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

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Abstract

Using a change in regulatory fees in Canada in April 2012 that affected high-frequency quote submissions and cancellations, we analyze the causal impact of algorithmic trading activities on the trading costs and intraday returns of retail and institutional traders. Following the change, the number of trades, quotes, and cancellations dropped by 30% and market-wide bid-ask spreads rose by 9%. Trading costs for market orders, measured by bid-ask spreads, increased for institutions, but remained unaffected for retail traders. Both groups incur higher adverse selection costs on their limit orders. Retail traders' intraday returns, especially from limit orders, declined, while institutions' returns from market orders increased.

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The past two decades have witnessed the growing importance of algorithmic trading, broadly defined as the use of computer algorithms for securities trading. This development has been a source of much controversy. Capable of making autonomous trading decisions at speeds that are orders of magnitude faster than humans, computer programs create, modify, cancel and execute orders within microseconds. To give a sense of the tremendous growth in recent years, during the Dotcom bull market in 2000 in the U.S., there were on average about 5 million trades and quotes per *day*; in the fall of 2012, at peak times there were up to 5 million trades and quotes per *second*.[1]

The initial growth of algorithmic trading was associated with a decline in trading costs, and it was viewed as a positive development by market participants and academics. For instance, using the switch from manual to automated quotes on the New York Stock Exchange in 2003, Hendershott, Jones, and Menkveld (2011) documented that the subsequent increase in algorithmic trading caused an improvement in liquidity.

As algorithmic trading has become more prevalent over the last few years, however, market participants have expressed mixed views as to its impact. For instance, investors report that they find it challenging to "[assess] posted liquidity due to the high propensity of some [algorithmic traders] to rapidly cancel quotes in real-time."[2] Moreover, processing millions of orders, cancellations, and trades requires large investments in IT infrastructure. There is thus a growing gap in the ability to monitor markets between traders who use low-powered technology, such as retail traders, and traders who seek to benefit from the highly sophisticated, computerized management of trading.[3]

Modern equity markets are organized as limit order books where traders either post

[1]See Larry Tabb's testimony to U.S. Congress, available at http://www.banking.senate.gov. On August 8, 2011, the U.S. credit rating was downgraded, the number of trades and quotes was almost 2.3 billion; see http://www.nanex.net/aqck2/3528.html.

[2]Tabb Forum October 24, 2013: "HFT: A Long-Term Investor's View." See also The Economist, February 25, 2012: "The fast and the furious."

[3]Even for 2003, Hendershott, Jones, and Menkveld (2011) report that the participation of human market makers declined after the introduction of automated quotes.

a quote by submitting a limit order or trade against an existing quote with a marketable order. The ability to monitor markets is especially important for trading with limit orders because traders must amend their quotes in response to new information. Traders who do not adjust their limit orders risk being systematically adversely selected by those with better information. The growing technology gap makes it particularly challenging for retail traders to correctly price and monitor their limit orders.

Retail traders play an important role in capital markets, for instance in terms of providing capital for corporations, and their ability to benefit from investments at reasonable costs affects their willingness to participate in the market. If algorithmic trading affects retail traders differently than the remainder of the market, then changes in market-wide measures may not fully reflect changes in their costs not least because there may be redistributive effects among different groups of traders.

Equipped with trader-level data, we study the impact of algorithmic trading on the trading costs and intraday returns for traders with different levels of sophistication, and we compare these findings with the effect of algorithmic trading on market-wide measures of trading costs. Our analysis features two groups of traders: retail traders[4] and traders who build large positions; for brevity, we refer to this latter group as "institutions." It is important to emphasize that, regulation in Canada mandates that all retail trades are sent to the public markets; retail orders cannot be internalized by the dealers.

The catalyst for our analysis that allows us to establish a causal relation is a change in Canadian regulatory fees that made a subset of algorithmic trading strategies significantly more expensive. As of April 1, 2012, the Investment Industry Regulatory Organization of Canada (IIROC)[5] began charging a portion of its cost recovery fees based on the number of market messages (i.e., trades and order submissions, cancellations, and modifications);

[4]We have proprietary information that allows the precise identification of retail traders.

[5]IIROC is a self-regulatory organization that oversees dealers and trading activities and performs real-time market surveillance. It operates on a not-for profit, cost-recovery model.

before April 1, 2012, IIROC's charges were based only on trading volume.[6] Following the change, the total number of market messages dropped by around 30% from March to April in our sample of S&P/TSX Composite securities.

An important group of algorithmic strategies that were disproportionately affected by the fee change are market making strategies. To avoid being adversely selected, market makers must amend limit orders in response to any new information, e.g., macroeconomic or firm-specific news or events in futures markets, and such strategies thus require the use of many messages, especially relative to trades. If, in response to the fee, market makers amend their orders less frequently, they face higher adverse selection risk and will thus post wider spreads; see e.g., Copeland and Galai (1983) or Foucault (1999).

Consistent with this intuition, we document that as the number of market messages declines after the fee change, effective bid-ask half-spreads increase, by about .35 basis points. We further observe an increase in the market-wide price impact, which is the signed change in the midpoint of the bid-ask spread five minutes subsequent to the trade. The price impact can be interpreted as the adverse selection cost incurred by limit orders, and the observed increase is consistent with the intuition that limit orders are updated less frequently after the fee change.

Computing these measures per trader group, we observe that institutions pay and receive significantly higher effective spreads after the fee change and that the price impact of their market orders increases. Retail traders, however, experience no significant change in the effective spread, whether received or paid, and the price impact of their market orders does not change. When trading with passive orders, both groups face higher adverse selection costs. Furthermore, the change in the effective spread that traders receive when

[6]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 Formally, IIROC charges the marketplaces (e.g., the Toronto Stock Exchange) and its dealer-members (e.g., Interactive Brokers), and these may then charge individual traders.

trading with limit orders does not sufficiently compensate either group for the increase in the price impact that they incur.

Institutions that build or unwind large positions commonly split their orders across time. For split orders, bid-ask spreads may not fully reflect the trading cost because price changes induced by early trades affect the cost of the entire order. For traders that trade against the split orders, the price change five minutes subsequent to a trade may not reflect the information content of the split order. We thus we compute, for each trader group, the intraday return per dollar traded from buying and selling a security, with the end-of-day portfolio holdings evaluated at the closing price. A positive return implies that a trader was able to "buy low or sell high" relative to the closing price. For institutional traders we observe that returns from market orders increase (in our data, these returns almost double), and that their returns to limit orders and to all orders combined do not change. For retail traders, we find no change in the returns to market orders, and decreases in the returns to limit order trades and all trades combined.

Our findings challenge the common perception that an increase in the bid-ask spread harms retail traders because they trade predominately with market orders. First, in our sample, retail traders trade less than 54% of their volume with market orders. Second, even though the market-wide bid-ask spread increases, we find no evidence for a change in the cost of market orders for retail traders. Our analysis further suggests that the negative shock to market-making algorithmic activities increased the adverse selection cost of retail traders' limit orders.

Related Literature. Our work contributes to two strands of the literature. First, we contribute to the literature on the behavior of retail traders. 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 investor-level dataset, Barber, Lee, Liu, and Odean (2009) find that retail traders lose on their aggressive trades. Kelley and Tetlock (2013) find that retail traders net buying has predictive power for future returns. Foucault, Sraer, and Thesmar (2011) show that trades by retail investors contribute to the idiosyncratic volatility of stocks. Complementing this literature, we study the short-run intraday returns and assess the impact of high-frequency quoting on retail traders.

Second, we contribute to the rapidly expanding literature on algorithmic and high frequency trading. Biais and Woolley (2011), Jones (2013), and Chordia, Goyal, Lehmann, and Saar (2013) survey this literature. Subsequent to our study, Lepone and Sacco (2013) confirm our finding regarding the increase in the bid-ask spread for one of Canada's smaller venues, Chi-X, using a 19-month event window.

