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Abstract

We analyze trading dynamics as successive high-frequency trading (HFT) firms begin to trade stocks in an equity market. Entrants compete with incumbents for volume, and there is crowding out. Earlier entry is associated with larger effects. After Passive HFT entry, incumbent spreads tighten. After Aggressive HFT entry, incumbent order flow loses informedness. Revenue data suggest entry reduces the profitability of HFT activity. The results show that part of the value of HFT comes from its competitiveness.

JEL classification: G20, G14, L1
Bank classification: Financial markets; Market structure and pricing

Résumé

Les auteurs analysent la dynamique des échanges après que des entreprises qui font des transactions à haute fréquence eurent commencé successivement à négocier des titres sur le marché des actions. Les nouveaux venus rivalisent avec les acteurs déjà présents pour obtenir plus de volume, ce qui entraîne un effet d'éviction. Les effets exercés par les premiers entrants sont plus prononcés. L'entrée de participants passifs donne lieu à un resserrement de la fourchette de cotation pour les participants existants. Après l'arrivée de participants agressifs, le contenu informationnel du flux d'ordres des participants existants diminue. En outre, les données tendent à indiquer une baisse de rentabilité des transactions à haute fréquence. Les résultats de l'étude montrent que l'intérêt de la négociation à haute fréquence réside en partie dans la compétitivité de cette activité.

Classification JEL : G20, G14, L1
Classification de la Banque : Marchés financiers; Structure de marché et fixation des prix

1. Introduction

Direct participation on equity markets had once been the reserve of a small number of well-connected specialists: access to order books was restricted by the trading venue, and a select few market-makers and seat members were located on-site. Today, a computer-based trader need only become a client of a sponsoring broker, the cost of computing hardware has fallen steadily, and there is no requirement to register as a market-maker. This has led to a mixture of technology and strategy referred to as high-frequency trading (HFT). HFT is the combination of low-latency connectivity, short holding periods and low inventory positions. Two features stand out in HFT: speed and competition. The speed of HFT is an increasingly well-understood contributor to market liquidity and price efficiency (e.g., Brogaard et al. 2013; Baron, Brogaard and Kirilenko 2014; Weller 2013). This paper examines the role of competition among HFT firms and how it changes their effect on liquidity and price efficiency.

We study a market in which successive HFT entrants interact with incumbents and other participants. HFT entry disturbs the trading environment and leads HFT incumbent firms to adapt. Following new HFT entry, HFT incumbents behave more competitively. The competitive improvements are largest following the first few entrants.

We observe evidence of competitive pressures in a number of dimensions. First, incumbents lose volume share to new entrants. Second, entry by Passive HFT firms, those that mainly provide liquidity, leads incumbents to tighten their spreads. Third, following entry by Aggressive HFT firms, those that mainly take liquidity, incumbents experience a loss in their ability to trade in the direction of future price movements. Finally, after new

HFT entry, HFT incumbents earn less revenue. Each of these effects diminishes as the HFT entry number increases. As more HFT firms begin trading a stock, they have a decreasing effect on volumes, trades, incumbents' spreads, incumbents' price impact and revenues.

The study uses data from the Alpha trading venue. Alpha is a Canadian alternative trading system now owned by the TMX Group, which also owns the Toronto Stock Exchange. Alpha provided data from its first day of operation in November 2008 to 25 September 2012. The data set for orders, messages and trades has sufficient information to identify the dates on which participants first began to trade on the venue.

We use a differences-in-differences methodology around the staggered entry dates of new HFT firms to isolate the impact of entry from other cross-sectional and time-series variations. We use a 20-day centred window around an entry to isolate the role of the HFT entrant. A nice feature of the setting is that the HFT entry date and the number of participants varies by stock, so there can be a control group of stocks that do not experience any HFT entry. We use two empirical criteria to identify participants as HFT: low overnight inventory holdings and frequent switching of the direction of their trades. Similar to much of the literature, we find that HFT competition is associated with improvements in the bid-ask quotes that HFT firms provide and in the randomness of the price path.

We find that HFT firms compete for volume. For the first few HFT entrants in a stock, the proportion of trading volume conducted by HFT increases. After the second HFT entrant, the increase is statistically no longer significantly different from zero. However, new HFT entrants take away volume from the incumbent HFT firms. This suggests that

there are particular trades that HFT firms want to engage in and the new entrants compete vigorously to capture trading volume.

We observe heterogeneity among HFT participants. Similar to Hagstromer and Norden (2013), we define two HFT subgroups: Passive HFTs and Aggressive HFTs. Passive HFTs are those that use marketable orders less than 33% of the time; Aggressive HFTs use marketable orders more than 75% of the time. The entry of Passive HFTs, whose behaviour is consistent with a market-making strategy, leads incumbents to quote more aggressively. After entry by Aggressive HFT firms, whose behaviour is consistent with high-speed price forecasting, incumbents experience a loss in their ability to trade in the direction of future price changes. Entry is associated with HFTs generating fewer revenues.

Furthermore, there are diminishing marginal effects of entry. Later-arriving entrants have less of an impact than earlier arrivals. After a third HFT begins trading a stock, the HFT share of volume and trades, the competitive pressure on HFT quoted spreads and trade informedness, and HFT revenues lose statistical significance. Later entrants do not generate new business for HFT but do significantly displace incumbents. Even though entrants beyond the third do not generate new business for HFT, they continue to enter.

As more Passive HFTs enter, the best bid-ask spreads quoted by incumbent firms tighten less and less, diminishing not only in magnitude but also in statistical significance. Interestingly, a new entrant does not typically undercut the best incumbent's prices; entrants quote, on average, slightly higher than incumbent HFTs. Entry impact similarly diminishes for Aggressive HFT entrants. After the entry of a new Aggressive HFT,

incumbents are less able to forecast short-term price movements. More firms are trading to impound information into prices, deteriorating the predictability of prices.

We show that the new HFT entrants' competitive pressures result in lower revenues for incumbents. While the results lack statistical significance, they consistently show that HFT entry is followed by a decrease in revenues. Nonetheless, the average HFT incumbent continues to realize positive revenues.

Microstructure theory is mixed on how competition should affect market participants. Competition generally improves outcomes for other market participants. Dennert (1993) models market-makers specifically and demonstrates that competition can result in higher bid-ask spreads because of the higher riskiness of each individual market-maker interacting with an informed trader.

Empirically, competition is well studied in financial markets. For instance, when exchanges compete, market participants usually benefit (Huang 2002; Mayhew 2002; Battalio and Jennings 1997), but Pagnotta and Philippon (2011) show competition can be harmful. Others study competition among formal market-makers. Market-making competition increases liquidity (Klock and McCormick 1999; Weston 2000; Van Ness, Van Ness and Warr 2005; Battalio 1997). The focus of this paper is to examine competition among HFT firms.

Competition among HFT firms is highlighted in the theoretical literature. Biais, Foucault and Moinas (2013) explain why slow traders may choose to become fast and that increased HFT participation will increase adverse selection costs. Pagnotta and Philippon (2011) show that competition among HFTs decreases profits, but that the competition is of

Cournot type and so profits remain positive, while Jovanovic and Menkveld (2010) model an environment in which HFTs compete away any profits.

