Do retail traders suffer from high frequency traders?[*]

Katya Malinova[†]
University of Toronto

Andreas Park[‡]
University of Toronto

Ryan Riordan[§]
University of Ontario Institute of Technology

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Abstract

We analyze the causal impact of high frequency trading on market quality, retail traders' trading costs and profits. On April 1^{st}, 2012 the Investment Industry Regulatory Organization of Canada started charging its members an initially unknown cost recovery fee per exchange message (e.g., orders, trades, cancellations) that had the potential to be very costly for high message traffic participants, predominantly high frequency traders (HFTs). Following the introduction of the fee, high HFT reduced their market activity significantly, both in absolute terms and as a percentage of overall market activity. Using the fee change as an exogenous instrument, we employ trader-level data to estimate the causal effect of HFT activities on market quality and on the costs and profits of other traders, in particular of retail traders. The retraction of HFTs from the market causes a decrease in market liquidity and in the trading profits (increased losses) of retail traders, particularly in high volume stocks. Our works suggests that, contrary to the commonly held opinion, HFTs appear to not impose negative externalities on the least sophisticated market participants and that they may be beneficial to slower and less sophisticated traders.

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[†]katya.malinova@utoronto.ca

[‡]andreas.park@utoronto.ca (corresponding author)

[§]ryan.riordan@uoit.ca

The advent of fully electronic trading platforms has changed the equity trading landscape dramatically over the last decade and has enabled the rise of trading by computer algorithms without any human interference. One of the most extreme forms of electronic trading is the practice of high frequency trading (HFT). HFT is an umbrella expression for a business model used by major brokerages and proprietary trading firms to generate trading profits by trading as fast as technology allows. Many of the trading strategies employed by HFTs involve sending a large number of orders over short time intervals. HFT order submission and cancellation activities may impose externalities on other traders, market centres and regulators as they strain the trading infrastructure and effectively force investors and brokers to invest in both ever-faster trading systems to keep up with the flow of information and to invest in trading strategies to account for speed disadvantages. As a consequence, HFT has been scrutinized by regulators and the investment industry, and their activities have received a lot of attention from the popular press, academics, and policy makers. For instance, the U.K. Department of Business Innovation and Skills recently published the results from a major research project, as part of which they commissioned a large number of studies by academics to study to impact of computerized trading on markets.[1] In this paper, we analyze whether and to what extent retail traders are affected by HFTs to bring clarity to the debate surrounding the externalities associated with HFTs.

Most of the evidence, and in particular with regard to HFT strategies that supply liquidity (Jovanovic and Menkveld (2011) or Menkveld (2011)), indicates that the development has been positive: price discovery and liquidity have improved. Yet many industry participants are skeptical and argue that these gains are illusions. Apart from some manipulative strategies that HFTs allegedly use,[2] practitioners also argue that even their "good" strategies, i.e. the liquidity supplying behaviour, can raise costs for long-term investors. The argument here is that HFT quoting activities crowd out natural traders (those who trade to get in and out of a long-term investment position) from the passive side of trades, forcing

[1]http://www.bis.gov.uk/foresight/our-work/projects/current-projects/computer-trading

[2]One common example of an abusive trading practice is quote stuffing, i.e. the practice of submitting large numbers of orders with the purpose of slowing down trading systems for everyone else. Abusive and manipulative strategies are not the focus of our study.

them to use expensive market orders. Following this thought, improvements in the bid-ask spread, which is a standard measure of market quality, would not help those that switch from (better priced) limit orders to market orders. Moreover, if the crowding-out phenomenon disproportionately affects a particular group of traders, such as unsophisticated retail traders, then one may worry that the implied redistribution has a negative impact on markets overall — even if standard market quality measures indicate improvements.

It is, however, challenging to assess the impact and possible externalities caused by HFTs. First, to establish an externality from HFTs to other traders, researchers need to be able to differentiate between different types of traders. A second issue is that electronic trading has increased over time, and high or low levels of HTF activity in a given stock at a point in time may be endogenous to the current market conditions. To determine *causal* effects of HFT on market quality, researchers require, for instance, a change in an exogenous factor that impacts HFT activities. In this study we use an exogenous event that led to a temporary, but significant drop in HFT activity on the Canadian market. Using a highly granular, trader-level data set we are able to draw conclusions on the impact of high frequency trading on overall market quality and, crucially, on the trading costs of non-high frequency traders. We study the effects of HFT on unsophisticated retail traders and other non-HFT traders and focus on the impact of HFT on the unsophisticated retail traders.

As of April 1^{st} 2012 (our event date), the Investment Industry Regulatory Organization of Canada (IIROC) fundamentally changed the calculation of the monthly charges that it levies on its members.[3] Before the change, members' fees were based on their market share of trading volume; after the change, members' fees were also calculated using the number of market messages that a member generates. In the pre-introduction news release, IIROC estimated that approximately 85% of firms would experience a fee decrease and 15% of firms would experience a fee increase. Most market participants agreed that firms that cater to HFTs would be facing significantly higher costs, and that the remainder of firms

[3]IIROC's official language refers to the fee schedule as the "integrated fee model"; see IIROC notice 12-0085; the monthly activity fees are divided into "Message Processing Fees" and "Trade Volume Fees" (where trade volume refers to the number of transactions); see http://www.iiroc.ca/Documents/2012/bf393b26-7bdf-49ff-a1fc-3904d1de3983_en.pdf

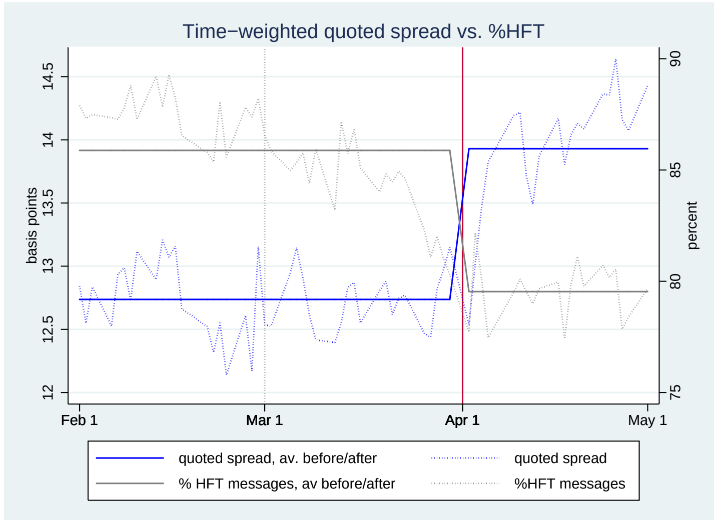
would see marginally lower costs. Importantly, costs depend on all market participants' behavior during a month. IIROC's charges are meant to recover the costs of its activities, such as real-time market monitoring, and these costs and the respective fees are determined at the end of a month. Since the per-message fee was unknown ex ante, there was notable uncertainty about the level of the fees.

The introduction of the per-message fee model on April 1^{st}, 2012 resulted in a significant drop in the total number of HFT generated messages both in absolute terms and as a percentage of all messages. Since fees are determined based on the each participants' percentage of the all messages, we study the impact of percentage changes rather than level changes.[4] Focussing on the constituents of the S&P/TSX Composite index (248 securities, after filtering), we find that in March 2012, before the introduction of the new fees, about 84.4% of messages are generated by HFTs. After the introduction of the per-message fee, the HFT share of the monthly average falls by almost 5%, and they reduced their total exchange messages by over 30%, to levels last seen in mid-2007.[5] Figure 2 plots the logarithm of the total number of daily messages across all instruments that were generated on the Toronto Stock Exchange between February 1^{st} and April 30^{th}, 2012, and illustrates the substantial drop. It is clear that the fee change had an impact. Conceptually, the introduction of the per-message fee was an exogenous shock to the costs of those existing HFT strategies that use a large number of order submissions and cancellations, and we can thus use the shock as an exogenous instrument to study the causal impact of HFT trading on other traders.

We analyze the impact of the reduction in the HFT-share of total messages (i.e. orders, traders, cancellations) on spreads, trading costs and trading revenues. As a first step, we show that the reduction in HFT activities significantly widens market-wide (NBBO) bid-ask spreads. Figure 1 provides a very clear picture of this effect: as HFTs reduce their activities, bid-ask spreads increase significantly. Although the bid-ask spread is commonly used as the main indicator of market quality, it is not clear that a drop in the spread has significant negative impact on non-HFT market participants. The reason is that non-HFTs commonly

[4]The results of our analysis are similar or even stronger when we use the level of HFT messages.
[5]See Figure 6, Panel C, in Malinova, Park, and Riordan (2013).

Figure 1
Bid-Ask Spreads vs. HFT Market Participation



trade at worse conditions,[6] and it is not clear that non-HFTs are actually able to access the best conditions that are reflected by standard measures. Thus, the observed increase in the spread may affect only those who trade at the best conditions, i.e., the HFTs. Moreover, as HFTs retract, it is also possible that non-HFTs now have more opportunities to trade with limit orders as opposed to market orders, and can lower their trading costs. The level of detail in the data allows us to observe that net trading costs for retail traders change insignificantly across the entire sample but that they increase in high volume stocks.

Our data also allow for an analysis of trading profits, computed as the intraday profits from buying and selling a security, with the end-of-day portfolio holdings evaluated at the closing price. As it is computed across all traders, these profits or losses are zero-sum, and changes represent redistribution between groups of traders. A positive profit implies that a trader was able to buy low or sell high relative to the closing price. Here we find that retail traders' profits fall strongly post event, while non-HFT traders' profits increase.

