Risk and Return in High Frequency Trading*

Matthew Baron, Jonathan Brogaard, and Andrei Kirilenko

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Abstract

This paper studies high frequency trading (HFT) in the E-mini S&P 500 futures contract over a two-year period and finds that revenue is concentrated among a small number of HFT firms who achieve greater investment performance through liquidity-taking activity and higher speed. While the median HFT firm realizes an annualized Sharpe ratio of 4.3 and a four-factor annualized alpha of 22.02%, revenues persistently and disproportionally accumulate to top performing HFTs, consistent with winner-takes-all industry structure. New entrants are less profitable and more likely to exit. Our results imply that HFT firms have strong incentives to take liquidity and compete over small increases in speed.

* Contact: Matthew Baron, Princeton University, e-mail: mdbaron@princeton.edu; Jonathan Brogaard, Foster School of Business, University of Washington, e-mail: brogaard@uw.edu; Andrei Kirilenko, MIT Sloan School of Management, e-mail: ak67@mit.edu. Please see the CFTC disclaimer on the following page. We thank Hank Bessembinder, Tarun Chordia, Richard Haynes, Harrison Hong, Charles Jones, Terry Hendershott, Robert Korajczyk, Norris Larrymore, Ananth Madhavan, Ryan Riordan, Ronnie Sadka and Wei Xiong for their valuable feedback. We also thank the participants at the Advances of Financial Mathematics conference, the Banff International Research Station for Mathematical Innovation and Discovery workshop, the Bank of Canada Market Microstructure conference, the NBER Market Microstructure conference, the Recent Advances in Quantitative Finance conference, the Western Finance Association meeting, and the World Federation of Exchanges conference, as well as seminar participants at Blackrock, Boston College, Boston University, the CFTC, the Federal Reserve Board of Governors, Fields Institute of Mathematics, Imperial College, London Business School, London School of Economics, MIT, the University of Massachusetts at Amherst, Northwestern University, Princeton University, Rutgers University, and the University of Washington, for helpful comments.

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Disclaimer

The research presented in this paper was co-authored by Matthew Baron, a former CFTC contractor who performed work under contracts CFCE-11-CO-0126 and CFOCE-12-CO-0154, and Jonathan Brogaard, a former CFTC contractor who performed work under contracts CFCE 11-CO-0236 and CFOCE-12-CO-0210. Andrei Kirilenko, former CFTC Chief Economist, was also a co-author who wrote this paper in his official capacity with the CFTC. The Office of the Chief Economist and CFTC economists produce original research on a broad range of topics relevant to the CFTC's mandate to regulate commodity future markets, commodity options markets, and the expanded mandate to regulate the swaps markets pursuant to the Dodd-Frank Wall Street Reform and Consumer Protection Act. These papers are often presented at conferences and many of these papers are later published by peer-review and other scholarly outlets. The analyses and conclusions expressed in this paper are those of the authors and do not reflect the views of other members of the Office of Chief Economist, other Commission staff, or the Commission itself.

Driven in part by their seeming ability to profit in all circumstances, high-frequency trading (HFT) firms have recently attracted a great deal of attention. Still, many basic questions about their strategies and profitability remain unanswered. For example, how do HFT firms make money? How do they compete with one another? And how useful is speed in driving revenue?

This paper seeks to address these questions, motivated by concerns raised in the academic literature and popular press concerning the incentives of individual HFTs to take liquidity and to compete over small increases in speed. We use a proprietary transaction-level data set from the Commodity Futures Trading Commission (CFTC) to study the these concerns through the lens of risk and return of individual HFT firms in the E-mini S&P 500 futures contract.[1]

Consistent with these concerns, we show that HFT firms who specialize in liquidity-taking (aggressive) strategies generate substantially more revenue than those who specialize in liquidity-providing (passive) strategies. Moreover, revenue persistently and disproportionally accumulates to the top performing HFTs, suggesting winner-takes-all market structure. We further show that speed is an important determinant of revenue generation, and the relation is strongest for HFTs with liquidity-taking (aggressive) strategies. Our results imply that, consistent with many of the concerns highlighted in the theoretical literature, HFT firms have strong incentives to take liquidity and to compete over small increases in speed.

We start by establishing some basic empirical facts regarding the risk and return characteristics of individual HFT firms. The median HFT firm demonstrates unusually high and persistent risk-adjusted performance with an annualized Sharpe ratio of 4.3 and a four-factor

[1] We identify "HFT" firms by using activity-based selection criteria introduced in Kirilenko, Kyle, Samadi, and Tuzun (2014). For brevity, we use the term "firm" to be synonymous with a specific trading account, even though several HFT firms in our data set have more than one trading desk, as it is our understanding that, due to regulatory and clearing requirements, most (but not all) trading desks operate as semi-independent trading entities.

(Fama-French plus momentum) annualized alpha of 22.02%.[2] Unlike for many non-HFT investment strategies, firm-level performance is strongly persistent over both days and months. Risks are kept low by strict inventory management and rapid turnover of contracts. Despite the strong outperformance on the firm level, effective HFT trading costs paid by non-HFT investors are only 0.22 basis points.

Our focus on distinguishing liquidity-demanding versus liquidity-providing trading strategies of HFTs is motivated by the idea that speed can be helpful in different ways. The theoretical literature puts forth several ideas about the ways that HFTs use speed to generate profits. Some theories (e.g., Martinez and Rosu, 2013; Foucault, Hombert and Rosu, 2013; and Biais, Foucault, and Moinas, 2014) view HFTs as aggressive (liquidity-demanding) traders who use speed and aggressive orders to trade an instant before others -- whether in reaction to news, order flow, or latency arbitrage -- and pick off stale limit orders or trade ahead of others' information. In this view, HFTs increase adverse selection and trading costs on other investors. Other theories, in contrast, (e.g., Jovanovic and Menkveld, 2012; Ait-Sahalia and Seglam, 2013; and various viewpoints presented in the mainstream media[3]), view HFTs as passive market makers who use speed to cancel or modify limit orders in response to informed trading, thus mitigating adverse selection and providing tighter bids and asks.

In distinguishing these two different views of HFTs, we find firm-level specialization: a majority of HFTs consistently specialize either in liquidity taking (whom we label Aggressive HFTs) or liquidity-provision (Passive HFT). More importantly, Aggressive HFTs earn

[2] As explained further in Section III, these returns assume fully-capitalized positions in the futures contract and should thus be interpreted as a highly conservative lower bound on returns. Given that margin requirements in the E-mini are about 10% of the notional value of the contract, actual HFT returns on capital are most likely several times higher than reported here.

[3] See, for example, http://www.bloombergview.com/articles/2014-03-20/why-do-high-frequency-traders-never-lose-money

substantially higher returns than Passive HFTs -- the average Aggressive HFTs earns an annualized alpha of 90.67%, while the average Passive firm earns 23.22% -- suggesting that there is a strong profit motive for liquidity taking rather than liquidity providing.

We further distinguish Aggressive and Passive HFTs in terms of their risk and return characteristics and trading behavior. Spectral analysis (following Hasbrouck and Sofianos, 1993) shows that Aggressive HFTs as a whole lose money on shorter time scales (presumably from the bid-ask spread and price impact) but gain money by predicting price movements on longer (but still intraday) time scales. In contrast, Passive HFTs show the opposite, making money at short horizons and losing money over longer intervals. We also decompose from whom (i.e. from which other trader types) HFT firms earn their trading revenue, and show that Passive and Aggressive HFTs win and lose from different trader types. In particular, Aggressive HFTs make about 45% of their revenue from adversely selecting the other HFT subtypes.

A second motivation for studying trading revenue and competition among firms is that the competitive trading structure of HFT firms can lead to a winner-takes-all environment, whereby the trader who is first able to identify and respond to a profitable opportunity will capture all the gains (see, for example, Budish, Cramton and Shim, 2013; Jones, 2013; Weller, 2013).[4] Other firms who are even milliseconds late will miss out: the magnitude of the profit may be sharply reduced or the trading opportunity may have disappeared completely. A winner-takes-all environment leads to socially inefficient investment in faster technology (Budish, Cramton and Shim, 2013; Biais, Foucault, and Moinas, 2014), as small increases in trading speed lead to large payouts, driving an arms race for seemingly small reductions in latency. This type

[4] Short-lived profit opportunities may derive from trading on news (for example, using direct data feeds) or on order flow (using information obtained from "pinging", flash quotes, or exploiting delays in public order book updates), taking advantage of mispriced orders or others' trading mistakes, or using other predictive, momentum or signal trading strategies.

of environment may further lead to incentives to exploit speed advantages via liquidity-taking trading strategies: picking off limit orders of slower traders and liquidity-providers, which may reduce liquidity or force effective trading costs upon other investors.

According to the winner-takes-all hypothesis, we expect to see a highly right-skewed cross-sectional distribution of revenue and a high concentration of revenue (measured by the Herfindahl index) that persists over time. Several other consequences may follow from a winner-takes-all environment. For example, Budish, Cramton and Shim (2013) theorize that that if speed advantages are relative, then increased competition won't drive profit opportunities to zero, since HFTs can always one-up the competition with an ever-smaller increase in speed. Thus, aggregate trading revenue and the concentration of revenue would not decrease over time. Additionally, we expect entrants to earn substantially lower returns than established HFT firms and be more likely to exit, as presumably incumbents have advantages due to their experience allowing them to capture most of the profits. Finally, we also expect speed to be a strong determinant of profitability, and the relation is strongest for HFTs with liquidity-taking (aggressive) strategies.

In looking at the data, we find evidence consistent the above predictions: the cross-sectional distribution of returns is highly right-skewed, with revenue disproportionally and persistently accumulating to top-performing firms. Revenue is concentrated among the top performers, as measured by the Herfindahl index. Both results are consistent with a winner-takes-all environment. Additionally, we find that aggregate revenue and concentration of revenue among top-performers does not decrease over our two-year sample, after adjusting for volatility and non-HFT trading volume. New entrants earn substantially fewer profits and are more likely to exit. Finally, we study a measure of relative (rank-order) speed developed in Weller (2013), which measures latency in terms of reaction time to incoming order flow. While Weller (2013) previously demonstrated that relative speed is correlated with returns, we show that the relation is strongest Aggressive HFTs. Each of the above findings is consistent with a winner-takes-all environment with speed and aggressiveness being key components of success. Overall, our analysis thus reveals an industry dominated by a small number of increasingly-fast, liquidity-taking incumbents with high and persistent returns.

The rest of the paper is as follows. Section II discusses the related literature, Section III describes the data and methods, Section IV examines the risk and return performance of HFTs, Section V analyzes competition, market concentration, and entry/exit of firms within the HFT sector, Section VI studies speed, and Section VII concludes.

II. Related Literature

This paper contributes mainly to two literatures: the growing body of work on HFT and the study of investment performance of different groups of traders. Given that there is no publicly available data set on HFT firms, several papers study HFT activity despite being unable to directly observe individual high frequency traders (e.g., Hasbrouck and Saar, 2013). Other papers make use of limited or aggregated proprietary data sets. For example, Jovanovic and Menkveld (2012) and Menkveld (2013) study the July 2007 entry into Dutch stocks of a single high-frequency market maker, and Brogaard, Hendershott, and Riordan (2013) study aggregated HFT activity on NASDAQ. In contrast to these papers, this paper uses a data set that allows us to identify the trades of individual HFT firms. In this way, our paper is similar to Kirilenko, Kyle, Samadi, and Tuzun (2014), which studies whether HFTs caused the Flash Crash of May 6, 2010.

Most empirical papers on HFT and algorithmic trading assess the potential costs and benefits of HFT using natural experiments, such as analyzing technological upgrades to trading venues (e.g., Hendershott, Jones, and Menkveld, 2011; Boehmer, Fong, and Wu, 2014; Riordan and Storkenmaier, 2012; and Gai, Yao, and Ye, 2013) or changes in fee structures only affecting HFT firms (e.g., Malinova, Park, and Riordan, 2013). These papers generally show that HFT activity improves liquidity (in terms of bid-ask spreads, depth, and price impact), lowers adverse selection (for example, more price discovery taking place via quotes rather than trades), and lowers transaction costs for institutional and retail traders. In contrast to these papers, this study looks at HFT from a risk and returns perspective and analyzes the incentives and competitive forces that shape HFT activity.

Finally, a number of previous studies have evaluated the investment performance of different types of traders. For example, Harris and Schultz (1998) study the profitability of SOES bandits, a group of individual traders in the 1990s who would quickly enter and exit trades and who were thought by some to have unfair advantages. Hasbrouck and Sofianos (1993) study the profitability of NYSE specialists. Like Ackermann, McEnally, and Ravenscraft (1999), who study the profitability of different hedge fund strategies, this paper studies different trading strategies of HFTs. Similar to studies look into factors that induce different traders to trade (e.g., Grinblatt and Keloharju, 2001), this paper studies incentives for entry and exit, speed, and aggressiveness.

III. Data and Methods

We use transaction-level data with trader identifiers for the E-mini S&P 500 stock index futures contract (E-mini). Our data set spans over two years, from the start of August 2010 to the end of August 2012.

The E-mini is a favorable setting for studying HFT for the following reasons.

First, it is an important and highly liquid market with several different types of market participants regularly trading, including a high number of HFT firms. The E-mini is the second-most traded futures contract in the world with a notional trading volume of approximately $200 billion per day in August 2010. Hasbrouck (2003) shows that the E-mini futures contract is the largest contributor to the price discovery process of the S&P 500 index.

Second, the contract is in zero net supply and buying and selling are symmetrical, so there are no short-selling constraints. Trading in the E-mini is a zero-sum game: one trader's profits come directly at the expense of the opposite trader.