At least two other empirical papers examine slightly different questions regarding HFT and competition. Menkveld (2013) finds that when an HFT firm begins to participate on the European Chi-X, bid-ask spreads decrease 50%. However, Breckenfelder (2013) finds that when multiple HFT firms enter the Swedish Nasdaq, market quality deteriorates. We extend both papers by examining how HFTs change their trading behaviour as a result of each new additional HFT competitor.

The approach in this paper helps to isolate the role of competition from the role of speed and aims to understand the channel by which competition affects markets. Our findings complement HFT market-quality papers. Most papers show a relationship between HFT and improved market quality (Brogaard, Hendershott and Riordan 2014; Hasbrouck and Saar 2013; Hagstromer and Norden 2013; Carrion 2013), while others find a mixed or negative relationship (Brogaard, Hendershott and Riordan 2013; Gai, Yao and Ye 2012). We are interested in the competition among HFT firms, which helps to explain some of the HFT and market-quality findings.

The rest of the paper is structured as follows: Section 2 describes the data and empirical design. Section 3 reports how HFT entry influences market dynamics. Section 4 concludes.

2. Data and Methodology

We use order message and trade data from the Canadian Alpha Alternative Trading System (ATS) equity trading venue. Alpha ATS opened for trade on 7 November 2008. It was independently operated until merging with the TMX Group as part of the Maple transaction on 1 August 2012. By January 2009, Alpha had the second-largest share of trading volume in Canada, and by January 2010, it had over 20% of Canadian trading volume. Alpha became a listing exchange February 2012. Figure 1 displays the time-series distribution of equity trading volume across exchanges.

INSERT FIGURE 1 ABOUT HERE

The data set contains all order messages received by Alpha and trade notifications sent by Alpha between 7 November 2008 and 25 September 2012. The data include all limit-order quotations, updates, fills and cancellations,[1] and they are millisecond time stamped. In addition to the order-book information that is publicly available, the data include an anonymous identification code that is specific to each market participant. The anonymous code allows us to identify the date each market participant began trading. We focus our analysis by sampling the data starting 1 January 2009 and sampling only the stocks that were, at some time between 2009 and 2012, a member of the 2012 S&P TSX 60 index or a member of the top 40 stocks by market cap in the 2012 S&P TSX 300 midcap index.

[1] There is a gap in the order-message data (although not the trade data) between 6 May 2010 and 1 July 2010 because of imperfections in the data on those dates. The omission has no effect on our analysis because no entry events occur in or near that interval. We supplement our data with publicly available data from Thomson Reuters' Sirca, when necessary.

Identification of HFT entry dates

A participant stock-entry date is the calendar day on which a participant first trades more than one lot (100 shares) on Alpha. The threshold is strictly more than the minimum lot to exclude days on which the participant is merely testing its connection. Stock-entry events are stock-specific, so the same participant can have different entry dates for different stocks.

A participant stock-entry date is classified as an *HFT entry date* if the market participant's behaviour satisfies two criteria during the two calendar weeks (10 trading days) after the stock-entry date. First, the participant must switch the sign of its trade (follow a buy with a sell or a sell with a buy) at least 33% of the time. Second, it must hold, on average, no more than 20% of its daily volume overnight. Participants who satisfy these criteria are called *HFT firms*. Whether or not a participant is an HFT firm is stock-specific. An entrant may be considered an HFT firm in one stock and not in another. This flexibility ensures that the entries we capture are those that exhibit HFT qualities.

The criteria were chosen to be consistent with the literature on how to distinguish HFT from other kinds of algorithmic trading. The first criterion distinguishes HFT from algorithmic execution. HFT firms trade frequently but do not build a position in a stock, so their trading direction should frequently reverse between buying and selling. The second criterion distinguishes HFT from strategies that bear significant longer-term risk. HFT firms hold very little inventory overnight because they do not wish to expose themselves to the risk that the asset value might change. We choose a relatively high inventory threshold of 20%, since there are multiple markets for the stocks traded on Alpha. An HFT firm may open a position on Alpha and close it on another exchange, or vice versa, resulting in what

would appear to be an inventory position from the researcher's perspective, even if the trader is neutral.

We do not use the order-to-trade ratio as an identifying characteristic of HFT because it identifies only passive HFT strategies, such as market-making, and may not capture HFT firms that are primarily aggressive.

If the participant associated with an entry date is identified as an HFT firm in the two weeks after that date, the date is a candidate HFT entry date for inclusion in the study. There is variation in how many stocks HFT-identified entrants begin trading at a time. Most HFT-identified entrants start trading several stocks on the same day. A few entrants start by trading just one stock and, after some time, begin trading other stocks.

Some participants begin participating on Alpha by trading quite lightly, perhaps to test whether their strategies behave as expected. After a week or so, they increase their trading volume to a much greater amount. To account for the possibility of an initial testing period, we search for a positive and statistically significant level shift in trading volume by the market participant during the 20 trading days after entry.

The model searches for shifts in the new entrant's level of volume in the specific stock. We use a univariate linear regression in which the sole variable is a dummy equalling one for varying dates after a candidate structural break date:

$$Volume_t = \alpha + \beta D_t + \epsilon_t \quad (1)$$

where α is a constant and D_t is the structural break dummy. The model is fit 20 times, once for each of the 20 trading days after entry. Each regression contains 20 observations, which

are the first four weeks of trading after the HFT entry date. If there are dates for which the estimated coefficient β is both positive and significant, the date with the highest R^2 is identified as the entry date, and we use it instead of the initial entry date.

Not all HFT entry dates are included in the final data set. The participant must generate at least 2% of daily volume on average during the two calendar weeks (10 trading days) after the date. The study excludes smaller participants to reduce noise in the sample. The share of daily volume that the excluded participants conduct is not economically significant. The volume restriction excludes 43 events. We also remove HFT entry dates that have more than four days of erroneous order-book data during the two weeks either before or after entry. Erroneous order-book data can occur for any of four reasons: orders reported out of temporal order, missing hours, missing days or unreadable data. Combined, these criteria result in the exclusion of 17 events.

Finally, we exclude entry events that occur on stocks we consider to be illiquid, defined as stocks that have an average bid-ask spread greater than 10 cents during the 10-day period before an HFT entry. The entry of HFT firms on an illiquid stock tends to have enormous effects. For example, for certain stocks on Alpha with large bid-ask spreads, an HFT entry decreases relative spreads by 500 bps. We exclude these entries, since we are unable to distinguish whether the decrease is due to the participant being an HFT or whether it is due to the stock gaining its first financial intermediary. This excludes 40 entries. All but three of the events that were excluded because of the size of the bid-ask spread occurred during the first half of 2009, when Alpha was a nascent and illiquid venue. After the restrictions, we observe 17 unique participants and a total of 240 HFT entry events.

Figure 2 displays a histogram of the number of HFT entry events over the time series.