Overall our analysis shows that the retraction of HFT has negatively impacted retail traders and we thus show, under 2012 market conditions, that HFTs provide non-negligible benefits to the least sophisticated market participants. The rest of the paper is organized as follows. Section I reviews the related literature on retail trading and high frequency

[6] Hendershott and Riordan (2012), for instance, show that algorithmic traders trade when conditions are most favourable.

trading. Section II describes the data, the sample, our trader classification and the trading cost and profit measures that we use. Section IV outlines our empirical methodology and main results. Section V discusses the results. Tables and figures are at the end of the paper.

I Literature on Retail and High Frequency Trading

Our work contributes to the literature on retail trader activities. Barber and Odean (2000) show that active retail traders' portfolios underperform the market. Barber and Odean (2002) show that as investors switch to online brokerages, and trade more, their performance falls. Using a Taiwanese dataset, Barber, Lee, Liu, and Odean (2009) find that retail traders lose on their aggressive trades. The evidence on retail traders suggests that particularly their active trading is detrimental to their investment performance. The research on retail traders suggests that other market participants are better at timing their trading decisions than retail traders, we find similar results in our data. Complementing this literature, we study retail traders' trading costs and the impact of HFT on them.

Our work also relates to the expanding literature on high frequency trading. Biais and Woolley (2011) and Jones (2013) provide an overview of this literature. Brogaard, Hendershott, and Riordan (2012) use 2008-9 data from NASDAQ that identifies HFT trades and show that HFT aggressive trades permanently impound information into prices, indicating that HFT predict future price movements. Hirschey (2011) uses data from NASDAQ that identifies trading by individual HFT firms and finds that aggressive HFT trades predict subsequent non-HFT liquidity demand. Kirilenko, Kyle, Samadi, and Tuzun (2011) study HFT in the E-mini S&P 500 futures market during the May 6th flash crash and suggest that HFT may have exacerbated volatility. Jovanovic and Menkveld (2011) model HFT as middlemen in limit order markets and examine their welfare effects. Menkveld (2011) studies how one HFT firm enabled a new market to gain market share and how this HFT firm affected the price discovery process. Ye, Yao, and Gai (2013) study technological advances in message processing on NASDAQ and finds that a reduction in latency from milliseconds to microseconds led to no improvement in market quality, suggesting that there are diminishing returns from technological improvements. Subsequent to our study, Lepone and Sacco (2013) confirm our findings on the increase in the bid-ask spread for one of Canada's smaller venues, Chi-X, using a 19-month event window.

Jones (2013) describes a number of examples of trading venues that impose some form of messages fees when traders exceed certain order-to-trade ratios. At first sight, a tax on financial transactions (FTT) has a similar flavor as a per-message fee. However, the per-message fee that we study is a new redistribution formula for existing fees and disproportionally affects the few traders that submit the bulk of messages. Additionally, the per-message tax is charged at the broker level and is, to the best of our knowledge, commonly not passed on to non-HFTs. In contrast, an FTT is paid by all investors.[7]

Our work is also related to algorithmic trading, of which HFT is a subset. Hendershott, Jones, and Menkveld (2011) show that algorithmic trading improves liquidity and makes quotes more informative. Boehmer, Fong, and Wu (2012) provide international evidence on algorithmic trading in equity markets. Chaboud, Chiquoine, Hjalmarsson, and Vega (2011) study algorithmic trading in foreign exchange markets. Hendershott and Riordan (2012) focus on the monitoring capabilities of algorithmic traders and find that they smooth liquidity over time as they demand liquidity when it is cheap and supply liquidity when it is expensive. Hasbrouck and Saar (2011) study low-latency trading, document substantial short horizon activity in NASDAQ's limit order book, and find that low-latency trading and market quality are positively related. Martinez and Rosu (2011) model HFT liquidity demanding activities; their results suggest a stabilizing role for HFTs as they incorporate new information into prices quickly. Biais, Foucault, and Moinas (2011) and Pagnotta and Philippon (2012) provide theoretical models where investors and markets compete on speed. They highlight some of the negative externalities associated with latency-based competition.

[7]Colliard and Hoffmann (2013), Haferkorn and Zimmermann (2013), and Meyer and Wagener (2013) study the 2012 introduction of the French transaction tax. All three studies find that market depth and volume decline after the introduction of the tax, though Colliard and Hoffmann (2013) show that the volume decline is temporary.

II Data, Trader Classification, and Measures

A Data

Our analysis is based on two proprietary trader-level datasets, one provided to us by the Toronto Stock Exchange (TSX), the other by Alpha Trading; our trade-based analysis is based only on the TSX data.[8] Data on shares outstanding (based on February 2012), splits, and index status is obtained from the monthly TSX e-Review publications. Data on the U.S. volatility index VIX is from the CBOE database in WRDS. IIROC's new, per-message fee became effective on April 1, 2012, and monthly charges were levied in early May 2012. We focus on trading in March and April 2012, and we use February for classification purposes.

The TSX data is the output of the central trading engine, and it includes all messages from the (automated) message protocol between the brokers and the exchange. Messages include all orders, cancellations and modifications, all trade reports, and all details on dealer (upstairs) crosses. Our focus is on trading in the TSX limit order book. We exclude opening trades, oddlot trades,[9] dealer crosses, trades in the special terms market, and trades that occur outside normal trading hours. The data also specifies the active (liquidity demanding) and passive (liquidity supplying) party, thus identifying each trade as buyer-initiated or seller-initiated. The "prevailing quote" identifies the best bid and ask quotes and is updated each time there is a Canada-wide change in the best quotes. For the TSX we also have continuous information on the depth at the best quotes.

IIROC's Per-Message Fee: As outlined in the introduction, IIROC levies fees on its members to recover the costs of market monitoring. Before April 1, 2012, members' fees were based on their market share of trading volume; after the change, members fees were additionally based on the share of market messages that they generate. The total charges are not known at the beginning of the month. According to a research report by CIBC (2013), in 2012 the per-message fee was roughly of \$0.00022 per message (it fluctuates from

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[9]Oddlot trades are portions of orders that are not in multiples of 100 shares; these are not cleared via the limit order book, but they are automatically cleared via the so-called registered trader.

month to month). As Table I shows, for our sample, there were about 16.9 million messages per day, resulting in around $3,700 in message fees. Notably, these fees are not additional fees (as would accrue with a tax), rather they are one way in which the regulator recovers costs. In our opinion, it is unlikely (and impractical) for brokers to pass the per-message fee on to most of their customers. Clients that generate many messages, however, such as high frequency traders, and related direct market access clients, will likely have to cover these fees as part of their arrangement with the broker.

B Sample Selection

We select symbols from the S&P/TSX Composite index, Canada's broadest index and require that the companies remain in the index for the entire sample period. We exclude securities with stock splits, with major acquisitions, with days with an average midprice below $1, with fewer than 10 transactions per day, or that changed cross-listing status during the sample period. We delete Fairfax Financial Holdings (ticker: FFH) because of its high price (>$400; the next highest price is below $90). This leaves us with 248 companies in the final sample. For the classification of HFTs we also use ETFs that have more 1,000 trades in February 2012 as per the TSX e-review publication; there are 42 such ETFs.

C Classification of Traders

Each message to the market consists of up to 500 variables, such as the date, ticker symbol, time stamp, price, volume, and order visibility. Crucial to our analysis is a unique identifier that is given, for example, to a licensed individual at a broker's trading desk or to a direct market access (DMA) client. We do not know how brokers organize their trading desks, and we do not know which unique identifiers are associated with DMA clients. The Canadian regulator IIROC requires, however, that each DMA client has a unique ID so that messages from a DMA client are not mixed with other order flow.

Retail. To classify retail traders, we use information contained in a dataset provided to us by Alpha Trading, Canada's second largest exchange.[10] Alpha operates the dark pool IntraSpread in which active, marketable orders can only be submitted by retail traders. We obtain the unique identifiers for these known retail traders from the Alpha data. Not all retail traders trade on Alpha, and thus we classify these retail traders as "other traders". As a robustness check, we classified unsophisticated traders as those unique identifiers that use stale orders and that are not inventory, specialist, or options market makers. A stale order is an order that remains in the limit order book overnight (or longer). There is substantial overlap between traders who use stale orders and retail traders as classified using the Alpha data. Figure 3 illustrates this point. In the past, researchers associated retail trades with small order sizes. In today's markets, such a classification is questionable because institutional trades are commonly split into very small orders — in fact, the average retail order in our data is larger than the average order.

High Frequency Traders. We base our classification of high frequency traders on the total number of messages and the message-to-trade ratios for each unique identifier, from the pre-sample month of February. Messages are defined as a trade, an order, a cancellation of an order, or a fill-or-kill submission. We use messages instead of orders because order messages alone would exclude fill-or-kill messages and these make up a large fraction of total activity. For each unique identifier, we compute the number of messages and the number of trades that this participant submitted across the entire sample of TSX Composite securities plus the ETFs in February 2012. We include exchange traded funds in the classification because HFTs often engage in ETF arbitrage or use ETFs for hedging (also from futures markets) and we feel that this larger set is well-suited to capture unique identifiers associated with HFTs.[11] To be classified as an HFT, we require that the unique identifier is both in

[10] Alpha Trading operated as exchange as of April 01, 2012. As of November 01, 2012, Alpha Trading and TMX have merged.

