Correlated High-Frequency Trading

Ekkehart Boehmer, Dan Li, and Gideon Saar*

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Abstract

This paper studies correlations between the strategies of high-frequency trading (HFT) firms, which is a manifestation of the extent of competition in which these firms engage when pursuing similar strategies. We begin by establishing new stylized facts about the magnitude of time-series and cross-sectional correlations for various measures of HFT strategies. We then conduct a principal component analysis, showing that there are several underlying common strategies and that multiple HFT firms compete on each of these strategies. We investigate whether competition between HFT firms creates a systematic return factor, but find no supporting evidence for such an influence. However, the short-interval return volatility of most stocks loads negatively on a market-wide measure of correlated HFT strategies. The mitigating impact of HFT competition on stock volatility appears to be driven at least in part by a market-making strategy. The paper ends by investigating the interrelationship between two forms of competition—that between HFT firms and that between trading venues.

*Ekkehart Boehmer (eboehmer@smu.edu.sg) is from the Lee Kong Chian School of Business, Singapore Management University; Dan Li (lidan@hku.hk) is from the School of Economics and Finance, University of Hong Kong; and Gideon Saar (gs25@cornell.edu) is from the Johnson Graduate School of Management, Cornell University. Dan Li thanks the Investment Industry Regulatory Organization of Canada (IIROC) for providing her with data used in this study during her work at IIROC as part of a research agreement, and Maureen Jensen for her support and many helpful discussions. All conclusions are those of the authors and do not represent the views of IIROC.

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1. Introduction

High-frequency trading (henceforth, HFT) constitutes a large portion of stock market activity nowadays. HFT firms use computerized algorithms for proprietary trading, and they engage in electronic market making, cross-trading venue price arbitrage, short-term statistical arbitrage, and various other opportunistic strategies.[1] Our goal in this paper is to investigate correlations between HFT firms and the relationship of these correlations with the market environment. The correlated activity of HFT firms represents similarity in their strategies driven by the manner in which they respond to market stimuli and their business models. This similarity has two important dimensions. First, it implies that multiple HFT firms compete for the same profit opportunities, in which case competition could enhance the services they provide to the market and reduce the rent they earn. Second, such similarity could mean that HFT firms would be active or withdraw their activity at the same time or in the same stocks, thereby increasing the fragility of our markets or even creating a risk factor that would affect returns.

The competition dimension is of interest in part because the HFT business is a relatively new phenomenon and not much is known about its industrial organization. The secretive nature of HFT firms and their algorithms does not lend itself to easy characterization of strategies, hence making it difficult to judge the extent of competition in particular segments of their activity. In a free-market system, determining whether HFT firms deploy monopolistic strategies or compete heavily over the same sources of profits is important. Presumably, competition between HFT firms could alleviate the need for regulation because the rent extracted by these firms would decline at the same time that the level of services they provide in terms of liquidity provision and arbitrage would increase.

The fragility dimension arises because HFT firms have driven out of the market many human intermediaries and have come to dominate market activity. If they tend to expand or

[1] High-frequency trading therefore does not include agency algorithms that execute orders on behalf of investors; the term "HFT" is used only to denote proprietary trading operations conducted by standalone firms or the trading desks of larger financial firms.

severely curtail activity based on similar stimuli, there is a greater likelihood of market stress.[2] Furthermore, if multiple HFT firms operate in tandem across stocks, their activity has the potential to introduce a systematic component to the trading environment. In other words, idiosyncratic activity in one security can influence HFT activity in multiple securities and hence could create systematic patterns in returns or volatility over and above fundamental systematic influences.

Our investigation of these issues is facilitated by data from the Investment Industry Regulatory Organization of Canada (IIROC), which is the national self-regulatory organization that oversees equity trading venues in Canada. One of the unique features of these data is our ability to observe both licensed dealers' HFT activity and that of HFT firms that use direct market access (DMA) arrangements for trading. Using a set of quantitative and qualitative criteria, we characterize 31 trading firms as "high-frequency traders" and study the correlation structure of their strategies. Our sample consists of S&P/TSX60 stocks, and we analyze activity from 30 days that represent bullish, bearish, and neutral trading environments during a period running from June 2010 through March 2011.

We begin by presenting stylized facts about the time-series and cross-sectional correlations of strategies for this set of HFT firms. We operationalize the concept of "strategies" by using measures that describe the HFT firms' active choices (e.g., submission and cancelation of orders) as well as their overall trading. We find that cross-sectional correlations are greater in magnitude than time-series correlations, and that larger HFT firms in terms of market share appear to follow much more related strategies than smaller HFT firms, which may increase the likelihood of market impairment. However, the correlation structure is similar on days with negative, positive, and flat return environments, which is encouraging insofar as we do not observe an increase in correlations when the market experiences stress.

Of key interest is the distinction between directional activity (buys minus sells) and total activity (buys plus sells). We observe that total activity correlations are much greater in magnitude than directional activity correlations. In other words, it appears that much of the

[2] The SEC/CFTC Flash Crash report noted that the occurrence of very high or low stock prices during the crash was driven by the withdrawal of activity by some HFT firms that normally help set prices.

activity by HFT firms involves either placing orders simultaneously on both sides of the market or buying and selling very rapidly within the same 1-second interval. Similarly, correlations in inventory positions are very low. These two findings are reassuring with respect to the fragility dimension because they suggest that HFT firms do not herd in terms of pushing prices in a certain direction.

We perform a principal component analysis to ascertain if there are underlying common strategies that represent much of the variability in the HFT firms' activity and to identify the firms that follow each underlying common strategy. We find extensive competition in at least three underlying common strategies: eight, six, and four HFT firms have significant loadings on the first, second, and third principal components, respectively. Given that it is difficult for HFT firms to collude because order flow in the market is anonymous, it is reasonable to conclude that eight, six, or even four firms that pursue a single underlying common strategy represent rather intense competition, and hence that the economic rent earned by these firms for making markets or arbitraging price differences across multiple trading venues is probably not very high.

We analyze the empirical representation of these underlying common strategies (i.e., the principal component scores) by regressing them on various attributes of the market environment. One of the underlying common strategies appears to be a market-making strategy pursued by the firms with the highest market shares that becomes more active when market making is both needed and more profitable. Another underlying common strategy appears to represent a cross-venue arbitrage strategy that moves liquidity across the market, while the third underlying common strategy could represent a short-horizon directional strategy that is active when volatility is high, the book is thinner, and prices differ among trading venues. Our results demonstrate that there is clear heterogeneity in the strategies that HFT firms pursue, suggesting that it may be more constructive to discuss the impact of HFT on the market environment in the context of specific strategies rather than in the aggregate.

We then investigate a particular concern regarding HFT firms' correlated behavior: whether their strategies form a link across stocks, thereby generating a systematic risk factor and hence increasing the risk of stocks. Our focus is on studying the impact of competition between HFT firms (or the extent of cross-sectional correlation in their strategies), not the magnitude of

HFT activity. Our results do not support the idea that the extent of correlation in HFT strategies creates a common factor in short-interval returns. However, we find that the short-interval volatility of stocks loads negatively on the market-wide measure of cross-sectional correlation between HFT strategies. This contrasts with the positive relationships that both market-wide volatility and the magnitude of HFT activity have with individual stock volatility, suggesting that the relationship we document with the cross-sectional correlation of HFT strategies constitutes a separate and distinct effect.

There could be more than one mechanism that drives the relationship we find between short-interval volatility and the extent of correlation between HFT firms. For example, competition in turning cross-stock "private" signals into public information could translate into lower adverse selection costs and hence a lower price impact of trades, which is a major driver of volatility in short intervals (see, e.g., Jovanovic and Menkveld (2015)). Alternatively, higher cross-sectional correlation of HFT strategies could reflect more efficient market making in the presence of correlated returns and order flow across stocks. This more intense competition in market making, ceteris paribus, lowers the compensation for liquidity provision in any given stock and hence lowers transitory price movements, which translates into lower interval volatility (see, for example, Ho and Stoll (1983)). Our analysis shows that the strongest driver behind this negative relation is competition between firms that follow a market-making strategy, suggesting that the reduction in volatility stems in part from a reduction in transitory price movements.

We end the paper by examining the interrelationship of competition between multiple trading venues with competition between HFT firms. One role for HFT firms in a fragmented market structure is to be the market consolidators that transform the environment into a virtual central electronic limit book (from the perspective of most investors) by moving orders across markets extremely quickly to ensure prices are the same across trading venues and liquidity exists where it is needed. While the support of HFT firms seems to be important for the success of new trading venues (Menkveld (2013)), no one has studied how competition between HFT firms, which is manifested in multiple firms following similar strategies, relates to the competitiveness of trading venues or the concentration of trading in the market.

We therefore examine, for each of the five Canadian trading venues that are organized as electronic limit-order books, whether more correlated HFT strategies on that specific venue increases the percentage of time that it features the best prices or the narrowest spreads, which we view as measures of the viability or competitiveness of the trading venue. We find that, for the smaller trading venues in terms of market share, greater competition between HFT firms within a trading venue is associated with greater viability. For the largest trading venue in terms of market share, however, we observe the opposite picture: higher correlation between HFT strategies on the dominant venue appears to be associated with a reduction in its competitive position. We further show that concentration of trading in the market as a whole is negatively related to competition in the strategies of HFT firms. This relationship, which could indicate both that HFT competition helps smaller trading venues become more viable and that greater profit opportunities in a fragmented market drive intensified HFT competition, demonstrates the interdependency in the competitive environments of both trading venues and HFT firms.

The rest of this paper proceeds as follows. The next section discusses the most relevant literature, while Section 3 provides information about our sample and data, and indicates how we identify HFT firms. Section 4 presents the correlations between the strategies of HFT firms and investigates various patterns in these correlations. Section 5 uses a principal component analysis to gain insights into competition between HFT firms as well as the nature of their strategies. Section 6 investigates the question whether correlated HFT activity exerts a systematic influence on short-interval returns or the volatility of stocks. Section 7 studies how correlated HFT activity interacts with competition between trading venues, and Section 8 presents our conclusions.

2. Review of Relevant Literature

Our paper joins a rapidly expanding body of literature on HFT in financial markets.[3] Among the theoretical contributions are those of Ait-Sahalia and Saglam (2014), Hoffmann (2014), Biais, Foucault, and Moinas (2015), Foucault, Hombert, and Rosu (2015), Han, Khapkp, and Kyle (2015), Jovanovic and Menkveld (2015), and Rosu (2015). In particular, Jarrow and Protter (2012) show that, when HFT firms respond to common signals, their correlated activity affects

[3] For recent surveys on the topic of HFT see Jones (2013) and Goldstein, Kumar, and Graves (2014).

the market price, increasing market volatility and generating abnormal profits for these firms. While we indeed show that the strategies of HFT firms are correlated, we find that the market-wide measure of cross-sectional correlation between HFT strategies affects the volatility of most stocks negatively, not positively. Budish, Cramton, and Shim (2014) as well as Menkveld and Zoican (2014) model HFT firms that pursue heterogeneous strategies in the market, which we also document empirically.

Many empirical contributions focus on intraday analysis of aggregate HFT behavior (e.g., Carrion (2013), Hasbrouck and Saar (2013), Hirschey (2013), Brogaard, Hendershott, and Riordan (2014), Jarnecic and Snape (2014), and Kirilenko, Kyle, Samadi, and Tuzun (2014)). Several papers use data on trading by individual HFT firms, rather than aggregate behavior, to investigate HFT strategies (Hagstromer and Norden (2013), Baron, Brogaard, and Kirilenko (2014), Benos and Sagade (2015), and Hagstromer, Norden, and Zhang (2014)), although they focus predominantly on whether HFT firms are demanding or supplying liquidity. Clark-Joseph (2014) uses index futures data from the CMA to examine exploratory trading by HFT firms.

More closely related to our analysis, Hagstromer and Norden (2013) find that activity of HFT firms that predominantly supply liquidity mitigates intraday volatility, which complements our finding pertaining to the relationship between HFT inter-firm competition and volatility.[4] Breckenfelder (2013) and Brogaard and Garriott (2014) examine one aspect of competition: the entry and exit of HFT firms. Specifically, Brogaard and Garriott have data from one alternative trading system in Canada, and show that new entrants take volume away from incumbents even as they increase the overall market share of HFT firms—although the effects decrease with each successive entry. They also find that market liquidity improves after the entry of an HFT firm and deteriorates after an exit (especially when there are only one or two HFT firms trading in a given stock). Breckenfelder uses data from the Stockholm Stock Exchange and finds the opposite result: deterioration of liquidity for entries of HFT firms and improvement for exits. Menkveld (2013) examines the strategy of one HFT firm and makes the case that this particular firm

[4] Brogaard, Riordan, Shkilko, and Sokolov (2014) identify short intervals with large price movements and show that NASDAQ HFT firms in the aggregate supply rather than demand liquidity during these intervals, hence possibly dampening volatility. Hasbrouck and Saar (2013) also find that aggregate HFT activity appears to lower the intraday volatility of NASDAQ stocks.

enhances the viability of a new trading venue, which is related to our result that competition between HFT firms is positively related to the viability of smaller trading venues and negatively related to the viability of the dominant trading venue.

Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) investigate algorithmic trading on the foreign-exchange EBS platform. While they observe only the aggregate trading of algorithmic traders, they create a measure of correlated algorithmic trading by comparing the frequency with which algorithmic traders are on both sides of a transaction with a benchmark model under the assumption of independent matching of algorithmic traders and humans. The higher their measure, the fewer triangular arbitrage opportunities are observed in the market (and hence the more efficient are prices), but they find no relationship between their measure and the autocorrelation of returns (or excess volatility). Benos, Brugler, Hjalmarsson, and Zikes (2015) use transactions data from the London Stock Exchange to study how ten HFT firms that are regulated by the UK Financial Conduct Authority interact with each other. They use vector autoregressions to show that there is a positive dynamic relationship between HFT firms: aggressive buying by one firm tends to follow aggressive buying by another firm (and similarly for aggressive selling), and firms tend to trade in response to the past trading activity of other firms. Benos et al. construct a measure of concurrent directional trading on the part of their ten HFT firms that is meant to capture correlated behavior and show that it has positive contemporaneous and lagged relationships with returns.

Lastly, our paper joins several other papers that use Canadian order-level data to investigate HFT-related issues. In particular, Malinova, Park, and Riordan (2014) study the cost of trading around changes in market structure that impacted mainly HFT firms and other algorithmic traders, Comerton-Forde, Malinova, and Park (2015) study the nature of liquidity provision around changes in dark trading regulation, and Korajczyk and Murphy (2015) examine HFT liquidity provision to large institutional trades.

3. Sample and Data

Our data come from the Investment Industry Regulatory Organization of Canada ("IIROC"), which is the national self-regulatory organization that oversees all dealers and equity trading venues in Canada (both exchanges and alternative trading systems). All trading venues are required to provide data feeds to IIROC, which performs both real-time and post-trade market surveillance of trading activities. Traders need to obtain an IIROC membership to directly connect to trading venues in Canada, and IIROC admits only security dealers as members. Other financial firms, such as asset managers, banks, insurance companies, and proprietary trading firms can trade through dealers' brokerage arms or via direct market access (DMA) arrangements provided by dealers. DMA arrangements allow non-dealer trading firms to directly access various trading venues without having to hand over their orders to brokers for execution.