INSERT FIGURE 2 ABOUT HERE

The entrants are staggered over the four-year window, providing a time-series control. Also, there is clustering of entry events at specific dates, meaning that some HFT firms choose to enter multiple stocks at the same time.

Classification of HFT entry events

We classify the HFT entry dates by the aggressiveness of the entrant. Aggressiveness is the percentage of a participant's orders that are marketable. Aggressive HFT firms are those for whom trades are entered using marketable orders at least 75% of the time. Passive HFT firms are those for whom trades are entered using marketable orders less than 33% of the time. Figure 3 depicts the distribution of aggressiveness over the set of entry events.

INSERT FIGURE 3 ABOUT HERE

The distribution is bimodal with large concentrations of events in which participants are predominately Passive (only limit orders) or Aggressive (only marketable orders). HFTs that are mixed do not cluster around any particular percentage of aggressiveness.

Table 1 provides summary statistics for the HFT entry events for all events and for Passive and Aggressive events. Each row of the table gives the average, standard deviation,

25%, median and 75% statistics of various measures. *Days of trade* is the number of days that the entrant executed at least one trade. *Daily volume* is the average number of shares the entrant traded daily. *Daily trades* is the average number of trades the entrant executed daily. *Per cent daily volume* is the average per cent of total daily volume the entrant contributed. *Per cent volume held at end of day* is the average per cent of its own daily volume the entrant held at the end of day. *Switching rate* is the percentage of the entrant's trades for which the entrant switched the direction of its trade—the per cent of the time it bought after it had sold or sold after it had bought. *Per cent aggressive* is the percentage of the entrant's trades for which the entrant initiated the trade (either through a market order or marketable limit order). Panel A shows statistics for all events, and panels B and C repeat them for the Passive and Aggressive entry events, respectively.

INSERT TABLE 1 ABOUT HERE

Once they have entered, the HFT firms continue to participate. In 191 of the 240 entry events, the entrant traded every day in the 10 days following entry. In the remaining 49, the entrant did not trade one of the days. Entrants trade an average of 60,000 shares a day and an average 15% of daily volume. For comparison, 15% of the average daily volume of IBM on NASDAQ is roughly 750,000 shares. Most participants held less than 10% of their daily trading volume overnight, and most participants switched the direction of trade more than 50% of the time.

There are some differences between the sample of Passive HFT entry events (Panel B) and Aggressive HFT entry events (Panel C). Passive HFT firms are more active than

Aggressive HFT firms. After entry, a Passive HFT firm trades 70,500 shares daily compared with only 40,800 by an Aggressive HFT firm. Another difference is that Aggressive HFT firms rarely use passive orders, while Passive HFTs frequently use aggressive orders. The average aggressiveness for Aggressive HFTs is nearly 100%, while the average aggressiveness for Passive HFTs is 9%.

Table 2 shows the average and standard deviation of the summary statistics by each event-order grouping. The same measures reported in the rows of Table 1 are represented in the columns of Table 2. The rows of Table 2 report the measures by the entrant grouping in a stock, from the first entrants to the sixth and later entrants.

INSERT TABLE 2 ABOUT HERE

A few trends stand out. Later entrants generate more daily volume than earlier entrants. The first entries trade on average 51,956 shares, while the sixth and later entries trade on average 65,573 shares. The daily volumes stop increasing after the third entrant grouping. In contrast, the per cent of daily volume of new entrant trades decreases, from 22% for the first entrants to 10% for the sixth and later entrants. Both statistics are consistent with a market growing in the number of participants and in size. Also, later entrant groupings are generally composed of more aggressive HFTs. The average aggressiveness of the first event group is 38%, whereas it is 88% for the last.

Empirical Design

This paper uses a differences-in-differences methodology. For each HFT entry (treatment) observation, we include contemporaneous observations from stocks not experiencing an HFT entry (controls). Any stock is eligible to be in the control group, except those stocks experiencing an HFT entry in the same 20-day window as the treatment stock. From the eligible set of stocks, the selection of the control stocks is based on a Mahalanobis ranking. For each treatment stock, the 30 stocks with the smallest sum of the squared percentage distance measures from the treatment stock are included in the control group. The distance measure is based on the bid-ask spread in the 10-day pre-entry window, 10-day daily price volatility and market capitalization as of September 2012. We use 30 control stocks, since this is the largest number of control stocks that would provide a balanced panel. A large number of control stocks minimizes the possibility of erroneous findings driven by idiosyncratic movements in a particular control stock.

After constructing the data set, we estimate entry impacts using the linear model,

$$Variable_{i,j,t} = \beta\, I_{i,j,t} + \gamma D_{i,t} + FE_{i,j} + \epsilon_{i,j,t} \qquad (2)$$

The quantity of interest is β, the average treatment effect of an HFT entry. The index *i* is the event group (1 through 240), j is the stock number (1 through 104), and t is the day of observation in the window (1 through 20). The dependent variable $Variable_{i,j,t}$ is the relevant dependent variable statistic of the regression. All $Variable_{i,j,t}$ values are winsorized at 99.9%. The variable $I_{i,j,t}$ is a dummy variable equalling one for the treatment stocks during the 10-day post-entry period and zero otherwise. The variable $D_{i,t}$ is a dummy variable equalling one for any stock during the 10-day post-entry period. For each

event group of control and experimental stocks, variable $D_{i,t}$ constitutes the first difference, hence β is a differences-in-differences coefficient. $FE_{i,j}$ are fixed effects for each stock and event group pairing. For example, if data from the same stock are used as a control for an HFT entry in 2010 and again in 2012, the model fits a separate fixed effect for each separate series of observations. There is no constant because the set of fixed effects spans the sample. For most of the analyses, we evaluate the entry events in separate regressions.

The standard errors tend to be underestimated in the differences-in-differences methodology (Bertrand, Duflo and Mullainathan 2004). To correct the underestimation, we double-cluster the standard errors by day and stock-event grouping (Petersen 2009; Thompson 2011) Because we are focusing on the localized effect of 20 days surrounding the entry and are reusing stocks, sometimes as a treatment stock and sometimes as a control stock, we cluster stocks separately. As such, we are more restrictive than the typical event study that has only one event group. A stock will have a separate clustering for each event grouping in which it is included.

3. HFT Competition

In this section we examine the role of HFT entry on market share, competitive pressures and revenues in order to understand how the industrial organization of HFT firms influences the trading dynamics among them.

Market Shares

We first examine the influence HFT entry has on the fraction of volume generated by the 17 HFT participants. In the following regressions and in all the regressions in this paper, we use a differences-in-differences event-study methodology and fit the model in equation (2). The dependent variable is *HFT volume share,* the per cent of trading volume (HFT shares traded / 2x total shares traded) executed by HFT firms for stock *i* on day *t*. The results are reported in Table 3, Column 1. Each row is a separate regression with the beta coefficient from the $I_{i,j,t}$ variable being reported with the *t*-statistic in parentheses. The coefficient can be interpreted as the per cent change in HFT activity in stock *i* following a new HFT entry. The first row shows the results for all events combined. The remaining rows include subgroups of the observations based on their entry number.