[11] We did not include ETFs in the trading cost analysis for a number of reasons. Most importantly, ETFs have designated market makers that maintain tight spreads — and it is possible that ETF providers have a contract with the designated market maker on the maximum size of the spread. ETFs as derivatives are also a different class of securities from the TSX Composite's common stocks.

the top 5% of message-to-trade ratios and in the top 5% of the total number of messages submitted. We further filtered the list of traders by eliminating traders from our HFT list that were classified as retail, that had stale orders, that were part of basket or program trades, and that submitted dealer crosses.

This classification is biased towards message-intensive high-frequency trading strategies. High frequency trading strategies that do not rely on a large number of messages will not be captured. Strategies that use few messages are unlikely be be directly affected by the introduction of per-message fees. This bias should be kept in mind when interpreting our findings in the remainder of the paper.[12] Finally, "fast" traders that use few messages would be classified as "other" traders.

There are 3,516 unique identifiers in February 2012; we classify 94 of these as HFTs and 125 as retail. Table I presents the summary statistics for the overall sample. We see that the number of HFT messages falls by roughly 31% from March to April and that the HFT fraction of all messages falls from roughly 84.4% to 79.5%. The summary statistics show that HFTs have the lowest active and net trading costs. In terms of trading profits, HFTs break even on average, not accounting for maker-taker fees.[13] Since HFTs trade with passive limit orders 74% of the time, they are net receivers of maker rebates. This will increase the overall profitability of their trading strategies.

There is little precedent in the academic literature as to how to classify high frequency traders. Baron, Brogaard, and Kirilenko (2012) include, for instance, end-of-day inventories in their criteria. However, their study covers a single security, the S&500 e-mini, that is exclusively traded on CBOE. We cannot use inventories because we could misclassify

[12] The classification is also likely biased to identify those HFTs that are active in the most frequently traded securities. For instance, for non-interlisted securities or the lowest tercile in terms of dollar-volume, we we also observe a drop in messages (on average by about 25%), but this drop is not caused by the traders that we classify as HFTs here. To capture the most message-intensive traders for these stocks would require a more tailored classification approach; considering the lack of precedent in HFT classification in the literature, we felt it prudent to focus on easily accessible and accepted criteria.

[13] Most North American exchanges employ so-called maker-taker fees, an incentive scheme used to attract trading volume to a particular venue. The International Organization of Securities Commissions (IOSCO) defines maker-taker fees as "a pricing model whereby the maker of liquidity, or passive [limit] order, is paid a rebate and the taker of liquidity or aggressive [market] order, is charged a fee." See Regulatory Issues Raised by the Impact of Technological Changes on Market Integrity and Efficiency, Consultation Report, July 2011, available at http://www.iosco.org/library/pubdocs/ pdf/IOSCOPD407.pdf.

traders that trade on other Canadian markets or, for cross-listed securities, in the U.S. In a robustness analysis, we classify HFTs purely on messages, based on the pre-sample month of February. The results for this robustness check coincide largely with those of the current paper. In an earlier version of the paper, we used a different classification that also was based on message to trade ratios; the results for this analysis are available from the authors.

In December 2012, IIROC (2012) published a collection of summary statistics on HFT, covering August-October 2011. The study focuses on trader IDs that have order to trade ratios in the top 11% and label these as "HOT" traders. Order to trade, message to trade, and cancel to order ratios are all very highly correlated.

D Subsample Analysis

We perform our analysis of the causal effect of high frequency trading for the set of all securities and for eight subsamples of securities. The subsamples are the lowest and highest trading volume terciles, the lowest and highest HFT liquidity provision competition terciles, the lowest and highest retail trading terciles, and non-crosslisted/cross-listed stocks. Specifically, the volume terciles are based on the groups of securities with the highest and lowest tercile of dollar-volume traded in February 2012. The competition terciles are determined based on the average daily February 2012 value for the inverse of the Hirschman-Herfindahl index for the shares of passive volume of HFTs; a high competition stock is one where, on average, a large number of HFTs provide liquidity. The retail trading terciles of the securities are determined as the terciles of the total February 2012 dollar volume that retail traders trade in a given stock. Commonly, the retail share is smaller in high-volume stocks. In our IV regression analysis, we focus only on the highest and lowest terciles and omit the middle group. Finally, cross-listed securities are those that, according to the TSX e-review publication, are cross-listed with U.S. exchanges.

III Measures of Market Quality and Transaction Costs

All trade based measures are computed as volume-weighted daily averages. To ensure that outliers do not drive our results, we winsorize all dependent variables at the 1% level.

Quoted Visible Liquidity. We measure quoted market liquidity as the time weighted quoted spreads using the best available bid and offer prices across the six visible Canadian marketplaces.[14] The *quoted spread* is the difference between the lowest price at which someone is willing to sell, or the best offer price, and the highest price at which someone is willing to buy, or the best bid price. We focus on the spread measures expressed in basis points of the prevailing midpoint of the national bid-ask spread, and we divide the spread by two to obtain the half-spread.

Effective Liquidity with and without Maker-Taker Fees. Quoted liquidity only measures posted conditions, whereas effective liquidity captures the conditions that traders decided to act upon. The costs of a transaction to the liquidity demander are measured by the *effective spread*, which is is the difference between the transaction price and the midpoint of the national best bid and ask quotes at the time of the transaction. This measure also captures the costs that arise when the volume of an incoming order exceeds the posted size at the best prices. For the t-th trade in stock i, the effective spread is defined as

$$espread_{ti} = q_{ti}(p_{ti} - m_{ti})/m_{ti}, \tag{1}$$

where p_{ti} is the transaction price, m_{ti} is the midpoint of the quote prevailing at the time of the trade, and q_{ti} is an indicator variable, which equals 1 if the trade is buyer-initiated and -1 if the trade is seller-initiated. Our data includes identifiers for the active and passive side of each transaction, precisely signing the trades. The data is message by message, and thus precisely reveal the prevailing quotes at the time of each transaction.

Traders who use marketable orders and thus "take" liquidity must pay a fee to the exchange, the "taker" fee. We thus compute the "cum fee" effective spread by adjusting

[14]Our data contains information on the national best-bid and offer price, but not on the depth offered at other venues — we only have information on depth on the TSX. In an earlier version of the paper we studied whether depth changed after the event, but found no effects. We thus omit the analysis here. The six visible marketplaces are the TSX, Alpha, Chi-X, Pure, Omega, and TMX Select.

the effective spread that trader j pays as follows

$$cum\ fee\ espread_{tij} = q_{ti}(p_{ti} - m_{ti})/m_{ti} + taker\ fee_{ti}/m_{ti}. \tag{2}$$

On the TSX, the taker fees can differ by broker, where high-volume brokers pay lower fees. We use the lowest taker fee, \$0.0033 per share, for our computations; the highest is \$0.0035. For orders that execute against a dark order, the taker fee is \$0.001.

In this paper, we are interested in particular in the costs of trading of the group of retail traders. We compute the trader-volume weighted average of the cum-fee effective spread across a group as follows: If $cum\ fee\ espread_{dij}$ is the volume-weighted average active costs for trader j on day d, $active\ volume_{dij}$ is the number of shares that j trades with marketable orders in stock i on day d, and $active\ volume_{di}$ is the total active volume of this group in stock i on day d, then the daily cum fee spread in stock i for the group of traders $j = 1, \ldots, J$ is

$$cum\ fee\ espread_{di} = \sum_{j=1}^{J} \frac{active\ volume_{dij}}{active\ volume_{di}} \times cum\ fee\ espread_{dij}. \tag{3}$$

The change in liquidity provider revenue is measured by decomposing the effective spread into its permanent and transitory components, the *price impact* and the *realized spread*,

$$espread_{ti} = priceimpact_{ti} + rspread_{ti}. \tag{4}$$

The price impact reflects the portion of the transaction costs that is due to the presence of informed liquidity demanders; a decline in the price impact would indicate a decline in adverse selection. Is is also amount by which the midpoint moves between time t and some time $t + x$ in the future. The realized spread reflects the portion of the transaction costs that is attributed to liquidity provider revenues. In our analysis we use the five-minute realized spread, which assumes that liquidity providers are able to close their positions at the midprice five minutes after the trade. The five-minute realized spread is defined as

$$rspread_{ti} = q_{ti}(p_{ti} - m_{t+5\ \min,i})/m_{ti}, \tag{5}$$

where p_{ti} is the transaction price, $m_{t+5\text{ min},i}$ is the midpoint of the quote 5 minutes after the t-th trade, and q_{ti} is an indicator variable that equals 1 if the trade is buyer-initiated and -1 if the trade is seller-initiated.

Traders who trade with a passive, liquidity providing order "make" liquidity and receive a maker rebate on their exchange fees from the exchange. Analogously to cum fee effective spreads we compute the cum fee realized spreads for trader j as follows

$$\textit{cum fee rspread}_{tij} = q_{ti}(p_{ti} - m_{t+5\text{ min},i})/m_{ti} + \textit{maker rebate}_{ti}/m_{ti}, \tag{6}$$

where $\textit{maker rebate}_{ti}$ is the per share maker fee rebate. As with taker fees, maker fees depend on the amount of dollar volume that a broker executes on the exchange. We use the highest possible rebate, \$0.0031 cents. Dark orders that clear against incoming marketable orders receive no rebate. Furthermore, as with cum fee effective spreads we compute the trader-volume weighted average cum fee realized spreads across groups.