Several recent studies, e.g., Hendershott and Riordan (2012), Boehmer, Fong, and Wu (2012), Brogaard, Hagströmer, Norden, and Riordan (2013), Menkveld and Zoican (2013), or Ye, Yao, and Gai (2013), have used upgrades in technology that affected the speed (or latency) of trading to assess the impact of algorithmic trading on markets. Our study differs in that first, the per-message fee has no effect on speed differences among traders and that second, the fee affects predominantly those algorithmic traders that use many orders relative to their trades. We contribute by analyzing trading costs and benefits to both limit and market orders for traders with different levels of sophistication.

The rest of the paper is organized as follows. Section I. develops testable implications from the theoretical literature. Section II. describes the data, the sample, and the details of IIROC's fees. Section III. explains the trader classification. Section IV. outlines our empirical methodology. Section V. establishes that the change in fees affected some traders' message submission behavior. Section VI. presents our results on market quality, Section VII. presents the results on trader level order choices, Section VIII. presents the results on traders' intraday returns. Section IX. discusses the results. Tables and figures are at the end of the paper.

I. Theoretical Background and Testable Predictions

Our empirical strategy exploits the change in regulatory fees. Prior to April 1, 2012, the Canadian regulator IIROC, a not-for profit entity, recovered its costs only through charging fees for executed trades. After April 1, they recovered their costs through fees on both trades and other market messages, such as submissions and cancellations of limit orders. The fee change increased the costs for strategies that involved numerous messages per trade, which we refer to as "message-intensive."

As Foucault (2012) highlights, some algorithmic trading strategies require the frequent amending of orders in response to new market information, such as macroeconomics or company-specific news, or to trade-related information, such as trades or quote updates in correlated securities. More specifically, based on a comment letter that Getco, a major high-frequency trading firm that operates as an electronic market maker worldwide,[7] submitted to IIROC, we conjecture that the introduction of a per-message fee increased the costs to algorithmic market making strategies. The notion that market making strategies involve a large number of messages relative to trades is also supported theoretically by Baruch and Glosten (2013). In an equilibrium of their model, liquidity providing traders modify their quotes each time they observe the state of the limit order book.

Bid-Ask Spread. In its comment letter, Getco argues that if market makers respond to a fee on message-intensive strategies by updating their quotes less frequently, then market makers would take on "additional risk during the time their quotations are placed on a market." They would thus require a higher risk compensation, and the bid-ask spread would widen (see e.g., Copeland and Galai (1983) or Foucault (1999)).

[7] Getco has since merged with Knight Capital to create KCG. The comment letter can be found at http://docs.iiroc.ca/CommentsReceived.aspx?DocumentID=E5F5A707F5CF494ABB4993A42BFDEF44&LinkID=750&Language=en.

Empirical Prediction 1 *After the change in the regulatory fee,*

1. *traders that employ message-intensive strategies reduce their quoting activities;*
2. *the market-wide quoted bid-ask spread widens;*
3. *traders who use market orders pay higher effective spreads.*

Information. Traders who use limit orders face the risk that new information arrives while their limit order is posted in the book. If they do not react to this information, their limit order may get "picked off" by a market order and trade at a "stale" price; see, for instance, Foucault (1999). As Jovanovic and Menkveld (2011) argue, a fast algorithmic trader may mitigate this adverse selection problem by being able to update the quote quickly in response to market events. The change in IIROC's regulatory fee increases the costs of changing the quote and thus hampers traders willingness to update their quotes.

Empirical Prediction 2 *After the change in the regulatory fee, the market-wide adverse selection component of trading costs increases.*

Although it is intuitive that fast, liquidity providing traders would face higher adverse selection costs, it is not clear how slower traders are affected. For instance, in Hoffman (2013)'s model of slow and fast traders, upon arrival of new information slow traders face the risk of being picked off by all traders, whereas fast traders can cancel their orders before slow traders can pick them off and they only face the adverse selection risk from other fast traders. As long as slow limit order submitters continue to trade against both types of traders, their adverse selection costs are determined by the probability of the arrival of new information in the interim and will not be affected by a cancellation fee (which does not feature in Hoffman (2013)). Based on this setup, we would predict that slow traders face no change in adverse selection after the fee change.

Empirical Prediction 3 *After the change in the regulatory fee,*

1. *fast, liquidity providing traders experience an increase in adverse selection;*
2. *slow traders who trade with limit orders do not experience a change in adverse selection.*

Benefits to Trading with Limit Orders. Limit orders are used by traders with different trading objectives. First, there are professional liquidity providers[8] who post two-sided quotes and aim to profit from the spread. Second, there are traders who want to build or unwind a position. The first group must at least break even on their limit orders. The second group faces a trade-off between the certain execution of a market order and the uncertain, but potentially more profitable execution of a limit order. For this group of traders, the attractiveness of a limit order is determined by both, the probability of execution of the order and by the profitability of the order, conditional on its execution.

Market order profits, limit order (realized) profits, and the probability of limit order execution, i.e. the fill rate, are therefore interrelated. If, for instance, the profit to submitting a market order increases, then either the fill rate or the profit to a limit order, conditional on its execution, must increase. The effect of the fee change on the individual measures, however, is ambiguous. For instance, if the total number of limit orders declines as a consequence of a per-message fee, ceteris paribus, the probability of each order execution should increase. At the same time, if the bid-ask spread widens (Empirical Prediction 1), some traders that used market orders prior to the fee change may switch to limit orders, reducing the probability of limit order execution.

[8] In fact, on the TSX, electronic liquidity providers face especially attractive fees under the so-called ELP program.

II. Regulatory Fees, Data, and Sample Selection

A. The Canadian Equity Market Structure

During our sample period, Canada has six trading venues that operate as public limit order books, namely, the TSX, Alpha Exchange, Chi-X, Pure, Omega, and TMX Select, and two venues that operate as dark pools, Alpha IntraSpread and MatchNow.[9] In July 2012, Alpha, and Alpha IntraSpread became part of the TMX Group (which had already owned the TSX and TMX Select). Based on IIROC statistics, the market share of the TSX in the first half of 2012 was around 62% of all dollar-volume traded in Canada.

B. The Change in IIROC's Regulatory Fees

The Investment Industry Regulatory Organization of Canada (IIROC) is a Canadian regulator that performs real-time market surveillance of all Canadian equity trading marketplaces. Owned by the investment dealers, IIROC operates on a cost-recovery basis and bills its dealer-members and the marketplaces for surveillance costs. It is our understanding that dealers directly pass on the regulatory fees to high activity clients, e.g. high-frequency traders, but that they charge retail clients only through commissions.

Before April 1, 2012, IIROC's fees were based on market shares of trading volume; after the change, fees were based on market shares of trades and, additionally, market shares of messages, where a message is a trade, or an order submission, cancellation, or modification. According to IIROC, the charges per trades are to cover the non-IT related costs of market surveillance, the charges per message are to cover the IT-related costs of market surveillance. IIROC does not directly provide information on the composition of its costs into IT and non-IT related components (these may vary every month). IIROC levies its monthly fees based on the past month's activities. Therefore, at the time of

[9]There are some smaller venues that had negligible market share. The TSX Venture is technically a separate exchange that trades only TSXV-listed securities — which we do not include in our sample.

the fee change, traders did not know how much they would have to pay per trade and per message for the month of April.

According to a January 2013 “Market Structure Briefing Note” by CIBC, the largest broker-dealer in Canada by volume, electronic traders paid over 95% of IIROC’s total surveillance fees (through trade and message fees) since April 2012, whereas before April, they had paid around 80%. Furthermore, according to the same report, in April 2012 the per-message fee was roughly \$.00022 per message, the per trade fee was about \$.055 (the fees fluctuate from month to month).

