extent to which HFTs provide liquidity to large stressful trades when there are other concurrent stressful trades.

Specifically, for each stock i and day t, we calculate the magnitude of net stressful trades as follows:

$$NETSTRESS_{it} = |\text{Number of Stressful Buys}_{it} - \text{Number of Stressful Sells}_{it}|.$$

We then run a regression of HFT liquidity provision on $NETSTRESS$ and the same control variables from the previous regression. The results are reported in Table 10. According to the regression in the column labeled (4), we find that HFT liquidity provision is slightly reduced when the magnitude of the count of net stressful trades is higher. For example, if there are three stressful buys and one stressful sells, then HFT liquidity provision is reduced by $2 \times 1.42 = 2.84$ percentage points. It is likely that when the magnitude of net stressful trades is high, it proxies for a stressful stock-day in general, which implies a reduction in HFT liquidity provision. Related to this, in the next subsection, we examine HFT liquidity provision when the absolute return on a given stock–day is particularly high.

8.4 Extreme Returns and HFT Liquidity Provision

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. In this section, we examine the nature of HFT liquidity provision to large trades when that day is experiencing an extreme contemporaneous movement in the stock price, which we will call a "stressful" return day.

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.

Specifically, we run the following regression:

$$\begin{aligned} HFTLIQ_{it} = \alpha + \gamma_d \quad &+ \quad \beta_1 \cdot STRESSRET_i + \beta_2 \cdot HIGHVOL_i \\ &+ \quad \beta_3 \cdot (STRESSRET_i \times HIGHVOL_i) + \\ &+ \quad \beta_4 \cdot STRESS_{it} + \beta_5 \cdot (STRESS_{it} \times HIGHVOL_i) + \gamma' X_{it} + \varepsilon_{it}. \end{aligned}$$

As a reminder, $STRESS_{it}$ indicates whether the large trade itself is stressful, $HIGHVOL_i$ indicates whether the large trade takes place within a high-volume firm, and X_{it} is a vector of control variables that includes AGG_{it}, $TIME_{it}$, $TSIZE_{it}$, and $TSIZE2_{it}$.

Table 11 reports the results from this regression. According to the regression in column (2), HFTs provide 0.64 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 1.50 percentage points less liquidity (0.64 percent plus 0.86 percent). This reduction is added to the existing 7.28 percentage point reduction in liquidity (1.50 percent plus 5.78 percent) if the trade itself is also stressful and within a high-volume firm. Therefore, the evidence in this section indicates that HFTs provide slightly less liquidity to large institutional trades if that stock–day is considered "stressful" due to extreme contemporaneous price movements.

9 HFT Behavior over the Course of Large Trades

Our results so far indicate that HFTs provide a lower percentage of liquidity to large stressful trades. However, the temporal nature of this lowered liquidity provision is still unclear and several possibilities exist. For example, an HFT could "go wide" during a stressful trade by withdrawing orders and resubmitting them at less favorable prices. It is also possible that an HFT simply reduces or withdraws participation during that stressful trade, thereby lowering the risk involved with perceived adverse-selection concerns. Finally, it is possible that an HFT "frontruns" these large orders, in that the HFT buys (sells) ahead of a large stressful buy (sell) and subsequently sells to (buys from) the large trader at a higher (lower) price. In this section, we expand upon our main results by examining HFT activity over the course of large parent trades.

To examine HFT activity over the course of large trades, we first divide large trades into time deciles. For example, if a large trade is executed over the course of five hours, then the first time decile of this large trade denotes the first thirty minutes of that trade. This way, we normalize time progression over all large trades with different times to total execution. To ensure that each time decile covers a reasonable window of time, and to reduce noise, we examine large trades that are executed over a minimum of 2.5 hours, which ensures that each time decile is at least 15 minutes in length, and in only high-volume stocks, to ensure that there is enough HFT activity within each time decile. Then, we calculate HFT activity within each of these time deciles—specifically, total shares bought or sold using passive or aggressive orders, and total shares within all HFT buy orders or HFT sell orders. Therefore, we now have information related to HFT activity for each time decile of each large trade.

Our first goal is to examine HFT net trading imbalances, in order to see if HFTs focus more on buying or selling during large institutional buy orders and sell orders. We define net passive trading (NPT) and net aggressive trading (NAT) in time decile d for large trade t as follows:

$$NPT_{d,t} = \frac{\text{Shares Passively Bought}_{d,t} - \text{Shares Passively Sold}_{d,t}}{\text{Shares Passively Bought}_{d,t} + \text{Shares Passively Sold}_{d,t}},$$

$$NAT_{d,t} = \frac{\text{Shares Aggressively Bought}_{d,t} - \text{Shares Aggressively Sold}_{d,t}}{\text{Shares Aggressively Bought}_{d,t} + \text{Shares Aggressively Sold}_{d,t}}.$$

These variables are also demeaned by their lagged average values within the past sixty trading days within that time of day. Within each time decile d, we then calculate the averages of these variables across all large trades, separated by two distinct groups: large stressful buys and large stressful sells.

The results are reported in Figure 4. First, we find that within the first time decile, HFTs have positive NPT for large stressful sells and negative NPT for large stressful buys, indicating that HFTs are initially providing more liquidity to the large trade. However, when we examine later time deciles, we see that this result substantially reverses. For example, for large stressful buys, HFTs consistently have positive NPT and NAT for time deciles greater than one, indicating that HFTs are engaged in proportionally more buying activity when a large stressful buy is being executed (similar results hold for large stressful sells).

Trade imbalances, however, do not tell the full story. It is possible that both HFT buying and selling activity have substantially increased, which might be beneficial to a large trader even if the imbalance were in the same direction as the large order. Therefore, we also examine abnormal HFT buying and selling activity within each time decile for stressful and non-stressful large buys and large sells. Specifically, we define HFT abnormal activity in time decile d for large trade t as follows:

$$\begin{aligned} APB_{d,t} &= \frac{\text{Shares Passively Bought}_{d,t}}{\text{Lagged MA of Shares Passively Bought}_{d,t}} - 1, \\ APS_{d,t} &= \frac{\text{Shares Passively Sold}_{d,t}}{\text{Lagged MA of Shares Passively Sold}_{d,t}} - 1, \end{aligned}$$

$$
\begin{aligned}
ABO_{d,t} &= \frac{\text{Total Shares in Buy Orders Submitted}_{d,t}}{\text{Lagged MA of Total Shares in Buy Orders Submitted}_{d,t}} - 1, \\
ASO_{d,t} &= \frac{\text{Total Shares in Sell Orders Submitted}_{d,t}}{\text{Lagged MA of Total Shares in Sell Orders Submitted}_{d,t}} - 1,
\end{aligned}
$$

where Lagged MA() denotes the lagged moving average of the variable over the past sixty days within the same time-of-day window. For example, if $APB_{d,t} = 0.10$, this means that HFTs have been passively buying 10 percent more shares than usual. Within each time decile d, we then calculate averages of these variables across all large trades, separated by four distinct groups: large stressful buys, large stressful sells, large non-stressful buys, and large non-stressful sells.

The results for HFT abnormal buying and selling activity (APB and APS) during large institutional buys (stressful and non-stressful) are reported in Figure 5. First, we find that HFT abnormal buying and selling activity is higher for non-stressful buys than it is for stressful buys, indicating that HFT activity is comparatively scaled back for the stressful buys. Second, we find a significant gap between HFT buying and selling activity for stressful buys, but not for non-stressful buys. This is reflective of the order-imbalance results we reported earlier: HFTs appear to be focusing more on buying activity, as opposed to selling activity, during these stressful buys. Finally, we find that HFT activity is higher during the beginning and end of any large buy—it is likely higher during the beginning because the HFT has not completely inferred yet that a large trade with potential price impact is underway, while it is likely higher during the end because HFTs have previously pulled back their sell orders (or aggressively bought the shares contained in other traders' sell orders) and are now offering the same shares through passive orders. At the bottom of this figure, we also include the share density of these large institutional buys. It is apparent that the density follows a "U" shape, meaning that more of the shares executed in a large-buy order are concentrated at the beginning and (especially) the end of the large trade program. Figure 6 similarly reports HFT abnormal buying and selling activity, but for large institutional sells. The results are similar, in that HFTs provide substantially less liquidity to stressful sell orders, focus more on selling activity for large stressful sell orders, and are most active at the beginning and end of the large sell order.