Net Costs of Trading. A small bid-ask spread is commonly considered to represent high market quality, because when spreads are tighter, traders using market orders face lower transaction costs. The reality, however, is more complex: traders may trade using market orders and pay the spread, or they may trade using limit orders and receive the spread. For instance, suppose competition for receiving executions of posted limit orders increases and bid-ask spreads decline. If a group of traders systematically switches from using limit orders (and receiving the spread) to market orders (and thus paying the spread), then the transaction costs for this group may increase. To reflect the joint effect of spreads, we compute the *net costs* by group as the difference of the cum fee effective spreads paid and the cum fee realized spreads received, weighted by the respective shares of active and passive volume. Formally, for each trader j,

$$\textit{net costs}_{dij} = \%\textit{active}_{dij} \times \textit{cum fee espread}_{dij} - \%\textit{passive}_{dij} \times \textit{cum fee rspread}_{dij}. \tag{7}$$

Here, $\%active_{dij}$ is the share his volume that trader j trades with marketable orders on day d in stock i, and $\%passive_{dij}$ is the share his volume that trader j trades with non-marketable limit orders orders. As with cum fee effective and realized spreads, in our regressions we use the trader-volume weighted average across groups.

Trader Profits. When taking positions or timing trade executions throughout the day, traders take into account price movements subsequent to their trades. If intra-day prices are always at the fundamental value plus a random noise component, then a trader who buys or sells at random should, on average, make no trading profits or losses other than the transaction costs from cum-fee bid-ask spreads. Common sense suggests that trading decisions are not random and that traders employ strategies to time liquidity and future price movements. Certain groups of traders may be better at this than other groups.

To understand how future price movements affect performance, we thus compute the daily trading profits aggregated over the trader groups. We measure these profits by computing a trader's profit from buying and selling a security and by valuing the end-of-day portfolio holdings at the closing price; we then scale this profit measure by the daily dollar volume to obtain the per-dollar traded profit. A positive profit implies that a group of traders was able to "buy low and sell high." For long-term investors, these intra-day profits are, arguably a measure of transaction costs that implicitly accounts for short-term price fluctuations, using the daily closing price as a benchmark. Formally, the per stock s, per day t, per trader-group i (retail, HFT, and institutional) profit is

$$profit_{its} = (sell\ \$\ vol_{its} - buy\ \$\ vol_{its}) + (buy\ vol_{its} - sell\ vol_{its}) \times closing\ price_{ts}, \tag{8}$$

where $sell\ \$\ vol_{its}$ and $buy\ \$\ vol_{its}$ are the total sell and buy volumes, measured in dollars, respectively, for the trader-group i, and $buy\ vol_{its}$ and $sell\ vol_{its}$ are trading volumes measured in shares for this group. The underlying idea is that $(sell\ \$\ vol_{its} - buy\ \$\ vol_{its})$ signifies the profit from intra-day trading; $(buy\ vol_{its} - sell\ vol_{its})$ is the end-of-day net position (assuming a zero inventory position at the beginning of each day), which we evaluate at the closing price, $closing\ price_{ts}$. Another way to think about the components of the profits is that ($\mathit{sell}\ \$\ \mathit{vol}_{its} - \mathit{buy}\ \$\ \mathit{vol}_{its}$) signifies the cost of the position and ($\mathit{buy}\ \mathit{vol}_{its} - \mathit{sell}\ \mathit{vol}_{its}$) $\times$ $\mathit{closing}\ \mathit{price}_{ts}$ signifies what the trader should have paid had he been able to trade at the (presumably) efficient benchmark price.

We acknowledge that our analysis is based on TSX trading only — traders may well trade on other Canadian venues or in the U.S. as part of a cross-venue or cross-country arbitrage strategy, and thus their actual trading profits may be different from the ones that we record. This issue is partly mitigated, as we focus on trading profits of *groups* of participants and study aggregated daily profits — for our profit measure to exhibit a systematic bias, the entire group of interest must persistently choose, for instance, to buy all the securities on the TSX and to sell them on a different exchange.

Malinova, Park, and Riordan (2013) present a graph that illustrates that for retail traders in particular this measure is persistently negative, i.e., it is indeed a cost. They argue that these costs are an order of magnitude larger than the costs associated with bid-ask spreads. Table I shows that retail trader profits are indeed negative, and that HFTs break even on average. Notably, the profit figure here does not include maker-taker fees and since HFTs trade with passive limit orders 74% of the time, they capture the maker rebate and they are thus profitable overall.

IV Results

We first show how HFT message traffic is correlated with liquidity, trading costs and profits. Second, we study the factors driving the changes in HFT message traffic around the event. Third, we study the causal effects of HFT trading on trading costs and profits, using an instrumental variable analysis, where we instrument the percentage of HFT trading with the introduction of the per-message fee. Finally, we look at causal effects in subsamples.

A Correlations: HFT, Spreads and Trading Costs

Figure 2 plots the level of all messages, HFT messages, and HFT messages as a percentage of all messages. The vertical red line represents the day of the introduction of the per-message fee model, April 1. The dotted lines graph the daily realizations, the solid lines graph the pre and post introduction averages. The figures illustrate that HFT message traffic is stable during February and March and that HFTs reduce their messaging activity noticeably at around event date, both in absolute terms and as a percentage of all messages; the drop in messages starts about one week before the event date. Such an anticipation effect can arise as HFTs need to update and test their codes. It is important to note that not all traders reduce their activities proportionately — HFTs reduce their activities more, underlining that HFTs are affected more strongly by the event.

In Panel A of Table II we present the correlations of the event, two measures of HFT activity (%HFT %, and HFT messages), the quoted spread, the spread decomposition (effective spreads, realized spread, and price impact), and the U.S. volatility index VIX. Both measures of HFT activity are negatively correlated with the event. The quoted spread, effective spread, and price impact are positively correlated with the event. The VIX is also positively correlated with the event and we use it as a control in the following instrumental variable analysis. It is important to emphasize that over longer horizons, HFT activity and market-wide volatility are positively related; see Malinova, Park, and Riordan (2013). %HFT is negatively correlated with the spread indicating that HFTs are active during times when spreads are low or in lower spread stocks. HFT activity is generally associated with lower price impacts. Panel A suggests that the event is associated with a general decline in market quality and that HFT is associated with better market quality.

Panel B of Table II reports the correlations of HFT activities and the net trading costs and trading profits of retail traders and other traders. The event is positively and significantly correlated with an increase in the net trading costs and negatively correlated with retail traders' trading profits. HFT activity is negatively associated with retail and other traders' trading costs. HFT activity is positively related to retail trading profits and negatively related to other traders' profits.

B Cross-Sectional Changes in HFT

The correlation tables and the figures show that HFTs reduce their trading activity after the introduction of the new integrated fee model. Simple intuition suggests that when the costs of submitting a message are expected to increase, market participants that submit many messages are most likely to retract. Furthermore, they will retract more in stocks where the marginal value of an additional message is low. Our classification of HFTs is biased towards message-intensive strategies, and such strategies are often used in liquidity-providing strategies (active orders, by virtue of their marketability, get executed right away, do not have to be reposted many times, and thus do not require many messages). Indeed, in our sample, HFTs trade 74% of their volume with non-marketable, passive limit orders. We will thus base our behavioral conjectures about changes in HFT behavior on the premise that they follow (predominately) liquidity-providing strategies.

High active trading costs make inventory management costly, because occasionally a liquidity provider may have to reduce the inventory with marketable orders. We thus conjecture that HFTs will reduce their activities for stocks with high cum fee effective spreads.

High benefits for liquidity provision, measured by the cum fee realized spread make the provision of liquidity in a stock more attractive. We thus conjecture that HFTs will not reduce their activities in stocks for which they receive higher cum fee realized spreads.

Since the minimum trade size is fixed and since HFTs commonly submit orders of, or close to, the minimum trade size (as per Malinova, Park, and Riordan (2013), the average HFT trade size is between 100 and 200 shares), higher prices, ceteris paribus, imply higher inventory risk. We thus conjecture that HFTs reduce their activities more for stocks with higher prices.

Finally, HFT trading and market capitalization are positively correlated in our data, (see also Brogaard, Hendershott, and Riordan (2012) and Menkveld (2011)), suggesting that the competition for liquidity provision is more intense for high market cap stocks. In light of a new per-message cost, competition for market share for such stocks may be more costly and we conjecture that HFTs will retract more in high market cap stocks.

To verify or falsify these conjectures, we regress the difference in %HFT and the logarithm of the total HFT messages, for April minus March, on the average per stock March cum fee effective spreads, $\overline{\mathrm{AC}}_i$, the average March cum fee realized, $\overline{\mathrm{PC}}_i$, the logarithm of the pre-sample, February 2012 marketcap, and the logarithm of the pre-sample, February 2012 price. Formally,

$$\Delta\mathrm{HFT}_i = \alpha + \beta_1\overline{\mathrm{AC}}_i + \beta_2\overline{\mathrm{PC}}_i + \gamma C_i + \epsilon_i. \tag{9}$$

Table III reports the results.

Consistent with our conjectures, we observe that HFTs decrease their activity in large stocks, high-price stocks and high cum fee effective spread stocks. The increase their activities in stocks where passive trading revenues, measured by cum fee realized spreads, are higher. The results for the change in the percentage of HFT activity are generally statistically stronger than for the log-messages measure.