During our sample period (June 2010 through March 2011), Canada has five trading venues organized as electronic limit-order books that trade stocks listed on the Toronto Stock Exchange: Alpha ATS Limited Partnership (ALF), Chi-X Canada ATS (CHX), Omega ATS (OMG), Pure Trading (PTX), and the Toronto Stock Exchange (TSX).[5] Trading on crossing networks ("dark trading") in Canada during our sample period is limited to essentially one dark pool (MATCH Now) with no more than 3% of the market share.[6]

3.1 Sample

Our empirical work is carried out on 30 trading days that are selected to capture variation across market conditions. We rank the daily returns of the S&P/TSX Composite Index from June 2010 through March 2011, and select the 10 worst days (down days), the 10 best days (up days), and the 10 days centered on and closest to zero return (flat days). This design allows us to examine whether the correlation structure of HFT strategies depends on market conditions (as summarized by the daily return on a broad index).

Our sample stocks consist of 52 constituents of the S&P/TSX 60 index, which accounts for approximately 73% of Canada's total equity market capitalization. Eight stocks are excluded from the 60-stock index, as they were converted from income trusts to corporate structures (five stocks), were delisted (one stock), had their symbols changed (one stock), or were listed for less

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[5] Alpha became a stock exchange on April 1st, 2012. In July 2012, Alpha was acquired by the TMX Group, which also owns TSX. During our sample period, however, Alpha and TSX were independent trading venues.

[6] MATCH Now also provides a real-time data feed to IIROC and is included in our data. Liquidnet Canada, another dark pool, executed only a few trades each day during our sample period. As a result, IIROC did not require it to participate in the real-time centralized data feed, instead requiring it to submit trade information manually at the end of the trading day.

than one year before the start of our sample period (one stock). For further analysis, we sort the sample by market capitalization and divide it into two subsamples, Large and Small, with equal numbers of stocks in each subsample. Panel A of Table 1 presents summary statistics for the sample stocks used in the study.[7] The mean market capitalization is 19.4 Billon Canadian Dollars (henceforth, CAD), with an average stock price of 39.1 CAD, and average daily volume of 78.2 Million CAD. The panel clearly shows that our sample period encompasses three distinct market conditions: the average daily returns of stocks on down, flat, and up days are –1.72%, –0.08%, and 1.66%, respectively.

3.2 Data

We obtain order-level data from IIROC that cover all Canadian trading venues. The data contain information about order submissions, cancelations, modifications, and executions with 10-millisecond time stamps. The time stamps from all trading venues are synchronized with the regulator's time stamps and reflect the local time at which the message (which is a general term used for submissions, cancelations, and executions of orders) is processed. The record of each message contains several pieces of information: ticker symbol, order side (buy or sell), trading venue, price, total quantity, non-displayed quantity, broker ID, trader ID, order type (e.g., client orders, inventory trading), various flags (e.g., short sell, market on close, opening trade), and order/trade ID. Trade messages are identified as buyer-initiated or seller-initiated. Events in the order's life, including modification, partial fill, full fill, and cancellation are identified with the same order ID.

Obtaining comprehensive information on each firm's activity across several trading venues in a fragmented market is a challenge for studies of HFT. IIROC requires that the same trader ID be used on all trading venues, which allows us to efficiently track firms' trading activities in the entire market. Most HFT firms in Canada do not operate as licensed dealers but rather gain access through DMA (Direct Market Access) arrangements with one or multiple dealers. We obtain tables that identify the trader IDs of all trading firms that use DMA

[7] Data on stock characteristics are obtained from the Summary Information Database of the Canadian Financial Markets Research Centre (CFMRC).

arrangements. Hence, we are able to accurately detect HFT firms' activities irrespective of whether they trade via multiple DMA arrangements with dealers or use multiple trader IDs.

3.3 Identifying HFT Firms

A key feature of our paper is that we use our own procedure to identify HFT firms based on a variety of quantitative and qualitative criteria rather than adopting a classification provided by an exchange. Since we have both trader IDs and a mapping of the trader IDs to the firms, we aggregate all trader IDs that belong to the same firm. We operate at the firm level because there are no rules (to the best of our knowledge) that guide how firms use Trader IDs. One possible concern is that firms assign multiple Trader IDs to the order flow of an algorithm and send orders via DMA arrangements with multiple dealers to make it more difficult for regulators to ascertain their activity. We choose to work at the HFT-firm level to make our analysis robust to whatever gaming could be going on in terms of the firm's discretionary assignment of Trader IDs to its orders.[8] If an HFT firm uses multiple algorithms and actually designates a separate Trader ID to each algorithm, our procedure will lump them together, although the principal component analysis we implement in Section 5 could potentially tease out these separate strategies.

We use an out-of-sample procedure to identify HFT firms to ensure that the identification is exogenous to the empirical analysis we carry out in the paper. Specifically, our procedure uses data from the 22 trading days in September 2010 to identify the HFT firms, while we carry out the empirical work on the 30 down, flat, and up days as described in Section 3.1.[9] We compute several measures for each trading firm: (1) the orders-to-trades ratio (defined as submissions and cancellations of limit and marketable orders divided by trades), (2) the number of times the firms' intraday inventory positions cross the end-of-day positions (or zero), (3) cross-trading-venue activity in the same time-stamp or a neighboring time-stamp, (4) median time-to-cancelation of non-marketable limit orders, (5) and number of daily trades. For each measure, we

[8] For dealers that may have brokerage arms in addition to proprietary trading operations, we exclude orders and trades made in the capacity of an agent, and include in our measurement of their HFT activity only those orders and trades identified in the order type field as proprietary activity.

[9] To ensure that the firms we identify operate during our sample period, which consists of 30 down, flat, or up days (none of which took place during September 2010), we require HFT firms to be active (i.e., to trade) in at least 10 out of the 30 days.

establish a criterion that identifies HFT activity. For example, an orders-to-trades ratio greater than 20, at least five times at which the intraday inventory position crosses zero (or the end-of-day inventory position), or cross-trading-venue activity occurring at least 1,000 times per day. Some firms satisfy more than one criterion, but the use of multiple criteria is motivated by our desire not to limit our sample to firms with high orders-to-trades ratios in order to allow for HFT firms that implement a variety of algorithms. For example, HFT firms that engage in arbitrage activity could have low orders-to-trades ratios because they carry out their strategies using marketable orders.

We use two qualitative criteria to help us identify HFT firms. First, trading firms that participate in the Toronto Stock Exchange Electronic Liquidity Providers Program are categorized as HFT. This is a program that offers fee incentives to firms that use proprietary capital and high-frequency electronic trading algorithms to provide liquidity on the exchange. ELPs are either independent proprietary trading firms or proprietary trading desks within large banks or financial firms, and the program requires that they trade passively at least 65% of their volume.

Second, we search in newspapers and on the web for information about the firms. Some firms have web sites on which they state that they engage in proprietary trading or explicitly state that they pursue high-frequency strategies. Other firms are mentioned in newspaper articles as engaging in HFT. We use this information to supplement our quantitative analysis and ensure that we identify HFT firms even if they do not satisfy some of the quantitative data criteria. Our procedure results in 31 firms identified as HFT firms. Some of these firms have a direct market access (DMA) arrangement with dealers while others are dealers engaged in proprietary trading. Our goal in this identification procedure is to ensure that our sample contains as complete a set of HFT firms that operate on these trading venues as possible.

We further categorize the set of 31 HFT firms into three subgroups by market share of trading volume: MS1 consists of four firms with market share greater than 4%, MS2 consists of six firms with market share between 1% and 4%, and MS3 consists of the rest of the firms. Similarly, we categorize HFT firms into three subgroups based on their orders-to-trades ratios:

OT1 consists of five firms with orders-to-trades ratios greater than 150, OT2 consists of six firms with orders-to-trades ratios between 50 and 150, and OT3 consists of the rest of the HFT firms.

Panel B of Table 1 provides summary statistics for the 31 HFT firms. The average market share of volume of a firm in MS1 is 6.58% (computed relative to total two-sided volume in the market), with 2.67% and 0.19% for the average firm in MS2 and MS3, respectively. Overall, these HFT firms have 46.4% of the market share in terms of volume. The average orders-to-trades ratio for the firms in OT1, OT2, and OT3 is 323.9, 116.3, and 27.8, respectively.[10] The mean (median) number of times the intraday inventory position of a firm in our sample crosses its end-of-day inventory increases with market share: 6.4 (2.2) for MS3, 21.3 (5.2) for MS2, and 133.0 (123.7) for MS1. Overall, these HFT firms trade often and send many messages to the market. The average number of daily trades of a firm in our sample is 19,445, but it ranges from 102,035 for firms in MS1 to 2,489 for firms in MS3. Similarly, the number of daily messages a firm sends to the market (submissions and cancelations of non-marketable limit orders as well as the number of marketable orders) is 1,063,974, ranging from 5,496,423 for firms in MS1 to 239,157 daily messages on average for firms in MS3.

4. Correlations of HFT Strategies

In this section we establish some stylized facts about the correlated behavior of HFT firms along two dimensions: time-series and cross-sectional. The time-series dimension indicates whether multiple HFT firms tend to intensify and diminish their activity at the same time in a particular stock. The cross-sectional dimension indicates whether multiple HFT firms tend to be more or less active in the same stocks at a particular time interval. We present the correlations separately for 1-second, 10-second, and 60-second intervals (henceforth, I1, I2, and I3, respectively) to see if their magnitude is affected by the interval length.

Throughout the paper, we use terms “strategy,” “activity,” and “behavior” of HFT firms somewhat interchangeably. While a strategy is often thought of as a plan of action, we are not privy to the specifics of the algorithms employed by each HFT firm. As empirical researchers

[10] The mean orders-to-trades ratio is computed as the average of the orders-to-trades ratios of the individual HFT firms, and therefore due to its non-linear nature and the heterogeneity of the firms is not equal to the cross-sectional mean number of messages divided by the cross-sectional mean number of trades.

who can measure only the outcomes of a strategy (e.g., submissions and cancelations of orders), however, it is natural to recognize that the actions we observe are the manifestations of a strategy, and hence treat measures of these actions as representing the strategy. Furthermore, there are multiple ways in which one can operationalize the activity of HFT firms for measurement purposes. We examine measures that count actions only if they are intentionally initiated by the firm at the instant the action is taken (e.g., the submission of an order), and we also examine a measure of trading that includes executed limit orders for which the timing of execution is not directly under the control of the firm.

4.1 Time-Series Correlations

We begin by looking at three measures of HFT firm activity in an interval. The first, MSG, is defined as the sum of three components: the number of submissions of non-marketable limit orders, the number of cancelations of non-marketable limit orders, and the number of marketable order executions. Hence, MSG for an interval (say one second) describes the total number of messages that the HFT firm sends to the market during the interval to initiate a change in its position (either in terms of presence in the limit order book or to transact immediately).[11] The second measure, TRD, is the number of trades made by an HFT firm in an interval. The trades could be the result of initiating marketable orders or executions of previously submitted limit orders that rested in the book. Therefore, TRD measures the change in inventory position of the HFT firm. The last measure, LMT, is comprised of all submissions and cancelations of non-marketable limit orders, and hence describes the actions the firm takes in the interval to change its presence in the limit order book.

The time-series correlations are computed as follows. Let Y_{itk} be the measure of HFT firm activity for stock i, interval t, and firm k. If k and l are two HFT firms, then $Cor_i(Y_k,Y_l)$ is the correlation over all intervals in the sample period between the measures of the two firms for stock i. There are $0.5*N*(N-1)$ such correlations for a group of N HFT firms, and our time-series

[11] An AMEND order type is considered as two messages, a cancelation and a resubmission, for the purpose of our measures. Our measures include both non-displayed and displayed orders. A refresh of an iceberg order (when the displayed part is executed and shares from the non-displayed part become displayed) does not lead to a change in price or quantity, hence only the initial order is counted. This standardizes the treatment for the various order types according to their economic functions, and lets us summarize all activity in terms of submissions and cancelations of non-marketable orders and executions of marketable orders.

correlation, $Cor(Y_i)$, is computed as the average of these correlations for all pairs of HFT firms. Table 2 presents the mean time-series correlations for the set of all HFT firms as well as for firms in our market share subgroups (MS1, MS2, and MS3) and orders-to-trades ratio subgroups (OT1, OT2, and OT3).

The first observation we make is that the magnitude of the correlation appears to be increasing in the market share of the HFT firms. For example, the correlation of the MSG measure for the MS1 subgroup, comprised of the four HFT firms with the largest market share of volume, is 0.249, which is much higher than the correlations for MS2 and MS3 (0.044 and 0.030, respectively, for the 1-second interval). Looking across the panels of the table, the same pattern can be observed for trades as well as for submissions and cancelations of limit orders. While the correlations we observe when considering the strategies of all HFT firms are rather low (e.g., 0.049 to 0.078 for MSG or 0.036 to 0.067 for TRD, depending on the interval length), the correlations between the activity of firms in MS1, which together constitute 26.3% of the market volume, are much higher and can reach 0.446 for trades or 0.322 for overall message activity in larger stocks (I3). This means that the larger HFT players in the market appear to follow more highly correlated strategies, which could potentially increase the likelihood of market impairment.

The second observation we make is that time-series correlations involving larger stocks are higher than those involving smaller stocks, especially for HFT firms in the MS1 subgroup. For example, the correlation between messages for the MS1 group is twice as high for larger stocks as for smaller stocks (0.341 vs. 0.158). Menkveld (2013) shows that the profitability of a single HFT that functions as a market maker is higher in large stocks than in small stocks. Greater profit potential in larger stocks could mean more room for multiple players to follow similar strategies, and hence we observe higher correlations. The third observation we make is that when we consider the total activity (MSG) of the largest HFT firms, there is no deterioration in the correlations as we move from 60-second intervals (0.237) to 1-second intervals (0.249). The high correlations at all interval lengths suggest that the strategies of these large HFT firms respond to the same stimuli.

4.2 Cross-Sectional Correlations

To study whether the strategies of multiple HFT firms are correlated across stocks we compute the cross-sectional correlations as follows. If k and l are two HFT firms, then $Cor_t(Y_k,Y_l)$ is the correlation for a specific interval t over the stocks in the sample between the measures of the two firms. There are $0.5*N*(N-1)$ such correlations for a group of N HFT firms in each time interval t, and our cross-sectional correlation, $Cor(Y_t)$, is computed as the average of these correlations for all pairs of HFT firms. Figure 1 shows an intraday plot of the 1-second cross-sectional correlations of the overall activity measure (MSG). We observe a reverse U-shape in which correlations increase rapidly in the first 10 minutes of trading, continue to increase modestly until around noon, and then decline after 3:30pm. Over a good portion of the trading day, however, the levels of these correlations seems to be relatively stable.

In Table 3 we present the mean cross-sectional correlation for the three measures: MSG, TRD, and LMT. As with the time-series correlations, we observe higher correlations for the HFT firms with the largest market shares (MS1). In general, however, the magnitude of the cross-sectional correlations is larger than that of the time-series correlations. For example, the correlations in trades for all HFT firms is 0.313 for 1-second intervals (versus 0.036 for the time-series correlation), and for the HFT firms with the largest market share it is 0.417 (versus 0.268 for the time-series correlation). The correlations between HFT firms for submissions and cancelations of limit orders (LMT) are 0.355 for MS1 and 0.197 for all HFT firms, compared with 0.245 and 0.048, respectively, for the time-series correlations. While in principle such high cross-sectional correlations could be driven by fundamental stock attributes, it is interesting to consider whether the influence runs in the opposite direction and the HFT strategies themselves introduce a systematic component into the trading environment of stocks. We investigate this issue in Section 6.

4.3 Directional Trading and Market Conditions

The simple correlation analysis also lends itself to examining other issues that are directly relevant to the economics of HFT strategies and the remaining analysis in this paper. The first issue we address concerns the distinction between correlations in directional activity versus those in total activity. The empirical literature on herding in financial markets (e.g., Wermers (1999), Khandani and Lo (2007, 2011), Choi and Sias (2009), Pedersen (2009), Brown, Wei, and Wermers (2014)) recognizes the destabilizing influence that simultaneous actions in one direction (buying or selling) by institutional investors can have on asset prices. If this is also of critical importance with respect to HFT firms, one should look at how directional HFT activity (buy orders minus sell orders) correlates across firms rather than total activity (buy orders plus sell orders) that we analyze in Table 2 and Table 3. In other words, the question we ask here is whether HFT firms potentially make the market more fragile by selling at the same time or by withdrawing from the market altogether at the same time.