To put the fees into perspective, consider a typical limit order, which is for 200 shares. Upon execution, this order receives a maker rebate of \$.62 to \$.64 from the exchange. Before April 1 2012, this order incurred the regulatory fees only if it trades; these fees were \$.022 per trade (our estimate; see the appendix for details). After the change, this order incurs the regulatory fee of \$.055 if it trades, and it additionally incurs the per message charge of \$.00022 irrespective of whether or not it trades.

Although the per message fee appears to be small after the fact, we believe that the change in fees did have a significant affect on some traders’ behavior because there was much uncertainty about the level of the new fees before April. It was costly and difficult for traders to obtain an estimate of their April fees for two reasons. First traders had to predict the total number of messages and trades across all 4,000 listed securities for April. Second, they had to predict their share of the trades and messages.

While IIROC publishes monthly statistics on the market-wide historical number of trades, they do not publish statistics on the historical total number of messages that accrue across all marketplaces. Algorithmic traders appear to specialize, for instance, in a subset of securities or particular marketplaces (as indicated in IIROC’s HOT Study). To determine the total number of messages, they would thus have to purchase, process, and store extra data. To determine their own share, traders would additionally have to assess how others would react to the change in fees. As was clear from the comment letters that IIROC received and published (e.g., by Getco or CNSX), market participants expected that the per message fee would disproportionately be paid by a small group of traders, e.g., electronic market makers. If a few of these traders would stay out of the market or significantly alter their behavior, the remaining traders could face very high costs.

Finally, the new rules also included a number of exemptions for registered market making traders (these do not include informal high-frequency market makers) and it may not have been clear how these exemptions affected the fees paid by non-exempt traders.

C. Data

Our analysis is based on proprietary trader-level datasets provided to us by the TMX Group.[10] Data on shares outstanding (based on February 2012), splits, and index composition is 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. Our sample period is March 1, 2012 through April 30, 2012, and we classify traders based on the pre-sample month of February 2012.

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 orders, cancellations and modifications, and trade reports. With the exception of traders' intraday returns, when computing market quality measures, we only include trades that happened in a limit order book during the continuous trading session.[11] Each trade is identified as buyer-initiated or seller-initiated, as the data specifies the active

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[11]We exclude the first 10 minutes and the last 20 minutes of the day to ensure that our results are not driven by the impact of market opening and closing auctions; the TSX starts disseminating information about the market-on-close auction 20 minutes prior to end of the trading day.

(liquidity demanding) and passive (liquidity supplying) party. Finally, the data contains information on the TSX and the Canadian Best Bid and Offer Prices.

D. Sample Selection

We base our analysis on 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 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.

III. Classification of Traders

In Canada, traders must send their orders to the exchange through a licensed broker. Brokers commonly organize their trading floors into different "desks" by the type of trader or investor that the desks caters to, for instance, retail, institutions, proprietary clients and so on. Consequently, each electronic message (e.g., an order or a trade) is associated with a unique identifier that belongs, for instance, to licensed individual at a broker's trading desk or to a so-called direct market access (DMA) client (an algorithm that accesses the exchange directly, possibly using co-located facilities).[12] Our data contains these unique identifiers. With the exception of retail traders, for whom we have proprietary information, we classify unique identifiers by their behavior.

Message-Intensive Algorithmic Traders. The increase in the trade fee affected all traders (even though many would not have been asked to directly pay these fees), the per message fee disproportionately affected those traders that use many messages in their

[12]The Canadian regulator IIROC requires that each direct market access (DMA) client has a unique ID. Consequently, messages from a DMA client are not mixed with other order flow.

trading strategies. As a first step in our analysis, we will show that traders who are message-intensive indeed reduce their activities in response to the change in the fee. We base our classification of message-intensive traders on the total number of messages and on the message-to-trade ratios for each unique identifier, using the pre-sample month of February. A message is defined as any system message that a trader sends to the exchange and that the exchange sends to a trader that relates to an order or trade (including order modifications, order cancellations, and cancellations of immediate-or-cancel or fill-or-kill orders). Our goal is to find unique identifiers that use message-intensive strategies because these will have been negatively affected by the event. For each unique identifier, we compute the number of messages and the number of trades that this market participant submitted across the entire sample of TSX Composite securities plus the 42 most frequently traded ETFs in February 2012.[13] A unique identifier is classified as message-intensive if this identifier is both in the top 5% of message-to-trade ratios and in the top 5% of the total number of messages submitted. We exclude traders that use orders that stay in the order book overnight. We include exchange traded funds in the classification to capture multi-asset and multi-asset-class strategies that are message intensive, such as ETF arbitrage or ETF hedging.[14]

Consistent with our intuition from Section I., the identifiers that we classify as message-intensive are likely involved in liquidity provision. They trade 74% of their volume with passive limit orders, and they are on the liquidity providing side of around 48% of all transactions in our sample period. While our classification may capture proprietary high frequency algorithms, it may also capture message-intensive agency algorithms that execute trading decisions on behalf of an institutional client. These traders are equally affected by the per-message fee and we are unable to differentiate between the impacts of

[13]Specifically, we chose those ETFs that had more than 1,000 trades in February 2012.

[14]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.

proprietary and agency high quoting activities. See also Hagströmer and Norden (2013) for a discussion on diversity of high-frequency traders.

For brevity, in what follows we use the acronym iAT (intensive algorithmic trader) to denote this group of identifiers.

Retail Traders. We obtain information about identifiers that are retail traders from a proprietary dataset. This dataset is based on the trading activity in Alpha IntraSpread, a dark pool in which active orders can only be submitted by retail traders. We obtain all the known retail unique identifiers. While this approach does not classify all identifiers that submit orders on behalf of retail clients, the ones that are classified are indeed retail and combined they are involved in about 10% of the dollar volume. Each identifier is associated with a trading desk at a brokerage, which is typically responsible for retail flow from a large number of the broker's retail clients. It is important to know that for the vast majority of retail clients, the decision of where to send their order rests with the broker; therefore a particular identifier using the Alpha IntraSpread dark pool does not provide any information on the level of sophistication of this identifier's retail clients. The sets of retail traders and high frequency traders do not overlap.

Institutional Traders. Our goal is to identify traders who handle large order volume and who build or unwind large client positions. For each unique identifier that is linked to a client (non-proprietary) account and that is neither retail nor message-intensive, we compute the per-stock cumulative dollar net position (buy dollar volume minus sell dollar volume) from February 1, 2012 to April 30, 2012. We then classify a unique identifier as an institutional trader for all securities and all days if for at least one stock on one day this identifier has an absolute cumulative net position that exceeds $25M. The $25M bound corresponds to selecting approximately the top 5% of identifiers with regards to their maximum net position.

This classification of institutional traders aims to capture the traders that accumulate the largest positions with TSX trading. Our results relating to institutional traders should thus be interpreted as relating to traders that trade very large positions (not necessarily in each security). There are caveats to this classification. First, it is possible that a trader, for instance, buys on the TSX and sells on another venue and thus does not actually hold the attributed inventory. Second, it is possible that we capture a smart order router that is programmed to deal with, for instance, all "buy" trades.

Trader Group Summary Statistics. There are 3,516 unique identifiers in February 2012; we classify 94 of these as message-intensive (iAT), 125 as retail, and 109 as institutions. In February 2012, the average message-intensive identifier submits 250,000 messages per day and is party to (roughly) 5,000 trades. Tables II and III presents some summary statistics for these groups; the presented figures are based on by stock and day computations. For instance, retail traders pay the largest bid-ask spreads and trade around 54% of their volume with marketable orders. iATs pay the lowest spreads when they use marketable orders, they trade 74% of their volume with non-marketable orders, and 99% of the order-volume that they submit are non-marketable orders. The small number of traders that we classify as message-intensive (3.6% of all traders) create most of the messages, on average 82% for the sample period. Furthermore, we classify only around 9% of all unique identifiers, but these are involved in 53% of the dollar-volume (or, per day per stock, 48% of the dollar volume).[15]

IV. Estimation Methodology

The summary statistics in Table I indicate that message-intensive traders reduce their activities substantially both in absolute terms and relative to the rest of the market. The

[15]Note that volume here is double-counted because we count both the active and the passive side. Thus, for instance, if an iAT would trade on the passive side in every transaction, then the iAT share would be 50%.

introduction of the fee thus had a substantial direct effect on the behavior of message-intensive traders. We estimate the effect of the reduction in message-intensive activities using two approaches.