C The Causal Impact of Changes in HFT on Market Quality

The results of the correlation analysis indicate that HFT activities and market quality are positively related. Figure 2 plots the time-weighted quoted spread, a standard measure of market quality, over the study period and it clearly indicates an increase in the quoted bid-ask spreads immediately following the event. As highlighted in the same figure, this increase is accompanied by a simultaneous drop in HFT activity. While the graphical evidence is compelling, it does formally establish a causal relationship. Since the per-message fee is smaller than the minimum tick size by an order of magnitude, the new fee cannot directly affect spreads (or other trading cost measures). The fee introduction is thus a valid instrument for HFT activities, and we can use it in an instrumental variable regression, to determine the existence of a causal relation. The first stage of the implied 2-stage estimation procedure estimates the following relationship:

$$\%\mathrm{HFT} = \beta_1 \mathrm{IIROC\ fee\ event}_t + \beta_2 \mathrm{VIX}_t + \gamma_i + \epsilon_{it}; \tag{10}$$

where IIROC fee event$_t$ is a dummy that is 0 before April 1^{st}, and 1 thereafter; γ_i are firm-level fixed effects and VIX$_t$ is the daily realization of the volatility index VIX.[15] As is standard we estimate the first and second stage of the IV regression jointly. We include the U.S. based volatility index VIX as control for market-wide volatility, because it is plausibly exogenous to Canadian market activities. To avoid biases in standard errors stemming from observations that are correlated across time by firm or across firms by time or both, we employ standard errors that are clustered by both firm and date for all panel-based specifications in this paper.[16]

Full Sample Results. Table IV presents the results of the full sample first-stage regression. We include the Kleibergen and Paap (2006) Wald statistic of under-identification, which, in our specification, is $\chi^2(1)$ distributed, and the Kleibergen and Paap (2006) statistic for weak identification (following the Andrews and Stock (2005) critical values; for our specification, the 10% maximal IV size critical value is 16.38). Our results highlight that the event caused a significant decline in HFT activity in the overall sample and that the event is a valid instrument for our IV approach.

Results for the Sub-Samples. Our results indicate differences across the subsamples: The fee change has a significant effect on HFT activities for high volume, high competition, low retail activity, and cross-listed stocks. For the remaining subsamples, we are unable to reject the under-identification tests.[17] Consequently, consistent with our observations from the preceding subsection, not only do HFTs reduce their activities conditionally, they do not retract as much in stocks where others are retracting, particularly small stocks.

[15]The presented regressions include firm fixed effects. In unreported regressions, we also analyzed a specification with a vector C_i of firm-level control variables, such as price and market capitalization. The results were similar.

[16]Cameron, Gelbach, and Miller (2011) and Thompson (2011) developed the double-clustering approach independently at around the same time.

[17]As discussed in the classification section, the traders that we classify as HFTs are predominantly active in high activity stocks. Even though they may have also retracted in lower volume stocks, in relative terms this retraction was less noticeable, causing the observed problems in the first stage estimation.

The second stage of the IV regression uses the following specification:

$$L_{it} = \alpha + \beta_1\%\text{HFT} + \beta_2\text{VIX}_t + \delta_i + \epsilon_{it}, \tag{11}$$

where L_{it} is the dependent variable of interest (e.g., the quoted spread); our main explanatory variable of interest, %HFT, is instrumented by its estimated value from the first stage regression; VIX_t is the daily realization of the volatility index VIX; δ_i are firm fixed effects.

Full Sample Results. Table V reports the results for the regression that uses the full sample of 248 securities. A negative coefficient indicates that the drop in the percentage of HFT activity increases the respective variable.

Panel A reports the results for the quoted spread and spread decomposition and shows that the decline in HFT activity caused an increase in the quoted spread, the effective spread (albeit weakly), and the price impact and conversely a decrease in the realized spread. In economic terms, the observed event induced decline in the percent of HFT by roughly 1.6% would lead to a $1.6 \times .3 = .48$ basis point increase in spreads, which is consistent with the increase seen in Figure 4. The coefficients are economically significant and statistically significant at the 5% level (except for the effective spread where the significance is at the 10% level). When decomposing the effective spread into the 5-minute realized spread and price impact, we observe that the realized spread falls with HFT retraction and that the price impact increases. These results suggest that post-event liquidity suppliers are hampered in their ability to manage their market exposure with limit orders.

There are various explanations for the result on the price impact. (1) HFT trading is uninformed and as their activity in the market falls, the remaining informed order flow relatively dominates; (2) HFT quoting activities impound information into posted prices that is now impounded by trades; (3) as spreads increase, uninformed traders that would trade with market orders retract from the market.

Panel B reports the results of IV regressions on net costs and trading profits of retail and other, non-HFT traders. The previous panels suggests that liquidity deteriorates and that the order-flow becomes more informed post-event. The first column indicates that retail traders face no change in their net costs. Other traders' costs increase economically and statistically significantly post event.

Trading costs are one component of the economics of trading, the other are the trading profits (often called revenues when costs aren't observed). Even though retail traders' net costs are unaffected, their trading profits fall significantly as HFTs retract. There are a number of possible explanations for the change. For instance, the increase in the price impact indicates that retail traders' passive limit orders may get "picked off" more often by informed traders. We further find that the trading profit of other traders is negatively related to %HFT, that is, as HFTs retract, other traders benefit. Since the computed profits are zero-sum across all traders (though not for the per-dollar figure), when retail traders lose, someone must gain.

Sub-samples results. In Panel A of Table VI we report the results of the IV regression for the quoted spread in the eight sub-samples. We present the estimation results for all subsamples. However, as the first stage results showed, for a number of subsamples, there is no change in HFT activities, and the specification is under-identified. Consequently, we will focus exclusively on the subsamples for which the first stage is identified.

The results present a consistent picture. HFTs retract in high-volume, high competition, low retail volume (as percent of total volume in that stock), and cross-listed stocks, causing a significant increase in quoted spreads (Panel A), effective spreads (Panel B), and price impacts (Panel D), and a decrease in realized spreads (Panel C), albeit the statistical significance for the latter is weak. The coefficients are of smaller magnitude compared to the overall sample. However, most of the stocks in these subsamples also trade at smaller spreads compared to the full sample; for instance, the quoted half-spread for high-volume stocks is around 3 basis points, whereas it is 6.7 basis points for the entire sample. Overall, the results on the spread measures are consistent with our findings for the entire sample.

Table VII reports the IV regressions for net costs and trading profits for the 8 subsamples. Panel A reports the impact of %HFT on net trading costs. Here we observe that retail traders net costs increase for high volume stocks and for cross-listed stocks. The observations of the variable *netcost* are generally noisier as is includes both spread and volume-share measures. Panel C reports the impact of the HFT retraction on trading profits and shows that retail profits decline for high volume and high competition stocks and for cross-listed stocks. The magnitude of the change is large compared to the effect for net costs; in other words, the drop in profits is not caused by changes in trading costs alone.

Panel B shows that other traders, too, are worse off as HFTs retract because their net costs increase. Finally, Panel D shows that for the non-retail, non-HFT traders profits increase for cross-listed securities as HFTs retract.

V Discussion and Conclusion

The results are surprising. The drop in message traffic around the introduction of the per-message fee is substantial. The increase in the market-wide bid-ask spread right at the introduction of the fee is starkly visible in the data. We found it intriguing that, at least for the full sample, net trading costs for retail traders did not go up, even as spreads increased, highlighting that the two-sidedness markets with traders using both market and limit orders in their strategies requires more attention in the literature. Finally, we were surprised to see that retail traders' intra-day profits decrease significantly as HFTs retract from markets. This profit measure, which is negative for retail traders, captures the costs associated with adverse price movements subsequent to their trades for the same day. As with all zero-sum measures, it highlights that there are likely redistributive effects away from the least sophisticated traders following the retraction of HFTs.

Regulators in many countries are discussing ways to regulate high frequency trading. They often cite anecdotal evidence or the perception that HFT are increasing the trading costs of smaller and unsophisticated investors. The results of this paper provides evidence that casts some doubts on this negative perception. The panels in Figure 5 probably provide the clearest illustration of the findings. We plot the percent HFT messages on the right axis and net trading costs and profits for retail traders on the left axes. The gray lines represent HFT activity and the blue lines represent trading costs and profits. As HFT activity falls, trading costs of retail traders increase and profits drop (even though we note that for the full sample, the effect for net costs for retail is insignificant). These figures complement the econometric analysis and further clarify the relationship.

Our results are generally consistent with findings in the literature, e.g. with Hendershott, Jones, and Menkveld (2011) who observe increases (over time) in algorithmic trading on NYSE that are contemporaneously associated with improvements in market quality. Our results differ in the sense that we establish a clear causality of HFT trading and in that, enabled by our high level of detail in the data, we can establish the impact of HFT activities on retail traders. Even though Canada is a smaller market compared to the U.S., studying high frequency trading in Canada is instructive because many of the same high frequency firms are active in Canada (this information is part of the public record).

Most of the proposed regulations on HFT include some sort of "tax" on HFT quoting activity, often based on the argument that the high level of HFT quoting activity imposes costs on other market participants as they must absorb the heavy message traffic. The IIROC integrated fee model was designed to allocate the regulator's market monitoring costs to the participants that are generating the most messages, in this case HFT. IIROC suggested, before the introduction, that most participants would pay less in fees post event. Arguably, the per-message fee most strongly affected the "good", liquidity-providing HFTs who use large number of messages in their strategies, and as our analysis shows, many traders will have paid more in terms of their trading costs.