INSERT TABLE 3 ABOUT HERE

An HFT entry increases the HFT share of volumes. In Column 1, HFT volume share increases by an average of 2.6%, and for the group of first entrants it increases by its maximum of 6.2%. Later HFT entrants contribute less and less to total HFT volume share, and the sixth and later entrants have essentially no impact.

In Table 3, Column 2, we repeat the regression analysis but focus only on incumbent HFTs. The dependent variable is *Incumbent HFT volume share*, the per cent of share trading volume executed by incumbent HFTs (e.g., all HFTs except the new entrant).

While entry increases an HFT's total volume share, it has the opposite effect on the share of incumbents. Incumbent volume share decreases by an average of 2.9%, and over the various entry groups it falls by varying amounts between 1.7% and 3.5%. For the first

two entrant groups, total volume share increases while incumbent volume share decreases. The early entrants are both generating new volume and displacing existing volume from incumbents. However, entrants quickly exhaust their ability to generate new volumes. The third and later HFT entrants have a statistically insignificant impact on HFT's volume share (Column 1). Later entrants are taking volume from incumbents without adding significant new volume.

In Column 3, we report the average share of volume generated by HFT during the 10 days before entry. The influence of HFT entrants on volume share diminishes according to the amount of volume that is already generated by HFT. For those events with HFT volume share already above 40% (third entrant and later), HFT entrants have no statistically significant impact on the total volume share. This suggests that there is a limited portion of the order flow in which HFT strategies have interest.

Table 3 measures HFT activity before and after the entry events. Only the first few entrants increase the level of overall HFT volume. There are two takeaways: First, the results suggest competitive behaviour among HFT participants. When new entrants join, they displace other market participants by taking their volume, forcing them to become more willing to trade and possibly crowding them out by sometimes trading with them. Second, there appears to only be a certain portion of order flow with which HFT firms want to trade. On Alpha, the threshold portion was between 40% and 50% of order flows. HFT entrants beyond the third event grouping were merely redistributing the flow among themselves and the incumbents.

Competitive Pressures

We have shown that HFT entrants compete against incumbent HFT firms for order flow. Now we examine whether HFT entry is associated with the exercise of competitive pressure. HFT can be used to take or provide liquidity. HFT strategies that use primarily limit orders are associated with market making or dealing and they derive profits off the spread between bid limit orders and ask limit orders (Ait-Sahalia and Saglam 2013; Hoffman 2013). We study whether incumbent HFTs react to Passive HFT entry by tightening spreads. In contrast, Aggressive HFT strategies are associated with informed trading, since they trade in the direction of future price movements (Biais, Foucault and Moinas 2013; Foucault, Hombert and Rosu 2012; Martinez and Rosu 2013). With more market participants monitoring for arbitrage opportunities, price predictability should decline. We study whether incumbent HFTs are less able to trade in the direction of future price changes.

To study the competitive pressure of entry, we compute two behavioural statistics for all 17 HFT firms whenever they appear in the sample. We compute the best bid-ask spread for each HFT (not the market best bid-ask spread, but the individual participant's best spread) and the price impact for each HFT. Some HFTs are present as incumbents in the first event grouping because their own entries failed the event selection criteria; that is, they are HFT firms, but their entry event was insufficient, since they either failed to trade 2% of volume, they entered a stock for which the bid-ask spread was greater than 10 cents or they entered in 2008. We then split the entry events that are passive from those that are aggressive. In addition, we remove from the sample those entries into stocks for which none of the 17 HFT firms was present. It is necessary to remove these entries because there is no incumbent in them to measure.

The sample selection criteria reject many entries, which makes the set of HFT entry events a conservative estimate. There remain only 20 first Passive HFT entries and only 8 first Aggressive HFT entries. Since so many of the first events are incumbent-free, there are more second Aggressive HFT entries with incumbents (17) than there are first entries with incumbents (8). Because of HFT exit between the dates of the first entry and of the second entry, there are fewer second entries for Passive HFT firms.

For Passive HFT entries, we focus on the bid-ask spread. Brogaard, Hendershott and Riordan (2013) show that Passive HFTs reduce the market-wide best bid-ask spread. Table 4 shows analysis of how incumbent HFTs adjust the HFT-only best bid-ask spread after new HFT entry. Since each incumbent may not always quote competitively, we focus on the best quote among all incumbents; that is, conditional on an HFT incumbent being on the limit-order book, we measure only the best (tightest) bid and offer prices among all the Passive HFT incumbents participating in the stock at five-second snapshots (*Tightest incumbent spread*). The $I_{i,j,t}$ coefficients from the differences-in-differences regressions with the *Tightest incumbent spread* as the dependent variable are shown in Table 4, Column 1. Each row is a separate regression, with the first considering all observations, and each subsequent row considering different subgroups of Passive HFT entries based on the number of previous entries.

INSERT TABLE 4 ABOUT HERE

Passive HFT entry leads to a tightening of the best incumbent bid-ask spread. As shown in Column 1, Row 1, incumbents tighten spreads by approximately 0.8 basis points

on average. The first entrants trigger the maximum change of 1.1, which is statistically significant at the 10% level. The remaining entrants have lower coefficients and all, except the fourth event, are statistically insignificant.

The analysis in Column 1 evaluates the change, but does not provide insights into the level of spreads, which is also important if we hypothesize that more competition should lead to lower spreads and if we want to compare incumbent spreads with new entrant spreads. In Column 2, we report the average tightest incumbent spread before entry, conditional on the presence of an HFT incumbent limit order. For comparison, in Column 3, we report the average new entrant's spread over the 10 days after its entry.

The incumbents post quotes with a 4.5 bps spread, on average, before the new entrant, while the new entrant posts bid and offer prices with a spread of 5.64 bps, on average. Interestingly, the average new entrant spread is not as tight as that of the incumbents, although the two are close, suggesting that the new entrant is actively competing with the incumbents.

From the regression analysis in Column 1, we see that this competition is good for other market participants, since it makes the incumbent HFT firms decrease their bid-ask spreads. The results are consistent with diminishing returns, with the first few entrants exercising the most competitive pressure. Moreover, columns 2 and 3 show that the best incumbent spreads tighten over time. The competitive quoting by the new HFT entrants is consistent with the earlier result that new entrants take market share from HFT incumbents.