Third, because the contract trades only electronically and only on the Chicago Mercantile Exchange (CME), there is no concern about unobserved trades occurring on other exchanges or on the floor.

Lastly, the E-mini has no designated market makers, no maker-taker fees or liquidity rebates for the front-month contract, and no obligations for certain market participants (such as quoting two sides or making prices continuous). There is no institutionalized class of intermediaries in this market. HFT trading activity is presumably in explicit pursuit of profits, undistorted by other requirements or competing incentives.

Our data set is trade-by-trade and contains common fields such as price, number of contracts traded, and time of the trade in units of seconds (and in milliseconds for a few months). The CME's Globex matching engine stamps a unique matching ID on each regular transaction, which enables us to construct the exact ordering of transactions. Cancelled and other irregular transactions are filtered out. In addition, the data set contains unique identifiers for the ultimate buyer and the ultimate seller (not just their brokers), an identifier for which side initiated the trade (passive for the side with the resting order, aggressive, otherwise), and an identifier for each executed order that allows us to group multiple transactions into a single underlying order (since large executable orders may be executed against several different resting limit orders).

Each E-mini contract is $50 times the value of the underlying S&P 500 index; as a result, the notional contract is valued at approximately $50,000. The tick size is $12.50. The contract is cash-settled against the value of the underlying S&P 500 index. Initial margins for speculators and hedgers (members) are $5,625 and $4,500, respectively, in August 2010; maintenance margins for all traders are $4,500. We exclude months in which the leading contract expires (March, June, September, December) in order to exclude rollover effects and multiple expirations trading simultaneously. Outside of the rollover months, the front-month contract usually has well over 99% of the trading volume, although we do analyze trades of all expirations. While the E-mini futures contract trades nearly around-the-clock, we only use data during normal trading hours: 8:30 a.m. - 3:15 p.m. Central Standard Time (CST).

One limitation of the paper is that our profit calculations do not account for all the costs of an HFT firm. While we know such direct costs of trading as trading fees ($0.15 per contract), the cost of direct data feeds, and the cost of co-location, we cannot adequately calculate other costs such as computer systems, labor, and risk management systems. We report gross trading revenues throughout to limit speculative assumptions from influencing our findings and because our focus is on trading performance.

Categorizing Traders

Following Kirilenko, Kyle, Samadi, and Tuzun (2014), we define different trader types based on two selection criteria: inventory and trading volume. HFTs are identified as those firms with extremely high volume, low intraday inventory and low overnight inventory. As shown in

Kirilenko, Kyle, Samadi, and Tuzun (2014) and confirmed by us, by analyzing all market participants along the dimensions of volume and inventories, HFT firms stand out as a distinct cluster, with daily trading volume orders of magnitude higher than other traders. In addition, we use the aggressiveness indicator (assigned by the matching engine) to group HFT firms into three different categories based on their liquidity impact.

The precise selection criteria for HFTs are as follows. For all individual market participants, we calculate four metrics: *median trading volume* (median trading volume across days which the firm is active, where active is defined as an HFT trading more than 1000 contracts per day), *end-of-day inventory ratio* (daily end-of-day inventory position divided by total volume, median across days which the firm is active), *intraday inventory ratio* (maximum daily position minus minimum daily scaled by daily total volume, median across days which the firm is active), and *aggressiveness ratio* (ratio of aggressive trading volume to total trading volume). For each month, there are three categories a potential trader must satisfy to be considered a HFT: (1) median trading volume greater than 5,000 contracts per day (about $250 million in notional daily trading volume)[5], (2) end-of-day inventory ratio less than 5%, and (3) intraday inventory ratio less than 10%. As a final step, we drop from our sample firms that are active fewer than 10 trading days per month. We find 85 firms satisfy these HFT criteria, though because of entry and exit, not all these firms necessarily trade in the same months.

We find that a majority of HFT firms (or HFTs) consistently specialize either in liquidity taking (Aggressive HFTs) or liquidity-provision (Passive HFTs) over the two-year sample we study. Thus, we categorize HFTs as follows: *Aggressive HFTs* have an aggressiveness ratio greater than 60%, while *Passive HFTs* have an aggressiveness ratio less than 20%. The

[5] This is a small (overly-inclusive) minimum requirement for trading volume compared to what most HFTs in our sample actually trade. The average daily trading volume per firm in our sample is 36,000 contracts (about $1.8 billion).

Aggressive HFT designation is meant to capture HFTs who are liquidity takers and generate trading profits by predicting future market movements, while the Passive HFT designation is meant to capture algorithmic market makers and liquidity providers whose revenue is partly generated by the bid-ask spread. We later show that these two classes of HFTs have markedly different characteristics in terms of trading behavior and profitability. We call firms that are not in either category *Mixed HFTs* and later show that they have characteristics that resemble a mix the two main categories. There are 18 Aggressive, 39 Mixed, and 28 Passive HFTs in our sample, though again not all these firms necessarily trade in the same months.

For each month we classify the rest of the universe of non-HFT firms into four different subcategories: Non-HFT Market Maker, Fundamental, Small, and Opportunistic traders. The non-HFT market maker category captures traditional market makers and liquidity providers, such as those examined by Hasbrouck and Sofianos (1993) and Coughenour and Saad (2004). Specifically, Non-HFT market makers are non-HFT market participants who have a (1) aggressiveness ratio less than 20%, (2) end-of-day inventory ratio less than 15%, and (3) median trading volume of at least 20 contracts (about \$1 million) per day. The fundamental trader category is meant to capture large institutional traders who adopt buy-and-hold strategies, such as those studied by Anand, Irvine, Puckett, and Venkataraman (2012) and Puckett and Yan (2011). Specifically, Fundamental traders have a (1) median trading volume of 1000 contracts per day (about \$50 million) and (2) end-of-day inventory ratio greater than 30%. The Small trader category most likely captures retail traders (e.g. Kaniel, Saar, and Titman, 2008; Seasholes and Zhu, 2010). Small traders have a median daily trading volume of less than 20 contracts (or about \$1 million). Note that HFTs and the above three categories are all mutually exclusive by definition. The remaining firms are designated Opportunistic. The Opportunistic category captures either medium-sized buy-and-hold investors (firms not big enough to be considered Fundamental traders) or large traders who unlike Fundamental traders move in and out of positions throughout the day but with significantly larger fluctuations and lower frequency than HFTs. This group likely captures arbitrageurs, small asset managers, hedge funds, and other hard-to-classify traders. In August 2010, we identify 737 Non-HFT Market Maker, 346 fundamental traders, 21,761 small traders and 8,494 opportunistic traders.

Table 1 presents a summary of trading behavior for these different trader types for August 2010.

INSERT TABLE 1 ABOUT HERE

For each trader type, we report two statistics: the daily percent of market volume traded and the daily aggressiveness ratios (aggressive contracts by trader category divided by total contracts by trader category). Table 1 Row 8 shows that, on average, 3.2 million contracts are traded in the E-mini market per day. The E-mini is an extremely liquid market with an average of about 70 contracts traded *every second*. HFTs as a whole trade 54.4% of the double-counted trading volume $\left(\frac{Buys_{HFT} + Sells_{HFT}}{2 * MktVolume}\right)$, or 1.73 million contracts daily (Row 1+2+3). The next largest category is Opportunistic, with 31.93% of contract volume by its 8,494 participants (Row 7).

The variation within the HFT categories over different days is considerable. For example, Aggressive HFTs range from 9.5% to 17.6% of market volume across days; they have the largest variation of the three HFT categories (Row 1). Passive HFTs make up a significantly smaller portion of HFT volume (8.87%, Row 3) than Aggressive HFTs (15.22%, Row 1). Looking at liquidity taking, Aggressive HFTs take liquidity in 84.22% (Row 9) of the contracts they trade, while Passive HFTs only take liquidity in 12.35% (Row 11). Fundamental traders make up

8.42% (Row 4) of trade quantity, while taking liquidity about half of the time (57.68%, Row 10). Small traders and non-HFT market makers are both a small share of the market, with 1.04% (Row 5) and 4.24% (Row 6) of the trade quantity, respectively, while taking liquidity 57.82% (Row 11) and 12.98% (Row 12) of the time, respectively. Opportunistic traders make up the largest share of trading volume at 31.93% (Row 7), while taking liquidity 59.08% (Row 13) of the time.

Figure 1 examines trading volume of the different trader types across the two-year span.

INSERT FIGURE 1 ABOUT HERE

Panel A shows the average daily HFT volume of the HFT subgroups for each month over the two year span. The total HFT market volume decreases over the two-year span from a peak of 3,187,011 contracts in August 2010 to 2,322,787 in August 2012. About half of that decline was from a reduction in Mixed HFT trading from 960,643 contracts in August 2010 to 564,200 contracts in August 2012, while Aggressive and Passive HFT volume was relatively constant.

Panel B looks at the percent of market volume traded by each trader type over the two year span. Although average daily market volume fluctuates considerably over the two-year span, the percent traded by each type is relatively stable. For example, HFT percentage volume starts in August 2010 at 54.37% and ends in August 2012 at 55.53%; However, Aggressive HFT volume increases over the two years from 15.22% to 22.63%, while Mixed HFT volume decreases from 30.28% to 24.59%. Overall, Figure 1 highlights the strong stability in HFT trading volume over a two year span in the E-mini S&P 500 futures contract.

Returns and Profitability

Throughout the paper, daily profits for each firm, *i*, are calculated for each trading day, *t*, according to marked-to-market accounting, assuming that each trader starts each day with a zero inventory position. More precisely, for each trader, we calculate the end-of-day profits as the cumulative cash received from selling short positions minus the cash paid from buying long positions, plus the value of any outstanding positions at the end-of-day, marked to the market price at close: $\pi_{i,t} = \sum_{n=1}^{N_{i,t}} p_n y_{i,n} + p_N y_{i,N}$ where p_n is the price of the *n*th trade (out of *N* total trades on day t) and $y_{i,n}$ is the signed quantity of the *n*th trade by trader *i*. As Table 5 shows, HFTs usually end the day flat, so marking-to-market at the end of the trading day is relatively innocuous.

Daily returns are calculated by dividing the daily profits of each firm by the assumed capitalization of each firm. Capitalization is calculated for each firm on a monthly basis by looking at the maximum position taken in the month and multiplying by the notional value of the contract. Since HFTs inventory generally exhibit sharp, well-defined maximum and minimum positions they're willing to take (for example, bounds of 100 or 200 contracts exactly), this number represents the maximum amount of capital that an HFT would need to execute its specific strategy.[6]

Finally, we evaluate the Sharpe ratios of HFTs (Sharpe, 1966). Four-factor (Fama-French plus momentum) alphas are computed for each HFT using the standard Fama-French model

[6] In practice, HFTs may use much less capital than the amount we calculate, since firms only have to satisfy margin requirements, which are generally about one-tenth the notional value of the contract. We decided to use the notional value of the contract rather than the margin requirement per contract to calculate the firm's capitalization because a firm that loses money on any given day will have to post new margins. The maximum possible capital that a firm would need is the full notional value of the contract. In practice, HFT returns on capital are presumably several times higher than we report, and thus these numbers should be interpreted as conservative lower bounds.

(Fama and French, 1993) plus the Carhart (1997) momentum factor, using daily portfolio returns data from Kenneth French's website. The Sharpe ratio for each trader is calculated as $SR_i = \frac{r_i - r_f}{\sigma_i} * \sqrt{252}$, where r_i is the average daily return, r_f is the risk-free rate, which is zero throughout our sample, and σ_i is the standard deviation of trader i's returns over the calculated sample period (usually one month).

IV. Risk and Return Performance of HFTs

In this section we present empirical facts about the investment performance of HFTs. First, HFTs consistently outperform the market, with the median HFT firm achieving an annualized Sharpe ratio of 4.3 and a four-factor annualized alpha of 22.02%. Aggressive HFTs earn substantially higher returns than Passive HFTs -- the average Aggressive HFTs achieves an annualized alpha of 90.67%, while the average Passive firm earns 23.22% -- suggesting that there is a strong profit motive for liquidity taking rather than liquidity providing. Second, the cross-sectional distribution of returns is highly skewed towards top earners whose Sharpe ratios and alphas are many times those of the median, and firm-level performance is strongly persistent over both days and months. We interpret this as showing profits persistently and disproportionally accumulate to the top performing HFTs, suggesting winner-takes-all competition. The winner-takes-all nature of returns is further confirmed in Section V when we look at industry concentration of returns and report high Herfindahl concentration indices.

Looking further into how HFTs minimize their risk, we show that high Sharpe ratios are achieved by minimizing positional risk through strict inventory control and rapid turnover of contracts. Finally, to help differentiate Aggressive versus Passive HFTs' strategies, we analyze returns to different types of HFTs by performing spectral analysis (following Hasbrouck and

Sofianos, 1993) and by decomposing from whom (i.e. from which other trader types) HFTs earn their profits. We show that Aggressive HFTs as a whole lose money on shorter time scales (presumably from the bid-ask spread and price impact) but gain money by predicting price movements on longer (but still intraday) time scales; in contrast, Passive HFTs show the opposite, making money at short horizons and losing money over longer intervals. In particular, Aggressive HFTs make a large part of their profits from adversely selecting Passive HFTs.

Finally, the decomposition of profits also shows that despite strong outperformance on the individual firm level, effective HFT trading costs imposed on non-HFT investors are only 0.22 basis points.

Distribution of Returns

To get a general sense of HFT returns, we first present the distribution of daily returns pooled across all firms within each subtype. We highlight the higher profitability of Aggressive HFTs, suggesting a stronger profit motive for liquidity taking than liquidity providing. In the next subsection, we look more specifically at the cross-sectional distribution across firms.