Our study cannot capture all costs associated with HFT activities and all benefits that may result from the reduction in their activities. Most notably, we have no data on the information processing costs of the message traffic. In recent work, Baron, Brogaard, and Kirilenko (2012) study the HFTs trading profits in the S&P500 E-Mini Futures. They find that HFTs benefit particularly when trading against "small" traders, where small traders in E-Minis are likely more sophisticated than most retail traders in equities. Our work is not concerned with the direct interaction between HFT and retail traders but complements theirs by showing the positive externalities that HFTs generate in equity markets.

It is important to emphasize that our study is not concerned with the per-message fee per se, but with the effect that the fear of the costs associated with the fee had on HFT activities and through it, on trading costs for non-HFTs. The fear was quite evident in the data, expressed by the strong reduction in messages that the HFTs displayed. However, just 5-6 weeks after the introduction of the per-message fee, message levels were back to the February levels, indicating that the message fee itself did not permanently affect HFT behaviour.

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Table I
Sample Summary Statistics

The table reports summary statistics on our sample firms. In total there are 248 firms in our sample. Market capitalization is based on March 01, 2012. Messages, HFT messages, and the percentage of HFT message are summed over the entire sample of securities. All other figures are per stock per day averages. The price is the time-weighted mid-point of the national bid-ask spread. The percent passive measure the fraction of volume that the respective group executes by non-marketable limit orders. The percent active measures the volume share of each group of the total trading volume. Intraday volatility is measured by the average daily 10-minute maximal mid-price fluctuation, scaled by the average midpoint.

	Who	Units	Mean	SD	Median	March	April	Difference
Market Capitalization		$ billion	6.7	11.6	2.3			
Price		$	24.86	18.34	20.58	24.87	24.85	0.02
% messages	HFT	%	82.1	2.9	81.1	84.4	79.5	−4.8
number of messages	HFT	1M messages	14.4	3.8	13.6	16.9	11.7	−5.2
Time-weighted share depth		10,000 shares	0.44	1.59	0.10	0.44	0.43	0.01
Time-weighted dollar depth		10,000 $	4.04	18.67	1.93	3.87	4.23	−0.35
Time-weighted quoted spread		bps	6.7	8.3	4.3	6.4	7.0	−0.61
Effective spread		bps	6.4	8.3	3.9	6.2	6.6	−0.46
Realized Spread		bps	−2.6	5.6	−1.5	−2.3	−2.9	0.64
Price Impact		bps	4.5	5.3	2.8	4.2	4.8	−0.55
Intra-Day volatility		bps	28.2	16.5	24.9	27.5	28.9	−1.38
Effective plus taker	retail	bps	8.9	11.2	5.6	8.7	9.1	−0.49
	HFT	bps	7.1	10.2	4.1	6.7	7.5	−0.74
	others	bps	8.1	11.1	4.8	7.8	8.4	−0.66
Realized plus maker	retail	bps	−2.8	14.4	−1.8	−2.5	−3.1	0.56
	HFT	bps	−0.1	5.7	−0.2	0.1	−0.4	0.46
	others	bps	−0.8	7.2	−0.5	−0.5	−1.0	0.57
Effective - Realized + taker-maker	retail	bps	6.2	8.9	4.3	5.9	6.5	−0.59
	HFT	bps	1.7	4.4	1.2	1.5	1.9	−0.41
	others	bps	5.1	6.9	3.0	4.8	5.5	−0.67
Percent passive within group	retail	%	46	18	47	46	46	0.11
	HFT	%	74	14	76	72	75	−2.83
	others	%	42	8	42	42	42	0.33
Percent active all volume	retail	%	13	10	11	14	12	1.35
	HFT	%	25	11	24	25	25	0.19
	others	%	62	13	63	61	63	−1.54
per dollar profit	retail	bps	−5.1	41.6	−1.5	−4.0	−6.3	2.35
	HFT	bps	−0.7	17.8	0.0	−0.7	−0.8	0.11
	others	bps	1.4	13.8	0.2	1.1	1.7	−0.52

Table II
Correlation Matrix

In Panel A this table reports the correlation of the event, HFT as a % of total message traffic, HFT message traffic, the quoted spread, the effective spread and the effective spread decomposed into realized spread and price impact, and the VIX. The results are generated using data from March and April 2012, spanning the April 1st event date. Panel B reports the correlation of the event, HFT as a % of total message traffic, HFT message traffic, net trading costs for retail, HF, and other traders, and trading profits for retail and other traders. * denotes significance of a non-zero correlation at the 10% level, ** at the 5% level, *** at the 1% level.

Panel A: Liquidity Measures

	Event	%HFT msg	No HFT msg	QSpr	Espr	RSpr	PImp	VIX
Event	1.00							
%HFT msg	−0.07***	1.00						
No HFT msg	−0.12***	0.48***	1.00					
QSpr	0.04***	−0.20***	−0.25***	1.00				
Espr	0.03**	−0.20***	−0.24***	0.98***	1.00			
RSpr	−0.06***	0.01	0.08***	−0.12***	−0.12***	1.00		
Pimp	0.05***	−0.17***	−0.23***	0.84***	0.85***	−0.63***	1.00	
VIX	0.48***	−0.04***	−0.01	0.02*	0.02*	−0.05***	0.04***	1.00

Panel B: Liquidity Costs and Profits

	Event	%HFT msg	No HFT msg	TC^{net}_{re}	TC^{net}_{hf}	TC^{net}_{to}	TP^{net}_{re}	TP^{net}_{ot}
Event	1.00							
%HFT msg	−0.07***	1.00						
No HFT msg	−0.12***	0.49***	1.00					
TC^{net}_{re}	0.03***	−0.12***	−0.18***	1.00				
TC^{net}_{hf}	0.05***	0.04***	−0.08***	0.17***	1.00			
TC^{net}_{to}	0.05***	−0.16***	−0.21***	0.47***	0.21***	1.00		
TP^{net}_{re}	−0.03**	0.04***	0.04***	−0.13***	0.02	−0.04***	1.00	
TP^{net}_{ot}	0.02*	−0.03**	−0.03**	0.11***	0.08***	0.08***	−0.50***	1.00

Table III
Changes in HFT Activities April – March

This table presents the results from an estimation on the changes in HFT activity from March to April, spanning the April 1st event date when the IIROC per-message fee was introduced. The dependent variables are the difference in the average daily fraction of messages by HFTs and the log of the average daily total messages by HFTs in April vs. March, ΔHFT_i in stock i. Explanatory variables are the average daily active and passive HFT trading costs in March for stock i, $\overline{\text{AC}}_i$ and $\overline{\text{PC}}_i$. The estimated equation is

$$\Delta\text{HFT}_i = \alpha + \beta_1\overline{\text{AC}}_i + \beta_2\overline{\text{PC}}_i + \delta_i + \epsilon_i$$

where δ_i are firm fixed-effects. We present the results with robust standard errors.
* indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Changes in HFT: April – March	% HFT msg	total HFT msg
$\overline{\text{AC}}_i$	-0.13^{**}	-0.01^{*}
	(0.07)	(0.00)
$\overline{\text{PC}}_i$	0.30^{*}	0.02^{**}
	(0.17)	(0.01)
Log(MarketCap)	-1.01^{***}	-0.04^{*}
	(0.38)	(0.02)
Log(Price)	-1.85^{**}	-0.01
	(0.87)	(0.05)
Constant	27.45^{***}	0.71
	(9.22)	(0.50)
R-Squared	0.052	0.032
Observations	248	248

Table IV
Impact of the per-message Fee on HFT Activity – First Stage Results

This table presents the results from the first stage regression on the impact of HFT activity and it thus displays the impact of the IIROC message submission fee change on the percentage of messages generated by HFT. The sample spans March and April 2012; the introduction of per-message fees occurred on April 1st. The explanatory variable is the percentage of total messages that are generated by HFTs, per stock per day; the variable of interest is the event dummy, IIROC fee$_t$, that is 1 after April 1st and 0 before. Our first stage results are then based on estimating the following equation

$$\%\mathrm{HFT} = \alpha + \beta_1 \mathrm{IIROC\ Fee}_t + \beta_2 \mathrm{VIX}_t + \gamma_i + \epsilon_{it}$$

VIX$_t$ is the daily realization of the volatility index VIX, and δ_i are firm fixed effects. We estimated the equation for the entire sample of 248 firms and for eight sub-samples. The sub-samples are the bottom and top terciles of firms split by trading volume, competition, retail trading, and the final sub-sample is split into interlisted and non-interlisted stocks. We include the Kleibergen and Paap (2006) Wald statistic of under-identification, which, in our specification is $\chi^2(1)$ distributed, and the Kleibergen and Paap (2006) statistic for weak identification (following the Andrews and Stock (2005) critical values; for our specification, the 10% maximal IV size critical value is 16.38). Standard errors are double-clustered by firm and date. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	full sample	$ volume		Competition		% retail of $ volume		Crosslisted	
		low	high	low	high	low	high	no	yes
event	-1.61***	-0.53	-3.48***	1.30	-5.36***	-2.72***	0.28	0.69	-5.87***
	(0.59)	(0.96)	(0.68)	(1.01)	(0.67)	(0.74)	(0.95)	(0.74)	(0.67)
VIX	-0.08	-0.20	0.03	-0.50**	0.33**	-0.06	-0.12	-0.39**	0.49***
	(0.13)	(0.19)	(0.13)	(0.23)	(0.15)	(0.17)	(0.17)	(0.17)	(0.15)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.013	0.003	0.101	0.006	0.214	0.037	0.000	0.004	0.232
Observations	10,408	3,485	3,443	3,442	3,481	3,485	3,442	6,755	3,653
Number of symbolid	248	83	82	82	83	83	82	161	87
underid.	5.1	0.3	10.2	1.6	13.0	7.1	0.1	0.9	13.3
weak id.	7.6	0.3	26.3	1.7	63.4	13.3	0.1	0.9	76.1