Figure 2 compares the magnitudes of the time-series (Panel A) and cross-sectional (Panel B) correlations for total HFT activity (buy plus sell orders) and directional HFT activity (buy minus sell orders). The picture that emerges from the figure is striking: the correlations involving total activity are four to ten times the magnitude of those involving directional activity. For example, the 1-second cross-sectional correlation of MSG for all HFT firms is 0.200 versus 0.023 for NetMSG, and similarly for the firms with the highest market share, the MSG correlation is 0.360 compared with 0.045 for NetMSG. The picture that emerges is consistent with HFT firms that operate simultaneously on both sides of the market, rather than pursuing very strong directional trading for long periods of time. In other words, it appear as if much of HFT firms' activity involves either placing buying and selling orders simultaneously or buying and selling very rapidly within the same 1-second interval.[12]

If correlations in directional trading are low, we would also expect the inventory positions of the HFT firms to have low correlations. While we cannot directly observe the inventory of the HFT firms, we can track their trading everywhere in Canada due to the comprehensive nature of our dataset.[13] We therefore compute for each HFT firm a measure of its inventory position (in CAD) in each interval under the assumption that the HFT firm starts with zero inventory each morning. Panel A of Table 4 presents the time-series and cross-sectional

[12] The same conclusions apply when we examine directional versus total activity using other measures of HFT strategies (e.g., TRD or LMT).

[13] Some stocks are cross-listed in the US, though, and HFT firms could potentially be trading in the U.S. as well (which we cannot observe in our data).

correlations for the inventory positions at the 1-second interval. The correlations are indeed very low, with magnitudes of 0.045 and 0.063 for the time-series and cross-sectional correlations of MS1 firms, respectively. The low directional activity and inventory correlations are somewhat reassuring in terms of market stability because they suggest that directional herding by HFT firms is unlikely to destabilize markets.

Another concern that one may have is that HFT firms react to adverse market conditions (in terms of declining prices) by changing their strategies and hence bring on greater fragility. Hasbrouck and Saar (2013) analyze the impact of a low-latency activity measure, which they view as a proxy for the activity of HFT firms, in two periods: one in which the NASDAQ Composite Index went up 4.34% and another in which the index went down 7.99%. They find that the impact of their proxy on market quality was similar in both periods. The design of our study is meant to enable us to analyze this question in greater detail. Specifically, we carry out the empirical work on the ten days with the most negative index returns from June 2010 through March 2011 as well as on the ten best days and ten days in which the index moved very little. Panel B of Table 4 presents the time-series and cross-sectional correlations of the overall HFT activity measure (MSG) at the 1-second interval length separately for down, flat, and up days, alongside the correlations for the entire 30-day period.

We observe that the time-series correlations are very similar: 0.055, 0.057, and 0.054 for down, flat, and up days, respectively. The cross-sectional correlations exhibit a similar pattern: 0.355, 0.361, and 0.362 for down, flat, and up days, respectively, for the trading strategies of the largest HFT firms in terms of market share (MS1). The summary statistics in Table 1 show that sample stocks lose 1.72% each day on down days, are essentially unchanged at –0.08% on flat days, and gain 1.66% on up days. We do not observe that these three distinct market environments result in correspondingly varying correlations between the strategies of HFT firms.[14] This, as well, is reassuring in terms of market fragility, although it does not preclude the possibility that the correlations would increase during times of extreme stress such as the Flash Crash in the US. The absence of such extreme episodes in Canadian markets, however, prevents

[14] The same conclusion also applies to other measures of HFT strategies (including TRD, LMT, and inventory positions).

us from examining this possibility empirically. Given our findings in this section, the analysis in the rest of the paper focuses on total (rather than directional) activity measures, and we present results for the entire sample period rather than breaking them down by market conditions.[15]

5. Principal Component Analysis of HFT Strategies

Our goal in this section is to examine the strategies of all HFT firms across stocks and over time and identify regularities in the manner in which they correlate. We study this issue by performing a principal component analysis in which the HFT firms' strategies are the "variables" that we seek to summarize. This analysis helps us understand HFT strategies in several ways. First, it tells us whether there are underlying common strategies that represent much of the variability in the HFT firms' activity. Second, it shows us the extent of the resemblance between each HFT firm's strategy and these underlying common strategies. Third, we are able to analyze the empirical representation of these underlying common strategies (i.e., the principal component scores) and how they relate to the market environment to gain a better understanding of these strategies.

5.1 HFT Firm Loadings on the Principal Components

The input for our analysis is a matrix of data in which there are 31 columns (one for each HFT firm) and the number of rows is equal to the number of stocks times the number of intervals in the sample period. While in the previous section we analyzed the time-series and cross-sectional correlations separately, here the stocks are stacked one on top of another and we analyze both sources of variation in HFT activity together. The measure of HFT activity that we use to characterize their strategies is MSG, which is comprised of all messages they actively send to the market in an interval (submission of non-marketable limit orders, cancelation of non-marketable limit orders, and marketable limit orders that result in trade executions).[16] Given the low latency that characterizes HFT strategies and our finding that the correlation structure in MSG does not

[15] We verified that the results of all the tests we present do not differ materially on down, flat, or up days.

[16] We provide the results using only the MSG measure to economize on the presentation in terms of the number of tables and the length of the discussion. We carried out the principal component analysis for other measures as well, and the insights we obtain are not very sensitive to the particular measure used.

break down as we shorten the length of the interval, we carry out the analysis using the shortest time intervals (one second).

When conducting the analysis we must first choose how many principal components to retain for subsequent analysis.[17] From an economic perspective, the question essentially asks how many separate underlying strategies are common to a significant number of the HFT firms in our sample. As usual with such data-driven methodologies, that determination is made based on patterns observed in the data. Specifically, we conduct a scree test by plotting the eigenvalues of the principal components and looking for a natural break. Since there are 31 HFT firms, each firm contributes 100/31=3.2% of the variance. However, meaningful principal components would naturally explain more of the variance, and our analysis suggests that the first principal component explains 11.66% of the variance, the second 4.5%, and the third 4.02%, together accounting for over 20% of total variation. We observe that further principal components account for less than 4% of the variance each, and there seems to be a natural break after three components. Hence, we extract three principal components for subsequent analysis.

The second choice when implementing the methodology involves determining the rotation of the principal components. The rotation is meant to help in interpreting the loadings, which are the coefficients of each HFT firm on each of the principal components. We utilize the commonly used varimax orthogonal rotation. The factor loadings using this rotation have a simple interpretation: they are equivalent to bivariate correlations between the HFT firms' strategies and the underlying common strategies represented by the principal components. Our conclusions are robust to using other rotations.[18]

Table 5 presents the loadings from the principal component analysis of the MSG measure. Each principal component can be viewed as representing a certain underlying common strategy that multiple HFT firms follow and which results in the correlated behavior of the firms.

[17] In a principal components analysis, the first component accounts for the largest portion of total variance in the observed HFT strategies and successive principal components account for portions of the variance that were not accounted for by previous principal components.

[18] In particular, we consider whether our conclusions change when using an oblique rotation (promax) that allows the principal components to be correlated. The results we obtain with this rotation are very similar to those with the orthogonal rotation: the loadings are similar in magnitude and the same HFT firms load on the same principal components. Furthermore, the regressions on components scores that we present in Section 5.2 yield similar conclusions irrespective of whether an orthogonal or an oblique rotation is used.

In other words, we use the terms "underlying common strategy" and "principal component" interchangeably, although strictly speaking the principal component is a linear combination of the MSG measures of the 31 HFT firms and therefore represents correlated behavior in terms of their actions. As before, we treat these actions as the outcomes of strategies, and hence the principal component represents a common element in the firms' strategies, which most likely respond to the same economic conditions and represent a similar business model. The larger (i.e., closer to 1) the loading of a particular HFT firm on a principal component, the greater the similarity of the HFT firm's strategy to that underlying common strategy. For each principal component, the loadings are sorted from the most positive to the most negative, and the 31 firms are represented by F01 through F31. Looking at the first principal component, for example, we observe that firm F14 has a very large positive loading (0.76) on the first principal component, signifying high correlation with the underlying common strategy represented by this component.

While the choice of a cutoff for the magnitude above which a loading is considered economically significant is somewhat arbitrary, it helps to have some cutoff in mind when considering the results. We consider loadings significant from an economic standpoint if they are greater than 0.35 and mark them with an asterisk on the table. Eight HFT firms have significant loadings on the first principal component, suggesting that it represents a strategy that is common to these eight firms. Similarly, there are six firms with significant loadings on the second principal component, ranging from 0.71 to 0.35, and four HFT firms with significant loadings on the third principal component. Four firms appear to follow more than one strategy: F31 and F28 (with significant loadings on the first and second principal components) and F17 and F20 (with significant loadings on the first and third principal components).

The challenge in interpreting the results of a principal component analysis lies in understanding the economic nature of the underlying common strategies represented by these principal components. It is possible to obtain relevant information by observing whether firms that load more heavily on a certain component share something else in common. Earlier we categorized firms into groups according to market share or orders-to-trades ratios. In Table 5 we note for each firm with a significant loading its membership in the high-market-share subgroups (MS1 and MS2) and high-orders-to-trades ratio subgroups (OT1 and OT2). Five out of the six

HFT firms that load on the second principal component have high market shares, suggesting that this could be a market-making strategy. In contrast, the two other principal components are dominated by firms with high orders-to-trades ratios, suggesting that these underlying common strategies require frequent submissions and cancelations of limit orders.

5.2 Regressions on Principal Components' Scores

A more direct way of examining the nature of the underlying common strategies represented by the principal components is to investigate another output of the principal component analysis: the component scores. Each principal component is essentially a linear combination of the observed variables (the 31 HFT firms' MSG measures), and the component scores are computed from the observed variables using the estimated loadings provided in Table 5 as weights. There is a separate score for each principle component in each time interval, allowing us to regress them on various market variables and examine the relationships between these component scores and the market environment.

We use a set of 13 variables that describe the market environment. The first two represent the degree of integration of the Canadian market. Specifically, TimeAorB is the percentage of time that the three trading venues with the highest market share post the same bid or ask prices, while TimeSprd is the percentage of time that the three trading venues have the same bid-ask spread. The next five variables represent the state of liquidity in the market as a whole (aggregated across all trading venues): total depth at the Market-Wide Best Bid or Offer (henceforth, MWBBO), total depth up to 10 cents from the MWBBO, depth imbalance at the MWBBO (defined as the absolute value of the difference between the number of shares at the bid and at the ask), depth imbalance up to 10 cents from the MWBBO, and percentage MWBBO spread.[19] The next three variables represent market conditions in the interval: return (computed from the last transaction price in each interval), volatility (computed as the absolute value of

[19] All measures are time-weighted. Messages are time-stamped to 10 milliseconds. There are orders that are submitted and canceled (or executed) within the same time stamp. When we consider orders that stay in the book to provide liquidity (e.g., for our measures of depth), we assume that a submitted order stays in the book for 10 milliseconds. The exceptions are the following special order types: immediate or cancel orders (IOC), fill or kill orders (FOK), all or nothing orders (AON), dealer's AG orders (that are generated to fulfil their market making obligations and execute against an incoming order), odd lot orders (OL), and marketable orders, which are assumed to be executed or canceled upon arrival to the market and hence are not added to the limit-order book.

return), and the average time between trades in the interval. The last three variables represent information about HFT: the number of shares traded among the HFT firms in the interval (#HFT), the number of shares traded between the HFT firms and others (#NoHFT), and the aggregate position of all HFT firms in Canadian dollars (cumulative from the beginning of the day and assuming that all of them start the day with zero inventory).

We are interested primarily in contemporaneous relationships, which is why the first three columns of Panel A of Table 6 show the results of regressions in which we line up the component scores with observations of the market environment over the same interval. We also provide, in the same table, regressions in which the component scores are regressed on lagged and lead values of the market variables. The idea behind comparing lagged and lead regressions with the contemporaneous relationship is to see whether strategies appear to lead changes in the market environment or respond to them. Looking across the columns, it is striking how the signs of the coefficients on almost all variables are the same in the contemporaneous, lagged, and lead regressions. There are some exceptions (e.g., the coefficients on #HFT and #NoHFT on the third principal components), but they seem to involve coefficients that are very small and hence do not represent material influences. The similarity between the contemporaneous, lagged, and lead regressions suggests that HFT strategies respond to certain market or book conditions that surround the 1-second intervals. In other words, we do not observe evidence consistent with the idea that HFT strategies create a pronounced change in the market environment such that the conditions in the following interval differ from the conditions in the preceding or contemporaneous intervals.

Panel B of Table 6 shows just the coefficients on the contemporaneous regressions together with t-statistics computed from double-clustered (along both the stocks and intervals dimensions) standard errors to focus our attention on the most significant relationships. We noted above that the HFT firms that load on the second principal component have high market shares, suggesting that it could represent a market-making strategy. We observe that the coefficients on the market integration variables (TimeAorB and TimeSprd) are both positive, which means that such a strategy is more active when prices and spreads are aligned across the trading venues, and may represent times at which market-making activity is most profitable (i.e., when market-making firms earn the spread rather than lose to changing prices). This underlying common strategy is more active when there is greater depth throughout the book but less depth at the best prices, creating ample opportunities for market making without excessive risk. Hence, the regression results support the interpretation that this underlying common strategy represents market making.

The underlying common strategies represented by the other two principal components appear to take advantage of very different trading opportunities. HFT firms that load on the first principal component are more active when prices are more volatile, and there is both greater imbalance and less depth at the best prices. These are times at which some trading venues post better spreads than others (a negative coefficient on TimeSprd) and there appears to be a need to move liquidity across trading venues, suggesting that this underlying common strategy probably represents a cross-venue arbitrage strategy. Firms that load on the third principal component are also more active when prices are more volatile, but also at times at which there is less depth throughout the book and the best prices are not the same across the trading venues (negative coefficient on TimeAorB). This pattern of relationships with the market environment could represent either a price arbitrage strategy or a short-horizon directional strategy that takes advantage of momentum in prices. Such short-horizon directional strategies would be more profitable when there is less depth throughout the book and prices are fragmented across the trading venues.

There are two main takeaways from this exercise. First, there is heterogeneity in the underlying common strategies, as evidenced by the relationships we document between each principal component and variables that represent various aspects of the market environment. This is important insofar as the insights generated by thinking about HFT as one "entity" could be rather limited because aggregating HFT activity hides heterogeneity in strategies that is important to understanding the manner in which HFT firms interact with markets and ultimately affect them. Second, each underlying common strategy is pursued by multiple HFT firms: eight, six, and four HFT firms load on the first, second, and third principal components, respectively. This represents a high degree of competition in the market because the anonymous nature of trading in electronic limit-order books constitutes a formidable hurdle for collusive behavior. In other words, evidence that each strategy is followed by several firms suggests that there is competitive pressure that drives down possible rents earned by these HFT firms for their activity in the market.[20]

6. Correlated HFT Activity and Returns

The relatively high cross-sectional correlations we document in Section 4 beg the question whether they could induce a systematic factor that would affect returns. Specifically, high cross-sectional correlations mean that strategies of multiple HFT firms are more active in some stocks and less active in others. It is conceivable that the activity of multiple HFT firms would impact returns over short intervals. If these firms are more or less active based on the manner in which their algorithms profit from the trading environment as opposed to fundamental factors that should affect stock returns, the extent of correlations in HFT activity could create systematic patterns in returns or volatility over and above fundamental systematic influences.