Figures 7 and 8 report abnormal HFT order submission activity during large buys and large sells, respectively. The results are similar to those above for abnormal HFT trading activity. Interestingly, HFT abnormal sell orders are mostly negative for large stressful buys and HFT abnormal buy orders are also mostly negative for large stressful sells. Based on our results, HFTs are clearly cutting back on orders that would have provided liquidity to these large trades, particularly in the trade deciles away from the beginning and end of the trade.[13]

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; this is also the case when the HFT had poor profitability in the previous week or when the stock is experiencing a large price movement. 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 effective spread (ES) for each large parent trade in our sample—this represents the cost of a trade due to price impact. For example, if ES equals 20 basis points for a large buy order, this means that the buyer paid 20 basis points more than it would have paid had there been unlimited liquidity at the initial bid–ask midpoint for this large buy order. If the buyer was interested in purchasing \$10 million worth of shares, it would have paid \$10.02 million due to price impact.

Our dependent variable of interest in this section is the effective spread. We examine how this variable relates to both HFT and DMM liquidity provision, as defined previously. In addition, to studying the effect of liquidity provision by HFTs and DMMs, we will examine the percentage of passive volume in the large trade that is aggressively executed by the HFT

[13]We obtain similar patterns (unreported) for HFT order-cancellation activity, which is unsurprising given that HFTs have very low order-to-cancel ratios and very high correlation between order submission and cancellation activity.

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:

$$HFTAGG_{it} = \frac{\text{HFT Active Dollar Volume}_{it}}{\text{Passive Large Trade Dollar Volume}_{it}},$$

$$DMMAGG_{it} = \frac{\text{DMM Active Dollar Volume}_{it}}{\text{Passive Large Trade Dollar Volume}_{it}}.$$

For this section of the analysis, we exclude large trades that exceed 90 percent aggressiveness so that we can reasonably measure variation in $HFTAGG$ and $DMMAGG$. We include the same control variables used in the regressions in the previous sections: AGG, $TIME$, $TSIZE$, and $TSIZE2$. In these control variables, we now also include indicator variables for large trades that execute in high-volume stocks and medium-volume stocks. We also include a control for the market return on that day and interact this return with indicators for whether that trade is a buy or a sell, since ex post effective spreads are related to contemporaneous market movements. Effective spread should be significantly higher for large sells on days with low market returns or for large buys on days with high market returns. The vector of control variables is denoted by Y.

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

$$\begin{aligned} ES_{it} = \alpha + \xi_d &+ \beta_1 \cdot HFTLIQ_{it} + \beta_2 \cdot DMMLIQ_{it} \\ &+ \beta_3 \cdot HFTAGG_{it} + \beta_4 \cdot DMMAGG_{it} + \xi' Y_{it} + u_{it}. \end{aligned}$$

The regression results are reported in Table 12. According to regression in column (2), if HFTs provide 10 percentage points more liquidity to the active component of a large trade, the ES of the trade is 3.9 basis points lower. HFT aggressive execution is somewhat significant in regressions (1) and (3), although insignificant when market returns are included as a control variable, as in regression (2), which indicates that HFTs tend to submit more aggressive orders on days with more extreme market returns. DMM liquidity provision and aggressive trades are not significantly related to the ES of a large trade, likely because they provide very little liquidity in the first place.

The coefficients on the control variables in this regression are as expected. Large trades that are executed with more aggressive orders have a higher ES. If a large trade takes a longer time to execute, then the ES is lower, likely because the trader is more successful in hiding the information content contained in the total order (or because the large trade contains less information and thus the trader can choose a longer execution time). ES is increasing in its total trade size but decreasing in total trade size squared, indicating a concave relationship. ES is lower in medium-volume stocks and even lower in high-volume stocks, likely because there is more liquidity provided within these stocks. Finally, ES is higher for large buys when market returns are positive and higher for large sells when market returns are negative.

11 Conclusion

We utilize a data set provided by the Investment Industry Regulatory Organization of Canada (IIROC), allowing us to identify a sample of over 150,000 large institutional-size trading packages in Canadian equities over the period from January 2012 to June 2013. We define a large trading package as a group of (at least 20) smaller trades by the same customer in the same direction (buy or sell) in the same stock, which totals a minimum of \$1 million in high-volume stocks or a minimum of \$0.5 million in lower-volume stocks.

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. HFTs provide less liquidity to stressful trades than non-stressful trades, while DMMs provide more liquidity to stressful trades. The increase in DMM 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 find that average HFT profit equals about \$0.0021 per share and that this profit primarily comes from liquidity rebates. Then, we show that HFT liquidity provision to large trades is significantly reduced if their profit per share was particularly low in the previous week, further confirming that HFT liquidity provision responds negatively to stressful events. In addition to this, we find that HFT liquidity provision is lower when there are multiple same-direction stressful trades, or when the absolute return on that stock–day is particularly high.

HFT behavior significantly affects the cost of executing institutional trades. The effective spread (ES) averages 12 basis points for large non-stressful trades and 42 basis points for large stressful trades. ES is significantly negatively related to HFT liquidity provision. In addition, ES 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. When the market moves in the same direction as the large trade, ES is positively and significantly affected. Incidentally, stressful trades are also associated with significant reductions in HFT liquidity provision, especially in high-volume firms.

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.

When examining HFT activity over the course of stressful trades, we find that, as time progresses in the large trade, HFTs quickly switch from accommodating to competing with the institutional trade. That is, they tend to emphasize buying activity during stressful buys and selling activity during stressful sells. Relative to non-stressful trades, total HFT trade and order activity is lower. There is no significant difference between HFT buying and selling activity for non-stressful trades, but there is for HFT stressful trades—in particular, their activity is comparably lower on the side opposite to the direction of the large institutional trade.

Our results shed light on the sources of profitability of HFTs, the effect of HFT liquidity provision on institutional trading costs, and the temporal change in HFT behavior as institutional trades evolve. We 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 the trade.