First, we perform an event study in which we estimate the following relationship:

$$\textit{dependent variable}_{it} = \alpha_1\, \textit{event}_t + \alpha_2\, \textit{VIX}_t + \delta_i + \epsilon_{it}; \tag{1}$$

where $\textit{event}_t$ is a dummy that is 0 before April 1 2012, and 1 thereafter; δ_i are firm-level fixed effects; and $\textit{VIX}_t$ is the daily realization of the volatility index VIX.[16] The coefficient of interest is α_1 and it reflects the total effect of the fee change on the dependent variable for the month of April.

Our second estimation approach is to use the fee change event as a binary instrument for message-intensive activities and use it in a two-stage least square instrumental variable regression. We then estimate

$$\begin{aligned} \textit{iAT activity}_{it} &= \beta_1\, \textit{event}_t + \beta_2\, \textit{VIX}_t + \delta_i + \epsilon_{it} \\ \textit{dependent variable}_{it} &= \beta_3 \textit{iAT activity}_{it} + \beta_4\, \textit{VIX}_t + \delta_i + \epsilon_{it}, \end{aligned} \tag{2}$$

where our main explanatory variable of interest, $\textit{iAT activity}_{it}$, is instrumented by its estimated value from the first stage regression. As above, δ_i are firm fixed effects. We use two measures for iAT activity. The first is the number messages from message-intensive traders as a percent of all messages; using this measure the estimate $\hat{\beta}_3$ describes how a 1% increase in relative iAT activity affects the dependent variable. The second measure is the logarithm of all messages from the group of message-intensive identifiers.[17] Then

[16]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.

[17]In addition to the results that we present and that make full use of our data, we also estimated a specification where we use Hendershott, Jones, and Menkveld (2011)'s proxy for algorithmic trading, the ratio of the number of the orders (including modifications and cancellations) to dollar volume; our results are qualitatively similar.

the interpretation of $\hat{\beta}_3$ is that it measures how a 1% absolute increase in the level of iAT activity affects the dependent variable.

Canadian and U.S. volatility are highly correlated. Volatility is known to affect trading variables, and we include the U.S. VIX as a control because it is plausibly exogenous to Canadian market activities, yet captures market-wide volatility. To avoid biases in standard errors stemming from observations that are correlated across time by security or across securities by time or both, we employ standard errors that are double-clustered by both security and date.[18] All regressions include stock fixed effects. To ensure that outliers do not drive our results, we winsorize all dependent variables at the 1% level.

The event study and the instrumental variable regressions relate in that the estimate for the event coefficient, $\hat{\alpha}_1$ from (1) should, on average be the same as the product of the estimates $\hat{\beta}_1 \times \hat{\beta}_3$ from (2). The interpretation of the IV regression is that it establishes a causal relation between iAT activity and the dependent variable.

V. The Impact of the Fee Per Message on Quoting Activities

Table I shows that the number of iAT messages falls by roughly 31% from March to April and that the iAT fraction of all messages falls from roughly 84.4% to 79.5%. Figure 1 plots the fraction of messages that are created by iAT identifiers. The percentage pertaining to iAT identifiers after the fee change is significantly lower.[19] iAT identifiers begin reducing their activities in the last days of March, which can be explained, for instance, by traders "re-training" their algorithms ahead of the fee change. This early decline implies that we may underestimate the size of the true effects.

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

[19]We do not have data on comparable U.S. market activities at the time. However, the market research firm Nanex has a plot of total messages for U.S. markets on its website Nanex.net; see http://www.nanex.net/aqck2/3528.html. While the level of messages is lower in 2012 compared to preceding years, there is no notable decline in messages at the time of our event in April 2012.

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), and the Angrist-Pitschke F-test. Our results highlight that the event caused a significant decline in iAT activity in the overall sample and that the event is a valid instrument for our IV approach. The estimated effect of the reduction in the fraction of iAT messages, in the first column, is 1.6% (and thus lower than the aggregate reduction), the estimated reduction in the level of their activities, in the second column, is 29%. We confirm that after the fee was introduced, iATs reduced their activities significantly.

In the estimation results of the second stage of the IV regression that we present in the following sections, a *negative* coefficient indicates that the decline in the percentage of iAT activity led to an *increase* in the respective dependent variable. The coefficients on *event* thus have the opposite sign as the coefficients on % iAT and log iAT messages.

VI. Trading Costs

We perform the analysis in this section for both the total sample and for the volume-weighted market quality measures for the groups of retail and institutional traders. For these groups, we compute the measures separately for trades with market and limit orders.

Bid-Ask Spreads. We measure bid-ask spreads by the time weighted quoted half-spread based on the Canadian best bid and offer prices and by the volume-weighted effective half-spread; both are measured in basis points of the prevailing midpoint. For security i the effective half-spread for a trade at time t is defined as

$$espread_{it} = q_{it}(p_{it} - m_{it})/m_{it}, \tag{3}$$

where p_{it} is the transaction price, m_{it} is the midpoint of the quoted spread prevailing at the time of the trade, and q_{it} 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 side (the market order that initiated the trade) and for the passive (the limit order) side of each transaction, precisely signing the trades as buyer- or seller-initiated. From our data we use the prevailing (Canadian) National best quotes at the time of each transaction.

Results. Figure 1 plots the time-weighted quoted spreads alongside the percent of iAT messages for the overall sample. The figure indicates that as message-intensive traders reduce their activities, the bid-ask spread increases. Panel A in Table V presents our results from estimating (1) and (2). The results support Empirical Prediction 1 and confirm that after the introduction of the fee, the bid-ask spread increases because iATs reduce their activities. Specifically, the decline in iAT activity led to an increase in the half-spread by .5 basis points; for every 1% decline in relative iAT activity, the spread increases by .3 bps, and a 10% total drop in iAT activity leads to a .17 bps increase in quoted spreads. Similarly, in Panel B in Table V we estimate the effect of the change in iAT behavior on the effective spread. As with the quoted spread, we observe that the reduction in iAT behavior led to an increase in the effective spread, of the same magnitude as the change in the quoted spread. The result for the relation to the change in the fraction of iAT trading is, however, only weakly significant.

As the summary Table III indicates, retail traders pay and receive a larger effective spread after the fee change, but Panels A and B in Table VI show that this change is statistically insignificant. Institutions pay but also earn significantly higher effective spreads.[20]

Price Impact. To measure adverse selection, we compute the five-minute price impact, which is the signed change in the midpoint of the bid-ask spread from the time of

[20]In untabulated regressions we estimated the aggregate effect by computing the sum of the effective spreads paid and received, respectively weighted by the relative shares of market and limit orders. For this aggregate measure we found no significant effect for either group.

the trade to five minutes later:

$$\textit{price impact}_{it} = q_{it}(m_{t+5\text{ min},i} - m_{it})/m_{it}. \tag{4}$$

Results. In Panel C in Table V, we test Empirical Prediction 2 on the effect of the change in iAT behavior on the price impact. Consistent with our prediction, we observe that the reduction of iAT activities led to an increase of the market-wide price impact of .8 bps.

Panels E and F of Table VI test Empirical Prediction 3. Contrary to our prediction, retail traders face a higher price impact when they trade with limit orders. We further find that there is no change in the price impact of their market orders. Institutions, on the other hand, both cause and face significantly higher price impacts.