Here we stress that our focus is not on the question whether the magnitude of HFT activity creates a systematic factor but rather whether the extent of correlations in the activity of multiple HFT firms does so.[21] This is an important distinction: HFT activity undertaken by multiple firms that follow unrelated strategies across stocks is unlikely to generate a systematic influence. On the other hand, HFT activity in which multiple HFT firms engage in strategies that are highly correlated across stocks could potentially turn idiosyncratic occurrences at the microstructure level into systematic patterns in returns or volatility. If such a systematic factor is created in returns, listed companies should have a particular interest in HFT and its impact of their cost of capital. Given the interest in the manner in which HFT affects volatility, the question whether competition between HFT firms systematically influences return volatility in short intervals is also of independent interest.

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[20] The impact of competition between HFT firms on rents could depend on the specifics of the particular strategy. If one thinks of HFT firms as informed traders, the models of Holden and Subrahmanyam (1992) and Foster and Viswanathan (1993) show that it is enough to have two competing informed traders to almost instantaneously eliminate their informational advantage and have their profits vanish in a continuous market. Li (2013) takes another approach. The informed traders in her model are endowed with identical flows of long-lived private information (as opposed to one-shot long-lived private information in the aforementioned two papers). As a result, the aggregate profits of the informed traders decrease in the number of informed traders (specifically, they are inversely proportional to the square root of the number of informed traders), but do not vanish.

[21] See Skjeltorp, Sojli, and Tham (2013) for a study of the impact of algorithmic trading on asset prices.

In this section we examine these two questions by running the following regressions:

$$r_{it} = a_{0i} + a_{1i}Cor\left(Y_t\right) + a_{2i}Y_{mt} + a_{3i}r_{mt} + a_{4i}\left|r_{mt}\right| + a_{5i}Volume_{mt} + error_{it} \tag{1}$$

$$\left|r_{it}\right| = a_{0i} + a_{1i}Cor\left(Y_t\right) + a_{2i}Y_{mt} + a_{3i}r_{mt} + a_{4i}\left|r_{mt}\right| + a_{5i}Volume_{mt} + error_{it} \tag{2}$$

where r_{it} is the return for stock i in interval t, and $|r_{it}|$ is the absolute value of the interval return (which we use as our measure of interval volatility).[22] Equation 1.1 originates in a market model for returns, where r_{mt} is the value-weighted return of all stocks in our sample.[23] Our chief interest is the impact of the cross-sectional correlation, $Cor(Y_t)$, which is a market-wide attribute of the extent of competition (or similarity in strategies) between HFT firms that is computed for each interval in the 30-day period for each of the three measures of HFT strategies investigated in Section 4: MSG (all messages an HFT firm sends to the market), TRD (trades), and LMT (only submissions and cancelations of non-marketable limit orders).

We add three control variables to the regressions in 1.1 and 1.2. First, since our goal is to study the effect of correlation in HFT strategies rather than the magnitude of HFT activity per se, we add as a control the magnitude of HFT activity in the market, Y_{mt}, which is the sum across all HFT firms of the same measure that we use for $Cor(Y_t)$. In other words, in the regressions with MSG as the measure of HFT activity, $Cor(Y_t)$ is the cross-sectional correlation of the MSG measure in interval t, while Y_{mt} is the sum of MSG for all HFT firms and all stocks in the same interval. Conventional wisdom suggests that the activity of HFT firms is driven by volume and volatility.[24] Therefore, we control for $Volume_{mt}$ (the aggregate volume in all stocks) and $|r_{mt}|$ (the absolute value of the market return).

Panel A of Table 7 presents the results from running 52 regressions (one for each stock) in which the dependent variable is the stock's 1-second interval return (Equation 1.1). For each variable, we present the average coefficients and t-statistics (computed using heteroskedasticity-and-autocorrelation-consistent standard errors) from the individual regressions, the number of negative coefficients, the number of negative coefficients that are significant at the 5% level, the

[22] The returns we use are computed from trade prices (using the trade closest to the end of an interval).
[23] The results are similar when we use the equal-weighted rather than the value-weighted return as a proxy for the market portfolio.
[24] In fact, the decrease in HFT activity in 2011 and 2012 was attributed to a decline in volume and volatility in the market. See, for example "High-speed trading no longer hurtling forward" by Nathaniel Popper, *New York Times*, October 14, 2012, and "High frequency trading loses its luster" by Ivy Schmerken, *Wall Street and Technology*, April 1, 2013.

number of positive coefficients, the number of significant positive coefficients, and the average R-squared. The results do not lend support to the idea that competition among HFT firms creates a systematic factor in returns. In particular, the HFT cross-sectional correlation is statistically significant in only a small fraction of the individual regressions and has approximately equal numbers of positive and negative coefficients.[25] Panel B of Table 7 presents the results for all three interval lengths side by side, but to economize on the size of the table we show only the $Cor(Y_t)$ coefficients. While the R-squared of the individual stock regressions increases with interval length (to 17.33% for the 60-second interval), the picture that emerges on the impact of correlated HFT strategies is the same irrespective of the measure we use (MSG, TRD, or LMT) or the time interval: we find no evidence consistent with the hypothesis that correlated HFT strategies across stocks create a common factor in returns.

Table 8 presents the results from running 52 regressions (one for each stock) in which the dependent variable is the stock's 1-second interval return volatility (Equation 1.2). Here we observe a very different picture: the average loading on the correlation between HFT strategies is negative, and at least 42 of the 52 individual stock regressions have negative and statistically significant coefficients. Panel B of Table 8 shows that the negative effect of competition between HFT strategies on individual-stock short-interval volatility is observed irrespective of whether we use 1-seond, 10-second, or 60-second intervals. It is instructive to contrast this predominantly negative loading with the predominantly positive loadings on the magnitude of HFT activity and the volatility of the market portfolio. These positive loadings show that when there is more fundamental news in the market as a whole, prices of individual stocks move to a greater extent and HFT activity, be it arbitrage or otherwise, intensifies. The fact that the loadings on the correlation between HFT strategies are predominantly negative rather than positive suggests that the correlation between HFT strategies is a separate and distinct effect.

Why would greater cross-sectional correlation between HFT firms' strategies decrease rather than increase stock return volatility? Jovanovic and Menkveld (2015) posit that HFT firms trade on "hard information," such as price changes in same-industry stocks or the market index.

[25] Statistical tests using the magnitudes of the 52 coefficients cannot reject the hypothesis that the mean is equal to zero.

Greater competition to turn these cross-stock "private" signals into public information implies lower adverse selection costs and hence a lower price impact of trades. As short-interval (e.g. 1-second) volatility is predominantly driven by the price impact of trades (as opposed to the public release of fundamental news, which is a relatively rare occurrence for a stock), it follows that greater cross-sectional correlation between HFT strategies would decrease short-interval volatility. It is also possible that the negative loadings are driven by the impact of correlated HFT strategies on the transitory, rather than the permanent, price impact of trades if they reflect greater competition in market-making activity. If returns and order flows of various stocks are correlated, efficient market making would necessitate algorithms that consider multiple stocks (e.g., Ho and Stoll (1983)). Competition among such market-making algorithms would appear as higher cross-sectional correlations of HFT strategies, and such competition would decrease the transitory price impact of trades, lowering short-interval volatility.

We investigate the channel through which competition between HFT firms lowers the short-interval volatility of stocks by examining competition in each of the underlying common strategies represented by the three principal components from Section 5. We run a regression similar to Equation 1.2 but replace the single cross-sectional correlation that is computed as the average of paired correlations of all HFT firms with three cross-sectional correlations, each computed as the average of paired correlations only for the firms that load significantly on one of the principal components.[26] Similarly, rather than having one MSG variable as a control, we have three control variables, each aggregating the messages of the HFT firms that load on one of the principal components.

Table 9 presents the summary statistics for the regressions in the same format as Panel A of Table 8. For both the MSG and LMT measures, the second principal component seems to drive a significant portion of the relationship: its correlation is the most negative, the average t-statistic is large, and there are 38 stocks (out of 52) for which this variable has a negative and statistically significant coefficient (compared with 12 with positive and significant coefficients).

[26] There are eight HFT firms with loadings greater than 0.35 on the first principal components, six firms with such loadings on the second principal component, and four firms that load on the third principal component. The three variables that we create are not highly correlated with one another (the highest correlation is 0.3), and hence there is no difficulty in having all three of them in the same regression.

This principal component represents the underlying common strategy that we associate with market making based on the analysis presented in Section 5. As such, this result suggests that the reduction in volatility is driven by lower transitory volatility due to competition between market makers (Ho and Stoll (1983)). The regressions with the TRD measure show strong results for both the second and third principal components, which could suggest that the reduction in volatility is due in part to an underlying common strategy that impounds hard information when there is high volatility and prices are not aligned across the trading venues (which is when the strategy represented by the third principal component is most active).

To summarize, contrary to concerns that correlated HFT activity may increase market fragility, we find that competition between HFT firms that gives rise to correlated HFT activity decreases the short-interval volatility of most individual stocks.

7. Correlated HFT Activity and Market Consolidation

The current market structure for equity trading in the U.S., Canada, and many other countries is characterized by the co-existence of multiple trading venues on which the same stocks can be traded. Such trading fragmentation may create negative externalities in the form of worsened price integrity and higher costs as liquidity is scattered across the trading venues. Against these negative externalities, proponents of this structure argue that the competition it induces between trading venues results in lower fees and greater innovation in terms of trading technology and services.[27] The activity of HFT firms appears very relevant to both sides of the equation: alleviating the negative externalities of fragmentation as well as facilitating competition between trading venues.

In such a fragmented market structure HFT firms can act as market consolidators, transforming the environment into a virtual central electronic limit-order book by moving liquidity from one venue to another and ensuring that prices are the same across the trading venues. Menkveld (2013) notes that a new trading venue in Europe became viable only when a large HFT began trading on it. To attract trading, a new venue must overcome its inferior

[27] See O'Hara and Ye (2011) for a recent study of the consequences of market fragmentation in the U.S. We stress, though, that the focus of much of the recent literature has been on fragmentation caused by crossing networks (see, for example, Buti, Rindi, and Werner (2011)) while the type of fragmentation that exists during our sample period in Canada consists almost exclusively of trading venues that are structured as electronic limit-order books.

position (relative to existing trading venues) in terms of liquidity provision. The willingness of HFT firms to provide liquidity on new trading venues can therefore be essential in fostering competition between venues. What is less well understood, however, is how competition between HFT firms, which is reflected in multiple firms following similar strategies, affects the competitiveness of trading venues and the concentration of trading in the market.

7.1 Correlated HFT Strategies and the Competitiveness of Trading Venues

In this section we consider whether correlated activity undertaken by HFT firms on a particular trading venue enhances the venue's competitive position. Specifically, for each of the five trading venues that are organized as electronic limit-order books, we examine whether higher correlation of HFT strategies on that specific venue increases the percentage of time that it displays the best prices or narrowest spreads.

Panel A of Table 10 provides cross-sectional summary statistics for market share in terms of volume as well as for the two measures of trading venue competitiveness (or viability) that we use: (i) the percentage of time that the trading venue posts either the best bid or the best ask in the market (where the market is defined as the aggregation of all five trading venues), and (ii) the percentage of time that the bid-ask spread on the trading venue is the narrowest spread in the market.[28] We observe that there is a dominant trading venue in Canada with a market share in terms of volume of 69.26%. This largest trading venue displays the best price 92% of the time (averaged across all stocks in our sample), and also has the lowest standard deviation (6.1%) and the highest minimum (71.1%). Other trading venues also frequently display the best prices, although the variability in the cross section is greater. Similarly, the largest trading venue has the narrowest spread 76.8% of the time (compared with 54.2%, 36.1%, 26.9%, and 9.4% for the other four trading venues).

Not all HFT firms in our sample are very active on multiple trading venues. We therefore focus on the firms with substantial activity on all five trading venues, which we define as sending at least 10,000 messages during our sample period to each of the trading venues. Eight HFT firms satisfy this criterion, and we compute trading-venue-specific time-series correlations

[28] We note that two or more trading venues could potentially be at the best bid or ask at the same time (or similarly have the same narrowest spread).

that tell us whether the strategies of these HFT firms are correlated over time for a given stock on a particular trading venue. These correlations are similar in nature to our time-series correlations from Section 4, except they are computed for each trading venue separately using only activity on that trading venue. For each trading venue *v*, we run the following cross-sectional regression:

$$\begin{aligned} C_{iv} = a_0 + a_1 Cor\left(Y_{iv}\right) + a_2 Y_{iv} + a_3 Spread_{iv} + a_4 BBOdepth_{iv} + \\ a_5 MktCap_i + a_6 Price_i + a_7 Volatility_i + error_{iv} \end{aligned} \tag{3}$$

where C_{iv} stands for one of the two competitiveness measures for stock *i* on trading venue *v*, and we use MSG (total messages sent by the HFT firm) as our measure of HFT strategies.[29] Since our goal is to study the effect of the extent of correlation in HFT strategies rather than the magnitude of HFT activity per se, we add the magnitude of HFT activity in stock *i* on trading venue *v*, Y_{iv}, as a control variable. The next two variables, time-weighted average spread and bid-and-offer (BBO) depth, are computed separately for each trading venue and are meant to control for the liquidity environment on that trading venue. The last three control variables—market capitalization, price level, and the standard deviation of 30-minute returns over the sample period—are meant to control for heterogeneity in fundamental attributes across stocks.

To economize on the size of the table, and because we want to present results for the five trading venues and the three interval lengths (I1, I2, and I3), we report in Panel B of Table 10 only the coefficient on $Cor(Y_{iv})$ from each regression (with heteroskedasticity-consistent *t*-statistics). We observe an interesting pattern. For both dependent variables, the coefficients on the smaller trading venues are positive, although not all of them are statistically significant. For the largest trading venue in terms of market share of volume, however, we observe the opposite result: the coefficient is negative and statistically significant in almost all regressions.[30] We observe that the impact of correlated HFT strategies on the viability or competitiveness of a trading venue depends on the nature of that venue. It benefits smaller venues that introduce competition into the market structure and hence detract from the dominant position of the largest

[29] Results using other measures of HFT strategies are similar in nature.
[30] The disparity in results between the smaller trading venues and the dominant exchange suggests that reverse causality is less likely to be a concern in these regressions. We also feel that the economics of trading on these venues suggests that the percentage of time a trading venue posts the best prices is determined by the strategies of the HFT firms, rather than vice versa, because HFT firms are the dominant players on these trading venues in terms of liquidity provision.

trading venue. If this is indeed the case, we should observe a negative relationship between HFT competition and the concentration of trading in the market, which we investigate next.

7.2 Correlated HFT Strategies and Market Concentration

To examine market concentration, we compute the Herfindahl-Hirschman Index (henceforth HHI) of market share in terms of volume for the five trading venues we investigate.[31] The lower the HHI, the less concentrated the market. The independent variable on which we focus is $Cor(Y_i)$, our time-series correlation measure from Section 4. Here, however, unlike in our analysis of the competitiveness measures, an HFT firm's activity is aggregated across all trading venues before the correlations are computed and we use all HFT firms. There is a separate $Cor(Y_i)$ for each stock, and we run the following cross-sectional regression on the 52 stocks in the sample:

$$\begin{aligned} HHI_i = a_0 + a_1 Cor\left(Y_i\right) + a_2 Y_i + a_3 Spread_i + a_4 Depth_i + \\ a_5 MktCap_i + a_6 Price_i + a_7 Volatility_i + error_i \end{aligned} \tag{4}$$

As in Section 7.1, including the magnitude of HFT activity as a control variable ensures that we pick up the effect of correlation in HFT strategies, not the magnitude of their activity per se., spreads and depth (now computed from the best prices in the entire market, not just on a single trading venue) are meant to control for the general liquidity environment of the stock, and the last three variables control for heterogeneity in fundamental attributes across stocks.