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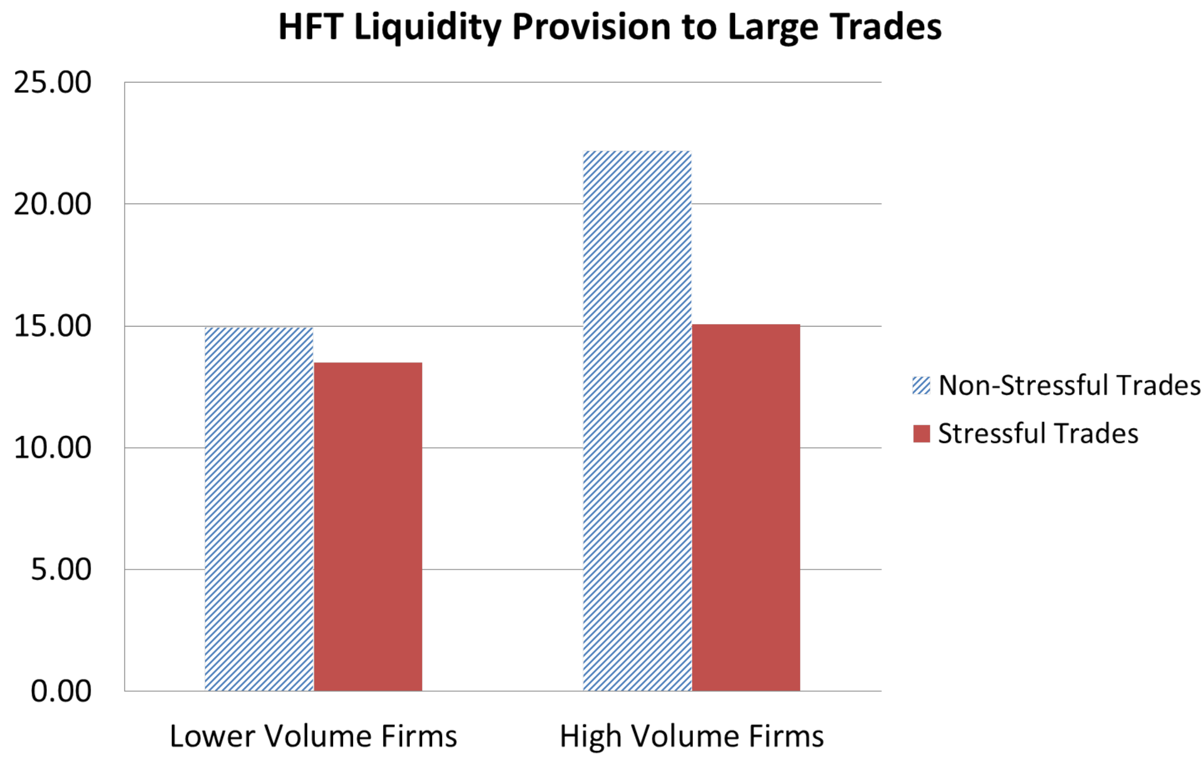

Figure 1. HFT Liquidity Provision for Stressful and Non-Stressful Trades. This graph plots HFT liquidity provision (as a percentage of total liquidity provision to the aggressive component of the large trade) for large trades that are stressful and large trades that are non-stressful, within both high-volume 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 4.

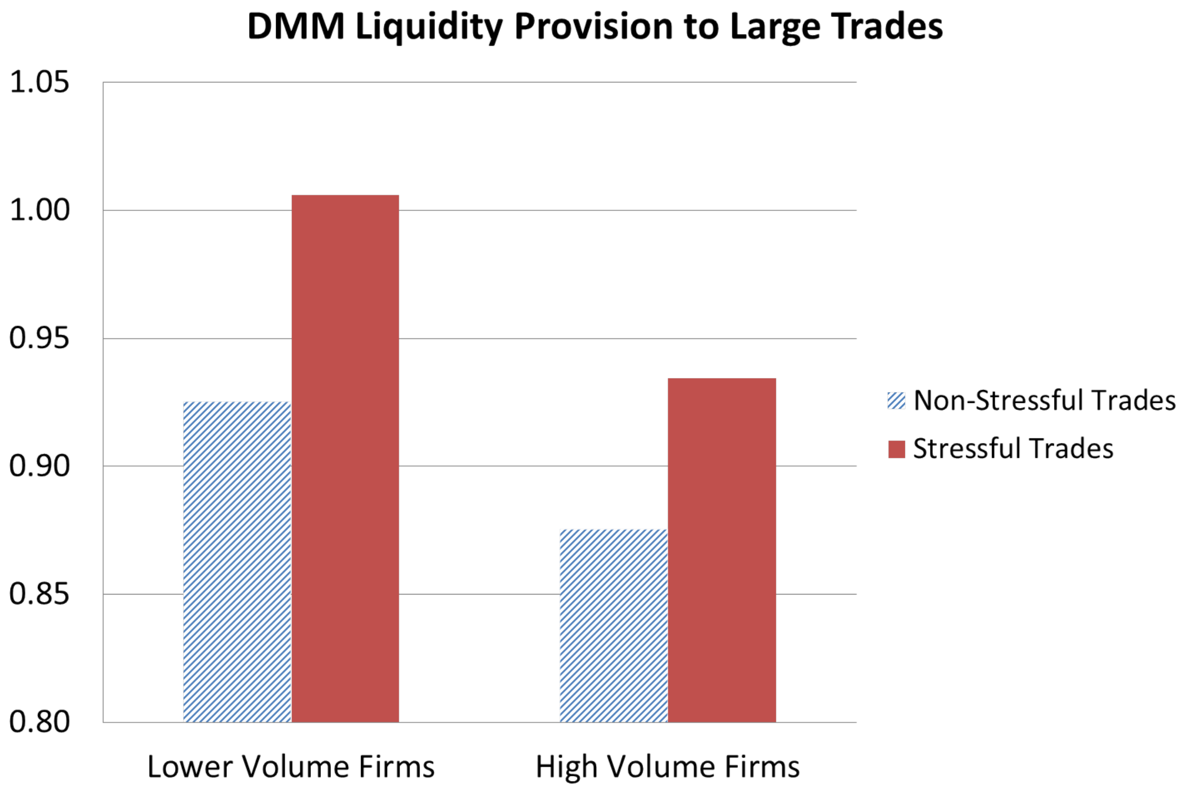

Figure 2. DMM Liquidity Provision for Stressful and Non-Stressful Trades. This graph plots DMM liquidity provision (as a percentage of total liquidity provision to the aggressive component of the large trade) for large trades that are stressful and large trades that are non-stressful, within both high-volume 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 5.

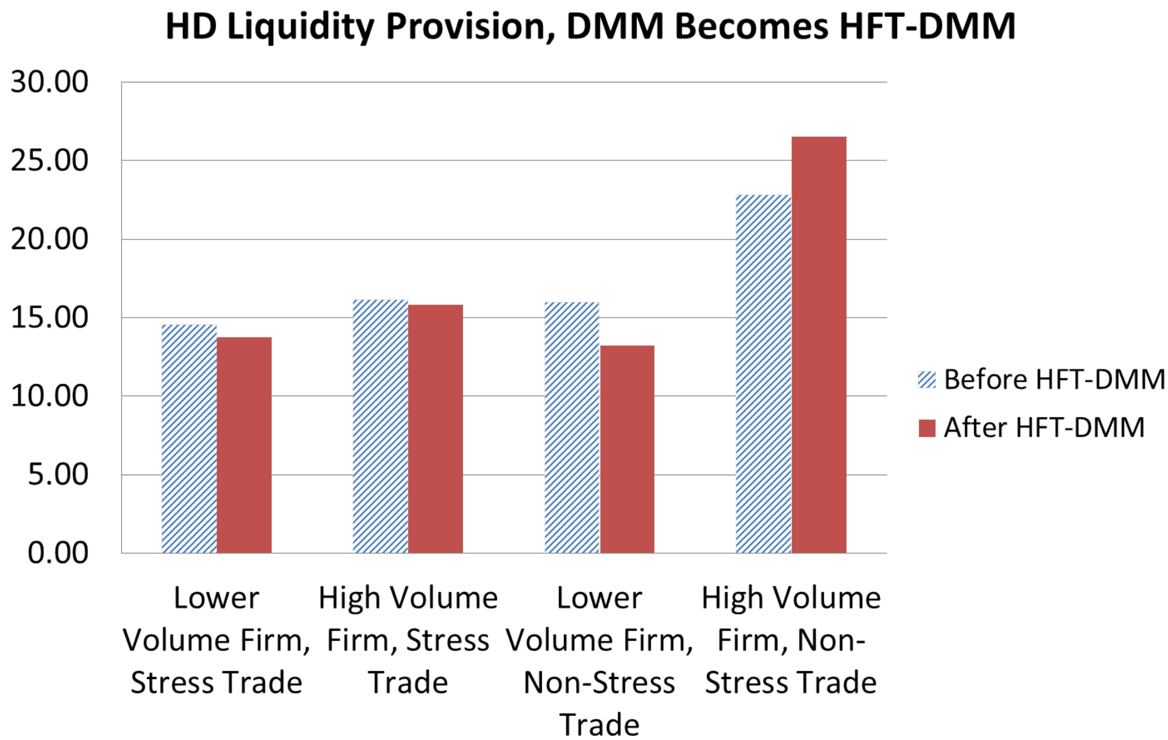

Figure 3. HD Liquidity Provision Before and After DMM Becomes HFT-DMM. This graph plots HFT and DMM combined liquidity provision (as a percentage of total liquidity provision to the aggressive component of the large trade) for 24 stocks in which each DMM became the same HFT-DMM on November 26, 2012. We examine HFT and DMM combined liquidity provision before and after this date, for stressful trades and non-stressful trades, and within high-volume and lower-volume firms. Numbers are based on the coefficients from the HD liquidity provision-regression from Table 7.