For Aggressive HFT entries, we focus on the random walk of the price path. Hirschey (2013) shows that HFT trades predict future returns. Specifically, we examine the ability of

HFT firms to trade in the direction of future price changes. We measure the five-second price impact, which is the number of cents by which the midquote price changes five seconds after a trade of $10,000. A positive price impact indicates informedness. The price-impact measure is created for each HFT stock day by estimating five-second midquote-price-impact coefficients of a participant's trades using the linear model,

$$\Delta Price_{i,j,(t,t+5)} = \beta_{i,t} Value_{i,j,t} + \epsilon_{i,j,t} \quad (3)$$

where i is the participant, j is the trade, and t is the day of trade. $\Delta Price_{i,j,(t,t+5)}$ is the signed five-second price change, and the independent variable $Value_{i,j,t}$ is the signed trade value (signed quantity times price). There is no constant, since we assume a zero-value trade has a price impact of zero. The price change is computed as the difference between the midquote price immediately after the trade execution and the midquote price five seconds after the execution. We use the midquote-price impact rather than the execution-price impact to isolate price predictability and to avoid measuring liquidity variation. To identify the most informed incumbent's price impact, for each stock-day-HFT firm we estimate a price-impact coefficient and select the incumbent HFT with the maximum price-impact coefficient, conditional on the coefficient being statistically significant at the 10% level. We report the variable *Maximum incumbent price impact* as the price impact for a trade of $10,000 in value (i.e., we report $\beta_{i,t}$ x 10,000).

A positive price-impact coefficient for participant i on day t, $\beta_{i,t}$, indicates informedness at the five-second time horizon. If an entrant were to increase price

efficiency, incumbents would be left with fewer and smaller price discrepancies to arbitrage.

Since we are interested in informedness, we focus our analysis on Aggressive HFT firms. This limits us to 63 entries. In Table 5, we use the differences-in-differences methodology to look at the maximum incumbent price-impact change after a new Aggressive HFT entrant. Similar to the Passive HFT entry analysis, since each incumbent may not always trade competitively, we focus on the most informed trader among all incumbents. The $I_{i,j,t}$ coefficients from the differences-in-differences regressions with *Maximum incumbent price impact* as the dependent variables are reported in Column 1. Each row is a separate regression, with the first considering all observations, and each subsequent row considering different subgroups of Aggressive HFT entries based on the number of previous entries.

INSERT TABLE 5 ABOUT HERE

Aggressive HFT entry decreases the price impact of the most informed incumbents' trades. The average incumbent price impact decreases on average by 0.3 cents for a trade of $10,000. The first Aggressive entries decrease the incumbents' price impact by a maximum of 1.3 cents.

Successive HFT entrants have a diminishing effect on incumbents' informedness. In fact, there is no statistically significant impact after the second event. This suggests that HFTs are less able to predict future prices and that HFT trades are more reflective of short-term information.

Column 2 shows the average maximum incumbent price impact over the 10 days before the HFT entry. The average price impacts generally decrease, albeit not uniformly. Column 3 shows the average new HFT entrant price impact 10 days after entry. The new entrants' price impact monotonically decreases with successive entrants. Relative to the HFT incumbents, the first three new HFT entrants are more informed than the most informed HFT incumbent market participant, which helps to explain why the price impact after entry declines for incumbents. The fourth and later entrants are less informed than the most informed incumbent, which helps to explain why the entry impact becomes insignificant. The most informed incumbent still carries out informed trades, on average.

Revenues

The results so far have shown that when an HFT firm enters, the new entrant competes for order flow and, depending on its strategy, either tightens HFT incumbent spreads or erodes the ability of HFT incumbents to predict prices. Both effects should be associated with a decline in revenue for HFT firms. In Table 6, we examine the revenue of HFT firms. We find that the competitive pressures are associated with HFT-sector revenue losses.

We return to using the entire set of 240 entry events. HFT revenues are calculated as the value of sales minus the value of purchases, less taker fees plus maker rebates, with any end-of-day inventory valued at the average daily midquote price. Because some HFT firms do much more business than others, we take a ratio of an HFT firm's daily revenue to its daily value traded to calculate its revenue per value traded. Revenues are computed once for all HFT firms present, once for only HFT entrants and once for only HFT

incumbents. Column 1 shows the change in total HFT revenue per $10,000 traded after entry using the differences-in-differences methodology. A negative regression coefficient suggests that as more HFT firms enter, revenues decrease.

Column 2 repeats the differences-in-differences methodology but considers only the revenue of incumbent HFT firms (i.e., excluding the new entrants).

Column 3 shows the average incumbent HFT revenue per $10,000 for the 10 days before the entry event. Note that the revenues after entry are not Column 3 minus Column 2, since the Column 2 statistic is the coefficient from the differences-in-differences regression and therefore takes into account time-series variation in the control group. In untabulated summary statistics, the average HFT revenue per $10,000 after entry remains positive, but lower than the before-entry level.

Each row in Table 6 shows a separate regression; the first considers all observations, and each subsequent row considers different subgroups of Aggressive HFT entries based on the number of previous entries.

INSERT TABLE 6 ABOUT HERE

HFT entry decreases both overall HFT revenues and HFT incumbent revenues. Column 2 shows that entry events reduce incumbents' revenues, on average, by $27 per $10,000 traded. Interestingly, when the new entrants are included, the coefficient decreases to -$36, which implies that the new entrants are less profitable than the incumbents. Why are they entering then? Their entry may be part of another business line that we are unable to track. Alternatively, they may be pursuing a loss-leading strategy to

push out incumbents, or they may take time to learn how to avoid losses. The latter possibility is consistent with Baron, Brogaard and Kirilenko (2014).

The revenue statistics are noisy and the HFT incumbent results are not statistically different than zero. Nonetheless, the coefficient sizes are informative. There is a trend in the order of entry. Early HFT entrants increase the revenues that HFT participants accrue, whereas later HFT entrants decrease the revenues. The impact of entry on incumbents is again competitive: entrants reduce the revenue of incumbents. The impact is largest in the second entry event. While the average HFT revenue increases from $36 to $45 from the first to second event, for the fourth and later events, the revenues are no higher than $17. While the revenue results are noisy and statistically weak, the size of the coefficients and the averages are consistent with the hypothesis that increasing competition reduces revenues.

4. Conclusion

Financial markets continue to adopt new technology. HFTs are among the most prevalent adopters of the latest technology that processes information quickly. A number of studies examine the role of speed in markets. At the same time, however, market changes were put in place that changed the competitive nature of the trading landscape. A select group of traders no longer has exclusive access to information or proximity. Today an individual or firm can purchase a server colocated at the exchange and begin trading directly with the market with full access to all available information. The same arrangement as their competitors is allowed. In this paper, we analyze a segment of technology adopters, HFT firms, but instead of focusing on their speed, we focus on their competitiveness.

We exploit a four-year time-series data set that provides order message trader-id resolution from the Canadian Alpha exchange. We isolate 17 HFT firms and study their entry into the largest 100 Canadian stocks.

When an HFT firm begins trading a stock, it disturbs the trading environment and leads incumbent HFT firms to change their behaviour. Part of the incumbents' volume share is lost to the entrant. Competition in providing liquidity leads incumbents to tighten their spreads. Entry results indicate that incumbent HFT price predictability decreases, consistent with markets becoming more efficient. The culmination is that revenues fall with competition. The influence of both Passive and Aggressive entrants diminishes with each subsequent entry.

The approach in this paper helps to isolate the role of competition from the role of speed and aims to understand the channel by which competition affects markets. Our findings complement papers on HFT market quality. We show that competition among HFT firms, not just speed, plays a role in how they behave in the market and consequently may be partially responsible for the documented relationships between HFT and market quality.