Table 11 provides the results for the three HFT measures: MSG, TRD, and LMT. The results are very strong: the coefficient on $Cor(Y_i)$ is negative and highly statistically significant in eight out of the nine regressions. This finding is consistent with the hypothesis that more highly correlated HFT strategies, which we view as a manifestation of competition between HFT firms, are associated with a less concentrated market structure. However, it is important to note that the relationship between these two variables—concentration and the correlation of HFT strategies—is best viewed as being jointly co-determined in equilibrium rather than as, strictly speaking, one's causing the other. While competition between HFT firms enhances the viability of smaller

[31] The HHI is computed as the sum of squared market shares of the trading venues, and with five trading venues it is always between 0.2 (if volume is equally divided among the five trading venues) and 1 (if volume concentrates on one trading venue).

trading venues, the multiplicity of trading venues could increase the profit opportunities from arbitrage and market making across trading venues and hence lead to intensified competition between HFT firms. Competition between HFT firms and competition between trading venues are therefore tightly linked in a “competition begets competition” manner.

6. Conclusions

Our paper examines correlations between strategies of high-frequency trading firms, which reflect competition between these firms in pursuing similar strategies. There are two motivations to look at these correlations. First, they can teach us about the industrial organization of the HFT space (e.g., how many common strategies there are and how many firms follow them). Second, they may reveal to us whether such competition creates a negative externality in the form of market fragility because they represent the tendency of HFT firms to do the same thing at the same time or with respect to the same stocks. Our results provide not only new and interesting stylized facts but also insights into competition between HFT firms and its impact on the market environment.

The first important stylized fact that we establish is that while there is substantial correlation between HFT strategies in terms of total activity (i.e., buy orders plus sell orders), there is little correlation in directional activity (i.e., buy orders minus sell orders). The fact that the correlations in directional activity are low has important implications for the stability of the market. Unlike the literature on institutional investor herding that focuses on how directional trading can negatively impact the market, our study indicates that HFT firms do not seem to have a strong predominant direction that is common to many firms and that could destabilize the market. The second important stylized fact is that the correlation structure is similar under a variety of market conditions. In other words, the correlations between HFT strategies do not increase on days in which stock prices drop significantly. This is reassuring insofar as services that HFT firms provide, both liquidity provision and the virtual consolidation of a market comprised of multiple trading venues, appear rather robust.

Our principal component analysis delves more deeply into the structure behind correlated HFT activity. Our analysis suggests that there are at least three underlying common strategies that are followed by multiple firms. These underlying common strategies relate differently to market conditions and serve correspondingly different functions. While some HFT firms appear to follow unique strategies that are uncorrelated with those of others, about half of the firms in our sample (representing most of the HFT firms' activity: 78.97% in terms of volume and 96.21% in terms of messages) compete for the same three types of profit opportunities. If these strategies represent market making and the elimination of arbitrage opportunities, then the rent extracted for providing liquidity and consolidating the fragmented market is probably low, reflecting the highly competitive environment.

While competition may eliminate excess rents, it can also introduce externalities by influencing returns or volatility. Our analysis, however, shows no systematic impact of correlated HFT activity on returns. This is important insofar as HFT does not seem to influence prices in a manner that requires additional compensation from investors. In fact, we find that the short-interval volatility of most individual stocks loads negatively on the market-wide measure of HFT competition. While this could potentially be due to a reduction in either permanent or transitory price movements, our finding that the strongest driver of this relationship is the market-making strategy suggests that it is due at least in part to a reduction in transitory price movements brought about by more efficient cross-stock market making by HFT firms.

The last set of results we provide tie competition among HFT firms to competition among trading venues. We show that greater HFT competition within a trading venue helps smaller trading venues become more competitive or viable in terms of posting better prices and narrower spreads. Furthermore, we document a strong negative relationship between trading concentration in the market as a whole and competition between HFT firms. This negative relationship is a manifestation of the interrelated ecosystem in which competing trading venues and competing HFT firms operate: fragmentation provides a source of profit for HFT firms at the same time that competition between HFT firms enhances competition between trading venues and hence contributes to the fragmentation of trading volume in the market.

Our study was facilitated by the availability of high-quality regulatory data. Regulators focus on judging whether particular algorithms are harming the market (or otherwise implementing illegal strategies) as well as evaluating the overall impact of algorithms on the market to determine whether they necessitate a regulatory response in terms of changing the rules governing interactions between traders. Our study is silent on the first issue, but our insights into correlated HFT activity are important for the second one. Strong competition between HFT firms could in principle benefit markets (e.g., lowering rents earned for services HFT firms provide) but could also come at a cost in terms of the potential for fragility or greater volatility. Our study documents high levels of competition in multiple strategies, but at the same time shows that concerns about fragility from such correlated activity could be exaggerated. If anything, we find the opposite result: competition between HFT firms helps investors by lowering the volatility of stocks. We hope that as more high-quality data are made available to academic researchers, additional insights into the impact of HFT will emerge and facilitate a better-informed dialogue concerning this issue among investors and regulators.

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Table 1
Summary Statistics

Our sample consists of 52 stocks from the S&P/TSX60 (S&P). We rank the daily returns of the S&P/TSX Composite index from June 2010 through March 2011, and select the 10 worst days ('Down days'), the 10 best days ('Up days'), and the 10 days closest to and centered on zero return ('Flat days') for a 30-day sample period. Panel A presents summary statistics for the sample stocks: market capitalization, price, standard deviation of 30-minute returns, daily volume (in Canadian dollars), and daily return. Panel B presents summary statistics for the 31 high-frequency trading (HFT) firms that we identify using data from the Investment Industry Regulatory Organization of Canada (IIROC). These 31 firms are further categorized into three subgroups according to market share of volume: MS1 (market share of at least 4%; 4 firms), MS2 (market share of between 1% and 4%; 6 firms), and MS3 (the rest of the HFT firms). Similarly, we categorize the 31 firms according to their orders-to-trades ratios into three subgroups: OT1 (ratio greater than 150; 5 firms), OT2 (ratio between 50 and 150; 6 firms), and OT3 (all other HFT firms). Market share (in terms of volume or trades) is computed by dividing the trading undertaken by each HFT firm by total trading in the market. Trades consist of executions of both marketable orders and non-marketable orders. Sub/Canc is the number of (non-marketable) limit-order submissions and cancelations (i.e., all non-execution messages) that the firm sends to the market, where a modification of an order counts as a cancelation and a resubmission. Messages are all the orders (both marketable and non-marketable) and cancelations that a firm sends to the market. Orders/Trades Ratio is defined for each HFT firm as Messages divided by Trades. CrossEndInventory is the number of times per day that an HFT firm's intraday inventory position crosses its end-of-day inventory position. We compute the measures for each HFT firm using all days in our sample period, and then provide in the table cross-firm means and medians for all HFT firms as well as for subgroups by market share or orders-to-trades ratio.

Panel A: Sample Stocks

Days	Stocks		MktCap (Million CAD)	Price (CAD)	StdRet (30min Ret)	CADVolume (1000; daily)	Return (daily)
All	S&P60	Mean	19,412	39.1	0.40%	78,156	-0.04%
		Median	11,401	36.9	0.40%	51,120	-0.04%
	Large	Mean	31,043	39.8	0.38%	115,013	-0.07%
		Median	27,574	37.1	0.38%	116,346	-0.12%
	Small	Mean	7,782	38.5	0.41%	41,299	-0.02%
		Median	7,731	36.7	0.41%	34,018	-0.03%
Down Days	S&P60	Mean	19,203	38.3	0.43%	81,195	-1.72%
		Median	11,299	36.4	0.43%	55,892	-1.56%
	Large	Mean	30,811	39.4	0.43%	123,636	-1.79%
		Median	27,802	36.8	0.43%	111,556	-1.76%
	Small	Mean	7,594	37.1	0.44%	38,755	-1.65%
		Median	7,544	35.8	0.44%	31,962	-1.35%
Flat Days	S&P60	Mean	19,499	39.7	0.34%	70,614	-0.08%
		Median	11,840	37.4	0.34%	50,078	-0.07%
	Large	Mean	31,063	39.8	0.32%	104,056	-0.11%
		Median	27,340	37.3	0.29%	104,396	-0.08%
	Small	Mean	7,935	39.5	0.36%	37,172	-0.04%
		Median	7,929	37.6	0.36%	31,421	-0.06%
Up Days	S&P60	Mean	19,535	39.5	0.39%	82,903	1.66%
		Median	11,574	37.0	0.37%	54,097	1.46%
	Large	Mean	31,254	40.0	0.37%	116,300	1.71%
		Median	28,022	37.3	0.35%	109,959	1.52%
	Small	Mean	7,816	38.9	0.41%	49,507	1.62%
		Median	7,721	36.8	0.41%	35,156	1.31%

Panel B: HFT Firms

HFT Firms		MktShare (Volume)	MktShare (Trades)	Trades (daily)	Sub/Canc (daily)	Messages (daily)	Orders/Trades Ratio	CrossEnd Inventory
All	Mean	1.50%	1.70%	19,445	1,056,838	1,063,974	92.7	25.6
	Median	0.34%	0.44%	5,035	97,146	97,288	40.4	3.4
MS1	Mean	6.58%	8.95%	102,035	5,466,547	5,496,423	49.5	133.0
	Median	7.23%	8.60%	98,048	3,272,863	3,312,989	42.2	123.7
MS2	Mean	2.67%	2.08%	23,730	982,137	995,868	38.3	21.3
	Median	2.79%	2.11%	24,003	147,090	162,729	6.9	5.2
MS3	Mean	0.19%	0.22%	2,489	238,236	239,157	116.5	6.4
	Median	0.05%	0.04%	714	40,129	40,268	71.4	2.2
OT1	Mean	0.11%	0.14%	1,549	767,533	767,949	323.9	2.4
	Median	0.04%	0.04%	425	97,146	97,288	257.9	2.2
OT2	Mean	1.89%	2.96%	33,716	3,132,973	3,140,817	116.3	60.5
	Median	0.37%	0.57%	6,487	273,318	276,226	117.1	11.7
OT3	Mean	1.72%	1.72%	19,637	506,324	514,927	27.8	20.9
	Median	0.42%	0.50%	5,727	26,340	37,771	19.4	3.6

Table 2
Time-Series Correlations

Our sample consists of 52 stocks from the S&P/TSX60 (S&P). We rank the daily returns of the S&P/TSX Composite index from June 2010 through March 2011, and select the 10 worst days, the 10 best days, and the 10 days closest to and centered on zero return for a 30-day sample period. We use data from the Investment Industry Regulatory Organization of Canada (IIROC) to identify 31 high-frequency trading (HFT) firms. These 31 firms are further categorized into three subgroups according to market share of volume: MS1 (market share of at least 4%; 4 firms), MS2 (market share of between 1% and 4%; 6 firms), and MS3 (the rest of the HFT firms). Similarly, we categorize the 31 firms according to their orders-to-trades ratios into three subgroups: OT1 (ratio greater than 150; 5 firms), OT2 (ratio between 50 and 150; 6 firms), and OT3 (all other HFT firms). The Time-Series Correlation measure indicates whether the strategies of HFT firms are correlated over time for a given stock ($Cor(Y_i)$). For each stock, we compute the correlation coefficient between HFT activities of any two pairs of HFT firms, and average across all pairs of firms in a certain group (where ALL consists of the 31 HFT firms). In Panel A, we examine HFT strategies in terms of the number of "messages" (MSG) they send to the market, where messages are defined as submissions and cancelations of nonmarketable limit orders as well as executions of marketable limit orders. In Panel B and Panel C we consider trades (TRD) and submissions/cancelations of nonmarketable limit orders (LMT). The measures representing HFT strategies as well as the correlations are computed separately for three interval lengths: I1 (1-second intervals), I2 (10-second intervals), and I3 (60-second intervals). In each panel, we provide the correlation for the sample of S&P/TSX60 as well as two equal subsamples (Large and Small) ranked by market capitalization (with *p*-value for a two-sided test indicating whether Large differs from Small).

Panel A: Time-Series Correlations of HFT Strategies in terms of Messages (MSG)

HFT	**I1**				**I2**				**I3**			
Group	S&P	Large	Small	*p*-val.	S&P	Large	Small	*p*-val.	S&P	Large	Small	*p*-val.
MS1	0.249	0.341	0.158	<.001	0.238	0.324	0.152	<.001	0.237	0.322	0.153	<.001
MS2	0.044	0.055	0.034	0.013	0.068	0.077	0.059	0.041	0.089	0.094	0.085	0.342
MS3	0.030	0.035	0.026	0.007	0.045	0.051	0.038	0.003	0.057	0.065	0.049	0.004
OT1	0.069	0.085	0.054	0.016	0.105	0.130	0.081	0.012	0.119	0.145	0.092	0.019
OT2	0.089	0.113	0.066	0.014	0.086	0.105	0.067	0.020	0.084	0.098	0.070	0.048
OT3	0.035	0.043	0.027	<.001	0.049	0.059	0.039	<.001	0.064	0.075	0.053	<.001
ALL	0.049	0.061	0.038	<.001	0.064	0.078	0.050	<.001	0.078	0.092	0.063	<.001

Panel B: Time-Series Correlations of HFT Trades (TRD)

HFT	**I1**				**I2**				**I3**			
Group	S&P	Large	Small	*p*-val.	S&P	Large	Small	*p*-val.	S&P	Large	Small	*p*-val.
MS1	0.268	0.341	0.195	<.001	0.314	0.400	0.228	<.001	0.351	0.446	0.257	<.001
MS2	0.056	0.060	0.052	0.232	0.086	0.090	0.081	0.199	0.120	0.126	0.114	0.168
MS3	0.012	0.012	0.012	0.424	0.019	0.020	0.018	0.276	0.029	0.031	0.027	0.214
OT1	0.017	0.017	0.017	0.971	0.027	0.025	0.029	0.612	0.040	0.039	0.041	0.799
OT2	0.052	0.062	0.041	0.005	0.064	0.077	0.051	0.003	0.078	0.095	0.062	0.001
OT3	0.035	0.038	0.033	0.042	0.050	0.056	0.045	0.001	0.069	0.076	0.063	0.004
ALL	0.036	0.039	0.032	0.010	0.049	0.055	0.044	<.001	0.067	0.075	0.059	<.001

Panel C: Time-Series Correlations of HFT Submissions and Cancellations of Limit Orders (LMT)

HFT	**I1**				**I2**				**I3**			
Group	S&P	Large	Small	*p*-val.	S&P	Large	Small	*p*-val.	S&P	Large	Small	*p*-val.
MS1	0.245	0.337	0.154	<.001	0.234	0.320	0.149	<.001	0.234	0.318	0.150	<.001
MS2	0.036	0.047	0.026	0.010	0.055	0.067	0.043	0.015	0.071	0.082	0.061	0.057
MS3	0.031	0.036	0.026	0.003	0.045	0.053	0.038	0.001	0.058	0.067	0.049	0.001
OT1	0.069	0.085	0.053	0.015	0.105	0.129	0.081	0.013	0.118	0.145	0.092	0.019
OT2	0.090	0.114	0.067	0.015	0.087	0.106	0.067	0.020	0.084	0.099	0.069	0.038
OT3	0.033	0.041	0.025	<.001	0.047	0.058	0.036	<.001	0.062	0.075	0.050	<.001
ALL	0.048	0.060	0.036	<.001	0.063	0.077	0.048	<.001	0.076	0.092	0.060	<.001

Table 3

Cross-Sectional Correlations

Our sample consists of 52 stocks from the S&P/TSX60 (S&P). We rank the daily returns of the S&P/TSX Composite index from June 2010 through March 2011, and select the 10 worst days, the 10 best days, and the 10 days closest to and centered on zero return for a 30-day sample period. We use data from the Investment Industry Regulatory Organization of Canada (IIROC) to identify 31 high-frequency trading (HFT) firms. These 31 firms are further categorized into three subgroups according to market share of volume: MS1 (market share of at least 4%; 4 firms), MS2 (market share of between 1% and 4%; 6 firms), and MS3 (the rest of the HFT firms). Similarly, we categorize the 31 firms according to their orders-to-trades ratios into three subgroups: OT1 (ratio greater than 150; 5 firms), OT2 (ratio between 50 and 150; 6 firms), and OT3 (all other HFT firms). The Cross-Sectional Correlation measure indicates whether the strategies of HFT firms are correlated across stocks at a given time ($Cor(Y_t)$). In each time interval, we compute the correlation coefficient between the activities of two HFT firms across the stocks in the sample, and average the correlations for all pairs of firms in a certain group (where ALL consists of the 31 HFT firms). In Panel A, we examine the HFT strategies in terms of the number of "messages" (MSG) they send to the market, where messages are defined as submissions and cancelations of nonmarketable limit orders as well as executions of marketable limit orders. In Panel B and Panel C we examine trades (TRD) and submissions/cancelations of nonmarketable limit orders (LMT). The measures representing HFT strategies as well as the correlations are computed separately for three interval lengths: I1 (1-second intervals), I2 (10-second intervals), and I3 (60-second intervals). In each panel, we provide the correlation for the sample of S&P/TSX60 as well as two equal subsamples (Large and Small) ranked by market capitalization (with *p*-value for a two-sided test indicating whether Large differs from Small).