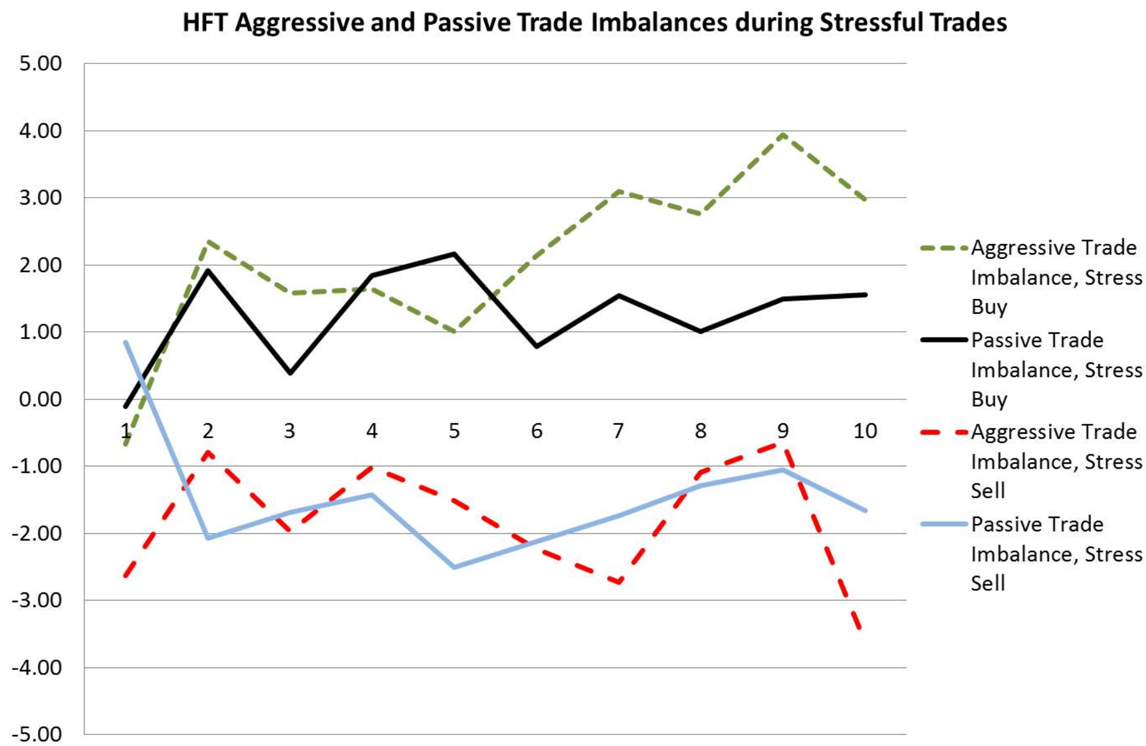

Figure 4. HFT Trade Imbalances during Stressful Trades. This graph reports the net aggressive trading imbalance (NAT) and net passive trading imbalance (NPT) for HFTs, averaged across all large stressful trades within each time decile (as defined in the main text of the paper). The x-axis reports the time decile of the trade.

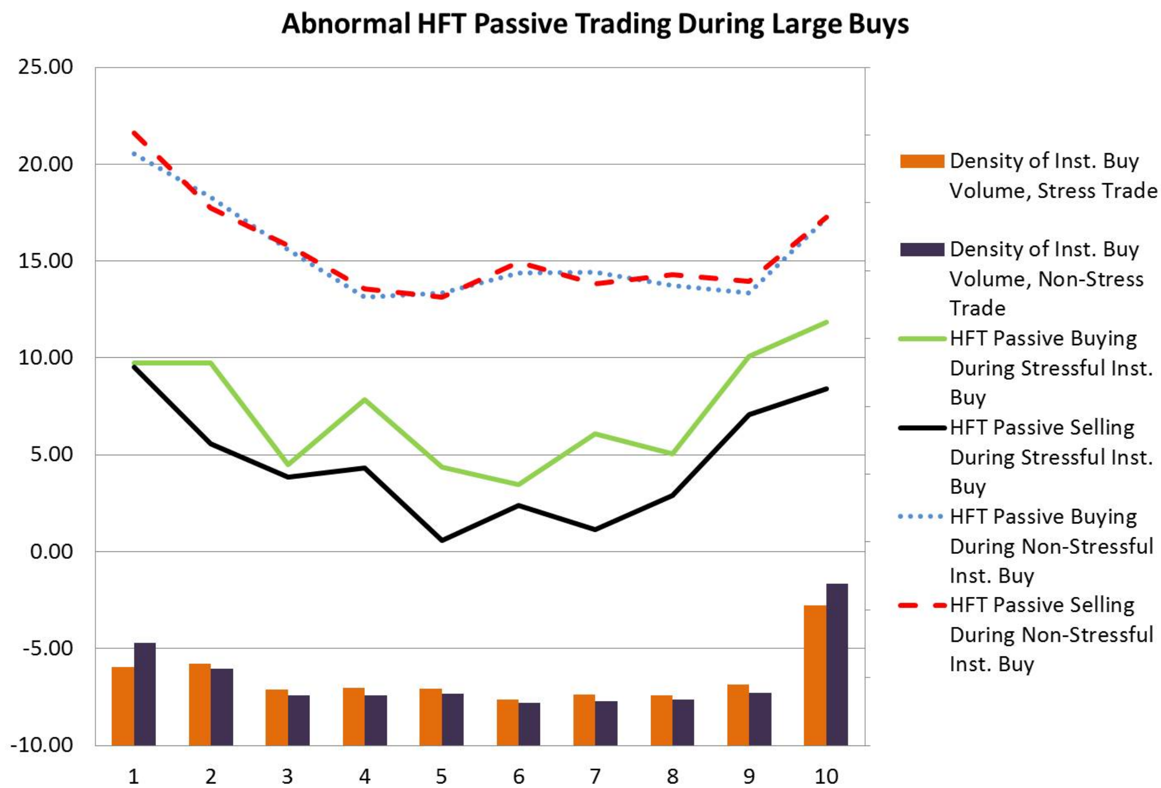

Figure 5. Abnormal HFT Liquidity Provision to Large Institutional Buys. This graph reports mean abnormal HFT buying and selling activity to stressful and non-stressful large institutional buys. The x-axis reports the time decile of the trade. The bar graph at the bottom reports the mean density of the percentage execution of large stressful and non-stressful buys.