Our finding on the increase in the price impact is consistent with the idea that limit orders are more likely to become stale (not reflecting the most recent information), the less frequently they are modified (see, e.g., Bernales (2013) and Hoffman (2013) for the theoretical analysis). The fee per message led to a stark decrease in the message traffic, and in particular, to a stark decline in the limit order cancellations.

Benefits to Liquidity Provision. Taken at face value, the increase in the bid-ask spread makes the provision of liquidity more attractive and one would thus predict that, ignoring the per-message fee, benefits to liquidity providers increased subsequent to the introduction of the per message fee. A common measure for these benefits is the realized spread, defined as:

$$\textit{rspread}_{it} = 2q_{it}(p_{it} - m_{i,t+5\text{ min}})/m_{it}, \tag{5}$$

where $m_{i,t+5\text{ min}}$ is the midpoint 5 minutes after the trade.

The price impact and the effective spread are mechanically related in the sense that the difference of the two is the realized spread, interpreted as the revenue that liquidity providers receive in the transaction. Formally,

$$espread_{it} = priceimpact_{it} + rspread_{it}. \tag{6}$$

Consequently, if the effective spread increases and the realized spread declines, the price impact of orders must have increased.

We use the five minute benchmark because it captures the adverse selection against traders who trade to build long-term positions. The five-minute realized spread is likely not a valid metric to assess the benefits from liquidity provision for iATs, because these traders may manage their inventories in such a way so that they wouldn't hold the position even until the five minute benchmark. Such a trader would not suffer the entire price impact that prevails five minutes after the trade. To capture the adverse selection that iATs face, one would need to compute the realized spreads for shorter horizons.

Results. Panel D of Table V shows that the realized spread *decreased* following the reduction in iAT activity. Therefore, even though the quoted spread increases, liquidity providers receive a smaller portion of the spread.

Split by groups of traders, Panels C and D of Table VI show that there is no change for the realized spreads that retail traders pay but that the realized spread that they receive (weakly) declines for their limit orders. Institutions both pay a lower realized spread when they trade with market orders and they receive a lower realized spread when they trade with limit orders. While the effect is larger for the limit orders, when we compute the total cost for each trader group, computed as the realized spread paid by the group on the their market orders minus the realized spread received on the their limit orders, we found no change (tables are omitted).

Notably, realized spreads are generally negative for all trader groups. There are at least two explanations. First, traders receive so-called maker rebates from the exchange for limit orders that execute against market orders. If the market for liquidity provision were perfectly competitive, then the realized spread would exactly equal the negative maker rebate.[21] Second, traders that build positions consider the trade-off between using market and limit orders. These traders may be willing to accept a loss on a limit order, provided that the loss does not exceed the trading cost of a market order.

VII. Traders' Order Submission Behavior

Our results in the previous section illustrate that the fee change has affected institutional traders' trading costs. The tradeoff that these traders face when choosing between market and limit orders further depends on the probability of execution of their limit orders, which is endogenous to traders' order submission behavior.

We compute four measures to study order submission behavior and the probability of limit order execution, by trader groups: first, the fraction of volume that is traded with limit orders; second, the fraction of the submitted order volume that is with limit orders; third, the fraction of the submitted orders that are limit orders; and fourth, the fraction of the submitted limit order volume that is filled. The latter measure can be interpreted as the fill rate or the probability that a limit order executes.

Results. We do not have theoretical predictions on these measures. Table VII presents our results on tests of changes in the usage of limit orders. For retail traders there are no statistically significant changes. We find that institutions trade more with market orders, submit more market orders relative to limit orders, and that (weakly) their limit orders get filled with lower probability.

These results highlight that there is heterogeneity in the reaction of traders to changes in iAT behavior.

[21] The highest maker rebate for electronic liquidity providers is \$0.0031 on the TSX. At an median price of \$20.6, the maker rebate is about 1.5 bps, and the realized spread for iATs is, on average -1.8bps.

VIII. Traders' Intraday Returns

The results thus far indicate that, as message-intensive traders reduced their activities, market order submitters pay a larger spread, limit order submitters receive a smaller portion of the spread, and institutions submit more market orders. In this section, we study traders' intraday returns to assess who benefits and loses from these changes.

Trading costs measured by bid-ask spreads are "snapshots", and these measures do not fully account for price movements subsequent to a trade. If prices include all information at any point in time, then any price movement subsequent to a trade is the result of new information (or noise). By holding the security, an investor then earns a return on his/her investment. On the other hand, if, for instance, an informed order is split into many small orders and the total information content of the order is only revealed over time, then anyone trading against the split order will lose. Uninformed traders must thus take into account that they may trade at the wrong time, before prices reflect all the available information. Informed investors, on the other hand, must take into account that they may move the price as they accumulate a position.[22] Our analysis in Section VI. documents that the fee change affected adverse selection. Retail traders in particular face a higher price impact when trading with limit orders.

To account for price movements subsequent to a trade beyond the five-minute benchmark, we compute the intraday returns, by trader group. We measure these returns by computing a trader's profit from buying and selling a security and we value the end-of-day portfolio holdings at the closing price; we then scale this profit measure by the daily dollar

[22]A common measure used by institutions to compute the costs of an order, in particular one that is split into many small orders, is the "implementation shortfall". This measure is, in essence, the volume weighted price of the order relative to the price that prevailed when the trader started to fill the order. Computing this measure with our data is impossible because we do not know when a trader started and completed filling an order and because our measures are computed for groups of traders. In an untabluated analysis, we employed the preceding day's closing price as the starting price to proxy for the shortfall. We found no significant effects of the fee change event.

volume to obtain the per-dollar return. Formally, the per stock i, per day t profit for a group of traders is

$$intraday\ return_{it} = \left((sell\$vol_{it} - buy\$vol_{it}) + (buy\ vol_{it} - sell\ vol_{it}) \times cprice_{it}, \right) / \$vol_{it} \quad (7)$$

where $sell\$vol_{it}$ and $buy\$vol_{it}$ are the total sell and buy dollar-volumes for trader-group i, $buy\ vol_{it}$ and $sell\ vol_{it}$ are the share-volumes, $\$vol_{it} = sell\$vol_{it} + buy\$vol_{it}$ is the overall dollar volume. The profit from intraday trading is $(sell\$vol_{it} - buy\$vol_{it})$; a positive value means that the trader group "bought low and sold high." The term $(buy\ vol_{it} - sell\ vol_{it})$ 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, $cprice_{it}$.

Our approach uses the closing price as the benchmark and we thus implicitly assume that the closing price reflects the total information that was generated during a trading day. We compute three versions of the profit measure: one for all orders, one for all orders where a trader is on the passive, liquidity providing side, and one where the trader is on the active, liquidity taking side.[23]

Results. Panel A in Table VIII displays the results from our estimation of the impact of iAT activities on trader profits. The table shows that retail traders' profits decrease significantly whereas profits for institutional traders are unaffected. Split by active vs. passive trades, we observe that there is evidence that as message-intensive traders reduce their activities, retail traders lose more on their passive limit orders and that institutions gain more on their active marketable orders. Combined with our earlier results on order submission behavior, we observe that institutions trade more with market orders. We further observe that they derive higher profits from such orders, despite the increase in the price impact of their market orders.

[23] Barber, Lee, Liu, and Odean (2009) shows that in their dataset, retail traders lose mostly on their aggressive orders. The profit measure that we compute is noisy, but we don't find major differences between profits for active and passive trades. As Table II shows, active vs. passive profits for retail traders for the entire sample are, -3.7 bps vs. -3.3 bps.

IX. Discussion and Conclusion

The introduction of the per-message fee in Canada was a unique event that increased the cost for some algorithmic trading strategies, including high frequency market making. The event had a noticeable impact: message-intensive traders, a group that likely includes high-frequency market makers, reduced their messages (trades, orders and cancellations) by almost 30%. We are not aware of any other market development that could have triggered this drop. The decline in activity was accompanied by an immediate, sharp increase in the market-wide bid-ask spread.