Panel A: Cross-Sectional Correlations of HFT Strategies in terms of Messages (MSG)

HFT	**I1**				**I2**				**I3**			
Group	S&P	Large	Small	*p*-val.	S&P	Large	Small	*p*-val.	S&P	Large	Small	*p*-val.
MS1	0.359	0.407	0.303	<.001	0.332	0.380	0.271	<.001	0.317	0.348	0.262	<.001
MS2	0.131	0.164	0.129	<.001	0.120	0.124	0.115	<.001	0.122	0.112	0.120	<.001
MS3	0.174	0.213	0.243	<.001	0.127	0.145	0.164	<.001	0.108	0.113	0.141	<.001
OT1	0.272	0.287	0.363	<.001	0.312	0.292	0.393	<.001	0.387	0.353	0.487	<.001
OT2	0.255	0.330	0.212	<.001	0.175	0.228	0.141	<.001	0.159	0.165	0.121	<.001
OT3	0.175	0.224	0.190	<.001	0.116	0.139	0.123	<.001	0.090	0.097	0.095	<.001
ALL	0.198	0.243	0.222	<.001	0.147	0.168	0.160	<.001	0.130	0.135	0.137	<.001

Panel B: Cross-Sectional Correlations of HFT Trades (TRD)

HFT	**I1**				**I2**				**I3**			
Group	S&P	Large	Small	*p*-val.	S&P	Large	Small	*p*-val.	S&P	Large	Small	*p*-val.
MS1	0.417	0.460	0.527	<.001	0.436	0.415	0.362	<.001	0.518	0.467	0.454	<.001
MS2	0.219	0.268	0.346	<.001	0.122	0.124	0.153	<.001	0.155	0.130	0.148	<.001
MS3	0.189	0.244	0.319	<.001	0.067	0.085	0.113	<.001	0.052	0.059	0.056	0.011
OT1	0.357	0.441	0.564	<.001	0.169	0.199	0.307	<.001	0.130	0.121	0.242	<.001
OT2	0.348	0.401	0.444	<.001	0.215	0.242	0.244	0.275	0.162	0.191	0.157	<.001
OT3	0.284	0.352	0.413	<.001	0.140	0.157	0.170	<.001	0.131	0.124	0.121	<.001
ALL	0.313	0.386	0.460	<.001	0.152	0.174	0.189	<.001	0.131	0.133	0.127	<.001

Panel C: Cross-Sectional Correlations of HFT Submissions and Cancellations of Limit Orders (LMT)

HFT	**I1**				**I2**				**I3**			
Group	S&P	Large	Small	*p*-val.	S&P	Large	Small	*p*-val.	S&P	Large	Small	*p*-val.
MS1	0.355	0.402	0.301	<.001	0.328	0.374	0.269	<.001	0.313	0.342	0.259	<.001
MS2	0.127	0.162	0.130	<.001	0.110	0.116	0.108	<.001	0.107	0.102	0.107	<.001
MS3	0.175	0.214	0.244	<.001	0.129	0.148	0.165	<.001	0.108	0.117	0.142	<.001
OT1	0.272	0.287	0.363	<.001	0.313	0.293	0.393	<.001	0.390	0.355	0.488	<.001
OT2	0.254	0.329	0.211	<.001	0.175	0.228	0.139	<.001	0.159	0.166	0.120	<.001
OT3	0.172	0.222	0.188	<.001	0.113	0.136	0.120	<.001	0.085	0.095	0.090	<.001
ALL	0.197	0.242	0.222	<.001	0.147	0.168	0.159	<.001	0.127	0.134	0.135	0.113

Table 4

Correlation Analysis of Inventory Positions and Market Conditions

Our sample consists of 52 stocks from the S&P/TSX60 (S&P). We use data from the Investment Industry Regulatory Organization of Canada (IIROC) to identify 31 high-frequency trading (HFT) firms. These 31 firms are further categorized into three subgroups according to market share of volume: MS1 (market share of at least 4%; 4 firms), MS2 (market share of between 1% and 4%; 6 firms), and MS3 (the rest of the HFT firms). Similarly, we categorize the 31 firms according to their orders-to-trades ratios into three subgroups: OT1 (ratio greater than 150; 5 firms), OT2 (ratio between 50 and 150; 6 firms), and OT3 (all other HFT firms). The Time-Series Correlation measure indicates whether the strategies of HFT firms are correlated over time for a given stock ($Cor(Y_i)$). For each stock, we compute the correlation coefficient between HFT activities of any two pairs of HFT firms, and average across all pairs of firms in a certain group. The Cross-Sectional Correlation measure indicates whether the strategies of HFT firms are correlated across stocks at a given time ($Cor(Y_t)$). In each time interval, we compute the correlation coefficient between the activities of two HFT firms across the stocks in the sample, and average the correlations for all pairs of firms in a certain group. In Panel A, we look at the correlations of the HFT firms' inventory positions. We compute each firm's time-weighted dollar inventory position in each stock and time interval assuming that the firm starts every day with zero inventory. We provide the correlation for the sample of S&P/TSX60 as well as two equal subsamples (Large and Small) ranked by market capitalization (with *p*-value for a two-sided test indicating whether Large differs from Small). In Panel B, we rank the daily returns of the S&P/TSX Composite index from June 2010 through March 2011, and select the 10 worst days (Down Days), the 10 best days (Up Days'), and the 10 days closest to and centered on zero return (Flat Days), for a total of 30 days (Entire Period). For each period we examine the correlations of HFT strategies in terms of the number of "messages" (MSG) they send to the market, where messages are defined as submissions and cancelations of nonmarketable limit orders as well as execution of marketable limit orders.

Panel A: Correlations of Inventory Positions at 1-Second Intervals

HFT Group	**Time-Series**				**Cross-Sectional**			
	S&P	Large	Small	t-stat.	S&P	Large	Small	t-stat.
MS1	0.045	0.067	0.024	0.017	0.063	0.060	0.074	<.001
MS2	0.024	0.020	0.028	0.425	0.032	0.039	0.036	<.001
MS3	0.012	0.013	0.011	0.619	0.014	0.012	0.015	<.001
ALL	0.015	0.018	0.013	0.289	0.022	0.020	0.025	<.001

Panel B: Correlations of Messages at 1-Second Intervals for Down, Flat, and Up Days

HFT Group	**Time-Series**				**Cross-Sectional**			
	Down Days	Flat Days	Up Days	All Days	Down Days	Flat Days	Up Days	All Days
MS1	0.271	0.242	0.262	0.249	0.354	0.361	0.362	0.359
MS2	0.042	0.049	0.048	0.044	0.122	0.145	0.127	0.131
MS3	0.036	0.037	0.033	0.030	0.157	0.195	0.171	0.174
ALL	0.055	0.057	0.054	0.049	0.183	0.214	0.198	0.198

Table 5

Principal Components Analysis: Loadings

Table 5 presents the loadings from a principal component analysis of the MSG measure (the number of messages that high-frequency trading (HFT) firms send to the market) using the 1-second interval (I1). For the purpose of the analysis, we think of the 31 HFT firms as the "variables," while the observations are all intervals during the 30-day sample period for all sample stocks. The principal component analysis uses the varimax orthogonal rotation, and the first three principal components are retained for further analysis. The loading of an HFT firm on each of the principal components signifies the extent to which the firm's activity corresponds to the underlying common strategy represented by that principal component; it is equivalent to the bivariate correlation between the firm's measure and the principal component, and is therefore between –1 and 1. For each principal component, the loadings are sorted from the most positive to the most negative. We mark with an asterisk all principal components that are greater than or equal to 0.35. In parentheses by the loadings that are greater than or equal to 0.35 we note the firm's membership in the market share subgroups MS1 and MS2 as well as in the orders-to-trades subgroups OT1 and OT2.

HFT	PC1 Loading	HFT	PC2 Loading	HFT	PC3 Loading
F14	0.76 * (MS1)	F27	0.71 * (MS1)	F17	0.51 * (OT1)
F16	0.67 * (OT1)	F08	0.52 * (MS1)	F23	0.48 * (OT2)
F04	0.57 * (OT1)	F31	0.41 * (OT2)	F19	0.47 * (OT2)
F24	0.54 *	F05	0.40 * (MS2)	F20	0.43 *(MS1/OT2)
F31	0.48 * (OT2)	F02	0.39 * (MS2)	F26	0.33
F28	0.46 * (OT2/MS2)	F28	0.35 * (MS2/OT2)	F12	0.22
F20	0.40 * (MS1/OT2)	F30	0.34	F08	0.20
F17	0.38 * (OT1)	F06	0.27	F18	0.18
F29	0.33	F12	0.24	F14	0.15
F08	0.32	F26	0.22	F29	0.13
F21	0.26	F10	0.17	F21	0.12
F27	0.26	F01	0.16	F03	0.12
F06	0.26	F20	0.13	F10	0.08
F07	0.23	F04	0.12	F30	0.05
F26	0.23	F24	0.11	F05	0.03
F08	0.22	F09	0.11	F02	0.03
F11	0.15	F23	0.10	F06	0.03
F12	0.08	F11	0.07	F16	0.02
F19	0.07	F18	0.06	F25	0.01
F05	0.04	F14	0.05	F13	0.01
F22	0.03	F03	0.04	F08	0.00
F10	0.01	F15	0.03	F09	0.00
F15	0.01	F25	0.02	F22	-0.01
F09	0.00	F22	0.01	F15	-0.01
F25	0.00	F13	0.01	F04	-0.02
F03	0.00	F29	0.00	F29	-0.07
F13	0.00	F16	-0.03	F31	-0.09
F02	-0.04	F21	-0.07	F24	-0.13
F30	-0.06	F07	-0.12	F07	-0.13
F23	-0.07	F19	-0.12	F11	-0.13
F18	-0.08	F17	-0.16	F01	-0.30

Table 6

Regressions using Principal Component Scores

Table 6 presents regressions of principal component scores on variables that represent the market environment. In the principal component analysis of the MSG measure, the 31 high-frequency trading (HFT) firms are the "variables" while the observations are all 1-second intervals during the 30-day sample period for all sample stocks. The principal component analysis uses the varimax orthogonal rotation, and the first three principal components are retained for further analysis. There are 13 variables that describe the economic environment in each regression. The first two represent the degree of integration of the three trading venues with the highest market share of trading: TimeAorB is the percentage of time that the three trading venues display the same bid or ask prices, while TimeSprd is the percentage of time that the three trading venues have the same bid-ask spread. The next five variables represent the state of aggregate liquidity in the market as a whole (aggregated across all trading venues): total depth at the Market-Wide Best Bid or Offer (henceforth, MWBBO), total depth up to 10 cents from the MWBBO, depth imbalance at the MWBBO (defined as the absolute value of the difference between the number of shares at the bid and at the ask), depth imbalance up to 10 cents from the MWBBO, and percentage MWBBO spreads. The next three variables represent market conditions in the interval: return (computed from the last transaction price in each interval), volatility (computed as the absolute value of return), and the average time between trades in the interval. The last three variables represent information about HFT: the number of shares traded among the HFT firms in the interval (#HFT), the number of shares traded between the HFT firms and others (#NoHFT), and the aggregate inventory position of all HFT firms in Canadian dollars (cumulative from the beginning of the day and assuming that all of them start the day with zero inventory). In Panel A, the first three columns report the coefficients of the contemporaneous regressions in which we line up the component score with observations of the market environment over the same interval. We also provide, side by side, the coefficients from regressions in which the component scores are regressed on lagged and lead values of the economic variables. In Panel B, we report the coefficients from the contemporaneous regressions with t-statistics computed using double-clustered (interval and stock) standard errors.

Panel A: Contemporaneous, Lagged, and Lead Regressions on Component Scores

	Contemporaneous			Lagged			Lead		
	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3
TimeAorB	-0.0330	0.0705	-0.0895	-0.0160	0.0954	-0.0854	-0.0374	0.0729	-0.0892
TimeSprd	-0.0960	0.0364	-0.0110	-0.0913	0.0408	-0.0134	-0.0980	0.0530	-0.0091
MWBBOdep	-1.E-06	-1.E-06	7.E-08	-2.E-06	-2.E-06	1.E-07	-1.E-06	-1.E-06	1.E-07
Dep10	-8.E-08	2.E-07	-8.E-08	-6.E-08	3.E-07	-8.E-08	-5.E-08	3.E-07	-8.E-08
|MWBBOimb|	1.E-06	9.E-07	-4.E-08	2.E-06	2.E-06	-1.E-07	1.E-06	1.E-06	-1.E-07
|Imb10|	-4.E-08	-2.E-07	6.E-08	-5.E-08	-2.E-07	6.E-08	-5.E-08	-2.E-07	6.E-08
%sprd	-4.46	0.61	0.97	-3.97	0.11	0.77	-5.22	0.13	1.11
Ret	16.43	5.70	8.05	4.31	1.29	4.43	3.60	2.56	7.26
|Ret|	280.86	8.40	211.64	108.69	-25.58	159.24	80.92	-6.14	108.09
TBT	-1.10	-0.47	-0.27	-0.59	-0.39	-0.22	-0.54	-0.34	-0.12
#HFT	0.0600	0.2285	0.0023	0.0194	0.0540	-0.0045	0.0097	0.0277	-0.0020
#NoHFT	0.1009	0.1829	-0.0102	0.0196	0.0457	0.0006	0.0034	0.0159	-0.0027
|Aggpos|	5.E-08	-1.E-07	3.E-08	4.E-08	-4.E-08	2.E-08	2.E-08	-3.E-08	9.E-09
Intercept	1.11	0.28	0.32	0.64	0.25	0.27	0.60	0.23	0.17
R^2	13.38%	27.25%	8.41%	2.76%	4.11%	0.61%	1.95%	2.36%	0.42%

Panel B: Contemporaneous Regressions with t-statistics using Double-Clustered Standard Errors