Table V
Impact of HFT Activity on Quoted Liquidity

This table presents the results from the second stage of our instrumental variable regression on the impact of HFT on liquidity, trading costs, and trading profits for the entire sample. Panel A reports results for the daily time-weighted quoted bid-ask spread based on the national best prices, the effective spread, realized spread, and price impact. Panel B reports results for the net liquidity costs for retail traders and other traders, and the trading profits for retail and other traders. Our main variable of interest is the percentage of total messages generated by HFT (%HFT), which we instrumented with the event dummy, IIROC Fee_t. The sample spans March and April 2012; the introduction of per-message fees occurred on April 1st. The estimated equation is

$$L_{it} = \alpha + \beta_1\%\text{HFT} + \beta_2\text{VIX}_t + \delta_i + \epsilon_{it}$$

where L_{it} is either the quoted spread or depth; VIX_t is the daily realization of the volatility index VIX; and δ_i are firm fixed effects. Standard errors are double-clustered by firm and time. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Overall Spread Results

	time weighted quoted spread	effective spread	5-minute realized spread	5-minute price impact
%HFT	-0.30**	-0.22*	0.28**	-0.25**
	(0.15)	(0.12)	(0.14)	(0.12)
VIX	0.03	0.03	-0.07	0.05
	(0.05)	(0.04)	(0.06)	(0.05)
Fixed Effects	Yes	Yes	Yes	Yes
Obs.	10,408	10,408	10,408	10,408
# of symbols	248	248	248	248

Panel B: Trading Costs and Profits by Groups of Traders

	net costs		profits	
	retail	other	retail	other
%HFT	-0.25	-0.32**	2.44**	-0.46*
	(0.17)	(0.15)	(1.17)	(0.24)
VIX	0.08	0.06	1.10**	-0.18
	(0.08)	(0.06)	(0.53)	(0.11)
Fixed Effects	Yes	Yes	Yes	Yes
Obs.	10,408	10,408	10,408	10,408
# of symbols	248	248	248	248

Table VI
Impact of HFT Activity on the Quoted Spread and Spread Decomposition

This table presents the results from the second stage of our instrumental variable regression on the impact of HFT on liquidity. All panels reports the results broken down into eight subsamples. The sub-samples are the bottom and top terciles of firms split by trading volume, competition, retail trading, and the final sub-sample is split into interlisted and non-interlisted stocks. Panel A reports results for the quoted spread. Panel B reports the effective spread. Panel C reports the realized spread and Panel D reports the price impact. The spreads are based on the national best bid and offer price. Our main variable of interest is the percentage of total messages generated by HFT (%HFT), which we instrumented by an event dummy, IIROC Fee_t. The sample spans March and April 2012; the introduction of per-message fees occurred on April 1st. The estimated equation is

$$\mathrm{L}_{it} = \alpha + \beta_1 \%\mathrm{HFT} + \beta_2 \mathrm{VIX}_t + \delta_i + \epsilon_{it}$$

where L_{it} is either the quoted spread, effective spread, realized spread, or the price impact; VIX_t is the daily realization of the volatility index VIX; and δ_i are firm fixed effects. Standard errors are double-clustered by firm and time. * indicates significance of non-zero correlation at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Quoted Spread

	Dollar Volume		competition		% retail		crosslisted	
	low	high	low	high	low	high	no	yes
%HFT	-1.54	-0.04***	0.35	-0.06***	-0.17**	2.98	0.75	-0.07***
	(2.87)	(0.02)	(0.36)	(0.02)	(0.08)	(10.11)	(0.81)	(0.02)
VIX	-0.24	0.02***	0.27*	0.04***	0.04	0.41	0.35	0.07***
	(0.77)	(0.01)	(0.16)	(0.01)	(0.04)	(1.20)	(0.29)	(0.02)
Obs.	3,485	3,443	3,442	3,481	3,485	3,442	6,755	3,653
Symbols	83	82	82	83	83	82	161	87

Panel B: Effective Spread

	Dollar Volume		competition		% retail		crosslisted	
	low	high	low	high	low	high	no	yes
%HFT	-0.97	-0.04**	0.13	-0.05***	-0.15**	2.08	0.50	-0.06***
	(1.89)	(0.02)	(0.25)	(0.02)	(0.07)	(7.11)	(0.55)	(0.02)
VIX	-0.12	0.01	0.16	0.02	0.00	0.32	0.25	0.04**
	(0.51)	(0.01)	(0.11)	(0.02)	(0.04)	(0.84)	(0.20)	(0.02)
Obs.	3,485	3,443	3,442	3,481	3,485	3,442	6,755	3,653
Symbols	83	82	82	83	83	82	161	87

Panel C: Realized Spread

	Dollar Volume		competition		% retail		crosslisted	
	low	high	low	high	low	high	no	yes
%HFT	1.09	0.06*	-0.31	0.02	0.18*	-1.36	-0.93	0.01
	(2.08)	(0.04)	(0.26)	(0.03)	(0.10)	(4.68)	(0.98)	(0.03)
VIX	0.06	-0.05*	-0.17	-0.10**	-0.08	-0.34	-0.43	-0.15***
	(0.58)	(0.03)	(0.15)	(0.04)	(0.07)	(0.57)	(0.37)	(0.05)
Obs.	3,485	3,443	3,442	3,481	3,485	3,442	6,755	3,653
Symbols	83	82	82	83	83	82	161	87

Panel D - Price Impact

	Dollar Volume		competition		% retail		crosslisted	
%HFT	-1.14	-0.05**	0.20	-0.04**	-0.17**	1.83	0.69	-0.05**
	(2.11)	(0.02)	(0.17)	(0.02)	(0.08)	(6.22)	(0.72)	(0.02)
VIX	-0.11	0.03**	0.15*	0.06***	0.04	0.35	0.33	0.10***
	(0.58)	(0.01)	(0.09)	(0.02)	(0.05)	(0.75)	(0.27)	(0.03)
Obs.	3,485	3,443	3,442	3,481	3,485	3,442	6,755	3,653
Symbols	83	82	82	83	83	82	161	87

Table VII
Impact of HFT Activity on the Components of the Spread Decomposition

This table presents the results from the second stage of our instrumental variable regression on the impact of HFT on trading costs and trading profits. All panels reports the results broken down into eight subsamples. The sub-samples are the bottom and top terciles of firms split by trading volume, competition, retail trading, and the final sub-sample is split into interlisted and non-interlisted stocks. Panel A reports results for the net trading costs for retail traders, Panel B reports for other trades. Panel C reports the trading profits of retail traders, and Panel D for other traders. Our main variable of interest is the percentage of total messages generated by HFT (%HFT), which we instrumented by an event dummy, IIROC Fee_t. The sample spans March and April 2012; the introduction of per-message fees occurred on April 1st. The estimated equation is

$$\mathrm{L}_{it} = \alpha + \beta_1\%\mathrm{HFT} + \beta_2\mathrm{VIX}_t + \delta_i + \epsilon_{it}$$

where L_{it} is either the net trading costs of retail or other traders, or trading profits of retail or other traders; VIX_t is the daily realization of the volatility index VIX; and δ_i are firm fixed effects. Standard errors are double-clustered by firm and time. * indicates significance of non-zero correlation at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Net Trading Costs Retail

	Dollar Volume		competition		% retail		crosslisted	
	low	high	low	high	low	high	no	yes
%HFT	-0.21	-0.11**	0.02	-0.04	-0.21	0.27	0.43	-0.10*
	(0.88)	(0.05)	(0.25)	(0.05)	(0.15)	(1.42)	(0.55)	(0.05)
VIX	0.15	0.03	0.17	0.07	0.07	0.29*	0.28	0.14*
	(0.29)	(0.04)	(0.11)	(0.07)	(0.10)	(0.17)	(0.21)	(0.08)
Obs.	3,485	3,443	3,442	3,481	3,485	3,442	6,755	3,653
Symbols	83	82	82	83	83	82	161	87

Panel B: Net Trading Costs Other

	Dollar Volume		competition		% retail		crosslisted	
	low	high	low	high	low	high	no	yes
%HFT	-1.50	-0.05*	0.31	-0.05**	-0.19**	2.69	0.91	-0.05**
	(2.76)	(0.03)	(0.26)	(0.02)	(0.09)	(9.10)	(0.94)	(0.02)
VIX	-0.16	0.04**	0.20	0.06**	0.05	0.47	0.42	0.15***
	(0.76)	(0.02)	(0.14)	(0.03)	(0.06)	(1.10)	(0.34)	(0.05)
Obs.	3,485	3,443	3,442	3,481	3,485	3,442	6,755	3,653
Symbols	83	82	82	83	83	82	161	87