Our main contribution is in documenting the differential impact of algorithmic activities on the costs and benefits for traders with different levels of sophistication. The drop in algorithmic trading that led to an increase in the market-wide bid-ask spread did not affect the spreads paid by retail traders. Our findings on intraday returns further suggest that high frequency quoting and trading does not affect all groups of traders in the same way but that it may lead to redistribution of gains from trade.[24]

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 because they must process the heavy message traffic. The per-message fee in Canada appears to have strongly affected the "good", liquidity-providing HFTs, and subsequently significantly intraday returns of retail investors dropped.

[24]It is important to emphasize that institutions often manage funds on behalf of retail clients and thus a policy change that benefits institutions also benefits their retail clients.

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Appendix: IIROC's Regulatory Fees

Using their proposal for the fee change (IIROC's Administrative Notice 10-0316) as well as their most recent financial statement, we estimate that IIROC's IT related costs are between \$.8-\$.9M per month. Namely, for Oct/09 to Mar/10 (the latest figures that IIROC presented in its discussion paper for the proposed fee change), IIROC estimates that, under the new fee model, TSX-based trades would account for roughly 58.8% of the integrated fees. With a market share of 55% of messages (which are charged for IT costs) and 61.5% of trades (which are charged for the non-IT costs), this implies that IT costs account for 43% of all costs. According to its most recent financial statement, IIROC spends about \$24M per year on market (UMIR) surveillance, and it thus spends \$.8-\$.9M per month on IT costs.

Under the old system, in Oct/09–Mar/10, TSX-based trades accumulated around \$1M per month in fees with around 9,000M shares traded. For a 200 share order, regulatory fees under the old fee structure were thus \$0.022. Under the new fee, the total fee for TSX-based trades would have been \$1.17M. Using the above argument, around 40% of this amount would be paid by per message fees. The remaining 60% of this amount would be paid in per trade fees; at an average of 14M trades per month this implies a per-trade fee of around \$0.05. The per-message fee is harder to estimate and IIROC does not publish market-wide statistics for the monthly number of messages. IIROC's HOT study indicates that in August-October 2011, there were around 3.3B messages per month across all marketplaces. To recover \$.85M per month, the per-message fee would be around \$0.00026. Both of the ballpark estimated for per-trade and per-message fees are close to the figures that CIBC revealed in its report.

Table I
Sample Summary Statistics – by Stock

The table reports summary statistics on our sample firms. In total there are 248 firms in our sample. Market capitalization is based on March 1, 2012. The percentage of messages by high messaging algorithmic traders (iATs) are summed over the entire sample of securities, per day. All other figures are per stock per day averages. The price is the time-weighted mid-point of the national bid-ask spread. Intraday volatility is measured by the average daily 10-minute maximal mid-price fluctuation, scaled by the average midpoint. We also add the overall sample average for the S&P/TSX60 constituents.

	how computed	by	Units	Mean	SD	March	April	Difference	TSX60 mean
quoted spread	time-weighted	stock & day	bps	6.7	8.3	6.4	7.0	0.6	2.4
depth	time-weighted	stock & day	$10,000	4.0	18.7	3.9	4.2	0.4	5.2
effective spread	volume-weighted	stock & day	bps	6.4	8.3	6.2	6.6	0.5	2.3
realized spread	volume-weighted	stock & day	bps	−2.6	5.6	−2.3	−2.9	−0.6	−1.3
5-minute price impact	volume-weighted	stock & day	bps	9.0	10.6	8.5	9.6	1.1	3.5
messages per minute		stock & day		180.2	246.4	206.6	151.3	−55.3	448.8
dollar volume per message		stock & day	$	264.8	462.6	266.9	262.6	−4.3	309.8
dollar volume		stock & day	$ million	17.1	31.6	19.3	14.7	−4.5	49.0
trades per minute		stock & day		5.7	6.8	6.0	5.4	−0.6	13.1
intra-day volatility	10-minute midpoint range	stock & day	bps	28.2	16.5	27.5	28.9	1.4	25.6
price		stock & day	$	24.2	18.5	24.5	24.0	−0.5	38.2
market capitalization		stock	$ billion	6.7	11.6	6.7	6.7	0.0	19.8
trade size		stock & day	$1,000	6.0	8.7	6.2	5.7	−0.5	8.3
total messages		day	million	17.4	4.0	20.0	14.6	−5.3	10.5
% iAT messages		day	%	82.1	2.9	84.4	79.5	−4.8	84.9

Table II
Sample Summary Statistics – by Trader Group (Part I)

The table reports summary statistics for our by-trader statistics. All figures are per stock per day averages for the respective groups. The percent dollar volume is the share of the dollar volume (of the total dollar volume per day per stock) that is traded by the respective group (volume is double-counted, i.e., a 100 share trade counts for 200 shares because we count both the active and the passive side); % passive volume traded is the fraction of the group's total (active plus passive) volume that a group trades with limit orders; % passive volume submitted is the limit order volume as a fraction of the group's total submitted order volume; % passive orders submitted is the number of limit orders as a fraction of the total number of orders submitted by the group; % passive volume filled is the fraction of the group's total submitted limit order volume that gets executed. Cum-fee total cost is the volume-weighted average of the cum-fee effective and realized spreads paid and received by the group, after accounting for the exchange's maker-taker fees, as defined by equation (7); intraday return is the group's daily profit as defined in equation (8), $\textit{profit}_{it} = (\textit{sell \$ vol}_{it} - \textit{buy \$ vol}_{it}) + (\textit{buy vol}_{it} - \textit{sell vol}_{it}) \times \textit{closing price}_{it}$ normalized by the group's daily dollar volume $\textit{sell \$ vol}_{it} + \textit{buy \$ vol}_{it}$; the intraday returns for market (limit) orders are defined similarly, except that only volume and dollar volume traded with market (limit) orders are used in computations (instead of the total volume/dollar volume). Furthermore, for the computation of *intraday return – all trades* we use all orders submitted, including at the open and close, whereas for market and limit orders we use only trades in the continuous market from 9:45 a.m. to 3:45 p.m.

	Who	Units	Mean	SD	Median	March	April	Difference
% dollar volume	retail		10.4	8.5	8.0	10.8	10.0	−0.7
(of the daily total per stock)	institutions		19.1	11.6	17.0	19.4	18.7	−0.7
	iAT		18.5	8.5	17.9	18.3	18.8	0.6
% passive volume traded	retail		46.3	18.4	47.1	46.4	46.3	−0.1
(of the group's total traded)	institutions		48.9	19.5	49.4	49.7	48.1	−1.6
	iAT		73.8	13.5	75.8	72.5	75.3	2.8
% passive volume submitted	retail		73.2	14.0	75.3	72.9	73.5	0.5
(of the group's submitted)	institutions		74.9	16.5	78.2	75.3	74.5	−0.8
	iAT		99.0	0.8	99.2	99.0	99.0	0.0
% passive orders submitted	retail		53.6	18.7	54.2	53.9	53.3	−0.6
(of the group's submitted)	institutions		79.7	15.2	84.0	80.3	79.2	−1.1
	iAT		98.8	1.1	99.1	98.8	98.8	0.0
% passive volume filled	retail		33.3	20.8	30.3	33.9	32.7	−1.2
	institutions		29.0	14.3	27.9	29.2	28.7	−0.6
	iAT		3.1	2.7	2.4	2.9	3.4	0.4
intraday return – all trades	retail	bps	−5.1	38.6	−1.5	−3.9	−6.4	−2.4
	institutions	bps	2.9	38.0	0.5	2.4	3.5	1.1
intraday return – market orders	retail	bps	−3.7	47.0	−2.7	−3.2	−4.3	−1.1
	institutions	bps	5.1	51.1	0.9	3.2	7.2	4.0
intraday return – limit orders	retail	bps	−3.3	60.9	2.5	−1.6	−5.2	−3.6
	institutions	bps	−0.8	56.7	0.0	−0.4	−1.2	−0.9

Table III
Sample Summary Statistics – by Trader Group (Part II)

The table reports summary statistics for our by-trader statistics. All figures are per stock per day averages for the respective groups, measured in basis points of the prevailing mid price. Cum-fee total cost is the volume-weighted average of the cum-fee realized spread paid (a trader's effective spread minus the price impact) minus the realized spreads received, after accounting for the exchange's maker-taker fees, as defined by equation (7).