Table 2 presents the distribution of HFT returns and profits per contract. Panel A reports annualized returns, determined from the daily returns of each HFT firm and aggregated into groups. Panel B reports profit per contract. Mean, median, skew, and kurtosis are reported for both returns and profits per contract.

INSERT TABLE 2 ABOUT HERE

Table 2 shows that Aggressive HFTs earn substantially higher returns than Passive HFTs suggesting that there is a strong profit motive for liquidity taking rather than liquidity providing. For example, Aggressive HFTs earn a mean annualized return of 122.10% (Column 2), while

Mixed and Passive HFTs earn significantly less: only 32.29% and 25.69%, respectively.[7] The p-values on the statistical significance of profits (Column 7) show that these values differ significantly from zero. While the averages are all positive, there is a sizeable distribution of profitability across observations: the standard deviation of returns (Column 4) has Aggressive HFTs realizing the highest variation in profits (28.39%) and Passive HFTs the lowest (8.89%). The daily skewness and kurtosis (Columns 5 and 6) statistics show that the distribution of profits is non-normal: there is excess weight in the tails, in the upper tail especially (positive skew), for all three types of HFTs.

Panel B reports profits per contract and similarly confirms that Aggressive HFTs are considerably more profitable than Mixed and Passive HFTs. We also find, in untabulated results, that in dollar terms the average Aggressive HFT firm earns a daily profit of $74,000 in gross trading revenues, while average Mixed and Passive firms earn $27,910 and $12,600, respectively. Annualized, these numbers corresponds to trading revenues of over $18.6, $7.0, and $3.2 million for Aggressive, Mixed, and Passive HFTs, respectively, in the E-mini alone. Overall, Table 2 highlights the higher profitability of Aggressive HFTs, suggesting a stronger profit motive for liquidity taking than liquidity providing.

HFT Risk and Return in the Cross-Section

Next, we look at the cross-section of HFTs to study the winner-takes-all nature of competition and find wide variation in returns across HFT firms in the cross-section. In particular, we analyze returns, abnormal returns (alphas), profits per contract, and Sharpe ratios. Other than profits per contract, the reported statistics are annualized. The cross-sectional

[7] We also calculate the returns for 24-hour continuous trading (as opposed to looking only at regular trading hours) and find qualitatively similar results for the three subtypes of HFTs.

distribution of returns is highly skewed towards top earners whose Sharpe ratios and alphas are many times those of the median.

Table 3 reports the mean and standard deviation across firms, in addition to the 10th, 25th, 50th, 75th and 90th percentiles. The results are broken down for Aggressive, Mixed, and Passive HFTs. The cross-sectional distribution of annualized returns (Rows 1-4) shows that there is a wide distribution of returns across firms.

INSERT TABLE 3 ABOUT HERE

We focus on alphas (abnormal returns), which provide a better sense of risk-adjusted performance than absolute returns. Alphas are reported for various specifications, though we emphasize the four-factor (Fama-French + Carhart momentum) alphas. The average HFT firm earns abnormal annualized returns of 39.92%. Comparing this number to absolute returns of 39.49% shows that the returns of HFTs are unrelated to market returns. The breakdown among the subcategories is striking. Aggressive HFTs earn alphas of 90.67% while Mixed and Passive earn 28.18% and 23.22%, again suggesting a stronger profit motive for liquidity taking than liquidity providing.

The fact about the distribution we wish to emphasize is the winner-takes-all aspect: that firms in the top decile strongly outperform those at the median. Firms in the bottom ten percent earn small negative returns, while firms above the median earn large positive profits. The distribution is right skewed, reflecting a few high earners at the top. For example, 25% of HFTs have annualized four-factor alphas greater than 50.92%, and 10% of HFTs have alphas greater than 70.51%. Similarly, the fact that the median firm's alpha (22.02%) is lower than mean firm's alpha (39.78%), especially for Aggressive HFTs (median = 37.06%, mean = 90.67%), suggests that the mean is driven by top performing firms who earn particularly high returns, providing further evidence for positive skewness in the cross-section of firms.

Table 3 also reports the distribution across firms of average daily profit per contract (rows 11-14). Similar to the raw returns and alphas, profit per contract is widely dispersed around the median with a pronounced positive skew: profit per contract in the top decile of firms is $2.01, compared with 0.46% for the median.

Lastly, we examine annualized Sharpe ratios, which show that while HFTs bear some risk, their risk-adjusted returns are unusually high. Menkveld (2013) has previously calculated the annualized Sharpe ratio of an HFT firm trading in equities markets to be 9.35. Passive HFTs generate the highest Sharpe ratio of 5.85, implying that they keep risk low, as their annualized returns are the lowest at 23.13%. Mixed and Aggressive HFTs earn the Sharpe ratios of 5.26 and 4.29, respectively. To get a sense of the magnitude of these numbers, the performance of the median HFT firm Sharpe ratio (4.30) is over 13 times higher than the Sharpe ratio of the S&P 500 (0.31) (Fama and French, 2002) and 18 times higher than the mean Passive HFT firm. Thus, while HFTs bear some risk, their risk-adjusted returns are high.

Yet even within these different types of HFTs, the Sharpe ratio for firms varies widely, especially with the top earners, consistent with the winner-takes-all idea. For example, 25% of HFTs have a Sharpe ratio greater than 9.10, and 10% of HFTs have a Sharpe ratio greater than 12.68. Again, firms in the top decile strongly outperform those at the median, suggesting winner-takes-all.

Persistence of Returns

Next we test for persistence of returns, both in terms of absolute returns and also relative to other HFT firms. Persistent profits over time suggest that something other than luck is driving a firm's performance. There is an extant literature showing that performance for actively-managed mutual funds in period *t* generally does not predict performance in period *t+1* (e.g. Carhart, 1997). However, there is evidence of persistence by some investors (e.g. Jagannathan, Malakhov, and Novikov (2010) for hedge funds and Kaplan and Schoar (2004) for private equity). Nonetheless, the expectation for most types of investors and funds is that ability has little influence in investing returns. The null hypothesis here is thus that HFT firms do not exhibit persistence in returns.

To formally analyze persistence of returns, we look at the role that lagged returns (or rank ordering versus other firms) have in predicting today's returns (or rank order), both using daily and monthly firm-level returns. We estimate the following ordinary least squares (OLS) regression:

$$r_{i,t} = \alpha + \beta r_{i,t-1} + \text{Time FEs} + \epsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is daily or monthly returns. While there may be higher idiosyncratic risk in daily returns, resulting in moderate persistence at the daily level, we find that returns are more strongly persistent on the monthly level. The regression is estimated for each group, Aggressive, Mixed, and Passive, separately. We also estimate Equation (1) with other dependent variables and their lags, including normalized returns, normalized profits, normalized profits per contract, Sharpe ratios, and the rank order of these metrics.[8]

[8] By normalized, we mean subtracting out the mean and dividing by the standard deviation *across firms for that day*. We normalize to control for the time-varying mean and volatility of HFT returns

The results are reported in Table 4. Results based on daily observations are reported in Panel A, those from monthly observations are reported in Panel B, and those based on rank ordering in Panel C. Regressions considering normalized dependent variables are performed without time fixed effects as the normalization removes any average time variation. With normalization, the estimate of the constant, which is always zero, is not reported.

INSERT TABLE 4 ABOUT HERE

Estimates for each type of HFT show that one-day lagged performance is a strong predictor of current performance. HFTs exhibit persistence. For daily returns, Aggressive HFTs have coefficients of 0.421 (for daily returns) and 0.723 (for monthly returns). Mixed and Passive HFTs have mild or no persistence on the daily level (0.109 and -0.73, respectively), at least before normalizing returns, but strong persistence on the monthly level (0.407 and 0.725, respectively). Normalized daily returns are qualitatively similar, though we see slightly weaker persistence for Aggressive HFTs on the daily level than before (0.276) and stronger persistence for Mixed and Passive HFTs on the daily level than before (0.169 and 0.205, respectively). The coefficients reported above are all statistically significant with $p<0.001$.

The adjusted R^2 estimates imply strong explanatory power of past returns: 25.5%, 7.9% and 12.4% for daily returns and 52.2%, 22.4% and 33.5% for monthly returns for Aggressive, Mixed and Passive HFTs, respectively. Persistence estimates using normalized profits and profits per contract are qualitatively similar, though slightly weaker, than those using returns. However, persistence estimates using monthly normalized Sharpe ratios, however, are particularly strong with coefficients of 0.639, 0.659 and 0.452 for Aggressive, Mixed and Passive HFTs, respectively, with also high adjusted R^2 estimates.

The above findings show that the level of performance in the past is predictive of the level of performance in the future. We perform a similar analysis in Panel C but instead consider whether relative rank among HFTs within their subcategories in the past is predictive of current rank. Rank is calculated using daily returns, monthly returns, monthly profits, monthly profits per contract, and Sharpe ratios. For each measure separately, we rank the relative performance of the HFT firms in each day or month, with 1 representing the best performing firm, 2 the second-best performing firm, etc. We then repeat the analysis in Equation (8). A positive coefficient means that if a firm performed well in the past, it is likely to perform well in the future. All measures and all subcategories suggest persistence in relative performance.[9]

In thinking about the drivers of persistence, it may be that human skill and experience allow firms to distinguish themselves. Alternatively, it could be purely technological advantages. A combination of the both is also probable. Regardless of the precise mechanism driving the persistence, persistent performance may lead to industry concentration as strong performing firms will continue to perform well. Less successful firms may exit the industry. In Section IV we observe both and analyze the implications of competition among HFT given strong persistence among firms.

Risk and Inventory Management

We've shown that HFTs earn unusually high risk-adjusted returns with a distribution that is strongly positively skewed: top earners achieve alphas and Sharpe ratios many times the median. In addition, firm-level performance is highly persistent over the sample. The next three

[9] As the dependent variables are both discrete and restricted to non-negative values there are additional econometric techniques that apply other than OLS. Two techniques include Poisson and negative binomial models. See Long (1997) for a thorough description these models and how to analyze count data. In untabulated results, we repeat the Table 4, Panel C analysis using both the Poisson and negative binomial models. The results are qualitatively the same.

subsections on inventory management, spectral analysis, and HFTs profits by counterparties provide further evidence of how HFTs consistently produce high risk-adjusted returns.

First, we show that high risk-adjusted returns (alphas and Sharpe ratios) are partly achieved by minimizing positional risk through strict inventory control and rapid turnover of contracts. As shown earlier, HFT risk is low, both in terms of systematic risk (as evidenced by the high alphas) and total risk (as evidenced by Sharpe ratios). Minimizing intraday positional risk not only minimizes HFT exposure to market risk but also puts a bound on maximum possible losses.

INSERT TABLE 5 ABOUT HERE

Table 5 provides evidence on the inventories of HFTs in the cross-section. The first row reports the Average Daily Volume, which captures the average number of contracts an HFT firm trades each day. The remainder of the table focuses on inventory. The average end-of-day inventory is the average number of contracts (across days) held at the end of the regular trading day, 3:15 CST, by the median firm. The end of day inventory is not always zero, but is generally very low. End-of-day inventory of the median Aggressive HFT is 49.3 contracts, while end-of-day inventory of the median Passive HFT is only 10.5 contracts. The small standard deviations (across firms) show almost all firms keep their average end-of-day inventories very low. To get a sense of how large a position this is for a given firm, we normalize the average end-of-day inventory for each firm by that firm's average daily trading volume. For Aggressive HFTs, this reveals that only 0.4% of trading volume is held at the end of the day by the median firm, while for Passive HFTs, it is only 0.1%.

The second measure of inventory is the average intraday inventory range, which represents the average (across days) of the maximum intraday inventory variation (daily maximum position minus minimum position). This is an estimate of how much exposure a firm is willing to bear. Aggressive HFT take a maximum variation in intraday positions as large as 525.9 contracts on average, while Passive HFTs take a maximum variation of 204.2 contracts. But a fractions of each firm's average daily trading volume though, these numbers are only 7.3% and 2.2%, respectively.

While we select HFTs based on low intraday and end-of-day inventories, Table 5 shows that intraday and end-of-day inventories for the majority of firms are substantially lower than the bounds in our selection criteria, implying that tight inventory management is not just an artifact of our selection criteria but an active goal of HFTs. The results show that minimizing positional risk, and elimination the potential large loss associated with a sizeable direction position, is an important component of HFTs maximizing risk-adjusted returns.

Spectral Analysis

To further understand the investment horizon of HFTs, we follow Hasbrouck and Sofianos (1993) and decompose HFT profits over different time horizons using spectral analysis. The time horizon over which HFTs make their profits provides insight into their trading strategies and allows us to further examine the differences between the types of HFTs. We find that Aggressive HFTs as a whole lose money on shorter time scales (presumably from the bid-ask spread and price impact) but gain money by predicting price movements on longer (but still intraday) time scales (after 1,000 market transactions). In contrast, both Mixed and Passive HFTs show the opposite, tending to make money at short horizons (1,000 transactions or fewer) and lose money over longer intervals.

Spectral analysis decomposes profits for each firm into different time horizons. Profits are calculated from two time series, prices and inventories, which are analyzed as sums of Fourier modes of varying frequencies. Intuitively, for any given frequency, if prices and inventories are waves that move in phase (traders buy before the price is going up), profits are generated, while if they are out of phase (traders buy before the price goes down), traders incur losses.