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Figure 1: Trading in Canada. This figure plots the dollar-volume market share of the Alpha exchange in the TSX 60 over the sample period, as well as the total trading dollar volume of the TSX 60 in Canada. The market shares are calculated using Bloomberg data on the monthly trading volume of stocks in the S&P TSX 60 index.

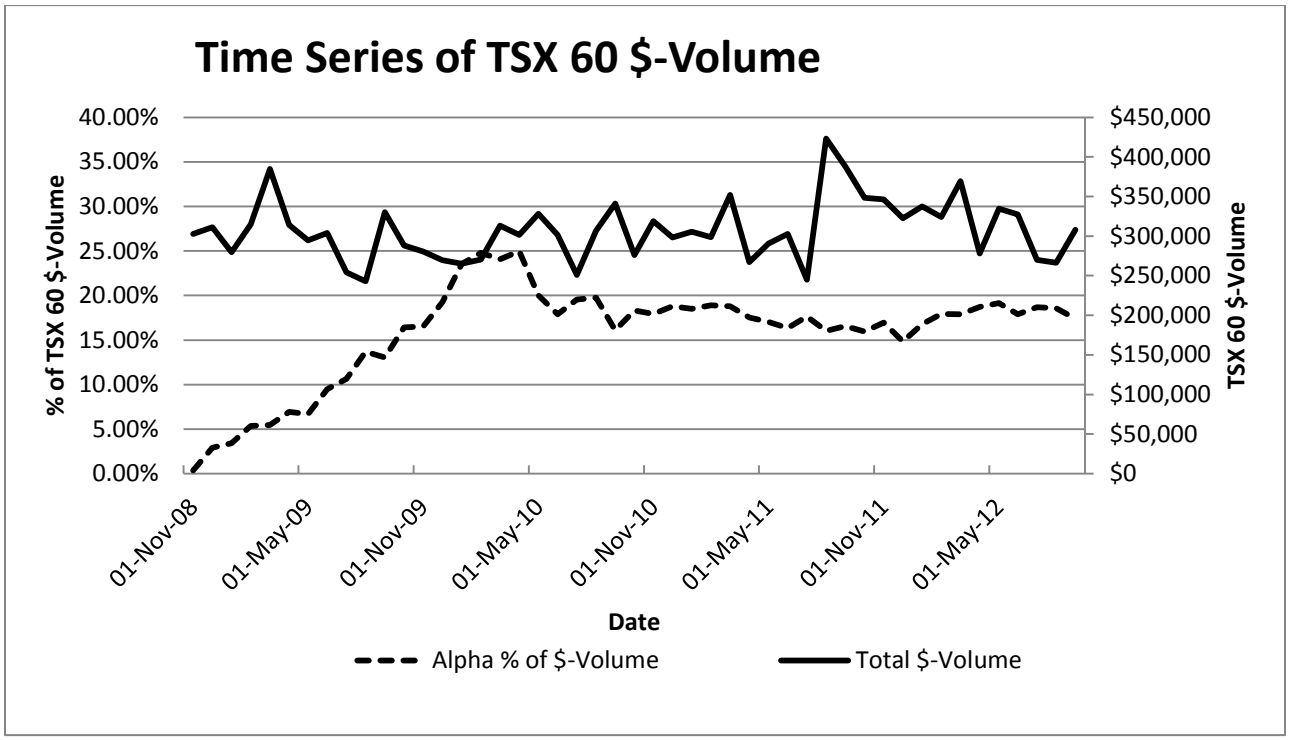

Figure 2: Time series of entrants. This figure plots the 240 HFT entry events in the Canadian Alpha Exchange. The X-axis presents the date; the Y-axis is the number of HFT entry events.

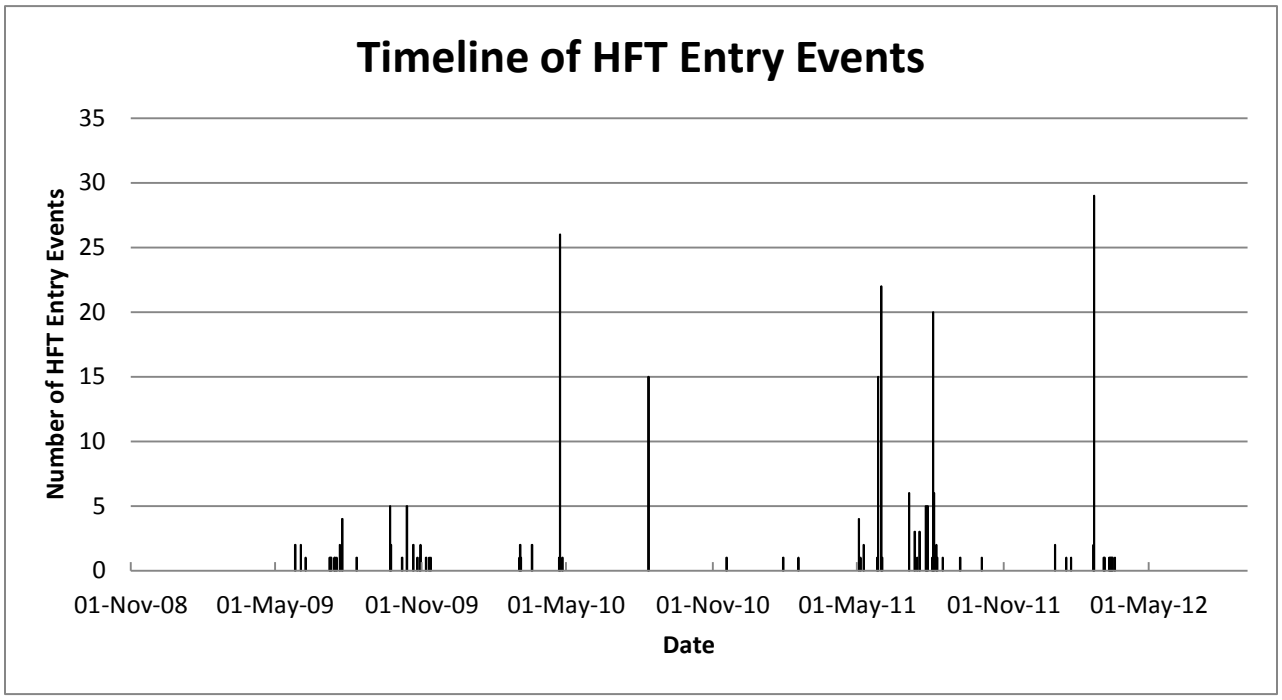

Figure 3: Aggressiveness over the 240 entry events. This figure plots the number of entry events into buckets based on the entrant's use of marketable trades as a proportion of all trades an entrant submits (aggressiveness). There are 240 events in which a participant identified as HFT begins trading a stock on Alpha.