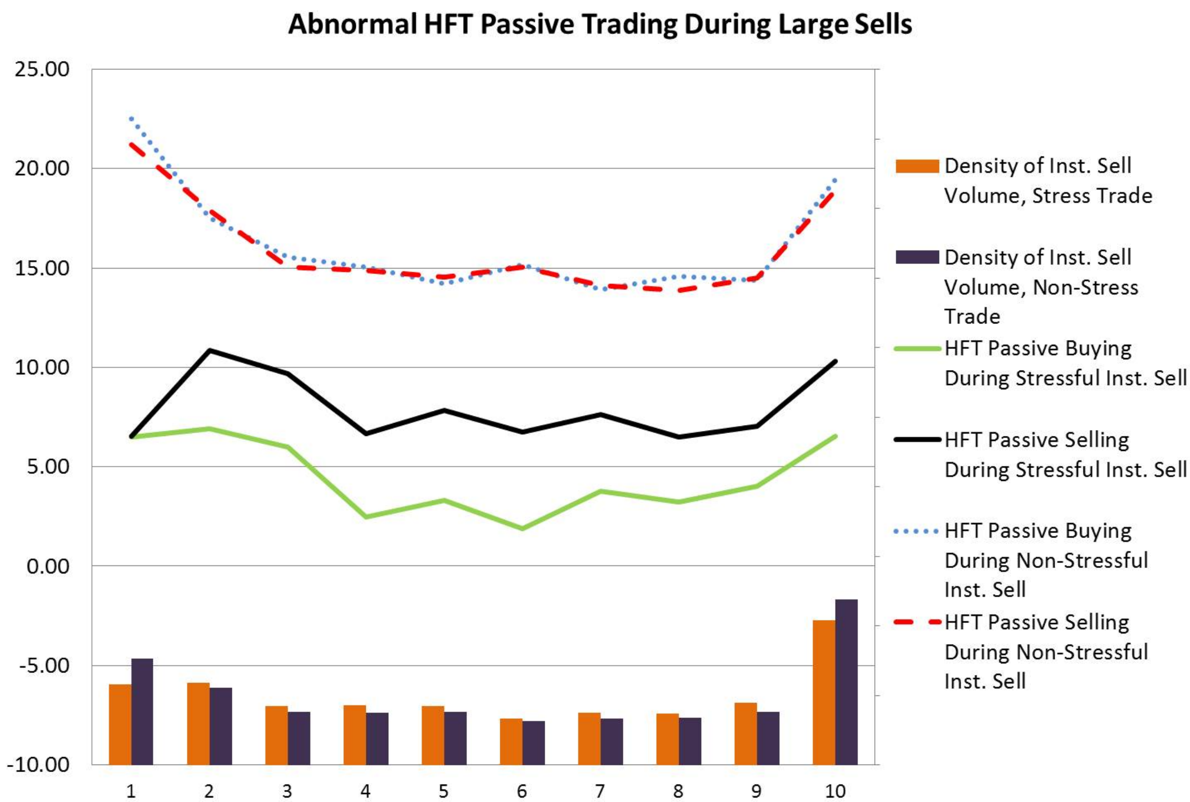

Figure 6. Abnormal HFT Liquidity Provision to Large Institutional Sells. This graph reports mean abnormal HFT buying and selling activity to stressful and non-stressful large institutional sells. The x-axis reports the time decile of the trade. The bar graph at the bottom reports the mean density of the percentage execution of large stressful and non-stressful sells.

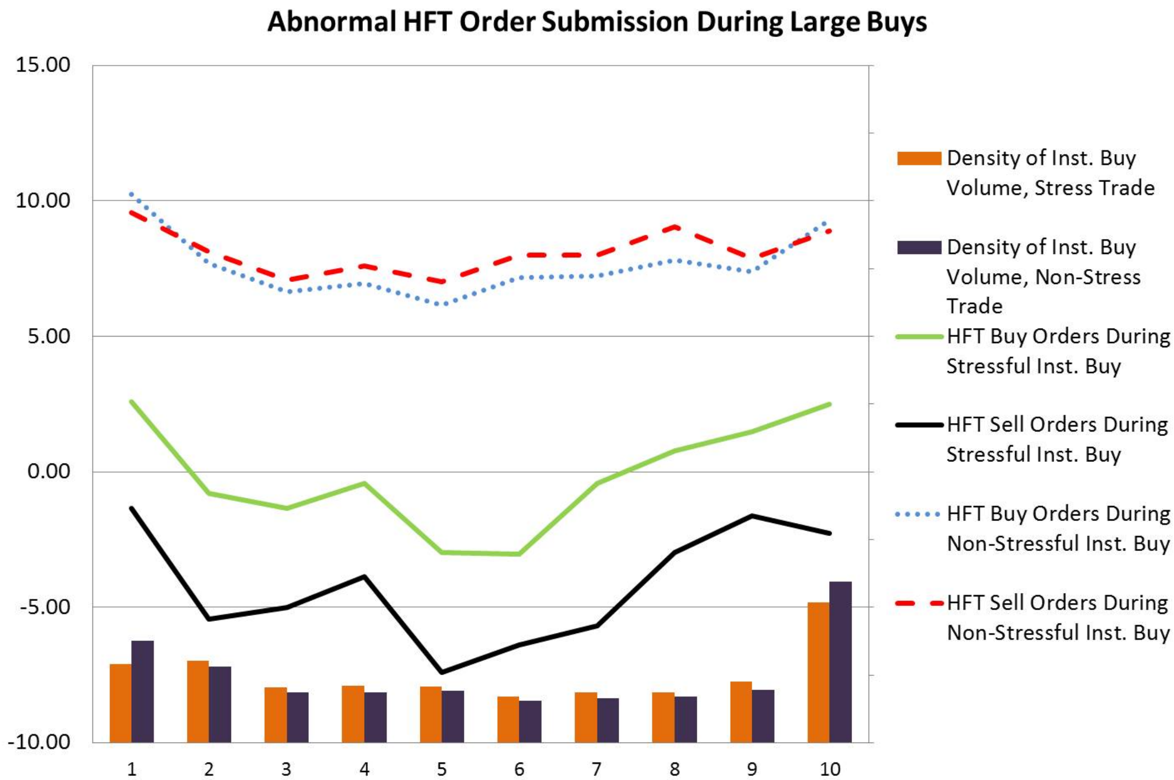

Figure 7. Abnormal HFT Order Submission during Large Institutional Buys. This graph reports mean abnormal HFT buy and sell order submissions activity during stressful and non-stressful large institutional buys. The x-axis reports the time decile of the trade. The bar graph at the bottom reports the mean density of the percentage execution of large stressful and non-stressful sells.