Panel C: Trading Profit Retail

	Dollar Volume		competition		% retail		crosslisted	
	low	high	low	high	low	high	no	yes
%HFT	7.50	1.09**	-1.16	1.04**	1.34	-11.32	-3.73	1.09***
	(13.33)	(0.54)	(1.62)	(0.44)	(0.82)	(40.34)	(5.13)	(0.38)
VIX	2.18	0.89*	-0.26	1.28**	1.29**	-1.22	-0.81	0.83
	(3.64)	(0.52)	(0.81)	(0.55)	(0.64)	(4.85)	(1.69)	(0.62)
Obs.	3,485	3,443	3,442	3,481	3,485	3,442	6,755	3,653
Symbols	83	82	82	83	83	82	161	87

Panel D - Trading Profit Other

	Dollar Volume		competition		% retail		crosslisted	
	low	high	low	high	low	high	no	yes
%HFT	-1.11	-0.17	0.19	-0.19*	-0.20	2.25	0.57	-0.23**
	(2.10)	(0.12)	(0.27)	(0.10)	(0.18)	(8.33)	(0.83)	(0.10)
VIX	-0.42	-0.14	0.02	-0.12	-0.12	-0.01	0.11	-0.08
	(0.59)	(0.10)	(0.20)	(0.13)	(0.13)	(0.98)	(0.31)	(0.14)
Obs.	3,485	3,443	3,442	3,481	3,485	3,442	6,755	3,653
Symbols	83	82	82	83	83	82	161	87

Figure 2
Message traffic on the Toronto Stock Exchange

The figure plots the log of the total number of messages, total HFT and HFT % of submitted on the TSX (not just for our sample). The vertical lines mark the event date, April 01, 2012. The solid horizontal lines signify monthly averages.

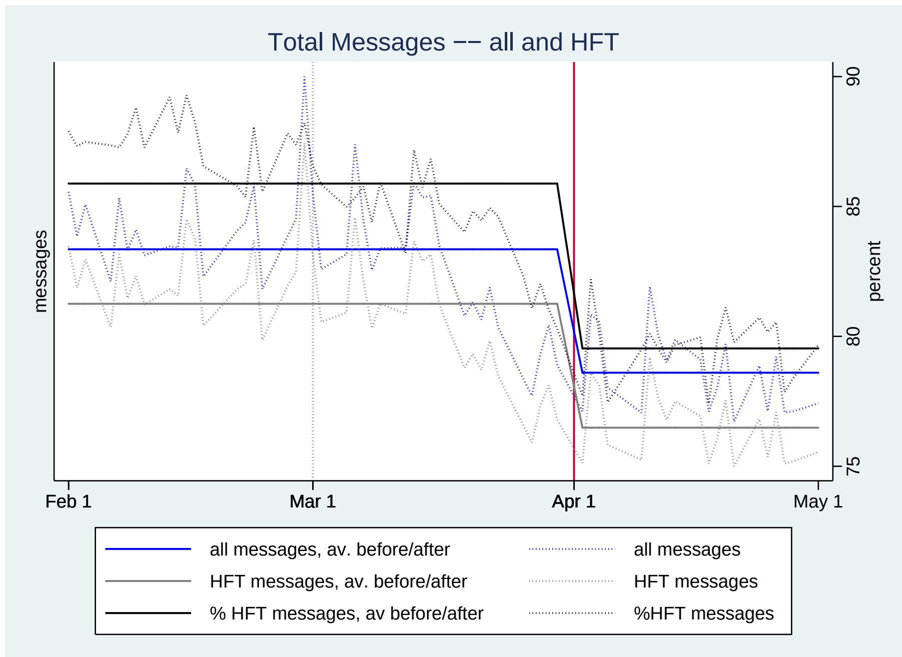

Figure 3
Trader Classification

Both panels are scatter plots of log trades against log total messages; each dot represents the total trades and messages of one specific trader in our data during the sample period from March to April. Panel A plots all traders; red dots indicate those that are classified as HFT. These traders have, by construction, a large number of traders and messages. Panel B plots only those traders that are candidates for being classified as retail or unsophisticated. Circles signify traders that use stale orders, i.e. orders that remain in the limit order book over night (or longer). Crosses signify traders that are classified as retail based on their usage of Alpha IntraSpread. There is a substantial overlap, especially for the very active traders. Not all retail traders that trade on Alpha trade also on the TSX and vice versa.

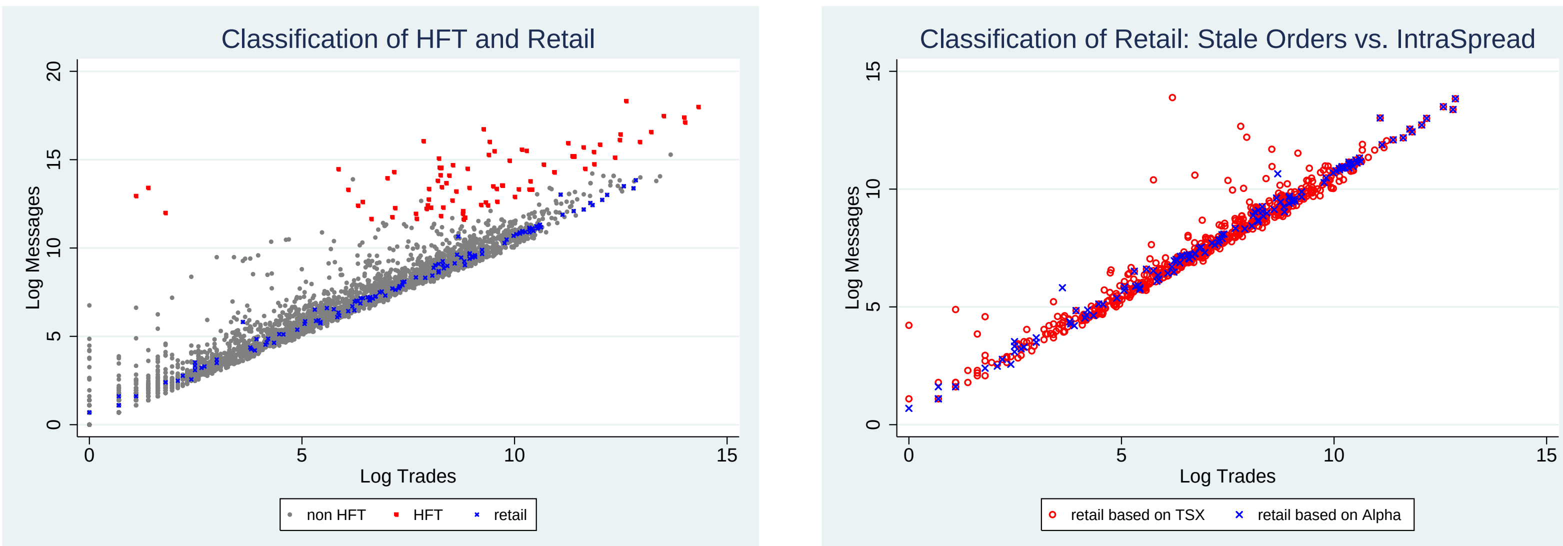

Figure 4
Percent HFT of Message Traffic and Spreads

The figure plots the percent of messages that are generated by traders who we classify as HFTs for our sample of TSX Composite securities. The vertical lines mark the event date, April 01, 2012. The solid horizontal lines signify monthly averages.

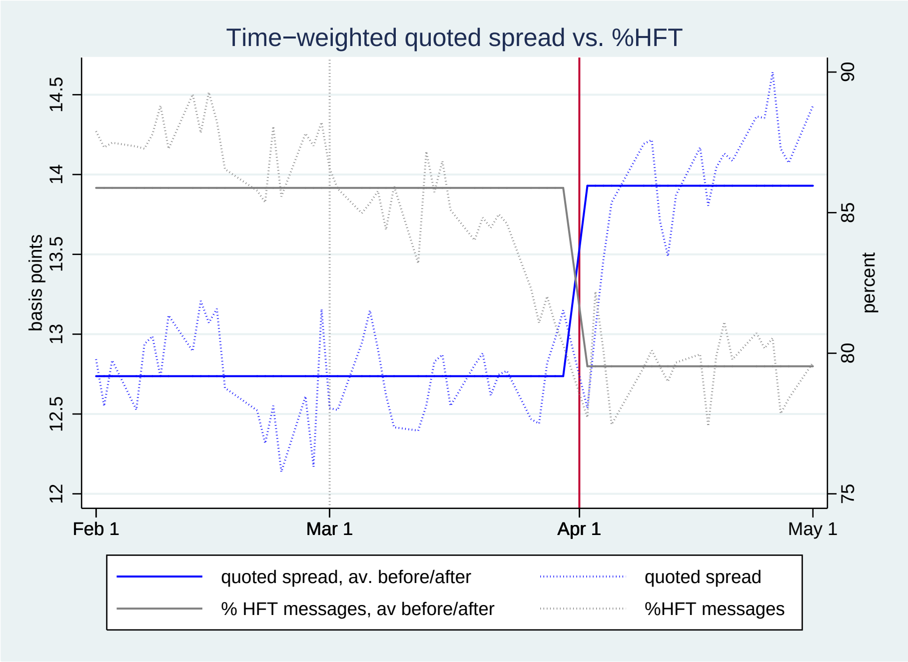

Figure 5
Trading costs and Profits vs. HFT Market Participation

The left panel plots the percentage of messages generated by HFTs and the net liquidity costs of retail traders for the full sample. The right panel plots the percentage of messages generated by HFTs and the trading profits for retail traders, for the full sample. The vertical lines mark the event date, April 01, 2012. The solid horizontal lines signify monthly averages.