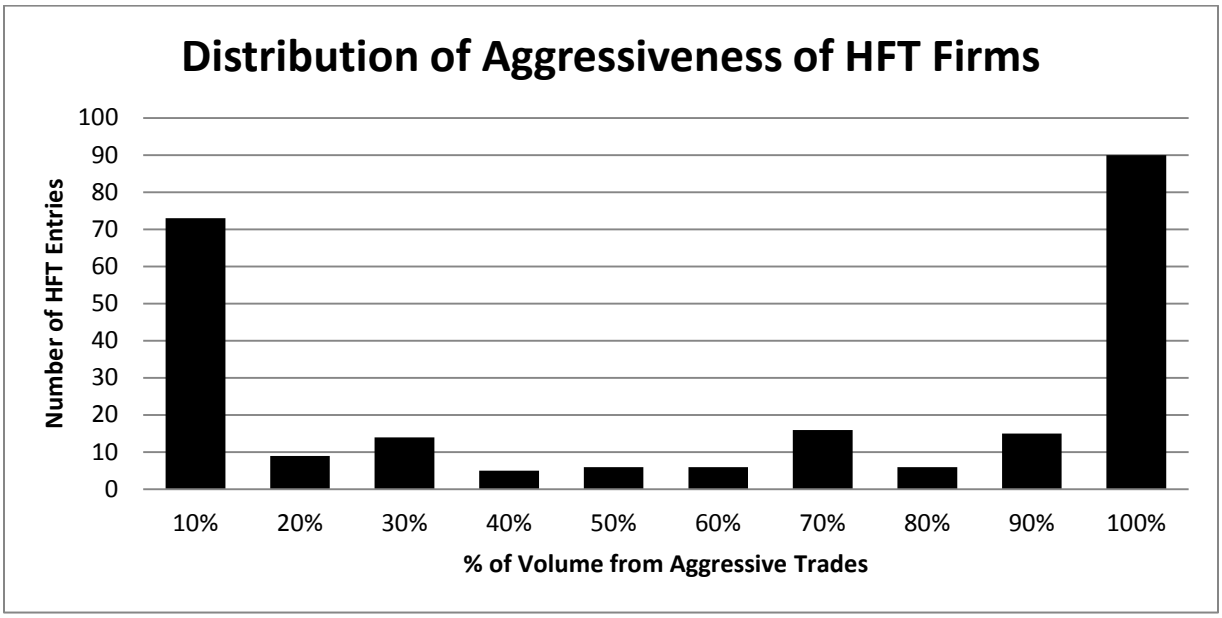

Table 1: Sample summary trading statistics for entrants. This table gives sample summary trading data for the entrants during the 10 days after their entry. *Days of trade* is the number of days that the entrant executed at least one trade. *Daily volume* is the average number of shares the entrant traded daily. *Daily trades* is the average number of trades the entrant executed daily. *Per cent daily volume* is the average per cent of total daily volume the entrant contributed. *Per cent volume held at end of day* is the average per cent of its own daily volume that the entrant held at the end of day. *Switching rate* is the percentage of the entrant's trades for which the entrant switched the direction of its trade—the per cent of the time it bought after it had sold or sold after it had bought. *Per cent aggressive* is the percentage of the entrant's trades for which the entrant initiated the trade (either through a market order or marketable limit order). Panel A shows statistics for all events, and panels B and C repeat them for the Passive and Aggressive entry events, respectively.

	Panel A: All Events					**Panel B: Passive Events**					**Panel C: Aggressive Events**				
	Mean	Std.	25%	Med.	75%	Mean	Std.	25%	Med.	75%	Mean	Std.	25%	Med.	75%
Days of trade	9.8	0.40	10	10	10	9.9	0.30	10	10	10	9.82	0.38	10	10	10
Daily vol. (1000s)	59.9	74.2	17.4	43.8	73.6	70.5	74.0	21.4	51.2	95.1	40.8	35.1	12	27.7	57.5
Daily trades	313	314	92	197	419	385	350	126	291	593	221	228	72	120	310
% Daily vol.	15%	12	8%	11%	19%	21%	15	11%	17%	25%	11%	7	7%	10%	14%
%.Vol. EOD	8%	7	1%	9%	13%	10%	6	6%	10%	14%	7%	7	1%	2%	13%
Switching rate	0.53	0.10	0.47	0.52	0.58	0.49	0.06	0.45	0.5	0.53	0.56	0.11	0.49	0.52	0.63
% Aggressive	57%	43	6%	70%	100%	9%	11	1%	4%	13%	100%	3	100%	100%	100%
N	240					99					107				

Table 2: Sample summary trading statistics for entrants by event order. This table gives sample summary trading statistics for the entrants during the 10 days after their entry, grouped by the order in which the entrant arrived relative to the other entry events for a stock. *Days of trade* is the number of days that the entrant executed at least one trade. *Daily volume* is the average number of shares the participant traded daily. *Daily trades* is the average number of trades the entrant executed daily. *Per cent daily volume* is the average per cent of total daily volume the entrant contributed. *Per cent volume held at end of day* is the average per cent of its own daily volume that the entrant held at the end of day. *Switching rate* is the percentage of the entrant's trades for which the entrant switched the direction of its trade—the per cent of the time it bought after it had sold or sold after it had bought. *Per cent aggressive* is the percentage of the entrant's trades for which the entrant initiated the trade (either through a market order or marketable limit order).

		Days of trade		Daily vol. (1000s)		Daily trades		% Daily vol.		% Vol. EOD		Switching rate		% Aggressive	
	N	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
First event	66	9.73	0.45	51956	77087	213	174	22%	18	9%	6	0.51	0.10	38%	40
Second event	63	9.67	0.48	59145	103268	294	324	14%	7	7%	4	0.56	0.11	66%	40
Third event	42	9.9	0.30	65116	54404	402	424	13%	9	8%	7	0.53	0.10	50%	45
Fourth event	28	9.93	0.26	66717	45794	446	290	13%	6	7%	7	0.53	0.08	52%	45
Fifth event	20	9.9	0.31	60857	41377	369	311	10%	5	7%	6	0.55	0.12	82%	35
Sixth and later	21	9.9	0.30	65573	49512	277	320	10%	5	10%	7	0.53	0.11	88%	30

Table 3: HFT competition and HFT's share of volume. Columns 1 and 2 of this table show the results of a differences-in-differences $Variable_{i,j,t} = \beta\, I_{i,j,t} + \gamma D_{i,t} + FE_{i,j} + \epsilon_{i,j,t}$ event study using the HFT entry events. For each treatment stock, the 30 stocks with the smallest sum of the squared percentage distance measures from the treatment stock are included. The distance measure is based on the bid-ask spread in the 10-day pre-entry window, 10-day daily price volatility and market capitalization as of September 2012. Each row is a separate regression with the beta coefficient from the $I_{i,j,t}$ variable being reported with the *t*-statistic in parentheses below. The first row shows the results for all events combined. The remaining rows include subgroups of the observations based on their entry number. In Column 1, the dependent variable is *HFT volume share,* the per cent of trading volume (HFT shares traded / 2x total shares traded) executed by any of the 17 HFT firms for stock *i* on day *t*. In Column 2, the dependent variable is *Incumbent HFT volume share*, the per cent of a stock's total daily trading volume generated by any of the 16 HFT participants other than the entrant. Column 3 shows the average share of volume generated by HFT during the 10 days before entry. Standard errors are double-clustered by day and stock-event grouping. *, **, *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Group	N	% Change, HFT volume share after entry	% Change, incumbent HFT volume share after entry	HFT volume share before entry
All	240	2.63***	-2.94***	36.01
		(4.68)	(5.34)	
First event	66	6.18***	-2.42***	22.44
		(5.41)	(2.94)	
Second event	63	1.96*	-3.30***	34.13
		(1.80)	(2.66)	
Third event	42	1.32	-3.15**	41.5
		(0.91)	(2.08)	
Fourth event	28	1.07	-3.50**	48.48
		(0.77)	(2.05)	
Fifth event	20	1.02	-1.66	47.33
		(0.77)	(1.21)	
Sixth and later	21	-0.31	-3.36**	47.81
		(0.26)	(2.37)	