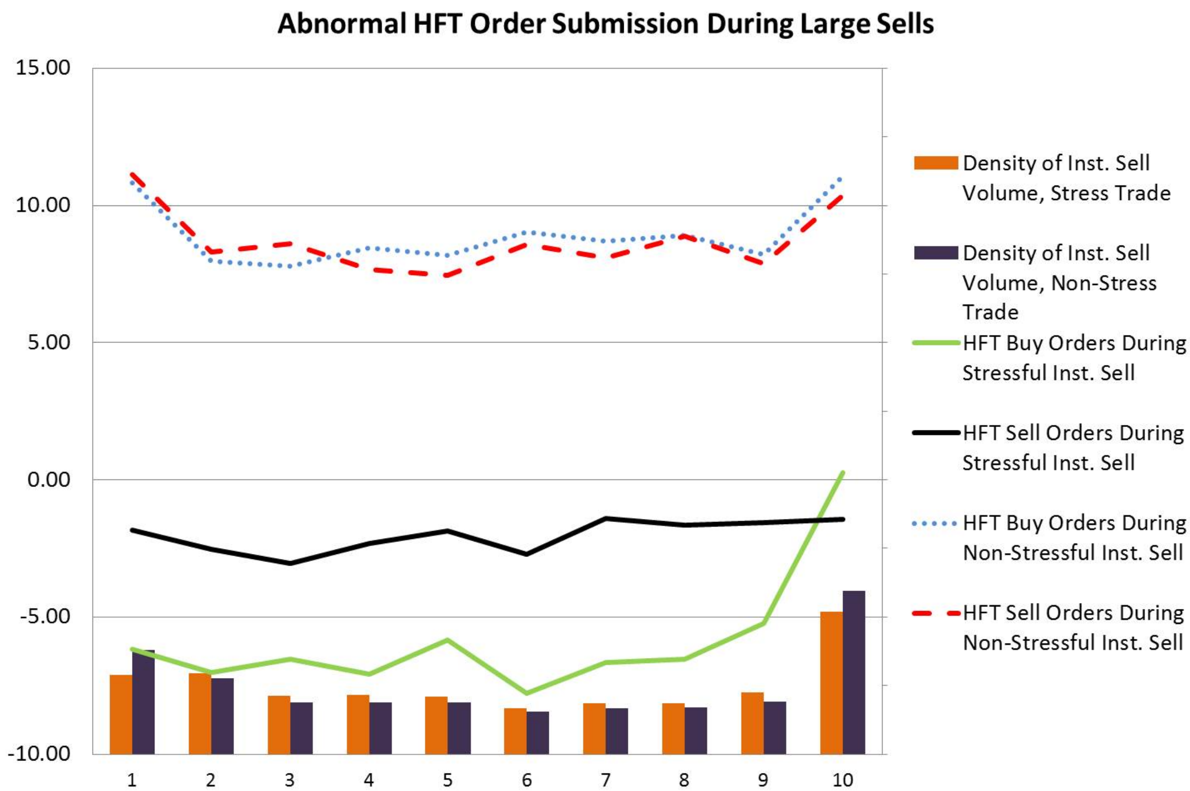

Figure 8. Abnormal HFT Order Submission during Large Institutional Sells. This graph reports mean abnormal HFT buy and sell order submissions to stressful and non-stressful large institutional sells. The x-axis reports the time decile of the trade. The bar graph at the bottom reports the mean density of the percentage execution of large stressful and non-stressful sells.

Table 1. Summary of Individual HFTs. Using our HFT identification methodology, 19 HFTs have been identified in our sample. Panel A reports summary statistics for each HFT. 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). OTC is the average order-to-cancel ratio (the within-stock average number of daily orders divided by number of daily order cancelations, then averaged across stocks). AGG is the percentage of dollar volume that is executed via marketable limit orders. EPOS is the HFT average net end-of-day inventory for that stock–day divided by share volume for that stock day. HFT Days is the percentage of active stock–days in which the HFT meets the criteria to be identified as an HFT. Panel B averages across HFTs within each of the three HFT subgroups (Super HFTs, Major HFTs, Minor HFTs) and across all HFTs. All columns are reported in percentage points except for HFT, Stocks, OTR, and OTC.

Panel A: Individual HFT Statistics

	HFT	Stocks	% Trades	OTR	OTC	% AGG	EPOS	HFT Days
Super HFTs	1	218	17.22	22.19	1.08	7.64	1.45	92.2
	2	126	9.77	27.21	1.12	37.25	7.05	81.7
	3	53	8.22	19.58	1.07	33.24	3.52	90.6
Major HFTs	4	38	6.58	22.78	1.07	12.14	0.03	93.6
	5	36	8.77	31.15	1.07	10.12	0.00	96.7
	6	27	7.73	18.60	1.09	19.51	4.33	86.7
	7	19	8.64	26.89	1.12	20.30	5.76	85.4
	8	17	3.48	16.13	1.15	28.45	1.16	87.4
	9	14	2.40	24.49	1.08	4.18	3.23	85.4
	10	13	8.97	15.16	1.15	39.65	3.49	83.2
	11	12	16.37	18.45	1.03	7.02	8.55	76.8
Minor HFTs	12	7	12.02	35.09	1.38	1.54	5.30	81.3
	13	6	4.32	25.94	1.05	52.17	1.19	89.3
	14	6	1.39	28.81	1.04	0.02	5.37	82.0
	15	4	2.11	14.55	1.13	4.03	2.11	80.1
	16	4	8.42	20.41	1.07	6.44	7.16	77.5
	17	1	5.32	59.74	1.08	25.26	1.64	75.4
	18	1	5.78	15.11	1.06	8.46	0.00	77.8
	19	1	2.62	8.25	1.07	1.13	4.30	77.3

Panel B: HFT Statistics by Subgroup

	HFT	Stocks	% Trades	OTR	OTC	% AGG	EPOS	HFT Days
Mean (Super)	1-3	132.3	11.74	22.99	1.09	26.04	4.00	88.2
Mean (Major)	4-11	22.0	7.87	21.71	1.10	17.67	3.32	86.9
Mean (Minor)	12-19	3.8	5.25	25.99	1.11	12.38	3.38	80.1
Mean (All)	1-19	31.7	7.37	23.71	1.10	16.77	3.45	84.2

Table 2. 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 (Panel A) and DMM (Panel B). 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, EPOS, 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. "Highvol", "Midvol", and "Lowvol" represent high volume stocks, medium volume stocks, and low volume stocks, respectively. Panel C reports trading statistics for the top five stocks by daily dollar volume, along with stocks grouped by volume bin. 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	EPOS	AGG	SIZE	N_{HFT}
Stock 1	30.5	9.1	35.8	23.4	23.5	12.3	0.2	22.8	8709.7	5.84
Stock 2	20.5	7.2	24.2	16.8	16.8	12.7	0.7	25.5	5466.0	3.96
Stock 3	19.1	3.5	24.8	12.9	13.0	19.4	1.3	15.2	10304.8	3.86
Stock 4	34.3	7.0	50.8	24.9	25.2	15.8	0.7	16.3	7402.2	6.84
Stock 5	9.1	0.7	11.9	9.0	9.0	29.9	1.1	7.1	20902.0	0.94
Highvol	15.2	3.3	20.6	11.3	11.4	19.4	1.0	16.3	5284.9	2.79
Midvol	11.8	1.8	17.5	9.1	9.2	27.3	1.7	13.0	2633.5	1.44
Lowvol	14.3	1.0	21.3	10.9	10.9	16.6	2.0	8.1	961.3	0.98

Panel B: DMM Statistics

	PVOL	AVOL	Orders	Buys	Sells	OTR	EPOS	AGG	SIZE	N_{DMM}
Stock 1	2.5	1.6	2.6	3.8	3.7	3.8	7.1	28.3	4705.0	1.07
Stock 2	0.8	0.7	0.0	1.6	1.5	0.0	0.8	19.5	2669.6	1.01
Stock 3	3.5	1.8	2.4	4.2	4.6	4.5	7.4	27.1	6530.8	1.04
Stock 4	2.3	1.4	0.0	2.8	3.3	0.1	0.9	31.2	5097.6	1.01
Stock 5	2.8	2.1	3.0	3.7	3.9	21.5	52.0	33.2	22653.7	1.00
Highvol	2.3	1.3	0.9	3.0	2.9	2.3	7.7	25.2	3331.2	1.03
Midvol	2.9	2.8	1.8	3.5	3.4	13.6	15.9	28.9	2479.6	1.02
Lowvol	2.2	1.9	0.4	2.4	2.5	0.8	21.9	26.4	781.0	1.01

Panel C: Volume Statistics

	Daily Volume ($M)	Daily Trades	Daily Orders
Stock 1	242.8	20,284	334,079
Stock 2	209.2	27,290	491,742
Stock 3	202.5	14,327	287,617
Stock 4	190.2	17,149	268,798
Stock 5	184.9	4,416	167,172
High-Volume Stocks	78.3	10,467	207,655
Mid-Volume Stocks	13.9	3,566	72,362
Low-Volume Stocks	3.4	1,970	26,003

Table 3. Summary of Large Trades. This table reports statistics for large trades, which are trades for at least \$1 million in high-volume stocks and at least \$500,000 in lower-volume stocks. Panel A reports statistics for large non-stressful trades, which are large trades that are not in the highest quartile of large-trade volume as a percentage of volume on that stock day (or days for large trades that span multiple days). Panel B reports statistics for large stressful trades, which are large trades that are in the highest quartile of large-trade volume as a percentage of volume on that stock day. Value of Trade is the total dollar value of the trade. Percent of Volume is Value of Trade divided by total volume on that stock–day. 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. Effective Spread, 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 Non-Stressful Trades (N=114,075)						
	Mean	P10	P25	P50	P75	P90
Value of Trade (\$M)	2.35	0.67	1.08	1.56	2.67	4.63
Percent of Volume	2.8	0.8	1.4	2.4	4.0	5.4
Number of Trades	375	106	168	272	447	725
Number of Orders	559	42	105	287	609	1179
% Liquidity Demanded	60.1	20.4	36.5	61.3	84.9	98.9
Time to Completion (hours)	5.5	0.9	1.9	4.6	6.4	11.7
Effective Spread (bps)	12	-81	-21	9	46	107