	When	Who	Mean	SD	Median	March	April	Difference
effective spread	paid when active	retail	7.1	8.1	4.7	7.0	7.3	0.3
		institutions	6.0	7.6	3.7	5.7	6.2	0.5
		iAT	5.3	7.1	3.2	5.1	5.6	0.5
	received when passive	retail	6.8	8.4	4.2	6.6	7.0	0.3
		institutions	5.8	7.7	3.5	5.6	6.1	0.5
		iAT	7.0	8.0	4.7	6.8	7.3	0.4
realized spread	paid when active	retail	0.0	9.7	0.2	0.1	−0.1	−0.2
		institutions	−2.1	8.5	−1.1	−1.7	−2.5	−0.7
		iAT	−0.7	8.3	−0.6	−0.7	−0.8	−0.1
	received when passive	retail	−4.5	12.8	−2.8	−4.1	−4.9	−0.8
		institutions	−3.7	8.0	−2.2	−3.3	−4.1	−0.9
		iAT	−1.8	4.7	−1.0	−1.5	−2.1	−0.6
price impact	caused when active	retail	7.2	12.0	4.2	6.9	7.4	0.5
		institutions	8.1	11.8	4.7	7.5	8.7	1.2
		iAT	6.0	8.3	3.8	5.8	6.3	0.6
	received when passive	retail	11.3	15.2	7.3	10.7	11.9	1.2
		institutions	9.4	12.4	5.8	8.8	10.1	1.4
		iAT	8.8	9.9	5.7	8.3	9.3	1.0

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

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

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

VIX_t is the daily realization of the volatility index VIX, and δ_i are firm fixed effects. We include the F-test, 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). * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Standard errors are in parentheses and they are double-clustered by firm and date.

	%iAT	log iAT messages
IIROC Fee_t	-1.61***	-0.29***
	(0.59)	(0.05)
VIX	-0.08	0.02*
	(0.13)	(0.01)
Observations	10,408	10,408
R-squared	0.013	0.071
firms	248	248
F-test	5.6	15.9
p-value F-test	0.0	0.0
under id	5.1	10.9
weak id	7.6	30.0

Table V
Impact of iAT Activity on Quoted Liquidity

This table presents the results from our event study and from the second stage of our instrumental variable regression on the impact of iAT on the daily time-weighted quoted bid-ask spread based on the national best prices, the effective spread, realized spread, and price impact. There are three explanatory variables of interest: the "plain" event effect (a dummy that is zero before April 1, 2012 and 1 thereafter), the percentage of total messages generated by iAT (%iAT), and the log of the number of iAT messages. The latter two are estimated in a two-stage least square, and %iAT and the log of the number of iAT messages are 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 equations are

(1) $L_{it} = \alpha + \beta_1 \text{IIROC Fee}_t + \beta_2 \text{VIX}_t + \delta_i + \epsilon_{it}$, (2) $L_{it} = \alpha + \beta_1 \%\text{iAT} + \beta_2 \text{VIX}_t + \delta_i + \epsilon_{it}$, (3) $L_{it} = \alpha + \beta_1 \log(\text{iAT msg}) + \beta_2 \text{VIX}_t + \delta_i + \epsilon_{it}$

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. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Standard errors are in parentheses and they are double-clustered by firm and date.

	Panel A: Quoted Spread			*Panel B: Effective Spread*			*Panel C: Price Impact*			*Panel D: Realized Spread*		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
IIROC Fee_t	0.49***			0.35***			0.82***			-0.44***		
	(0.14)			(0.13)			(0.19)			(0.13)		
%iAT		-0.30**			-0.22*			-0.51**			0.28**	
		(0.15)			(0.12)			(0.24)			(0.14)	
log iAT messages			-1.69***			-1.21**			-2.82***			1.54***
			(0.54)			(0.51)			(0.87)			(0.57)
VIX	0.05***	0.03	0.09***	0.04**	0.03	0.07***	0.14***	0.10	0.21***	-0.09***	-0.07	-0.13***
	(0.02)	(0.05)	(0.02)	(0.02)	(0.04)	(0.02)	(0.04)	(0.10)	(0.05)	(0.03)	(0.06)	(0.04)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,408	10,408	10,408	10,408	10,408	10,408	10,408	10,408	10,408	10,408	10,408	10,408

Table VI
iAT Activity and Market Quality by Retail Traders and Institutions

This table presents the results from our event study and from the second stage of our instrumental variable regression on the impact of iAT on market quality measures, computed by trader groups and by type of order (marketable vs. non-marketable limit): the effective spread (Panels A (marketable limit) and B (non-marketable limit)), the realized spread (Panels C and D), and price impact (Panel E and F); all dependent variables are volume-weighted daily averages. There are three explanatory variables of interest: the "plain" event effect (a dummy that is zero before April 1, 2012 and 1 thereafter), the percentage of total messages generated by iAT (%iAT), and the log of the number of iAT messages. The latter two are estimated in a two-stage least square, and %iAT and the log of the number of iAT messages are 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 equations are as in Table V. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Standard errors are in parentheses and they are double-clustered by firm and date.

Panel A: effective spread paid for marketable limit orders

	Retail traders			Institutional traders		
	(1)	(2)	(3)	(1)	(2)	(3)
IIROC Fee$_t$	0.15			0.49***		
	(0.14)			(0.14)		
%iAT		-0.10			-0.30**	
		(0.10)			(0.15)	
log iAT messages			-0.53			-1.68***
			(0.51)			(0.55)
VIX	0.08***	0.08**	0.10***	0.02	-0.00	0.06**
	(0.02)	(0.03)	(0.03)	(0.02)	(0.05)	(0.03)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,375	10,375	10,375	10,374	10,374	10,374

Panel B: effective spread received for non-marketable limit orders

	Retail traders			Institutional traders		
	(1)	(2)	(3)	(1)	(2)	(3)
IIROC Fee$_t$	0.24			0.41***		
	(0.15)			(0.14)		
%iAT		-0.15			-0.25*	
		(0.12)			(0.14)	
log iAT messages			-0.84			-1.41**
			(0.55)			(0.55)
VIX	0.06**	0.05	0.08***	0.06**	0.04	0.09***
	(0.02)	(0.04)	(0.03)	(0.02)	(0.05)	(0.02)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,274	10,274	10,274	10,384	10,384	10,384

Panel C: realized spread paid for marketable limit orders

	Retail traders			Institutional traders		
	(1)	(2)	(3)	(1)	(2)	(3)
IIROC Fee_t	-0.19			-0.48***		
	(0.25)			(0.18)		
%iAT		0.12			0.30*	
		(0.17)			(0.17)	
log iAT messages			0.64			1.67**
			(0.89)			(0.73)
VIX	-0.03	-0.03	-0.05	-0.15***	-0.13*	-0.19***
	(0.06)	(0.07)	(0.06)	(0.05)	(0.08)	(0.05)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,375	10,375	10,375	10,374	10,374	10,374

Panel D: realized spread received for non-marketable limit orders

	Retail traders			Institutional traders		
	(1)	(2)	(3)	(1)	(2)	(3)
IIROC Fee_t	-0.70*			-0.71***		
	(0.41)			(0.23)		
%iAT		0.44			0.44*	
		(0.33)			(0.23)	
log iAT messages			2.42			2.47***
			(1.56)			(0.90)
VIX	-0.09	-0.05	-0.15	-0.10	-0.07	-0.16**
	(0.11)	(0.14)	(0.10)	(0.08)	(0.11)	(0.08)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,274	10,274	10,274	10,384	10,384	10,384