Mathematically, we start with marked-to-market profit for any individual trader at transaction time[10] τ:

$$\pi_\tau = \sum_{t=0}^{\tau} x_t(p_t - p_{t-1}) = \sum_{t=0}^{\tau} x_t \cdot \Delta p_t \tag{2}$$

where x_t is the inventory holdings of that trader and p_t is the price at time t.[11] By defining the following functions:

$$\hat{x}(\omega) = \sum_{t=0}^{T} x_t e^{2\pi i t\omega/T} \tag{3}$$

$$\widehat{\Delta p}(\omega) = \sum_{t=0}^{T} \Delta p_{t+1} e^{2\pi i t\omega/T} \tag{4}$$

where ω is interpreted as a wavelength having units of transaction time and $\hat{x}(\omega)$ and $\widehat{\Delta p}(\omega)$ are the spectral densities of the x_t and p_t, we can re-express marked-to-markets profits using the following formula (see Hasbrouck and Sofianos, 1993, for mathematical details)[12]:

$$\pi_T = \frac{1}{T}\sum_{\omega=1}^{\infty} \hat{x}(\omega)\overline{\widehat{\Delta p}(\omega)} = \frac{1}{T}\sum_{\omega=1}^{\infty} 2 * Real(\hat{x}(\omega)\overline{\widehat{\Delta p}(\omega)}) \tag{5}$$

The $2 * Real(\hat{x}(\omega)\overline{\widehat{\Delta p}(\omega)})$ term captures the component of the marked-to-market profits generated at trading wavelength ω. Thus, if the summation in Equation (5) is broken up into

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[10] For computational reasons, spectral analysis must be conducted in transaction time, as opposed to clock time. For reference, there are approximately 10 transactions per second.

[11] Spectral analysis requires us to assume that x_t and Δp_t are stationary processes, which is a valid assumption to make given that x_t, HFT firms' inventories, is a mean-reverting process and Δp, is the first difference of the price process.

[12] *Real* is the function that takes the real part of a complex number. The last equality follows because the imaginary part of $\hat{x}(\omega)\overline{\widehat{\Delta p}(\omega)}$ sums to 0.

wavelength blocks, then it is possible to decompose profits into the following time horizons bins (expressed in units of market transactions): ω = 1-10, 11-100, 101-1,000, 1,001-10,000, 10,000-100,000, and 100,000+. We thus decompose profits into these time horizon bins each HFT firm. Then for each time horizon, we take the median profits across days and then across firms (along with the 25th and 75th percentiles across firms). Spectral analysis results are reported in Table 6.[13]

INSERT TABLE 6 ABOUT HERE

Table 6 shows that in Aggressive HFTs tend to make positive profits at medium time scales, in the 1,001-10,000 and 10,001-100,000 transaction range, with negative profits at short ranges (11-100 and 101-1,000 transaction intervals) and the longest time scale of 100,000+ transactions. In order for an aggressive trade to be profitable, an HFT must not only predict the direction of the price process but also overcome the bid-ask spread. We suspect that this is the reason Aggressive HFTs fail to make money at the shortest time intervals. The spectral analysis results are consistent with the notion that Aggressive HFTs make money by anticipating price movements in the 1,000 – 100,000 transactions range, while losing money at both very short and long time scales. In contrast, both Mixed and Passive HFTs tend to gain money at short time scales (1-10, 11-100, and 101-1,000 transactions) while losing money on longer time scales (1,001-10,000, 10,001-100,000, and 100,000+ transactions). These results are consistent with the idea that Mixed and Passive HFTs earn the bid-ask spread in the short-run but are adversely selected on a longer time scale.

[13] We only analyze one month (August 2010) rather than two years of HFT profits due to the computational challenges involved in doing spectral analysis. However, results from several other months were qualitatively similar.

HFT Profits by Counterparty

We would like to know from whom HFTs earn their profits. We decompose HFT profits by counterparty, analyzing both dollar profits and profits-per-contract. Analyzing dollar profits tells us where the money is (which groups HFTs have strong incentives to target), and analyzing profits-per-contract tells us about adverse selection costs and which traders are informed traders or best able to evade HFT activity. Interestingly, Aggressive HFTs make about 45% of their profits from adversely selecting the other HFT subtypes.

To calculate from whom HFTs earn their profits, we divide the remaining universe of traders in the E-mini into four categories of traders, as discussed in Data and Methods: Fundamental traders (likely large institutional traders), Non-HFT market makers, Small traders (likely retail traders), and Opportunistic traders (likely arbitrageurs, small asset managers, hedge funds, and other hard-to-classify traders). We find that: 1) HFTs in aggregate make most of their largest dollar profits from Opportunistic traders, 2) on a per-contract basis, Fundamental traders incur the least cost to HFTs, while Small traders incur the most, 3) interestingly, Aggressive HFTs make a large fraction of their profits from Mixed and Passive HFTs, and 4) the effective HFT transaction cost on non-HFT trades is approximately 0.22 basis points.

Whether HFTs make more or fewer profits from different types of other traders is hard to predict using theory. For example, Fundamental traders may trade in a way that makes their order flow noticeable and leaves a detectable pattern in their trading activity (as in Hirschey, 2013; Heston, Korajczyk and Sadka, 2010), in which case HFTs would make more profits against them. On the other hand, due to their size and sophistication (as in Badrinath, Kale, and Noe, 1995; Boehmer and Wu, 2008; Boulatov, Hendershott, and Livdan, 2013; Hendershott, Livdan, and Schurhoff, 2012), Fundamental traders may be more skilled at evading HFTs and minimizing price impact, in which case HFT would profits less against them.

Similarly, Small traders (retail investors) might be relatively less informed (e.g., Hvidkjaer, 2008; Kaniel, Saar, and Titman, 2008; Barber, Odean, and Zhu, 2009) and thus incur significant losses to HFTs. However, because retail traders are small and trade noisily, they may not leave patterns in the data and consequently HFTs may have a more difficult time detecting them and thus earn less from them. As noted earlier, the result that we find is, on a per-contract basis, Fundamental traders incur the least cost to HFTs while Small traders incur the most, demonstrating that size and sophistication (even at the expense of leaving detectable order-flow patterns) are likely important for minimizing HFT-related trading costs.

Table 7 breaks down the trading profits by trading pairs in August 2010: the rows identify who receives the profits, whereas the different columns represent from whom the profits are derived. Table 7 is constructed by considering *only* the trades (in August 2010) between two groups and calculating the profit flows that result from those trades. To illustrate, we calculate the Aggressive HFT-Fundamental profit flows by removing all trades except those for which one party was an Aggressive HFT and the other party was a Fundamental trader. Since gains/losses from large, long-term positions can make profits look extremely volatile, we calculate *short-term profits*: defined here as gains/losses resulting 1 minute after each trade. Since the futures market is a zero-sum game, the resulting profits matrix is symmetrical and zero along the diagonals.[14]

INSERT TABLE 7 ABOUT HERE

[14] Note that our focus is on returns during a short horizon. A loss during this interval does not imply that the trader (or trader category) loses money overall. In addition, we only observe a market participant's activities in the E-mini, which may be one of multiple markets in which a trader participates. For instance, Fundamental traders may be using the E-mini contract as a hedge against real-world risks and Opportunistic traders may be doing cross-market arbitrage. Thus, a loss in the E-mini market does not imply the trading firm loses money overall.

Panel A shows that Aggressive and Mixed HFTs make positive profits from *all* other types of traders, while Passive HFTs make positive profits from all other types of traders except from fundamental traders. In particular, Aggressive HFTs make about 45% of their profits (= (7,190,140 + 2,557,038) / 21,952,215 = 44.4%) from adversely selecting the other HFT subtypes. Panel A shows that all types of HFTs make the majority of their dollar profits from opportunistic traders. Panel B describes the profits and losses on a per contract basis. These results provide an estimate of the effective transaction costs involved in trading with certain groups. Since we compute profits on a 1 minute basis while resetting each trader's inventory to zero, their profits can be interpreted as short-term transaction costs extracted from the rest of the market, not gains from long-term directional positions. For example, Fundamental traders incur a loss of -$1.92 (Column 2, Row 5) when trading with Aggressive HFTs, while Small traders experience a much larger loss of -$3.49 (Column 2, Row 7). Interestingly, Small traders lose similar amounts per contract to non-HFT traders.

Finally, the "Total" column in Panel A allows us to calculate the effective HFT transaction cost imposed on all other traders. Since HFTs make $35.23 million from all non-HFTs in August 2010 (= $21.95 million + $12.77 million + $0.50 million), while everyone else trades 31.96 million contracts (see Table 1), the effective HFT cost per trade on all other traders is $1.10 per contract. Scaling this per-contract transaction cost by $50,000 the approximate price of a contract yields an estimated HFT-imposed transaction cost of 0.0022% or 0.22 basis points.

V. **Competition**

We analyze competition in the HFT industry to show and understand why profits are concentrated among a small number of incumbents who realize high and persistent returns.

According to the winner-takes-all idea, we expect to see a high concentration of profits (measured by the Herfindahl index) that persist over time. Combined with the evidence from the previous section showing high firm-level persistence and strong outperformance of top-earning firms, this section provide evidence of an industry with profits concentrated among a small number of established firms.

In trying to understand the strong performance and persistence of returns to HFT firms, we also examine new entry. New entrants can potentially introduce competition and drive down both firm-level and industry profits. Given HFTs' high profitability, one might expect there to be strong incentives for entry, especially for firms that already have the technological capabilities and financial expertise to trade (market makers, hedge funds, broker-dealers, etc.), leading to increased competition and downward pressure on both firm-level and industry profits. However, in contrast to this expectation, we find that new entrants are substantially less profitable than incumbents and more likely to exit. Likely as a result, we further observe that industry concentration (as measured by the Herfindahl index) remains high and relatively constant over the two year sample. Also, aggregate profitability does not decrease, after adjusting for volatility and non-HFT trading volume. Combined with the evidence from the previous section showing high firm-level persistence and strong outperformance of top-earning firms, this section provides evidence of an industry dominated by a handful of established firms that are somehow able to keep the challengers at bay.

Our results are consistent with theoretical predictions regarding winner-takes-all competition based on speed. As mentioned previously, Budish, Cramton and Shim (2013) theorize that that if speed advantages are relative, then increased competition won't drive profit opportunities to zero, since HFTs can always one-up the competition with an ever-smaller increase in speed. Thus, aggregate profits and the concentration of profits would not decrease over time. Additionally, we expect entrants to earn substantially lower returns than established HFT firms and be more likely to exit, as presumably incumbents have advantages due to their experience allowing them to capture most of the profits.

HFT Market Concentration over Time

Here we show that the HFT industry concentration (as measured by the Herfindahl index of profits or trading volume) remains high and relatively constant over the two-year sample and also that aggregate profitability does not decrease, after adjusting for volatility and non-HFT trading volume. Our results indicate that the HFT industry exhibits concentration, in line with competition and new entry not decreasing the profitability of the most successful HFT firms. Combined with high firm-level persistence of returns, a high and steady Herfindahl index suggests that top performing incumbents maintain their position in the market.

We calculate Herfindahl indices, a commonly used measure of concentration of market share or earnings within an industry, for both profits and trading volume. The profit Herfindahl index is calculated as

$$Herfindahl_{i,t} = \sum_{i=1}^{N} \left[\frac{Profit_{i,t}}{HFT\ Profit_t}\right]^2 \tag{6}$$

where N is the number of firms in the HFT subgroup (Aggressive, Mixed, or Passive) in month t that earn non-negative profits, $Profit_{i,t}$ is firm *i*'s total trading profits in month *t*, and $HFT\ Profit_t$ is the total trading profits of all HFT firms in the HFT subgroup. The volume Herfindahl index is calculated using the same formula but considering the number of contracts traded instead of trading profits. The Herfindahl index has a range of (0,1].

Table 8 reports the Herfindahl index for each subgroup of HFTs, first by calculating the index for each trading day and then averaging over days for every half-year block in the data set. Standard deviations are reported in parentheses, and stars indicate the significance from a t-test comparing the daily Herfindahl index in 2010 to the current half-year period.

INSERT TABLE 8 ABOUT HERE

A larger number implies a more concentrated industry, which is a proxy for the level of competition in the industry. As a reference, Van Ness, Van Ness, and Warr (2005) find that market makers have an average Herfindahl index (created with trading volume, instead of profit) on NASDAQ of .14, with a range of .037 to .439. The results in Table 8 for both the Profit-based and Volume-based number are in line with this range. Perhaps more interesting, however, than the level is the direction. By performing a regression with time-based dummy variables, we show that Profit-based and Volume-based Herfindahl indices between 2010 and each subsequent half-year block are not decreasing, and in fact are somewhat increasing for Mixed and Passive HFTs.

For example, for Aggressive HFTs, the profit and volume Herfindahl indices are 0.362 and 0.2, respectively; these Herfindahl indices increase to 0.381 and decrease to 0.183 in the second half of 2011 and is not significant for other half-year blocks. In other words, there is no apparent directional trend. However, contrast those results with those of Passive HFTs, whose Profit Herfindahl index increases from 0.287 in 2010, trending steadily upward, to 0.545 in the second half of 2012; similarly the volume Herfindahl index of Passive HFTs increases from 0.129 in 2010, trending steadily upward, to 0.331 in the second half of 2012. We conclude that for Mixed and Passive HFTs, concentration of volume and profits actually increases between 2010 and 2012.

HFT is a rather new industry, and so one might expect concentration to decrease as new entrants join the market. We observe the opposite.

HFT Profitability over Time

In line with HFT industry concentration not decreasing over time, we find that HFT daily returns, profits and profits-per-contract have not fallen, and in some cases have actually increased over time, after taking into account market volatility and non-HFT trading volume.