Panel B: Large Stressful Trades (N=37,780)						
	Mean	P10	P25	P50	P75	P90
Value of Trade (\$M)	3.31	0.62	0.87	1.58	3.42	7.29
Percent of Volume	13.0	7.3	8.3	10.7	15.1	21.7
Number of Trades	648	139	242	431	769	1,323
Number of Orders	838	50	132	395	884	1,803
% Liquidity Demanded	62.0	25.5	42.3	64.0	83.1	95.9
Time to Completion (hours)	5.8	1.6	3.2	5.2	6.4	11.2
Effective Spread (bps)	42	-61	-9	25	79	164

Table 4. 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 quartile 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 (for example, a large order where 25 percent of its volume is executed using aggressive trades will have $AGG = 25$). TIME is the number of hours is takes to execute the large trade. TSIZE is the dollar value (in millions) of the large trade and TSIZE2 is TSIZE squared. Standard errors are clustered by firm and t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	19.26	13.31	14.96	12.88	6.90	8.37
	(15.42)	(15.22)	(15.16)	(10.60)	(7.03)	(7.78)
Stress Trade	-6.05	-1.26	-1.46	-6.24	-1.41	-1.63
	(-5.61)	(-2.44)	(-2.74)	(-5.77)	(-2.85)	(-3.18)
High-Volume Firm		8.04	7.23		8.05	7.21
		(4.59)	(4.49)		(4.65)	(4.54)
Stress x Highvol		-4.42	-5.65		-4.48	-5.76
		(-3.38)	(-3.52)		(-3.48)	(-3.62)
Aggressiveness			-0.028			-0.027
			(-5.04)			(-4.82)
Time to Completion			-0.05			-0.05
			(-2.00)			(-1.99)
Trade Size			0.40			0.42
			(2.91)			(3.00)
Trade Size Squared			-0.002			-0.002
			(-2.43)			(-2.56)
Day Fixed Effects	No	No	No	Yes	Yes	Yes
Adjusted R-Squared	0.030	0.074	0.081	0.049	0.093	0.100
N	151119	151119	151119	151119	151119	151119

Table 5. 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 quartile 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 (for example, a large order where 25 percent of its volume is executed using aggressive trades will have $AGG = 25$). TIME is the number of hours it takes to execute the large trade. TSIZE is the dollar value (in millions) of the large trade and TSIZE2 is TSIZE squared. Standard errors are clustered by firm and t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	1.37	1.55	0.93	1.70	1.89	1.30
	(12.55)	(8.41)	(4.68)	(12.09	(8.7)	(5.8)
Stress Trade	0.08	0.04	0.08	0.09	0.05	0.09
	(0.71)	(0.33)	(0.67)	(0.84)	(0.39)	(0.75)
High-Volume Firm		-0.24	-0.05		-0.25	-0.06
		(-1.07)	(-0.21)		(-1.12)	(-0.24)
Stress x Highvol		-0.20	-0.02		-0.19	-0.01
		(-1.20)	(-0.11)		(-1.14)	(-0.06)
Aggressiveness			0.0030			0.0026
			(3.03)			(2.75)
Time to Completion			0.082			0.082
			(5.71)			(5.62)
Trade Size			-0.062			-0.063
			(-3.44)			(-3.47)
Trade Size Squared			0.0002			0.0002
			(2.34)			(2.37)
Day Fixed Effects	No	No	No	Yes	Yes	Yes
Adjusted R-Squared	0.000	0.001	0.015	0.002	0.003	0.017
N	151119	151119	151119	151119	151119	151119

Table 6. 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
11/19/12	9	517	$1,527,098	11/19/12	136	747	$4,563,382
11/20/12	9	662	$2,137,486	11/20/12	151	689	$3,592,483
11/21/12	8	638	$1,761,786	11/21/12	143	726	$3,981,145
11/22/12	14	582	$2,198,969	11/22/12	325	1015	$11,386,931
11/23/12	10	675	$2,090,191	11/23/12	261	897	$8,410,121
11/26/12	13743	2604	$16,658,721	11/26/12	61579	1920	$14,963,364
11/27/12	14901	2587	$16,443,534	11/27/12	17940	2272	$19,844,678
11/28/12	13860	2219	$14,833,054	11/28/12	18212	1658	$12,820,071
11/29/12	30716	4170	$29,203,356	11/29/12	20080	4272	$41,967,859
11/30/12	17333	2792	$18,637,773	11/30/12	23207	2494	$20,815,559

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

Table 7. 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. Standard errors are clustered by firm and t-statistics are reported in parentheses. All other variables are defined as before.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	14.87	14.95	15.98	8.79	8.46	9.36
	(17.05)	(16.71)	(15.88)	(8.97)	(8.21)	(8.48)
Stress Trade	-1.22	-1.28	-1.43	-1.37	-1.43	-1.60
	(-2.35)	(-2.39)	(-2.59)	(-2.73)	(-2.8)	(-3.01)
High-Volume Firm	7.79	7.42	6.83	7.80	7.35	6.74
	(4.47)	(4.26)	(4.23)	(4.52)	(4.29)	(4.25)
Stress x Highvol	-4.62	-4.25	-5.28	-4.68	-3.41	-5.38
	(-3.54)	(-3.29)	(-3.32)	(-3.64)	(-3.41)	(-3.44)
New DMM		-2.73	-2.73		-0.83	-0.86
		(-1.73)	(-1.68)		(-0.52)	(-0.53)
New DMM x Stress Trade		1.97	1.93		1.88	1.85
		(2.29)	(2.28)		(2.38)	(2.37)
New DMM x High-Volume Firm		6.57	6.47		6.50	6.41
		(1.84)	(1.82)		(1.83)	(1.82)
New DMM x Stress x Highvol		-6.13	-5.96		-5.69	-5.52
		(-2.11)	(-2.07)		(-1.97)	(-1.93)
Aggressiveness			-0.025			-0.024
			(-4.61)			(-4.45)
Time to Completion			0.04			0.04
			(1.36)			(1.39)
Trade Size			0.33			0.34
			(2.45)			(2.55)
Trade Size Squared			-0.002			-0.002
			(-2.16)			(-2.27)
Day Fixed Effects	No	No	No	Yes	Yes	Yes
Adjusted R-Squared	0.067	0.070	0.076	0.084	0.089	0.095
N	151119	151119	151119	151119	151119	151119

Table 8. HFT and DMM Daily Profit Summary Statistics. This table reports daily profit-per-stock summary statistics for the primary HFT, where an HFT is considered primary if its trading volume is higher than that of other HFTs possibly present in that stock, and DMM in each stock for days with no stressful trades and days with at least one stressful trade. Trade Profit is calculated as the value of shares sold minus the value of shares bought, and any remaining inventory for that day is marked to market using the closing price. Rebate Profit is calculated as liquidity rebates minus fees. Total Profit is the sum of Trade Profit and Rebate Profit. Profit per Share (PPS) is Total Profit divided by the maximum of total shares bought and total shares sold. Standard Deviation of PPS (Stdev(PPS)) is calculated as the standard deviation of daily profit per share within a stock. All numbers reported in this table are first averaged across days within each stock and then averaged across stocks within each subgroup (high-volume, mid volume, low-volume, all).