Table 4: Passive HFT competition and incumbent spreads. Column 1 of this table shows the results of a differences-in-differences $Variable_{i,j,t} = \beta\, I_{i,j,t} + \gamma D_{i,t} + FE_{i,j} + \epsilon_{i,j,t}$ event study using the Passive HFT entry events. Passive HFTs are those that use marketable orders less than 33% of the time. For each treatment stock, the 30 stocks with the smallest sum of the squared-percentage-distance measures from the treatment stock are included. The distance measure is based on the bid-ask spread in the 10-day pre-entry window, 10-day daily price volatility and market capitalization as of September 2012. Each row is a separate regression with the beta coefficient from the $I_{i,j,t}$ variable being reported with the *t*-statistic in parentheses below. The first row shows the results for all events combined. The remaining rows include subgroups of the observations based on their entry number. In Column 1, the dependent variable is *Tightest incumbent spread,* the best (tightest) bid and offer prices for stock i on day t provided among all the Passive HFT incumbents participating in the stock conditional on an HFT incumbent being on the limit-order book. The order book is analyzed at 5-second snapshots. Column 2 shows the average tightest incumbent spread before the entry, conditional on an HFT incumbent limit order being present during the 10 days before entry. Column 3 shows the average new entrant's spread, conditional on the entrant being present on the limit order during the 10 days after entry. Standard errors are double-clustered by day and stock-event grouping. *, **, *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Group	N	Change, tightest incumbent spread after entry	Average tightest incumbent spread before entry	Average entrant spread after entry
All	79	-0.76**	4.5	5.64
		(2.14)		
First event	20	-1.13*	7.25	8.99
		(1.77)		
Second event	17	-0.9	5.08	5.47
		(0.67)		
Third event	21	-0.5	3.24	5.21
		(1.35)		
Fourth event	14	-0.48*	2.67	3.13
		(1.90)		
Fifth event	4	-0.67	2.81	3.14
		(1.27)		
Sixth and later	3	-0.77	2.06	2.06
		(1.48)		

Table 5: Aggressive HFT competition and incumbent informedness. Column 1 of this table gives the results of a differences-in-differences $Variable_{i,j,t} = \beta\, I_{i,j,t} + \gamma D_{i,t} + FE_{i,j} + \epsilon_{i,j,t}$ event study using the Aggressive HFT entry events. Aggressive HFTs are those that use marketable orders less than 75% of the time. For each treatment stock, the 30 stocks with the smallest sum of the squared percentage distance measures from the treatment stock are included. The distance measure is based on the bid-ask spread in the 10-day pre-entry window, 10-day daily price volatility and market capitalization as of September 2012. Each row is a separate regression with the beta coefficient from the $I_{i,j,t}$ variable being reported with the *t*-statistic in parentheses below. The first row shows the results for all events combined. The remaining rows include subgroups of the observations based on their entry number. In Column 1, the dependent variable is *Maximum incumbent price impact,* the price impact for a trade valued at $10,000 (i.e., we report $\beta_{i,t}$ x 10,000) five seconds after the trade for the most informed HFT incumbent (HFT incumbent for each stock day with the greatest price impact that is statistically significant at the 10% level). Column 2 shows the average maximum incumbent price impact during the 10 days before entry. Column 3 shows the average entrant price impact during the 10 days after entry. Standard errors are double-clustered by day and stock-event grouping. *, **, *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Group	N	Change, maximum incumbent price impact after entry	Average maximum incumbent price impact before entry	Average entrant price impact after entry
All	67	-0.3¢**	0.9¢	1.0¢
		(2.40)		
First event	8	-1.3¢*	1.0¢	1.8¢
		(1.76)		
Second event	17	-0.3¢**	0.9¢	1.4¢
		(1.42)		
Third event	11	-0.3¢	1.0¢	1.1¢
		(0.72)		
Fourth event	6	-0.3¢	0.7¢	0.5¢
		(1.10)		
Fifth event	9	-0.1¢	0.7¢	0.5¢
		(1.22)		
Sixth and later	16	0	0.8¢	0.4¢
		(0.49)		

Table 6: HFT competition and HFT revenues. Columns 1 and 2 of this table show the results of a differences-in-differences $Variable_{i,j,t} = \beta\, I_{i,j,t} + \gamma D_{i,t} + FE_{i,j} + \epsilon_{i,j,t}$ event study using HFT entry events. For each treatment stock, the 30 stocks with the smallest sum of the squared percentage distance measures from the treatment stock are included. The distance measure is based on the bid-ask spread in the 10-day pre-entry window, 10-day daily price volatility and market capitalization as of September 2012. Each row is a separate regression with the beta coefficient from the $I_{i,j,t}$ variable being reported with the t-statistic in parentheses below. The first row shows the results for all events combined. The remaining rows include subgroups of the observations based on their entry number. In Column 1, the dependent variable is *HFT revenue per $10,000 traded,* where revenue is calculated as the value of sales minus the value of purchases, less taker fees plus maker rebates, with any end-of-day inventory valued at the average daily midquote price. The regression in Column 2 focuses on HFT incumbents and has as the dependent variable incumbent *HFT revenue per $10,000 traded,* which considers only the revenues of incumbent HFT firms. Column 3 shows the average incumbent HFT revenue per $10,000 traded during the 10 days before the new HFT entry. Standard errors are double-clustered by day and stock-event grouping. *, **, *** represent statistical significance at the 10%, 5% and 1% level, respectively.

Group	N	Change, HFT revenue/10K after entry	Change, incumbent HFT revenue/10K after entry	Average incumbent HFT revenue/10K before entry
All events	240	-$36**	-$27	$34
		(1.99)	(1.24)	
First event	66	-$39	-$6	$36
		(0.78)	(0.09)	
Second event	63	-$67	-$66	$45
		(1.62)	(1.54)	
Third event	42	-$28	-$29	$45
		(1.61)	(1.57)	
Fourth event	28	-$9	-$4	$15
		(0.51)	(0.22)	
Fifth event	20	-$10	-$11	$17
		(0.75)	(0.78)	
Sixth and later	21	-$7	-$8	$14
		(0.52)	(0.59)	