INSERT FIGURE 2 ABOUT HERE

Figure 2, Panel A shows that the aggregate monthly profits of HFTs vary substantially, though there is no clear directional trend. Aggressive HFTs consistently earn positive daily profit over the two-year span, with a mean of $395,875 per day over the two-year span, a high of $2,745,724 per day in August 2011 and a low of -$86,296 in January 2012. Mixed HFTs earn an even higher positive average daily profit over the two-year span (because there are more firms, even though each firm individually makes less), with a mean of $525,064 per day over the two-year span, a high of $890,828 per day in October 2010 and a low of $63,027 in January 2011. Passive HFTs earn the lowest average daily profit over the two-year span, with a mean of $107,239 per day over the two-year span, a high of $403,259 per day in January 2012 and a low of -$22,499 in February 2011.

The same is roughly true of profits per contract: Panel B shows the time-series of total monthly profits divided by total monthly contracts traded. Aggressive HFTs earn the highest average daily profits per contract over the two-year span, with a mean of $0.85 over the two-year span, a high of $2.01 in May 2011 and a low of $0.09 in January 2012. Mixed HFTs earn less with a mean of $0.52 per day over the two-year span, a high of $0.93 in May 2011 and a low of -

$0.23 in January 2011. Passive HFTs earn the lowest with a mean of $0.46 over the two-year span, a high of $1.18 in January 2012 and a low of -$0.47 in February 2011.

More formally we examine the daily returns per firm, after controlling for daily volatility and non-HFT trading volume, which may affect returns on a daily or longer-term basis. To do this analysis, we estimated the following regression, where we use indicator variables to evaluate the average profits over half-year blocks:

$$r_{i,t} = \alpha_{\text{2010 baseline}} + \beta_1 1_{\text{1st half 2011}} + \ \dots + \beta_4 1_{\text{2nd half 2012}} \qquad (7)$$
$$+ \beta_5 \text{log volatility}_t + \beta_6 \text{log non-HFT volume}_t + \epsilon_{i,t}$$

where the indicator variables take the value of 1 during the corresponding half-year period, and controlling for daily log volatility (calculated in transaction time) and daily non-HFT trading volume [15]

INSERT TABLE 9 ABOUT HERE

The coefficients are reported in Table 9 for average daily returns, daily profits and daily profit per contract for Aggressive, Mixed and Passive HFTs. The constant α is interpreted as the average HFT returns or profitability for 2010 (after controlling for volatility and non-HFT volume), and the coefficients β_1 through β_4 capture the cumulative increase or decrease in average returns or profits (after controlling for volatility and non-HFT volume) since 2010. According to, the baseline HFT returns for 2010 (α) are 0.219%, 0.105% and 0.0841% for Aggressive, Mixed and Passive HFTs, respectively; the baseline HFT average daily profits for 2010 (α) are $68,100, $58,800 and $2,140 for Aggressive, Mixed and Passive HFTs,

[15] Both controls (log volatility and log non-HFT volume) are reported as deviation from the average so that the constant in the regression can be interpreted as the average profitability in 2010 when volatility and volume are average.

respectively; and the baseline HFT average daily profits per contract for 2010 (α) are \$1.74, \$0.872 and \$0.254 for Aggressive, Mixed and Passive HFTs, respectively.

Interestingly, the coefficients on log volatility are positive and statistically significant for Aggressive HFTs and negative or not significantly different from zero for Mixed and Passive HFTs, suggesting that Aggressive HFTs benefit from increased volatility (perhaps more opportunities to adversely select other traders), whereas Mixed and Passive HFTs are harmed by increased volatility (more opportunities to be adversely selected themselves). The coefficients on log non-HFT volume are positive but only sometimes statistically significant, suggesting that increasing that increased trading by non-HFT market participants increases returns and profits, especially for Aggressive HFTs, though may have no effect on returns and profits for Mixed and Passive HFTs.

The indicator coefficients, β_1 through β_4, test whether average daily returns and profitability decreases over the two year sample. In most cases, they are not statistically significantly different from zero. When the coefficients are significant, they are positive for all but one coefficient, suggesting that profits per firm were constant or increasing from 2010 to 2012. The non-statistically significant coefficients are evenly divided between being positive and negative, suggesting that the issue isn't simply a lack of statistical power but that there is no downward trend on returns and profits over time. Taken together the evidence fails to support the hypothesis that HFT profits and returns have decreased over time. They appear to be highly variable day-to-day and month-to-month, but there is no trend either up or down in the aggregate or on the firm level.

Entry and Exit

We analyze entry and exit of HFTs into the E-mini market. Focusing on new entrants, we find that new entrants (especially Aggressive HFT entrants) underperform established HFTs and have a higher probability of exiting. We regress returns and profitability measures on indicator variables for length of time in the market, designating less than 1 month, 2 months or 3 months as indicators of new entry[16]. We exclude the observations in 2010 as this is when we first observe any firm. Formally, we estimate the following OLS regression equation:

$$r_{i,t} = \alpha + \beta_1 \mathbf{1}_{one-month\ i,t} + \beta_2 \mathbf{1}_{two-month\ i,t} + \beta_1 \mathbf{1}_{three-month\ i,t} + \text{day FE} + \epsilon_{i,t} \qquad (8)$$

If new entrants are less competitive and profitable than established firms, the coefficient on the one-month dummy should be negative; the two- and three-month dummy coefficients should also be negative but increasing, showing that experience in the market matters. Based on the regression specification, the constant is interpreted as average returns for established firms. In addition to daily returns, we also look at normalized returns, normalized profits and normalized profits per contract: coefficients in the normalized regressions are interpreted as how many standard deviations new entrants performance are above or below the mean.

INSERT TABLE 10 ABOUT HERE

The results are reported in Table 10, Panel A. Looking at daily returns (Columns 1-3), Aggressive HFTs have statistically significant negative coefficients corresponding to the new entry dummies, with the largest negative value for the 1-month dummy (-0.749%) and decreasing over time (-0.625% and -0.254%). By comparing these coefficients to the constant

[16] Specifically, the *1 month old* indicator variable takes the value 1 (otherwise 0) for firm *i* during days t to t + 30 if firm *i* began trading on day *t-1*. The *2 and 3 month old* indicators likewise use t + 60 and t + 90 windows, respectively. In accounting for entry and exit, we look at the entire lifetime of each firm, not just the months for which the firm is classified as an HFT or as a specific type of HFT. Finally, we ignore gaps and just count the overall first and last trading days of a firm as entry and exit dates.

(0.665%), we can see that new entrants have negative returns for the first month and only slowly increase their profitability over the subsequent two months. Thus, new Aggressive HFTs show a large discrepancy in average daily returns between new entrants and established firms.

For Mixed HFTs, the coefficients are less negative and only significant for the 1-month dummy; comparing the 1-month coefficient (-0.065%) to the constant (0.144%), we see that new entrants who are Mixed HFTs still have positive returns, though less so than established firms. For Passive HFTs, the results are even weaker, suggesting that there is no disadvantage for new entrants who are Passive HFTs. Similar results hold when looking at normalized daily returns (Column 4-6), normalized daily profits (Columns 7-9) and normalized profits per contract (Columns 10-12): for Aggressive HFTs (and less so for Mixed HFTs) entrants are considerably less profitable than established firms, while for Passive HFTs entrants are associated with no such disadvantage.

For further evidence on the lack of competition, we examine whether new entrants are more likely to exit. We find that new Aggressive and Mixed HFTs have an approximately 1% per day increase in the probability of exit than more established HFTs. To address the probability of exit, we perform a probit regression on each month separately to determine whether new entrants are more likely to exit:

$$\text{Pr}\,[Exit_{i,t} = 1] = \Phi[\alpha + \beta_1 \mathbf{1}_{x-month\; i,t} + \text{day FEs} + \epsilon_{i,t}] \tag{9}$$

where $Exit_{i,t}$ takes the value 1 on day t for firm i if that is the last day firm i trades. The coefficients of interest are again those on the dummy variable for new entrants, x-month, which takes the value one, two, or three for either one-, two- or three-months after first appearing as an HFT, depending on the regression specification. We do not count exits in August 2012, due to it being the last month of the data set.

The marginal effects corresponding to the coefficients of the probit regression are reported in Table 10, Panel B. The Pseudo R^2 is reported below the coefficients. Column 1 shows that Aggressive HFTs who are new entrants (1 month) are much more likely to stop trading than their more experienced competitors, with a coefficient of 0.0186: a new entrant has an increased daily probability of exit of 1.86%, which is reasonably high considering that this is the increased probability of exit for *each day* (not the cumulative probability of exit at any future point). Aggressive probability of exit for new entry is statistically significant and positive for the first three months. Mixed HFT new entrants have heightened exit probabilities in months two and three. However, for Passive HFTs the marginal effects are not statistically significant.

In conclusion, new entrants are less profitable and more likely to exit than established HFTs. This finding helps explain the continued concentration of profits among a small subset of established firms: if new entrants are less profitable and tend to exit, then concentration of profits will continue or even increase among established firms. Furthermore, we speculate that new entrants' propensity to exit will limit the degree to which competitive forces reduce the profits of existing HFTs.

VI. Speed

Why might HFT be dominated by a small number of incumbents whose past experience allows them to stay ahead of the competition and maintain their market share? In Section IV, we show that Aggressive HFTs outperform their Mixed and Passive counterparts. Here we focus on another important factor, relative (rank-order) speed, which we show to be an important determinant of profitability, especially for Aggressive HFTs.

We look at the relationship between speed and profits and show a positive association. Our measure of latency comes from Weller (2013): we measure latency of a firm as the 5th percentile of the duration between switching from a passive trade to an aggressive trade, measured in milliseconds. While this measure may not be ideal for every HFT, such as HFTs that trade all passively or all aggressively, it is a way to capture an *active decision* that is likely a response to market events. In contrast to other measures such as the duration between switching from an aggressive buy to an aggressive sell, which may suggest more about the timing of a firm's inventory management strategies, our latency measure aims to capture a firm's reaction speed to market events given its technological constraint.

We sort Aggressive, Mixed and Passive HFTs' firm-day observations into decile bins corresponding to latency. *Speed* is the reciprocal of the average latency (plus 1 millisecond, to ensure we do not divide by zero). Figure 3 plots the average of *Speed* versus average profits overall all firm-day observations within each decile bin.

INSERT FIGURE 3 ABOUT HERE

Panel A shows *Speed* vs. average profits for Aggressive and Mixed HFTs (grouped together), and Panel B shows the same for Passive HFTs. The three lines trace the relationship between speed and profits at approximately one-year intervals (October 2010, July 2011, August 2012).[17] Figure 3 suggests a positive relationship between profits and *Speed*. In the months examined, there is a roughly increasing relationship between profits and *Speed*.

The graphs, which trace the relationship between *Speed* and profits at approximately one-year intervals (October 2010, July 2011, August 2012), show that *Speed* is increasing over the two-year span. Between October 2010, July 2011 and August 2012, the average *Speed* of the top

[17] Because millisecond time stamps were needed for this analysis, we are limited to which months we can analyze.

decile increases from approximately 0.4 to 0.75 to 1. To interpret, a value of 0.5 implies that an HFT switches from aggressive to passive, or vice versa, in one millisecond. A value of 1 implies that an HFT switches within the same millisecond. The speed of the second-to-top decile increases from approximately 0.27 to 0.32 to 1. There are similar increases in *Speed* for Passive HFTs. Although *Speed* increases over the two-year span, average profit fluctuates month-to-month with no clear trend over time.

For a formal analysis, we estimate the following regression from firm-day observations of HFT profitability:

$$\log\,(Profits_{i,t}) = \alpha + \beta_2 RelativeSpeed_{i,t} + \text{time FEs} + \epsilon_{i,t} \tag{10}$$

where log($Profits_{,i,t}$) is a modified version of log profits, actually sign(profits)*log(1+|profits|), to allow for negative values, $RelativeSpeed_{i,t}$ is the firm's ranking that day in terms of speed among all firms of that subtype scaled by the total number of firms that day of that subtype. The results are reported in Table 11.

INSERT TABLE 11 ABOUT HERE

Table 11 shows that for all three subtypes of HFTs relative speed is important, with statistically significant coefficients of -6.72, -4.44 and -2.62 for Aggressive, Mixed, and Passive HFTs, respectively. The signs of the coefficients are as one would expect: profits are decreasing in relative speed (higher relative rank means higher profits). The coefficient is highest for Aggressive HFTs. Given that the left-hand side of the regression is in logs, this translates to a four order-of-magnitude higher change in profits for Aggressive HFTs than Passive HFTs, conditional in a one-rank improvement in speed. By showing that speed is an important determinant of profitability, our analysis suggests that HFTs have strong incentives to compete over small increases in speed in an industry dominated by a small number of incumbents earning high and persistent returns.

VII. **Conclusion**

We study the risk and return performance of HFT firms. We document several important descriptive statistics, many of which suggest superior investment performance of HFTs. HFTs earn Sharpe ratios that are several times higher than those for other asset classes or trader types. HFT returns are highly persistent, while risks are kept very low through tight inventory control and rapid turnover of contracts. HFT profits accumulate to the fastest and most aggressive liquidity-taking incumbents, while new entrants are less profitable and more likely to exit.

These facts highlight the importance of understanding the industrial organization of HFTs. Economists generally think that competition from new entrants will improve markets: there will be more liquidity, greater price efficiency, lower transaction costs for investors, and less potential for any one firm to influence markets. However, the cutthroat competitive environment in which HFTs interact may influence their impact on market quality. With limited competition from new entrants to engage incumbent HFTs, market quality may not improve as much as it would otherwise. Recent theoretical papers have highlighted concerns of faster traders adversely selecting slower traders and competition on speed leading to socially inefficient arms races for speed.