Panel A: HFT Profit, Days with no stressful trades

	Trade Profit	Rebate Profit	Total Profit	PPS	Stdev(PPS)
Highvol Firms	-115.79	634.31	518.53	0.00272	0.0251
Midvol Firms	-97.52	350.01	252.51	0.00219	0.0184
Lowvol Firms	-95.51	181.63	86.12	0.00197	0.0089
All Firms	-102.85	380.21	277.37	0.00228	0.0183

Panel B: HFT Profit, Days with stressful trades

	Trade Profit	Rebate Profit	Total Profit	PPS	Stdev(PPS)
Highvol Firms	-78.45	393.72	315.27	0.00247	0.0187
Midvol Firms	-97.53	259.00	161.47	0.00211	0.0203
Lowvol Firms	-120.48	251.57	131.09	0.00167	0.0127
All Firms	-96.23	303.50	207.27	0.00213	0.0183

Panel C: DMM Profit, Days with no stressful trades

	Trade Profit	Rebate Profit	Total Profit	PPS	Stdev(PPS)
Highvol Firms	-102.53	41.29	-61.24	0.0135	0.0414
Midvol Firms	-260.70	-39.00	-299.70	0.0112	0.0395
Lowvol Firms	31.07	-7.26	23.81	0.0102	0.0291
All Firms	-106.34	5.85	-100.49	0.0119	0.0378

Panel D: DMM Profit, Days with stressful trades

	Trade Profit	Rebate Profit	Total Profit	PPS	Stdev(PPS)
Highvol Firms	145.27	39.19	184.46	0.0163	0.0431
Midvol Firms	55.12	12.91	68.02	0.0136	0.0423
Lowvol Firms	49.53	-14.27	35.26	0.0107	0.0326
All Firms	90.40	18.55	108.95	0.0141	0.0411

Table 9. HFT Liquidity Provision Following Large Losses. The dependent variable in these regressions is HFTLIQ, which is the percentage of liquidity provided by HFTs to the active component of large trades. Bad Week is an indicator variable that equals one if the primary HFT was in the lowest decile of average profit per share during the previous week (five business days). Standard errors are clustered by firm, and t-statistics are reported in parentheses. All other variables are defined as before.

	(1)	(2)	(3)	(4)
Intercept	13.30	13.85	15.70	9.37
	(19.21)	(16.07)	(16.46)	(8.93)
Bad Week	-4.95	-4.90	-5.09	-5.16
	(-7.65)	(-7.70)	(-7.85)	(-7.99)
High Volume Firm	7.78	7.91	7.09	7.08
	(4.94)	(4.61)	(4.52)	(4.60)
Bad Week x High Volume Firm	-0.29	-0.11	-0.03	-0.14
	(-0.16)	(-0.06)	(-0.01)	(-0.08)
Stress Trade		-1.18	-1.37	-1.55
		(-2.40)	(-2.70)	(-3.17)
Stress Trade x High Volume Firm		-4.35	-5.58	-5.69
		(-3.42)	(-3.56)	(-3.67)
Aggressiveness			-0.031	-0.030
			(-6.25)	(-6.00)
Time to Completion			-0.048	-0.047
			(-2.00)	(-1.97)
Trade Size			0.40	0.41
			(2.93)	(3.03)
Trade Size Squared			-0.0019	-0.0020
			(-2.44)	(-2.58)
Day Fixed Effects	No	No	No	Yes
Adjusted R-Squared	0.073	0.083	0.091	0.110
N	151119	151119	151119	151119

Table 10. HFT Liquidity Provision and Multiple 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. Netstress is calculated as absolute value of the number of stressful buys minus the number of stressful sells on that stock-day. Standard errors are clustered by firm, and t-statistics are reported in parentheses. All other variables are defined as before.

	(1)	(2)	(3)	(4)
Intercept	20.11	14.15	15.78	9.20
	(14.84)	(15.82)	(15.70)	(8.67)
Netstress	-1.98	-1.41	-1.36	-1.42
	(-5.34)	(-5.30)	(-5.53)	(-5.73)
Stress Trade	-4.88	-0.67	-0.88	-1.03
	(-5.65)	(-1.32)	(-1.73)	(-2.09)
High Volume Firm		7.73	6.95	6.92
		(4.54)	(4.43)	(4.48)
Stress Trade x High Volume Firm		-4.07	-5.28	-5.38
		(-3.26)	(-3.42)	(-3.52)
Aggressiveness			-0.029	-0.027
			(-5.13)	(-4.90)
Time to Completion			-0.045	-0.045
			(-1.91)	(-1.90)
Trade Size			0.39	0.41
			(2.85)	(2.95)
Trade Size Squared			-0.0019	-0.0020
			(-2.38)	(-2.51)
Day Fixed Effects	No	No	No	Yes
Adjusted R-Squared	0.037	0.077	0.084	0.104
N	151119	151119	151119	151119

Table 11. 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. Standard errors are clustered by firm and t-statistics are reported in parentheses. All other variables are defined as before.

	(1)	(2)	(3)	(4)
Intercept	12.79	15.11	6.36	8.50
	(18.29)	(15.07)	(7.30)	(7.78)
Stress Return	-0.46	-0.64	-0.48	-0.66
	(-2.30)	(-3.00)	(-2.43)	(-3.18)
High-Volume Firm	8.25	7.56	8.32	7.54
	(5.10)	(4.66)	(5.17)	(4.71)
Stress Return x Highvol	-0.71	-0.86	-0.81	-0.94
	(-2.20)	(-2.38)	(-2.56)	(-2.68)
Stress Trade		-1.50		-1.67
		(-2.79)		(-3.22)
Stress Trade x Highvol		-5.78		-5.88
		(-3.58)		(-3.68)
Aggressiveness		-0.03		-0.03
		(-5.27)		(-5.05)
Time to Completion		-0.05		-0.05
		(-1.91)		(-1.90)
Trade Size		0.42		0.44
		(3.01)		(3.10)
Trade Size Squared		-0.002		-0.002
		(-2.49)		(-2.61)
Day Fixed Effects	No	No	Yes	Yes
Adjusted R-Squared	0.068	0.087	0.086	0.106
N	149507	149507	149507	149507

Table 12. Effective Spread and Market-Maker Liquidity Provision. The dependent variable in this regression is Effective Spread (in basis points). HFTAGG (DMMAGG) is the HFT (DMM) active dollar volume within a large trade as a percentage of all passive volume from that large trade. HIGHVOL (MIDVOL) equals one for high (mid) volume stocks. MKTRET is the percent market return on the day of the large trade and this is interacted with a large buy indicator (BUY) and a large sell indicator (SELL). All other variables are defined as before. Standard errors are clustered by firm and t-statistics are reported in parentheses.

	(1)	(2)	(3)
Intercept	61.48	53.22	65.79
	(12.88)	(9.95)	(6.00)
HFT Liquidity Provision	-0.47	-0.39	-0.43
	(-9.84)	(-9.23)	(-9.84)
HFT Active Volume	0.22	0.05	0.13
	(3.15)	(0.79)	(1.81)
DMM Liquidity Provision	-0.28	-0.06	-0.03
	(-2.23)	(-0.49)	(-0.22)
DMM Active Volume	0.09	0.06	0.08
	(0.66)	(0.44)	(0.55)
Highvol	-41.30	-51.12	-49.71
	(-8.59)	(-10.54)	(-10.33)
Midvol	-31.90	-35.22	-34.12
	(-6.29)	(-6.92)	(-6.78)
Aggressiveness		0.30	0.32
		(8.34)	(8.71)
Time to Completion		-1.60	-1.61
		(-6.04)	(-5.96)
Trade Size		3.10	3.06
		(7.93)	(7.87)
Trade Size Squared		-0.02	-0.02
		(-4.27)	(-4.26)
Market Return x Buy		0.36	
		(19.84)	
Market Return x Sell		-0.38	
		(-20.50)	
Adjusted R-Squared	1.2%	6.3%	3.1%
N	121201	121201	121201
Day Fixed Effects	No	No	Yes