	PC1		PC2		PC3	
	Coef	t-stat	Coef	t-stat	Coef	t-stat
TimeAorB	-0.0330	-0.65	0.0705**	3.10	-0.0895**	-3.66
TimeSprd	-0.0960**	-3.46	0.0364*	2.26	-0.0110	-1.01
MWBBOdep	-1.E-06**	-3.65	-1.E-06**	-2.64	7.E-08	0.49
Dep10	-8.E-08	-1.80	2.E-07**	4.12	-8.E-08**	-2.78
|MWBBOimb|	1.E-06**	3.61	9.E-07*	2.24	-4.E-08	-0.33
|Imb10|	-4.E-08	-0.57	-2.E-07	-1.91	6.E-08	1.60
%sprd	-4.46	-1.90	0.61	1.01	0.97	1.48
Ret	16.43**	2.79	5.70	1.39	8.05	1.51
|Ret|	280.86*	2.32	8.40	0.21	211.64**	3.04
TBT	-1.10**	-6.47	-0.47**	-3.16	-0.27**	-2.64
#HFT	0.0600**	3.21	0.2285**	15.60	0.0023	0.43
#NoHFT	0.1009**	6.62	0.1829**	13.70	-0.0102	-1.33
|Aggpos|	5.E-08	1.01	-1.E-07	-1.82	3.E-08	0.93
Intercept	1.11**	4.77	0.28	1.66	0.32*	2.45
R^2		13.38%		27.25%	8.41%	

Table 7

Regressions of Returns on the Correlation of HFT Strategies

This table presents the regressions of individual stock returns on the cross-sectional correlation of high-frequency-trading (HFT) strategies. Our sample consists of 52 stocks from the S&P/TSX60. For each stock, we estimate the following regression over all intervals in the sample period:

$$r_{it} = a_{0i} + a_{1i} Cor\left(Y_t\right) + a_{2i} Y_{mt} + a_{3i} r_{mt} + a_{4i} \left|r_{mt}\right| + a_{5i} Volume_{mt} + error_{it}$$

where r_{it} is the return for stock i in interval t (computed from the trade price closest to the end of the interval), and r_{mt} is the value-weighted return of all stocks in our sample. We are chiefly interested in the impact of the cross-sectional correlation between HFT firms as measured by Cor(Y_t), which is defined in Section 4 as the average over all pairs of HFT firms of their correlations across stocks (for a particular activity measure). Cor(Y_t) is a market-wide attribute of the extent of competition (or similarity in strategies) between HFT firms in the market, and is computed for each interval in the 30-day period. We use the three measures of HFT strategies investigated in Section 4: MSG (all messages HFT firms send to the market), TRD (all their trades), and LMT (only submissions and cancelations of non-marketable limit orders). We add three control variables to the regressions: the magnitude of HFT activity in the market, Y_{mt} (which is the sum across all HFT firms of the same measure that we use for Cor(Y_t)), $Volume_{mt}$ (the aggregate volume in all stocks) and $|r_{mt}|$ (the absolute value of the market return). For each variable, we present the average coefficient across the 52 stocks, the average t-statistics from the individual regressions (computed using heteroskedasticity-and-autocorrelation-consistent standard errors), the number of negative coefficients, the number of negative coefficients that are significant at the 5% level (from a two-sided test), the number of positive coefficients, the number of significant positive coefficients, and the average R^2. In Panel A we present the coefficients on all variables from the regressions using the 1-second intervals. In Panel B, we present just the coefficient on Cor(Y_t) side by side for the 1-second, 10-second, and 60-second intervals.

Panel A: Regression of 1-Second Interval Return on the Cross-Sectional Correlation of HFT Strategies

	Variable	Avg. Coef	Avg. t-stat	# Coef < 0	# t-stat < 1.96	# Coef > 0	# t-stat > 1.96	Avg. R-sqrd	# Obs.
MSG	**Intercept**	1.23E-07	0.35	24	4	28	10	4.47%	52
	Cor(Y_t)	-9.63E-08	-0.14	28	3	24	3		
	MSG_{mt}	1.50E-11	0.21	23	0	29	4		
	R_{mt}	8.04E-01	38.38	0	0	52	52		
	$\|R_{mt}\|$	-6.29E-03	-0.67	36	10	16	1		
	$Volume_{mt}$	4.80E-14	0.41	19	0	33	2		
TRD	**Intercept**	1.86E-07	0.65	16	2	36	10	4.51%	52
	Cor(Y_t)	-1.18E-07	-0.27	27	6	25	1		
	TRD_{mt}	-1.49E-10	0.08	24	3	28	4		
	R_{mt}	8.06E-01	38.27	0	0	52	52		
	$\|R_{mt}\|$	-6.78E-03	-0.66	38	7	14	0		
	$Volume_{mt}$	5.10E-14	0.49	19	1	33	2		
LMT	**Intercept**	1.21E-07	0.35	25	4	27	10	4.47%	52
	Cor(Y_t)	-9.16E-08	-0.13	30	3	22	2		
	LMT_{mt}	1.59E-11	0.21	23	0	29	4		
	R_{mt}	8.04E-01	38.38	0	0	52	52		
	$\|R_{mt}\|$	-6.30E-03	-0.67	36	10	16	1		
	$Volume_{mt}$	4.80E-14	0.41	19	0	33	2		

Panel B: Coefficient on Cor(Y_t) from Regressions of Return on the Correlation of HFT Strategies

Variable	Interval	Avg. Cor(t) Coef	Avg. Cor(t) t-stat	# Coef < 0	# t-stat < 1.96	# Coef > 0	# t-stat > 1.96	Avg. R-sqrd
MSG	**I1**	-9.63E-08	-0.14	28	3	24	3	4.47%
	I2	2.29E-07	-0.14	30	2	22	1	9.44%
	I3	-4.27E-06	-0.11	27	1	25	0	17.33%
TRD	**I1**	-1.18E-07	-0.27	27	6	25	1	4.51%
	I2	-9.43E-07	-0.12	28	2	24	2	9.43%
	I3	-2.01E-06	-0.05	26	3	26	3	17.32%
LMT	**I1**	-9.16E-08	-0.13	30	3	22	2	4.47%
	I2	-7.87E-07	-0.16	31	2	21	0	9.44%
	I3	-2.42E-06	-0.10	26	1	26	0	17.33%

Table 8

Regressions of Interval Volatility on the Correlation of HFT Strategies

This table presents the regressions of individual stock interval return volatility on the cross-sectional correlation of high-frequency trading (HFT) strategies. Our sample consists of 52 stocks from the S&P/TSX60. For each stock, we estimate the following regression over all intervals in the sample period:

$$|r_{it}| = a_{0i} + a_{1i}Cor(Y_t) + a_{2i}Y_{mt} + a_{3i}r_{mt} + a_{4i}|r_{mt}| + a_{5i}Volume_{mt} + error_{it}$$

where $|r_{it}|$ is the absolute value of the return for stock *i* in interval *t* (computed from the trade price closest to the end of the interval), which is our measure of interval return volatility, r_{mt} is the value-weighted return of all stocks in our sample, $|r_{mt}|$ is the absolute value of the market return, and $Volume_{mt}$ is the aggregate volume in all stocks. We are chiefly interested in the impact of the cross-sectional correlation between HFT firms as measured by $Cor(Y_t)$, which is defined in Section 4 as the average over all pairs of HFT firms of their correlation across stocks (for a particular activity measure). $Cor(Y_t)$ is a market-wide attribute of the extent of competition (or similarity in strategies) between HFT firms in the market, and is computed for each interval in the 30-day period. We use the three measures of HFT strategies investigated in Section 4: MSG (all messages HFT firms send to the market), TRD (all their trades), and LMT (only submissions and cancelations of non-marketable limit orders). We also add as a control variable the magnitude of HFT activity in the market, Y_{mt} (which is the sum across all HFT firms of the same measure that we use for $Cor(Y_t)$). For each variable, we present the average coefficient across the 52 stocks, the average t-statistics from the individual regressions (computed using heteroskedasticity-and-autocorrelation-consistent standard errors), the number of negative coefficients, the number of negative coefficients that are significant at the 5% level (from a two-sided test), the number of positive coefficients, the number of significant positive coefficients, and the average R^2. In Panel A we present the coefficients on all variables from the regressions using the 1-second intervals. In Panel B, we present just the coefficient on $Cor(Y_t)$ side by side for the 1-second, 10-second, and 60-second intervals.

Panel A: Regressions of 1-Second Interval Volatility on the Cross-Sectional Correlation of HFT Strategies

	Variable	Avg. Coef	Avg. t-stat	# Coef < 0	# t-stat < 1.96	# Coef > 0	# t-stat > 1.96	Avg. R-sqrd	# Obs.
MSG	**Intercept**	8.00E-06	14.41	6	5	46	45	5.47%	52
	Cor(Y_t)	-1.72E-05	-12.41	43	39	9	6		
	MSG_{mt}	5.76E-09	26.14	5	5	47	47		
	R_{mt}	-6.29E-03	-0.79	36	10	16	1		
	$\|R_{mt}\|$	8.22E-01	30.07	0	0	52	52		
	$Volume_{mt}$	1.35E-12	2.12	5	3	47	45		
TRD	**Intercept**	1.39E-05	31.02	1	1	51	48	5.81%	52
	Cor(Y_t)	-1.78E-05	-33.28	50	49	2	1		
	TRD_{mt}	2.67E-07	23.34	5	4	47	47		
	R_{mt}	-6.01E-03	-0.78	36	10	16	2		
	$\|R_{mt}\|$	7.27E-01	22.38	0	0	52	52		
	$Volume_{mt}$	-3.45E-13	-1.11	43	22	9	3		
LMT	**Intercept**	7.99E-06	14.53	7	5	45	45	5.46%	52
	Cor(Y_t)	-1.71E-05	-12.33	43	40	9	6		
	LMT_{mt}	5.74E-09	25.97	5	5	47	47		
	R_{mt}	-6.30E-03	-0.79	36	10	16	1		
	$\|R_{mt}\|$	8.24E-01	30.20	0	0	52	52		
	$Volume_{mt}$	1.38E-12	2.13	5	3	47	46		

Panel B: Coefficient on Cor(Y_t) from Regressions of Interval Volatility on the Correlation of HFT Strategies

Variable	**Interval**	Avg. Cor(t) Coef	Avg. Cor(t) t-stat	# Coef < 0	# t-stat < 1.96	# Coef > 0	# t-stat > 1.96	Avg. R-sqrd
MSG	**I1**	-1.72E-05	-12.41	43	39	9	6	5.47%
	I2	-2.43E-04	-8.52	46	43	6	5	9.65%
	I3	-6.51E-04	-3.75	45	36	7	4	14.93%
TRD	**I1**	-1.78E-05	-33.28	50	49	2	1	5.81%
	I2	-1.71E-04	-12.34	45	42	7	2	9.84%
	I3	-2.13E-04	-2.02	35	28	17	6	14.39%
LMT	**I1**	-1.71E-05	-12.33	43	40	9	6	5.46%
	I2	-2.50E-04	-8.84	46	42	6	5	9.65%
	I3	-7.14E-04	-4.11	46	37	6	4	14.95%

Table 9

Regressions of Interval Volatility on the Correlation of HFT Strategies by Principal Component

This table presents the regressions of individual stock interval return volatility on the cross-sectional correlation of HFT strategies computed separately for the firms that significantly load on the three principal components presented in Table 5. For each stock, we estimate the following regression over all 1-second intervals in the sample period:

$$|r_{it}| = a_{0i} + a_{1i}\text{Cor}(Y_t)\,\text{PC1} + a_{2i}\text{Cor}(Y_t)\,\text{PC2} + a_{3i}\text{Cor}(Y_t)\,\text{PC3} + a_{4i}Y_{mt}\text{PC1} + a_{5i}Y_{mt}\text{PC2} + a_{6i}Y_{mt}\text{PC3} + a_{7i}r_{mt} + a_{8i}|r_{mt}| + a_{9i}\text{Volume}_{mt} + error_{it}$$

where $|r_{it}|$ is the absolute value of the return for stock *i* in interval *t*, which is our measure of interval return volatility, r_{mt} is the value-weighted return of all stocks in our sample, $|r_{mt}|$ is the absolute value of the market return, and Volume_{mt} is the aggregate volume in all stocks. We compute the cross-sectional correlation $\text{Cor}(Y_t)\text{PC1}$ as the average over the correlations of all pairs of HFT firms from among the eight firms that load on the first principal component, and similarly we compute $\text{Cor}(Y_t)\text{PC2}$ ($\text{Cor}(Y_t)\text{PC3}$) for the six (four) firms that load on the second (third) principal component. Each of these cross-sectional correlations is a market-wide attribute of the extent of competition (or similarity in strategies) between HFT firms with significant loadings on a particular principal component. We compute three measures of HFT strategies: MSG (all messages HFT firms send to the market), TRD (all their trades), and LMT (submissions and cancelations of non-marketable limit orders). We also add as a control variable the magnitude of HFT activity (i.e., the sum across all HFT firms of the same measure that we use for correlations) of the firms that load on the three principal components: $Y_{mt}\text{PC1}$, $Y_{mt}\text{PC2}$, and $Y_{mt}\text{PC3}$. The table presents for each variable the average coefficient across the 52 stocks, the average t-statistics (using heteroskedasticity-and-autocorrelation-consistent standard errors), the number of negative coefficients, the number of negative coefficients that are significant at the 5% level (from a two-sided test), the number of positive coefficients, the number of significant positive coefficients, and the average R^2.

	Variable	Avg. Coef	Avg. t-stat	# Coef < 0	# t-stat < 1.96	# Coef > 0	# t-stat > 1.96	Avg. R-sqrd	# Obs.
MSG	**Intercept**	8.92E-06	10.87	8	8	44	42	5.96%	52
	Cor(Y_t)PC1	-8.22E-07	0.47	30	28	22	17		
	Cor(Y_t)PC2	-6.80E-06	-8.64	39	38	13	12		
	Cor(Y_t)PC3	-1.38E-06	-1.93	43	35	9	8		
	MSG_PC1	7.83E-10	3.36	14	6	38	27		
	MSG_PC2	4.81E-10	1.25	27	14	25	18		
	MSG_PC3	9.66E-09	16.69	4	3	48	47		
	Rm	-6.74E-03	-0.62	33	8	19	3		
	|Rm|	8.74E-01	30.77	0	0	52	52		
	Volume	2.21E-12	2.91	4	4	48	46		
TRD	**Intercept**	3.92E-05	7.35	2	0	50	45	12.50%	52
	Cor(Y_t)PC1	-1.03E-05	-1.82	41	26	11	3		
	Cor(Y_t)PC2	-1.96E-05	-3.16	51	40	1	0		
	Cor(Y_t)PC3	-2.96E-05	-4.48	47	40	5	3		
	TRD_PC1	1.20E-07	1.44	8	1	44	18		
	TRD_PC2	1.76E-07	2.18	3	0	49	34		
	TRD_PC3	3.86E-07	2.67	5	0	47	33		
	Rm	7.55E-03	0.04	22	4	30	4		
	|Rm|	9.86E-01	13.06	0	0	52	52		
	Volume	-4.89E-13	-0.74	37	10	15	0		
LMT	**Intercept**	8.12E-06	9.49	10	9	42	41	5.98%	52
	Cor(Y_t)PC1	-3.47E-07	0.80	30	28	22	17		
	Cor(Y_t)PC2	-7.06E-06	-8.98	39	38	13	12		
	Cor(Y_t)PC3	-1.25E-06	-1.71	42	34	10	8		
	LMT_PC1	1.19E-09	4.74	7	1	45	38		
	LMT_PC2	1.98E-09	3.98	16	6	36	30		
	LMT_PC3	8.84E-09	15.07	5	3	47	47		
	Rm	-6.59E-03	-0.61	33	8	19	3		
	|Rm|	8.73E-01	30.66	0	0	52	52		
	Volume	2.19E-12	2.90	4	3	48	46		