Our results suggest that HFTs have strong incentives to take liquidity and compete over small increases in speed in an industry dominated by a small number of incumbents earning high and persistent returns. Understanding the industrial organization of HFTs allows researchers to think more comprehensively about the role and implications of HFTs in financial markets.

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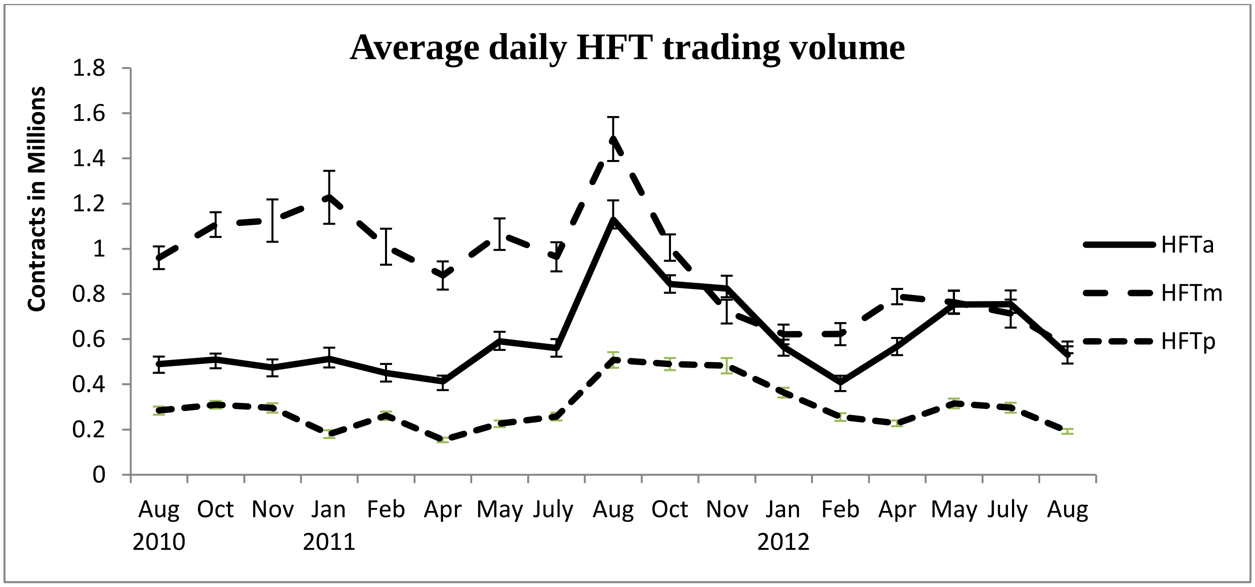
Figure 1: Aggregate HFT trading activity

Panel A shows the average daily HFT volume of all HFT accounts combined (with standard error bars). Panel B shows the percent of market volume by trader type.

Panel A: HFT average daily trading volume



Panel B: Percent market volume by trader types

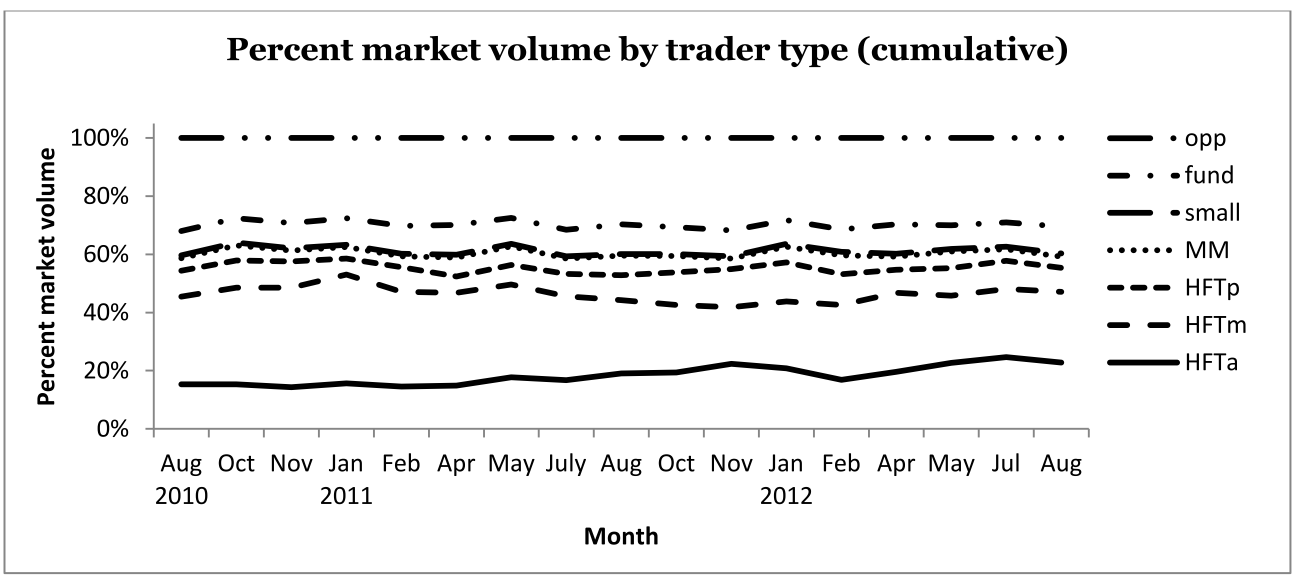
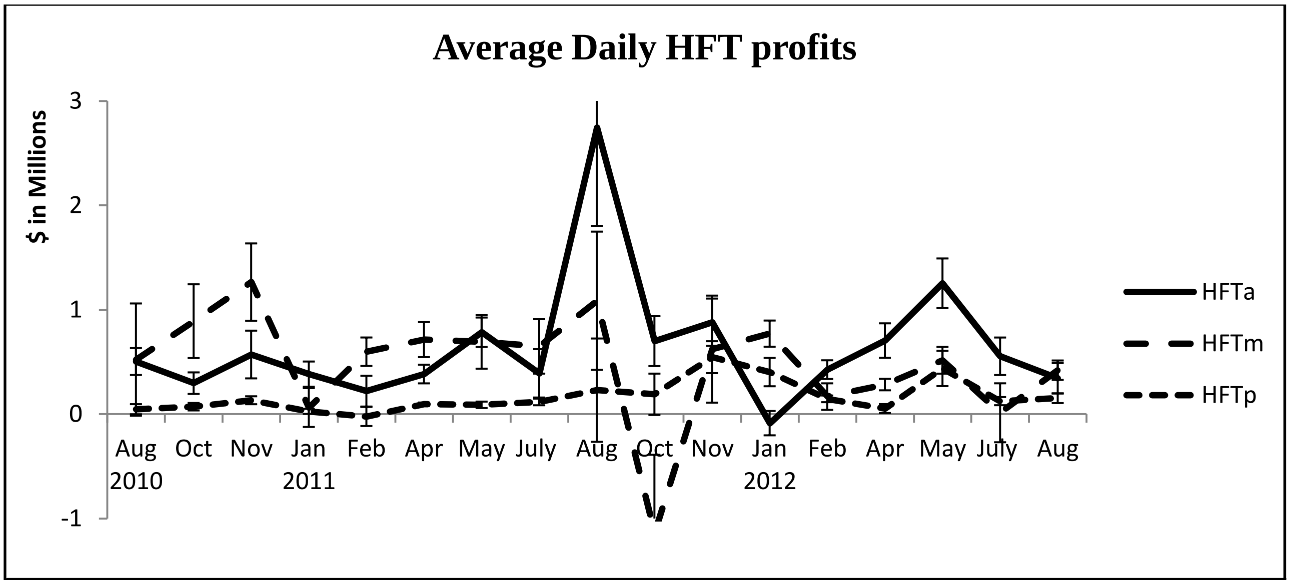


Figure 2: Aggregate HFT returns and profitability

Panel A shows the average daily HFT returns of all HFT accounts combined. Panel B shows average daily profits per contract, where the contract price is approximately $50,000. Standard error bars are calculated based on daily observations.

Panel A: Aggregate HFT profits



Panel B: Aggregate HFT profits per contract

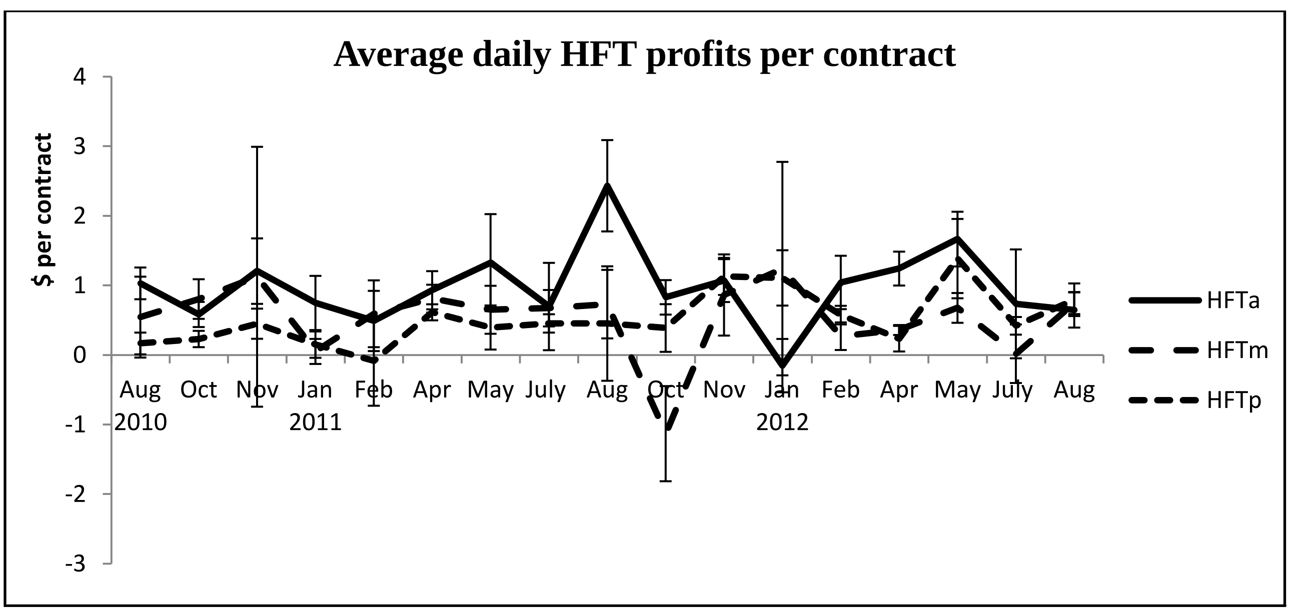
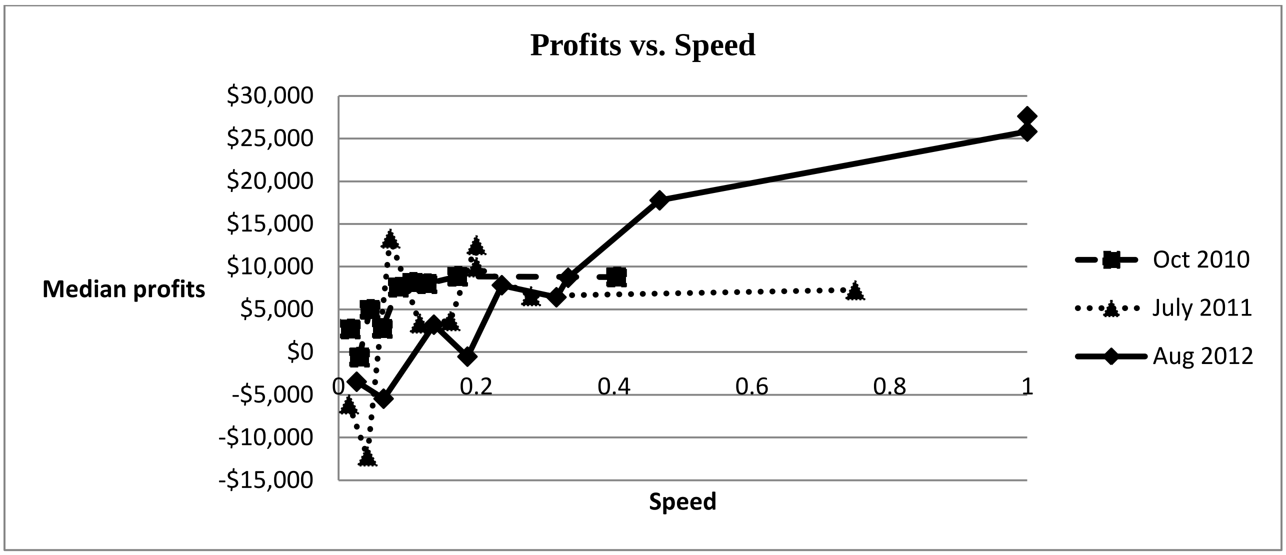


Figure 3: Speed and profitability

The figures shows the relationship between speed and profits. $Speed_{i,t} = (1+Latency_{i,t})^{-1}$, where $Latency_{i,t}$ is calculated as the 5th percentile (within each firm-day) of the time in milliseconds between successive trades that switch from a passive trade to an aggressive trade. Speed observations are grouped into decile bins, which are plotted against median profits within each bin. Panel A analyzes Aggressive and Mixed HFTs, and Panel B analyzes Passive HFTs. Within each panel, the relationship between speed and profits is plotted separately for three months for which we have millisecond data , October 2010, July 2011, and August 2012.