Panel E: price impact caused with marketable limit orders

	Retail traders			Institutional traders		
	(1)	(2)	(3)	(1)	(2)	(3)
IIROC Fee_t	0.35			0.99***		
	(0.24)			(0.24)		
%iAT		-0.22			-0.61**	
		(0.19)			(0.29)	
log iAT messages			-1.21			-3.41***
			(0.92)			(1.08)
VIX	0.12*	0.10	0.15**	0.17***	0.12	0.25***
	(0.06)	(0.08)	(0.06)	(0.05)	(0.12)	(0.07)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,375	10,375	10,375	10,374	10,374	10,374

Panel F: price impact suffered for non-marketable limit orders

	Retail traders			Institutional traders		
	(1)	(2)	(3)	(1)	(2)	(3)
IIROC Fee_t	0.94**			1.14***		
	(0.42)			(0.29)		
%iAT		-0.59			-0.71**	
		(0.38)			(0.34)	
log iAT messages			-3.29*			-3.96***
			(1.68)			(1.21)
VIX	0.16	0.11	0.24**	0.15*	0.10	0.25***
	(0.11)	(0.16)	(0.11)	(0.08)	(0.15)	(0.09)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,274	10,274	10,274	10,384	10,384	10,384

Table VII
iAT Activity and Retail and Institutions Trading Behavior

This table presents the results from our event study and from the second stage of our instrumental variable regression on the impact of iAT on for activity variables: the fraction of the group's total volume (in %) that a group trades with limit orders (Panel A); the fraction of submitted order volume (not necessarily traded) that are limit orders (Panel B); the fraction of submitted orders that are limit orders (Panel C); and the fraction of limit order volume that gets executed (Panel D). There are three explanatory variables of interest: the "plain" event effect (a dummy that is zero before April 1, 2012 and 1 thereafter), the percentage of total messages generated by iAT (%iAT), and the log of the number of iAT messages. The latter two are estimated in a two-stage least square, and %iAT and the log of the number of iAT messages are 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 equations are as in Table V. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Standard errors are in parentheses and they are double-clustered by firm and date.

Panel A: % volume traded with limit orders

	Retail traders			Institutional traders		
	(1)	(2)	(3)	(1)	(2)	(3)
IIROC fee$_t$	0.42			-1.80**		
	(0.62)			(0.71)		
%iAT		-0.26			1.12*	
		(0.42)			(0.58)	
log iAT messages			-1.44			6.26**
			(2.20)			(2.78)
VIX	-0.32**	-0.34*	-0.28*	0.11	0.20	-0.04
	(0.15)	(0.18)	(0.15)	(0.16)	(0.23)	(0.18)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,395	10,395	10,395	10,403	10,403	10,403

Panel B: % submitted volume that are limit orders

	Retail traders			Institutional traders		
	(1)	(2)	(3)	(1)	(2)	(3)
IIROC fee$_t$	0.92*			-0.53		
	(0.54)			(0.61)		
%iAT		-0.57			0.33	
		(0.41)			(0.39)	
log iAT messages			-3.20*			1.84
			(1.80)			(2.19)
VIX	-0.23*	-0.28*	-0.16	-0.13	-0.11	-0.18
	(0.13)	(0.17)	(0.10)	(0.15)	(0.17)	(0.15)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,406	10,406	10,406	10,406	10,406	10,406

Panel C:% of submitted orders that are limit orders

	Retail traders			Institutional traders		
	(1)	(2)	(3)	(1)	(2)	(3)
IIROC fee_t	-0.51			-1.30**		
	(0.50)			(0.63)		
%iAT		0.32			0.81	
		(0.33)			(0.51)	
log iAT messages			1.77			4.50*
			(1.77)			(2.41)
VIX	-0.08	-0.06	-0.13	0.11	0.18	0.00
	(0.11)	(0.12)	(0.10)	(0.14)	(0.21)	(0.15)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,407	10,407	10,407	10,407	10,407	10,407

Panel D: % of limit order volume that is filled

	Retail traders			Institutional traders		
	(1)	(2)	(3)	(1)	(2)	(3)
IIROC fee_t	-1.11			-1.04*		
	(0.78)			(0.56)		
%iAT		0.69			0.65	
		(0.51)			(0.42)	
log iAT messages			3.84			3.62*
			(2.48)			(1.95)
VIX	-0.05	0.00	-0.15	0.30*	0.35*	0.21
	(0.28)	(0.29)	(0.23)	(0.18)	(0.20)	(0.19)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,400	10,400	10,400	10,404	10,404	10,404

Table VIII
iAT Activity and Other Traders' Intraday Returns

This table presents the results from our event study and from the second stage of our instrumental variable regression on the impact of iAT on the intra-day returns, measured by $\textit{intra-day return}_{it} = (\textit{sell \$ vol}_{it} - \textit{buy \$ vol}_{it}) + (\textit{buy vol}_{it} - \textit{sell vol}_{it}) \times \textit{closing price}_{it}$, scaled by the daily dollar volume. We compute the intraday returns for all trades (Panel A), trades with market orders (using volumes for trades with market orders only) (Panel B), and trades with limit orders (using volumes for trades with limit orders only) (Panel C). There are three explanatory variables of interest: the "plain" event effect (a dummy that is zero before April 1, 2012 and 1 thereafter), the percentage of total messages generated by iAT (%iAT), and the log of the number of iAT messages. The latter two are estimated in a two-stage least square, and %iAT and the log of the number of iAT messages are 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 equations are as in Table V. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Standard errors are in parentheses and they are double-clustered by firm and date.

Panel A: intraday return — all trades

	Retail traders			Institutional traders		
	(1)	(2)	(3)	(1)	(2)	(3)
IIROC Fee_t	-3.93**			1.36		
	(1.64)			(1.11)		
%iAT		2.44**			-0.84	
		(1.17)			(0.78)	
log iAT messages			13.61**			-4.69
			(5.57)			(3.94)
VIX	0.90*	1.10**	0.57	-0.15	-0.21	-0.03
	(0.47)	(0.53)	(0.41)	(0.28)	(0.35)	(0.25)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,406	10,406	10,406	10,407	10,407	10,407

Panel B: intraday return — market orders

	Retail traders			Institutional traders		
	(1)	(2)	(3)	(1)	(2)	(3)
IIROC Fee_t	-1.85			5.20***		
	(1.49)			(1.97)		
%iAT		1.15			-3.19*	
		(0.89)			(1.75)	
log iAT messages			6.40			-17.98**
			(5.04)			(7.73)
VIX	0.45	0.54	0.29	-0.69	-0.94	-0.26
	(0.44)	(0.45)	(0.36)	(0.48)	(0.73)	(0.50)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,375	10,375	10,375	10,374	10,374	10,374

Panel C: intraday return — limit orders

	Retail traders			Institutional traders		
	(1)	(2)	(3)	(1)	(2)	(3)
IIROC Fee_t	-5.85*			-1.83		
	(3.33)			(1.79)		
%iAT		3.67			1.13	
		(2.33)			(1.22)	
log iAT messages			20.36*			6.35
			(11.38)			(6.57)
VIX	1.36	1.66*	0.87	0.59	0.68	0.44
	(0.84)	(0.97)	(0.74)	(0.48)	(0.58)	(0.43)
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Obs.	10,274	10,274	10,274	10,384	10,384	10,384

Figure 1
Percent iAT of Message Traffic and Spreads

The figure plots the percent of messages that are generated by traders who we classify as iATs for our sample of TSX Composite securities. The vertical lines mark the event date, April 1, 2012. The solid horizontal lines signify monthly averages.