Table 10

Trading Venue Competitiveness and the Correlation of HFT Strategies

This table presents summary statistics of measures of competitiveness (or viability) of trading venues and regression results that relate them to competition between high-frequency trading (HFT) firms. The five trading venues we investigate are all organized as electronic limit order books and together execute 97.7% of the volume during our sample period. We denote the five trading venues in the table by the letters A through E. Panel A provides cross-sectional summary statistics for market share in terms of volume as well as for the two measures of trading venue viability or competitiveness: (i) %TimeBestPrices, defined as the percentage of time that the trading venue posts either the best bid or the best ask in the market (where the market is defined as the aggregation of all five trading venues), and (ii) %TimeSmallSpreads, defined as the percentage of time that the bid-ask spread on the trading venue is the narrowest spread in the market. In Panel B we examine whether correlated activity of HFT firms on a particular trading venue is helpful for the competitive position of the trading venue by manifesting in better prices and spreads. Not all HFT firms in our sample are very active on multiple trading venues. We therefore focus on the firms with substantial activity on all five trading venues, which we define as sending at least 10,000 messages to each of the five trading venues. There are eight HFT firms that satisfy this criterion, and we compute trading-venue-specific time-series correlations that provide information regarding whether the strategies of these HFT firms are correlated over time for a given stock on a particular trading venue. These correlations are similar in nature to the time-series correlation measure from Section 4, except they are computed for each trading venue separately using only activity on that trading venue. For each trading venue *v*, we run the following cross-sectional regression:

$$C_{iv} = a_0 + a_1 Cor\left(Y_{iv}\right) + a_2 Y_{iv} + a_3 Spread_{iv} + a_4 BBOdepth_{iv} + a_5 MktCap_i + a_6 Price_i + a_7 Volatility_i + error_{iv}$$

where C_{iv} is one of the two viability measures, and we use MSG (total messages sent by the HFT firm) as our measure of HFT strategies for computing $Cor(Y_{iv})$ and Y_{iv}. The next two variables, average spread and bid-and-offer (BBO) depth, are computed separately for each trading venue and are meant to control for the liquidity environment of the stock on that trading venue. The last three control variables—market capitalization, price level, and the standard deviation of 30-minute returns over the sample period—are meant to control for heterogeneity in fundamental attributes across stocks. To economize on the size of the table, and because we want to present results for the five trading venues and the three time intervals (I1, I2, and I3), we report in Panel B only the coefficients on $Cor(Y_{iv})$ from each regression (with heteroskedasticity-consistent t-statistics).

Panel A: Summary Statistics for Market Share and Competitiveness Measures

		A	B	C	D	E
%Market Share of Volume	Mean	14.32%	11.83%	0.40%	1.91%	69.26%
	Std.Dev.	6.68%	3.43%	0.60%	1.29%	7.99%
	Min	4.77%	3.73%	0.01%	0.42%	45.07%
	25th Perc	9.50%	9.78%	0.05%	1.19%	64.29%
	Median	13.53%	12.21%	0.10%	1.59%	70.44%
	75th Perc	16.67%	14.03%	0.48%	2.33%	75.90%
	Max	34.79%	17.57%	2.70%	7.24%	82.76%
	N	52	52	52	52	52
%TimeBestPrices	Mean	65.2%	83.2%	32.7%	66.0%	92.0%
	Std.Dev.	22.6%	13.7%	17.4%	33.0%	6.1%
	Min	15.0%	39.6%	8.1%	0.1%	71.1%
	25th Perc	50.9%	80.6%	20.8%	37.0%	89.8%
	Median	71.9%	87.0%	28.0%	79.6%	92.5%
	75th Perc	84.9%	91.0%	40.7%	96.3%	96.7%
	Max	92.2%	98.0%	82.8%	99.3%	98.9%
	N	52	52	52	52	52
%TimeSmallSpread	Mean	36.1%	54.2%	9.4%	26.9%	76.8%
	Std.Dev.	24.0%	15.8%	14.3%	19.9%	8.0%
	Min	1.8%	13.2%	0.1%	0.0%	50.4%
	25th Perc	13.4%	44.2%	1.9%	6.4%	72.8%
	Median	37.0%	58.1%	3.3%	27.3%	78.5%
	75th Perc	57.1%	65.3%	10.7%	44.9%	82.5%
	Max	83.5%	83.8%	69.3%	67.6%	89.8%
	N	52	52	52	52	52

Panel B: Coefficients on Cor(Y_{iv}) from Regressions of Competitiveness Measures

	Interval	A	B	C	D	E
%TimeBestPrices	I1	0.658	0.220	0.970	4.281	-0.340
		(2.15)	(0.92)	(1.27)	(3.20)	(-3.64)
	I2	0.704	0.325	1.474	2.091	-0.199
		(2.85)	(1.46)	(2.17)	(1.11)	(-2.15)
	I3	0.661	0.348	1.427	0.781	-0.096
		(2.70)	(1.76)	(3.31)	(0.53)	(-1.26)
%TimeSmallSpread	I1	1.218	0.891	0.735	2.472	-0.875
		(2.64)	(2.61)	(1.17)	(2.77)	(-4.63)
	I2	1.188	0.891	0.966	1.375	-0.660
		(2.77)	(2.73)	(1.79)	(1.39)	(-3.37)
	I3	1.042	0.794	0.818	0.539	-0.438
		(2.60)	(2.68)	(2.48)	(0.72)	(-2.72)

Table 11

Market Concentration and the Correlation of HFT Strategies

This table presents regression results that relate concentration of trading across the trading venues to competition between high-frequency trading (HFT) firms. The five trading venues we investigate are organized as electronic limit-order books and together execute approximately 97.7% of the trading volume during our sample period. To examine market concentration, we compute the Herfindahl-Hirschman Index (henceforth HHI) of market share in terms of volume for the five trading venues for each stock. The HHI is computed as the sum of squared market shares of the trading venues, and the lower the HHI, the less concentrated the market. We run the following cross-sectional regression:

$$HHI_i = a_0 + a_1 Cor\left(Y_i\right) + a_2 Y_i + a_3 Spread_i + a_4 Depth_i + a_5 MktCap_i + a_6 Price_i + a_7 Volatility_i + error_i$$

where Cor(Y_i) is the time-series correlation among HFT strategies that we use to represent competition in the HFT space, and Y_i stands for one of the three measures of HFT strategies we use: MSG (total messages sent), TRD (trades), and LMT (submission of cancelations of non-marketable limit orders). The next two variables, market-wide average spread and bid-and-offer depth, are meant to control for the liquidity environment of the stock. The last three control variables—market capitalization, price level, and the standard deviation of 30-minute returns over the sample period—are meant to control for heterogeneity in fundamental attributes across stocks. We report results side by side for the three time intervals (I1, I2, and I3) with heteroskedasticity-consistent t-statistics.

	MSG			TRD			LMT		
	I1	I2	I3	I1	I2	I3	I1	I2	I3
Intercept	0.918	0.892	0.771	0.909	0.865	0.642	0.916	0.884	0.756
	(91.37)	(42.12)	(19.74)	(66.01)	(30.27)	(12.64)	(92.94)	(42.98)	(20.38)
Cor(Y_i)	-0.738	-1.135	-1.696	-0.757	-1.234	-0.627	-0.723	-1.093	-1.641
	(-5.28)	(-5.78)	(-5.72)	(-2.53)	(-3.13)	(-1.12)	(-5.29)	(-5.84)	(-5.94)
Y_i	-9.1E-06	-1.3E-04	-7.4E-06	-2.3E-02	-5.0E-02	-6.1E-02	-4.5E-06	-1.3E-04	-3.0E-05
	(-0.32)	(-1.85)	(-0.07)	(-5.64)	(-7.07)	(-5.08)	(-0.18)	(-2.21)	(-0.39)
Spread	0.777	1.134	1.692	0.772	0.968	1.797	0.821	1.194	1.696
	(2.90)	(3.09)	(3.29)	(3.28)	(3.39)	(3.00)	(3.08)	(3.29)	(3.32)
Depth	3.0E-08	-3.1E-08	-1.0E-08	1.5E-07	-6.7E-09	-9.9E-09	5.5E-08	-2.4E-08	-8.4E-09
	(0.53)	(-3.53)	(-5.69)	(2.40)	(-0.64)	(-4.89)	(0.98)	(-2.84)	(-4.76)
MktCap	-7.0E-10	-1.6E-09	-1.8E-09	-2.7E-10	-5.5E-10	-7.1E-10	-6.6E-10	-1.6E-09	-1.6E-09
	(-5.63)	(-7.25)	(-5.35)	(-1.94)	(-2.53)	(-2.04)	(-5.06)	(-6.68)	(-4.48)
Price	2.4E-04	3.8E-04	7.8E-04	1.9E-04	3.2E-04	1.1E-03	2.1E-04	3.4E-04	7.4E-04
	(2.02)	(1.69)	(2.10)	(1.99)	(2.19)	(3.90)	(1.77)	(1.57)	(2.02)
Volatility	-3.170	-8.521	-7.023	0.078	0.635	8.645	-3.228	-8.212	-5.682
	(-1.14)	(-1.64)	(-0.94)	(0.03)	(0.14)	(0.97)	(-1.16)	(-1.59)	(-0.78)

Figure 1

Cross-Sectional Correlation of HFT Strategies over the Trading Day

This figure presents the intraday pattern of cross-sectional correlations between high-frequency trading (HFT) firms (which examine whether the strategies of HFT firms are correlated across stocks at a particular time interval). We use data from the Investment Industry Regulatory Organization of Canada (IIROC) to identify 31 HFT firms. In each 1-second time interval, we compute the correlation coefficient between the activities of two HFT firms across the stocks in the sample, and average the correlations for all pairs of firms to obtain the cross-sectional correlation. Our sample consists of 52 stocks from the S&P/TSX60 (S&P). We rank the daily returns of the S&P/TSX Composite index from June 2010 through March 2011, and select the 10 worse days, the 10 best days, and the 10 days closest to and centered on zero return for a 30-day sample period. In the figure, we plot the average over the 30-day sample period of the cross-sectional correlation for each interval during the day.

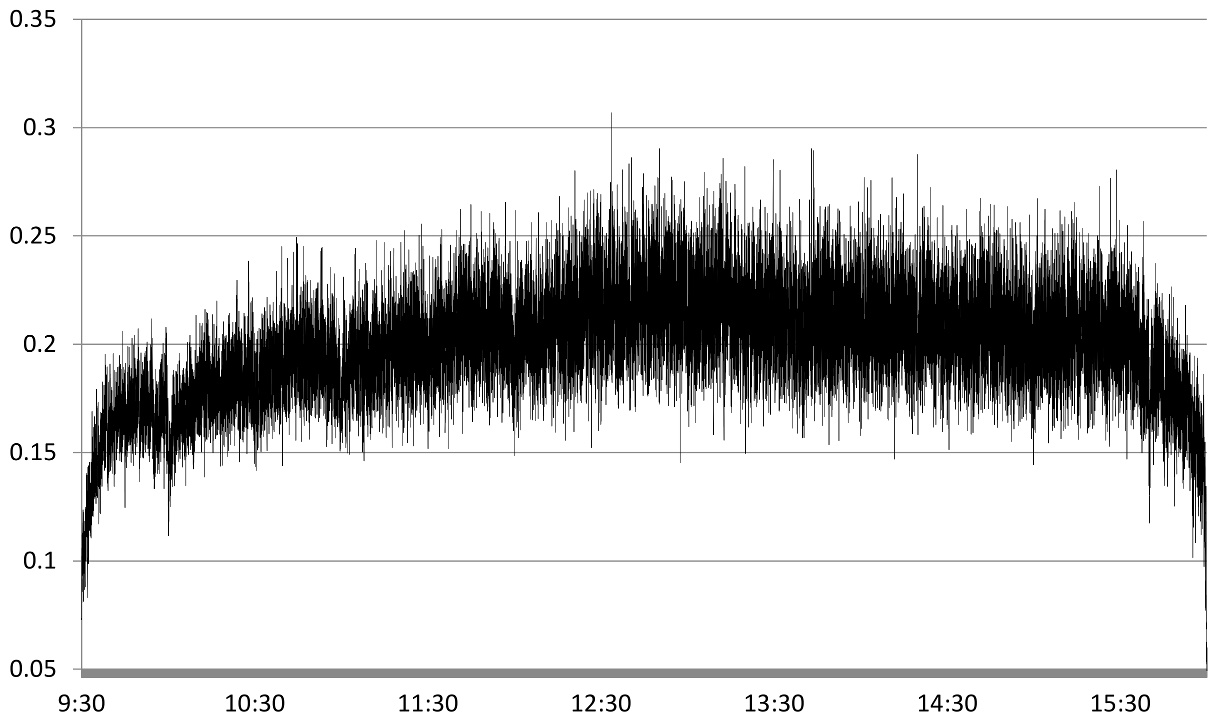
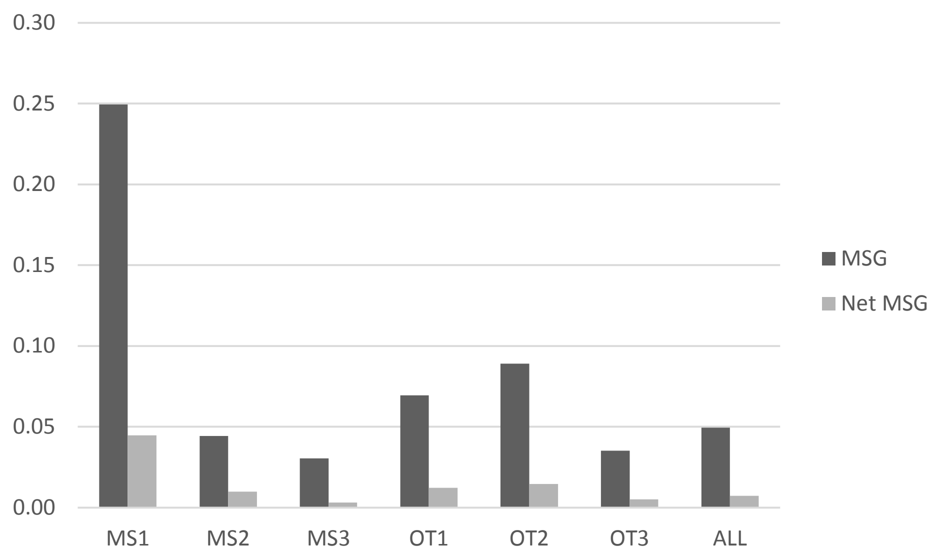


Figure 2

Correlations of HFT Strategies: Total versus Directional

This figure compares the correlations between strategies of high-frequency trading (HFT) firms for total versus directional measures. We use data from the Investment Industry Regulatory Organization of Canada (IIROC) to identify 31 HFT firms. These firms are further categorized into three subgroups according to market share—MS1 (market share > 4%), MS2 (market share of between 1% and 4%), and MS3 (the rest)—and their orders-to-trades ratios—OT1 (ratio > 150), OT2 (ratio between 50 and 150), and OT3 (the rest). We compare the magnitudes of the time-series (Panel A) and cross-sectional (Panel B) correlations for total HFT activity (MSG, defined as buy plus sell orders) and directional HFT activity (NetMSG, defined as buy minus sell orders). The time-series correlation indicates whether the strategies of HFT firms are correlated over time for a particular stock. For each stock, we compute the correlation coefficient between HFT activities of any two HFT firms, and average these across all pairs of firms. The cross-sectional correlation measure indicates whether the strategies of HFT firms are correlated across stocks in a particular time interval. In each 1-second time interval, we compute the correlation coefficient between the activities of two HFT firms across the stocks in the sample, and average the correlations for all pairs of firms.

Panel A: Time-Series Correlations



Panel B: Cross-Sectional Correlations