Panel A: Aggressive and Mixed HFT



Panel B: Passive HFT

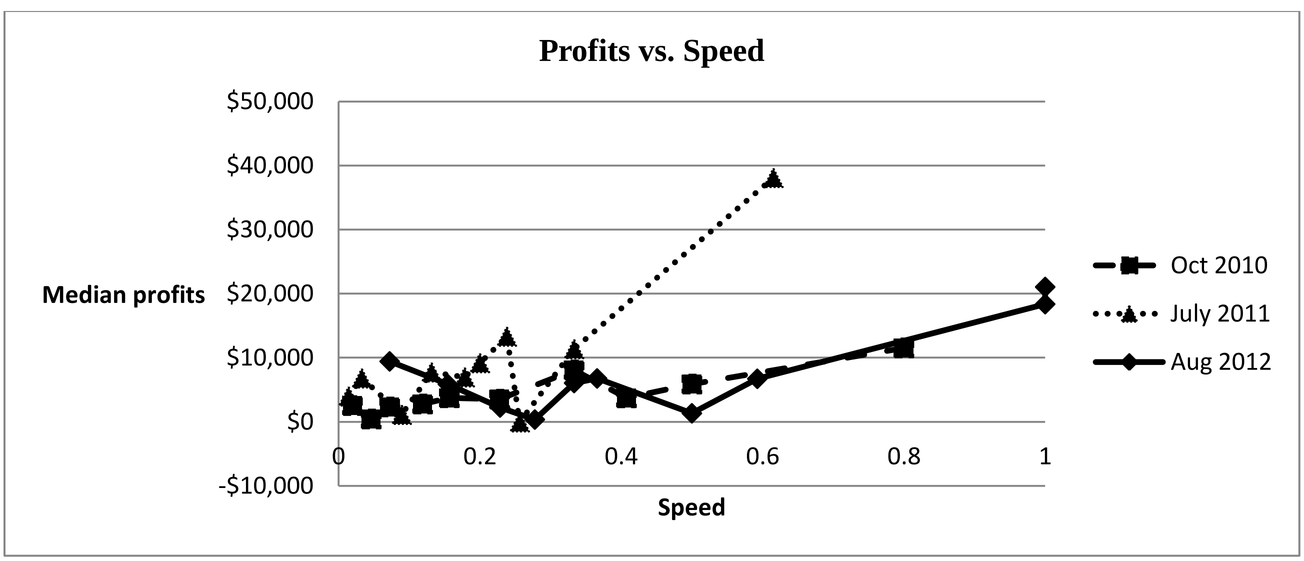


Table 1: Summary statistics of S&P 500 E-mini market, August 2010

The mean, standard deviation, minimum, median, and maximum of the daily trading activity of seven different trader types' trading activity are reported: Aggressive HFTs (HFT^A), Mixed HFTs (HFT^M), Passive HFTs (HFT^P), fundamental, small trader, non-HFT market maker, and opportunistic. Two different statistics are reported: *Daily % Market Volume* is the daily percent of market volume traded and *Daily Aggressive Ratio* is the daily fraction of contracts that are liquidity taking.

Daily % Market Volume	**Mean**	**Std. Dev.**	**Min.**	**Median**	**Max**
HFT^A (n=14)	15.22%	1.89%	9.50%	15.74%	17.57%
HFT^M (n=30)	30.28%	1.65%	27.46%	30.11%	33.94%
HFT^P(n=21)	8.87%	0.96%	6.36%	8.96%	10.93%
Fundamental (n=346)	8.42%	1.17%	6.97%	8.26%	12.69%
Small Trader (n=21761)	1.04%	0.11%	0.82%	1.02%	1.24%
Non-HFT Market Maker (n=737)	4.24%	0.37%	3.60%	4.31%	4.83%
Opportunistic (n=8494)	31.93%	1.40%	29.78%	31.77%	34.44%
Total (n=31403)	3,187,011	819,419	1,652,052	3,081,016	4,465,574
Daily Aggressive Ratio					
HFT^A	84.22%	1.90%	80.05%	84.26%	87.79%
HFT^M	37.08%	1.56%	34.66%	37.29%	40.08%
HFT^P	12.35%	1.45%	10.73%	11.83%	15.54%
Fundamental	57.68%	3.83%	48.68%	57.58%	64.90%
Small Trader	57.82%	1.25%	55.64%	57.53%	59.94%
Non-HFT Market Maker	12.98%	0.99%	11.45%	12.88%	15.12%
Opportunistic	59.08%	1.21%	56.80%	58.91%	61.89%

Table 2: HFT returns

The table reports statistics on the daily returns and profitability of HFT firms from August 2010 to August 2012. Each observation is a firm-day. Panel A reports returns and Panel B reports profits per contract (nominal contract value of approximately $50,000). The labels HFT^A, HFT^M, and HFT^P correspond to Aggressive, Mixed, and Passive HFTs, respectively. Means, medians, and standard deviations are reported annualized, while skewness and kurtosis are based on daily observations. The p-value tests whether daily means are statistically significantly different from zero (tested over N=530 trading days).

Panel A: Annualized Returns (in %)

	N	Mean	Median	Std. Dev.	Skew.	Kurt.	P-Value
HFT (all)	13713	51.67	18.56	16.78	6.816	147.154	< 0.001
HFT^A	3274	122.10	25.15	28.39	5.679	65.525	< 0.001
HFT^M	6147	32.29	18.84	11.40	0.547	58.503	< 0.001
HFT^P	4292	25.69	15.35	8.89	6.402	249.666	< 0.001

Panel B: Profit Per Contract

	N	Mean	Median	Std. Dev.	Skew.	Kurt.	P-Value
HFT (all)	13713	$0.641	$0.519	$0.486	$0.125	$79.320	< .05
HFT^A	3274	$1.296	$0.792	$0.536	$5.556	$96.318	< .001
HFT^M	6147	$0.404	$0.466	$0.568	$-2.044	$46.798	0.15
HFT^P	4292	$0.481	$0.470	$0.268	$-3.986	$183.799	< 0.01

Table 3: Cross-sectional distribution of returns across firms

The table reports statistics on the cross-section of HFT firms who are active for at least three months. Returns, alphas, profits per contract (on a notional value of approximately $50,000), and Sharpe ratios (based on daily observations and reported in annualized terms) are first calculated for each firm; statistics on the cross-section of firms are reported below. The labels HFT^{A}, HFT^{M}, and HFT^{P} correspond to Aggressive, Mixed, and Passive HFTs, respectively. Data-use restrictions prevent certain top and bottom percentiles from being reported.

	N	Mean	S.D.	10%	25%	50%	75%	90%
Returns (% annualized)								
HFT (all)	85	39.49	87.83	-0.35	8.07	20.40	51.14	74.13
HFT^{A}	18	91.08	170.55			46.64		
HFT^{M}	39	27.42	45.61			22.51		
HFT^{P}	28	23.13	22.24			15.02		
Alphas (% annualized)								
HFT (all), CAPM	85	39.92	88.81	-0.26	8.95	19.20	51.15	73.33
3-factor	85	39.74	89.43	-1.49	8.09	19.10	50.82	72.93
4-factor	85	39.78	89.21	-1.80	8.13	22.02	50.92	70.51
HFT^{A} 4-factor	18	90.67	174.74			37.06		
HFT^{M} 4-factor	39	28.18	44.90			23.15		
HFT^{P} 4-factor	28	23.22	22.24			14.88		
Profit per contract ($)								
HFT (all)	85	0.54	1.43	-0.16	0.28	0.46	0.82	2.01
HFT^{A}	18	0.65	1.56			0.65		
HFT^{M}	39	0.40	1.68			0.46		
HFT^{P}	28	0.66	0.91			0.41		
Sharpe Ratios (annualized)								
HFT (all)	85	5.25	5.01	-0.18	2.16	4.30	9.10	12.68
HFT^{A}	18	4.29	4.57			3.86		
HFT^{M}	39	5.26	5.75			4.38		
HFT^{P}	28	5.85	4.18			4.52		

Table 4: Persistence of returns

The table analyzes persistence in firms' returns and profits on both a daily and monthly level. The following regression is estimated: $Returns_{i,t} = \alpha + \beta Returns_{i,t-1} + \text{time FEs} + \epsilon_{i,t}$. Regressions are also estimated in which the dependent variable (and lag) is normalized across firms for each day (or month) to account for the time-varying mean and variance of returns. With normalization, the regression is performed without time fixed effects as the normalization removes any average time trend, and the estimate of the constant, which is always zero, is not reported. Similar regressions are estimated with profits, profits-per-contract, and Sharpe ratios. Panel A analyzes persistence using daily observations, Panel B uses monthly observations, and Panel C considers persistence of rank ordering of firms on each day or month. *, ** and *** correspond to p-values < 5%, 1%, 0.1%, respectively. Standard errors are in parentheses.

Panel A: Daily persistence

	Returns(i,t)			Normalized returns(i,t)			Normalized profits(i,t)			Normalized profits-per-contract(i,t)		
	HFT^A	HFT^M	HFT^P	HFT^A	HFT^M	HFT^P	HFT^A	HFT^M	HFT^P	HFT^A	HFT^M	HFT^P
Dependent var (i,t-1)	.421*** (.0193)	.109*** (.0147)	-.073*** (.0167)	.276*** (.0195)	.169*** (.0147)	.205*** (.0174)	.16*** (.0199)	.141*** (.0148)	.227*** (.0173)	.111*** (.0202)	.093*** (.015)	.074*** (.0176)
Constant	.271*** (.0322)	.111*** (.0103)	.11*** (.0086)									
Adj-R^2	0.255	0.079	0.124	0.077	0.029	0.044	0.035	0.021	0.054	0.018	0.010	0.010
N	2703	4728	3458	2702	4724	3454	2702	4724	3454	2702	4724	3454

Panel B: Monthly persistence

	Returns(i,t)			Normalized returns(i,t)			Normalized profits(i,t)			Normalized profits-per-contract(i,t)			Normalized Sharpe ratio(i,t)		
	HFT^A	HFT^M	HFT^P	HFT^A	HFT^M	HFT^P	HFT^A	HFT^M	HFT^P	HFT^A	HFT^M	HFT^P	HFT^A	HFT^M	HFT^P
Dependent var (i,t-1)	.723***	.407***	.725***	.809***	.449***	.699***	.416***	.33***	.616***	.418***	.296***	.52***	.639***	.659***	.452***
	(.0654)	(.0569)	(.0978)	(.0495)	(.0541)	(.0623)	(.0839)	(.0585)	(.0523)	(.0812)	(.0598)	(0.080)	(.0634)	(.0441)	(.0686)
Constant	.149*	.0779***	.0234												
	(.061)	(.0165)	(.0158)												
Adj-R^2	0.522	0.224	0.335	0.656	0.216	0.428	0.176	0.114	0.452	0.208	0.099	0.246	0.439	0.470	0.212
N	161	270	197	161	270	197	161	270	197	161	270	197	161	270	197

Panel C: Persistence of rank ordering

	Daily returns(i,t)			Monthly returns(i,t)			Monthly profits(i,t)			Monthly profits-per-contract(i,t)			Sharpe ratio(i,t)		
	HFT^A	HFT^M	HFT^P	HFT^A	HFT^M	HFT^P	HFT^A	HFT^M	HFT^P	HFT^A	HFT^M	HFT^P	HFT^A	HFT^M	HFT^P
Dependent var (i,t-1)	0.376***	0.238***	0.278***	0.695***	0.474***	0.444***	0.679***	0.490***	0.402***	0.479***	0.328***	0.289***	0.629***	0.555***	0.479***
	(0.0152)	(0.0121)	(0.014)	(0.0504)	(0.0478)	(0.0551)	(0.0515)	(0.0474)	(0.0562)	(0.0616)	(0.0513)	(0.0588)	(0.0545)	(0.0452)	(0.0539)
Constant	3.868***	7.802***	5.678***	2.150***	5.775***	4.978***	2.265***	5.607***	5.347***	3.677***	7.384***	6.362***	2.614***	4.892***	4.666***
	(0.111)	(0.144)	(0.128)	(0.422)	(0.61)	(0.575)	(0.431)	(0.604)	(0.588)	(0.515)	(0.654)	(0.615)	(0.456)	(0.576)	(0.564)
Adj-R^2	0.141	0.056	0.077	0.481	0.223	0.194	0.458	0.238	0.159	R-sq	0.225	0.105	0.393	0.306	0.226
N	2703	4728	3458	161	270	197	161	270	197	161	270	197	161	270	197

Table 5: HFT inventories

Inventory statistics are reported for Aggressive HFTs (HFT^A), Mixed HFTs (HFT^M), and Passive HFTs (HFT^P). Median and standard deviations across firms are reported for three statistics: *Average Daily Volume* (in thousands), *Average end-of-day inventory* (both in number of contracts and as a percentage of the firm's average daily trading volume), and *Average intraday inventory range*. Medians (and s.d.) across firms are calculated by taking the average across days for each firm and then the median (and s.d.) across firms.

	Median (and s.d.) across firms		
	HFT^A	**HFT^M**	**HFT^P**
Average Daily Volume (thous.)	7,838	9,134	8,693
	(28,087)	(36,826)	(17,895)
Average end-of-day inventory	49.3	16.7	10.5
	(154.6)	(266.2)	(203.8)
- Normalized by firm's average daily trading volume	0.4%	0.2%	0.1%
	(4.6%)	(1.3%)	(1.3%)
Average intraday inventory range	525.9	313.6	204.2
	(861.1)	(1030.0)	(659.3)
- Normalized by firm's average daily trading volume	7.3%	4.0%	2.2%
	(5.8%)	(3.7%)	(3.4%)

Table 6: Spectral Analysis

The table analyzes trading profits in August 2010 over different time horizons using spectral analysis, following the methods of Hasbrouck and Sofianos (1993). We first compute the spectral decomposition of profits for each individual HFT firm and each trading day, decomposing profits over the following intervals: 1-10, 11-100, 101-1,000, 1,001-10,000, 10,000-100,000 and 100,000+ market transactions. For each HFT firm we calculate the median profit across days for each interval, and then report the median and the 25th and 75th percentiles (in brackets) across firms.

	Transaction interval					
	1-10	**11-100**	**101-1,000**	**1,001-10,000**	**10,001- 100,000**	**100,000+**
HFT^A	$870	-$678	-$5,348	$21,939	$22,108	-$8,637
	[$-2825, $8252]	[$-10887, $5997]	[$-45231, $12597]	[$-9633, $73428]	[$6213, $44481]	[$-19056, $4234]
HFT^M	$12,145	$23,171	$8,811	-$21,832	-$8,483	-$1,935
	[$7825, $19111]	[$12301, $35883]	[$-5835, $27894]	[$-36494, $-5288]	[$-13018, $2360]	[$-4179, $1452]
HFT^P	$5,236	$12,991	$11,408	-$7,917	-$9,774	-$3,428
	[$3840, $11170]	[$10174, $20701]	[$7920, $19186]	[$-14282, $-1512]	[$-20778, $-6990]	[$-9596, $-2509]

Table 7: Profit Breakdown

The table analyzes the decomposition of average daily short-term profits among different trader types in August 2010. The table is constructed by considering the trades between each pair-wise group and calculating the profit flows that result from those trades. We calculate each type's short-term profits (gains/losses realized on a trade one-minute after that trade). The rows identify who receives the profits, whereas the different columns represent from whom the profits are derived. Panel A analyzes average daily trading profits, and Panel B describes the profits on a per contract basis.

	Counterparty							
Profits to:	**HFT^A**	**HFT^M**	**HFT^P**	**Non-HFT MM**	**Fundamental**	**Opportunistic**	**Small**	**Total**
Panel A: Profits								
HFT^A	$0	$7,190,140	$2,557,038	$1,962,675	$1,691,738	$8,171,350	$379,275	$21,952,215
HFT^M	-$7,190,140	$0	$1,400,125	$1,607,400	$376,300	$15,358,325	$1,219,050	$12,771,060
HFT^P	-$2,557,038	-$1,400,125	$0	$84,300	-$373,438	$4,323,100	$425,538	$502,338
Non-HFT MM	-$1,962,675	-$1,607,400	-$84,300	$0	-$382,688	$1,060,000	$120,525	-$2,856,538
Fundamental	-$1,691,738	-$376,300	$373,438	$382,688	$0	$2,321,775	$119,550	$1,129,413
Opportunistic	-$8,171,350	-$15,358,325	-$4,323,100	-$1,060,000	-$2,321,775	$0	$339,150	-$30,895,400
Small Trader	-$379,275	-$1,219,050	-$425,538	-$120,525	-$119,550	-$339,150	$0	-$2,603,088
Total	-$21,952,215	-$12,771,060	-$502,338	$2,856,538	-$1,129,413	$30,895,400	$2,603,088	$0
Panel B: Profit/Loss Per Trade								
HFT^A	$0.00	$2.02	$1.93	$2.64	$1.92	$2.49	$3.49	$2.04
HFT^M	-$2.02	$0.00	$0.94	$1.95	$0.18	$1.92	$4.42	$0.60
HFT^P	-$1.93	-$0.94	$0.00	$0.75	-$0.62	$1.79	$5.05	$0.08
Non-HFT MM	-$2.64	-$1.95	-$0.75	$0.00	-$1.59	$1.11	$4.25	-$0.97
Fundamental	-$1.92	-$0.18	$0.62	$1.59	$0.00	$1.45	$2.87	$0.19
Opportunistic	-$2.49	-$1.92	-$1.79	-$1.11	-$1.45	$0.00	$2.05	-$1.38
Small Trader	-$3.49	-$4.42	-$5.05	-$4.25	-$2.87	-$2.05	$0.00	-$3.67
Total	-$2.04	-$0.60	-$0.08	$0.97	-$0.19	$1.38	$3.67	$0.00

Table 8: HFT Herfindahl Concentration

The table reports estimates on the Herfindahl index for each class of HFTs over successive six-month sample windows and analyzes whether market concentration is increasing or decreasing over time. We report a profit-based Herfindahl Index as well as a volume-based one. The profit Herfindahl index is calculated as $Herfindahl_{i,t} = \sum_{i=1}^{N}\left[\frac{Profit_{i,t}}{HFT\ Profit_t}\right]^2 \epsilon\ (0,1]$, and the volume Herfindahl is calculated similarly using trading volume instead of trading profits. A larger index implies a more concentrated industry. To assess whether market concentration is increasing or decreasing over time, the first-half of 2010 is used a baseline, and subsequence six-month sample periods are tested against the baseline. *, ** and *** correspond to p-values < 5%, 1%, 0.1%, respectively. Standard errors are in parentheses.

	Profit Herfindahl Index			Volume Herfindahl Index		
	HFT^A	**HFT^M**	**HFT^P**	**HFT^A**	**HFT^M**	**HFT^P**
1st half 2010	0.362 (0.131)	0.287 (0.135)	0.287 (0.167)	0.2 (0.059)	0.239 (0.061)	0.129 (0.056)
1st half 2011	0.377 (0.202)	0.316 (0.164)	0.495*** (0.236)	0.195 (0.106)	0.26 (0.142)	0.329*** (0.104)
2nd half 2011	0.318* (0.155)	0.259 (0.135)	0.471*** (0.229)	0.183* (0.039)	0.174*** (0.136)	0.289*** (0.083)
1st half 2012	0.34 (0.178)	0.376*** (0.156)	0.513*** (0.286)	0.199 (0.054)	0.266 (0.132)	0.348*** (0.182)
2nd half 2012	0.347 (0.144)	0.412*** (0.141)	0.545*** (0.219)	0.199 (0.062)	0.248 (0.063)	0.331*** (0.129)

Table 9: Long-run profitability

The table analyzes long-run trends in HFT profitability by reporting estimates of the following OLS regression: $Returns_{i,t} = \alpha_i + \beta \mathbf{1}_{\text{six\_month\_window},t} + \text{controls}_t + \epsilon_{i,t}$. The notation $\mathbf{1}_{\text{six\_month\_window},t}$ corresponds to a series of indicators capturing six-month windows in 2011 and 2012; a positive coefficient on one of these indicators would correspond to an increasing trend in HFT firms' profits in comparison to the benchmark year 2010 (the first year in which we have data). We control for daily volatility and non-HFT-volume. *, ** and *** correspond to p-values < 5%, 1%, 0.1%, respectively. Standard errors are in parentheses.

	Daily returns (%)			**Daily profits ($, thous.)**			**Daily profit-per-contract**		
	HFT^A	**HFT^M**	**HFT^P**	**HFT^A**	**HFT^M**	**HFT^P**	**HFT^A**	**HFT^M**	**HFT^P**
Constant (2010 baseline)	.219***	.105***	.0841***	68.1***	58.8***	2.14	1.74***	.872*	.254
	(.0567)	(.0232)	(.0227)	(13.2)	(11.5)	(9.66)	(.303)	(.347)	(.195)
1st half of 2011 indicator	-.0233	.0258	-.032	.132	-17.8	-4.04	-.501	-.332	-.218
	(.0762)	(.0333)	(.0369)	(17.7)	(16.4)	(15.7)	(.407)	(.498)	(.317)
2nd half 2011 indicator	.0494	.0645*	.128***	7.36	-33.5*	35.4*	-.762	-.391	.627*
	(.0771)	(.0328)	(.0349)	(17.9)	(16.2)	(14.8)	(.412)	(.49)	(.299)
1st half 2012 indicator	.321***	.132***	.0632	21.8	-13.1	25.1	-.38	.016	.575
	(.0752)	(.0331)	(.0345)	(17.5)	(16.3)	(14.7)	(.402)	(.495)	(.296)
2nd half 2012 indicator	.353***	.0584	-.0719	10.3	-31.1	8.83	-.897	-.177	-.691
	(.0917)	(.0426)	(.0443)	(21.3)	(21)	(18.9)	(.49)	(.637)	(.38)
Log volatility$_t$	.209**	-.0331	-.0326	43.4**	-44.6**	-23.3	.892*	-.861	-.719*
(deviation from mean)	(.0669)	(.0334)	(.0344)	(15.6)	(16.5)	(14.6)	(.358)	(.5)	(.295)
Log non-HFT volume$_t$	.196*	.18***	.047	68.7***	39.7	3.49	.177	.813	.699
(deviation from mean)	(.0777)	(.0488)	(.0429)	(18.1)	(24)	(18.2)	(.415)	(.728)	(.367)
Adj-R^2	0.026	0.009	0.013	0.027	0.004	0.004	0.006	0.001	0.008
N	3195	4525	2679	3195	4525	2679	3195	4525	2679

Table 10: HFT Entry and Exit

The table analyzes the performance of new HFT entrants. Panel A reports the results of the following OLS regression: $r_{i,t} = \alpha + \beta_1 \mathbf{1}_{one-month\ i,t} + \beta_2 \mathbf{1}_{two-month\ i,t} + \beta_1 \mathbf{1}_{three-month\ i,t} + \text{day FE} + \epsilon_{i,t}$ The notation $\mathbf{1}_{one-month\ i,t}$ takes the value 1 if firm *i* began trading in the last 30 days, otherwise 0; two and three month dummy variables are defined similarly. We exclude the observations in 2010 as this is when we first observe any firm. Panel B reports the results of the probit regression $\Pr\,[Exit_{i,t} = 1] = \Phi[\alpha + \beta_1 \mathbf{1}_{x-month\ i,t} + \text{day FEs} + \epsilon_{i,t}]$ where $Exit_{i,t}$ takes the value 1 on day *t* for firm *i* if that is the last day firm *i* trades. The coefficient of interest is again the dummy variable, $x\text{-}month_{i,t}$, defined as above, but regressions are univariate (one indicator at a time, with x-month representing either one-, two-, or three- months) in contrast to Panel A. In addition to the excluded observations described in Panel A, this regression excludes observations in August 2012, the last month of the analysis, due to this being the last month of the data set. *, ** and *** correspond to p-values < 5%, 1%, 0.1%, respectively. Standard errors are in parentheses.

Panel A: Profitability of New Entrants

	Daily returns(i,t)			Normalized daily returns(i,t)			Normalized daily profits(i,t)			Normalized profits-per-contract(i,t)		
	HFT^A	**HFT^M**	**HFT^P**	**HFT^A**	**HFT^M**	**HFT^P**	**HFT^A**	**HFT^M**	**HFT^P**	**HFT^A**	**HFT^M**	**HFT^P**
< 1 month old indicator	-.749***	-.0653*	-.0169	-.479***	-.144***	-.0283	-.396***	-.173***	-.0394	-.144**	.0047	.003
	(.0858)	(.0276)	(.0224)	(.0511)	(.039)	(.0419)	(.0513)	(.039)	(.0419)	(.0517)	(.0391)	(.0419)
< 2 month old indicator	-.625***	-.0605	.0176	-.316***	-.132*	.128*	-.179	-.154*	-.0237	-.0356	-.0388	.0254
	(.16)	(.044)	(.0325)	(.0953)	(.0622)	(.0607)	(.0957)	(.0622)	(.0607)	(.0964)	(.0623)	(.0607)
< 3 month old indicator	-.254*	.006	-.0734*	-.103	.0418	-.0032	-.0357	-.121*	-.112*	-.0034	.0082	-.0886
	(.12)	(.0338)	(.029)	(.0715)	(.0478)	(.0542)	(.0718)	(.0478)	(.0542)	(.0724)	(.0479)	(.0542)
Constant	.665***	.144***	.113***	.138***	.0366*	-0.0063	.103***	.066***	0.0323	0.0345	0.001	0.0104
	(0.04)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Adj-R^2	0.134	0.074	0.113	0.026	0.003	0.001	0.018	0.004	0.001	0.002	0.000	0.001
N	3695	6433	4741	3694	6429	4737	3694	6429	4737	3694	6429	4737

Panel B: Probability of Exit, marginal effects

	HFT^{A}		HFT^{M}		HFT^{P}	
< 1 month old indicator	0.0186**	(0.009)	0.0046	(0.005)	0.0017	(0.005)
Pseudo R^2	0.057		0.0076		0.0032	
< 2 month old indicator	0.0204**	(0.008)	0.0123*	(0.007)	0.0003	(0.004)
Pseudo R^2	0.076		0.053		0.0026	
< 3 month old indicator	0.0184***	(0.007)	0.0082*	(0.005)	0.0024	(0.003)
Pseudo R^2	0.077		0.053		0.0055	

Table 11: Speed and Profits

The table reports coefficients from the regression: $\log(profits)_{i,t} = \alpha_t + RelativeSpeed_{i,t} + controls + \epsilon_{i,t}$, where $\log(\text{profits})_{,i,t}$ is a modified version of log profits, namely sign(profits)*log(1+|profits|) to allow for negative values. $RelativeSpeed_{i,t}$ is the firm's ranking that day in terms of speed among all firms of that sub-type scaled by the total number of firms that day of that sub-type. *, ** and *** correspond to p-values < 5%, 1%, 0.1%, respectively. Standard errors are in parentheses.

	HFT^A	HFT^M	HFT^P
Relative Speed	-6.72*** (1.3)	-4.44*** (0.73)	-2.62*** (0.77)
N	730	1693	1334
Adj-R^2	0.035	0.020	0.009