# The Trading Profits of High Frequency Traders*

Matthew Baron

Jonathan Brogaard

Andrei Kirilenko

First Draft: October 2011

Current Draft: November 2012

**Abstract:** We examine the profitability of high frequency traders (HFTs). Using transaction level data with user identifications, we find that high frequency trading (HFT) is highly profitable: HFTs collectively earn over $23 million in trading profits in the E-mini S&P 500 futures contract during the month of August 2010. The profits of HFTs are mainly derived from Opportunistic traders, but also from Fundamental (institutional) traders, Small (retail) traders, and Non-HFT Market Makers. While HFTs bear some risk, they generate unusually high average Sharpe ratios with a median of 4.5 across firms in August 2010. Finally, HFTs profits are persistent, new entrants have a higher propensity to underperform and exit, and the fastest firms (in absolute and in relative terms) earn the highest profits.

*Contact: Matthew Baron, Princeton University, (Email) mdbaron@princeton.edu, Jonathan Brogaard, Foster School of Business, University of Washington, (Email) brogaard@uw.edu, Andrei Kirilenko Commodity Futures Trading Commission (CFTC), (Email) akirilenko@cftc.gov. The views expressed in this paper are those of the authors and do not represent the official position of the CFTC, its Commissioners or staff. Matthew Baron and Jonathan Brogaard acknowledge funding from the CFTC. We thank Hank Bessembinder, Tarun Chordia, Richard Haynes, Charles Jones, Norris Larrymore, Wei Xiong, and Ryan Riordan for their valuable feedback, and the seminar participants at the Bank of Canada Market Microstructure Conference, Blackrock, the CFTC, Northwestern University, Princeton University, and the University of Washington for helpful comments.

## I. Introduction

In financial markets speed matters, whether using expedited information to make an investment or being able to quickly enter trades. A new phrase, high frequency trading (HFT; or HFTs for high frequency traders), has been used to identify a strategy that relies crucially on speed. HFTs have surpassed floor traders as being the quickest to access markets, respond to changes in market conditions, and intermediate trades. The time scale of such activities can be measured at microsecond time frames, with position holding periods of mere seconds. Whether it is using expedited information to make an investment, reduce risk, or mitigate the costs of adverse selection, those quickest to react to information can best intermediate trading and capture informational rents.

In this paper, we examine the link between HFT speed, liquidity provision, and trading profits. We have four main findings. First, HFTs are profitable, especially Aggressive (liquidity-taking) HFTs, and generate high Sharpe ratios. Second, HFTs generate their profits from all other market participants, and do so mainly in the short and medium run (seconds to minutes). Third, firm concentration in the HFT industry is not decreasing over time, nor is its profitability. We conjecture this is tied to our fourth finding that HFTs profits are persistent, new entrants have a higher propensity to underperform and exit, and the fastest firms (in absolute and in relative terms) make up the upper tail of performance.

We start by describing several stylized facts about the profitability of the HFT industry and the distribution of profits across firms. We find that an important determinant of profitability is the level of liquidity provision of a HFT firm. We find that the aggressiveness of a given HFT firm is highly persistent not only across days but over a two-year span, and use this finding to classify HFTs into three categories based on liquidity provision: Aggressive HFTs (if >60% of their trades are liquidity taking), Mixed (if between 20% and 60% of their trades are liquidity taking), and Passive (if <20% of their trades are liquidity taking). We show that the level of profits is significantly higher for liquidity-taking HFTs than for liquidity-providing ones: The average Aggressive HFTs earns $45,267 in gross trading profits in August 2010, while Mixed and Passive HFTs earn significantly less: only $19,466 and $2,461 per day, respectively.

These stylized facts mask a wide dispersion of profitability on the individual account level, in particular that the distribution of profits is highly concentrated toward a small number of firms, in particular towards Aggressive HFTs. Furthermore, we find that the distribution of total profits across HFT firms is widest within the Aggressive HFT category, with profits highly concentrated toward a small number of these firms; in contrast, Passive HFTs have less dispersion and lower profits. While HFTs bear some risk, they generate unusually high average Sharpe ratios in the range of 3 to 20, with a median of 4.5 across firms in August 2010.

Next we study how HFTs generate these profits. We decompose traders' profits by their trading partners. We find that HFT firms' profits are mainly derived from Opportunistic traders, but also to a smaller extent from Fundamental (institutional) traders, Small (retail) traders, and Non-HFT Market Makers. Second, we perform a spectral analysis on HFT firms' profits. We find that Aggressive HFTs make profits mainly on positions that they hold in the 1,000 – 100,000 transactions range, while Mixed and Passive HFTs lose money in this range but earn profits in the very-short term (the 1 – 1,000 transactions range), perhaps reflecting the capturing of the bid-ask spread.

We evaluate further by considering the performance of individual firms. While the earlier results show that HFTs on average outperform, the results do not track a single HFT firm. It could be that while HFTs as a whole outperform, each particular HFT firm's profits are random. We test for persistence in profits at the firm level. We find that a firm's profits yesterday positively predict its profits today, in addition to its profits even months later. Persistent profits over time suggest that something other than luck is driving a firm's performance. Persistent performance may lead to concentration as strongly performing firms will continue to perform well, but less successful firms will exit the industry.

Next we analyze the profitability of new entrants and find they are not as profitable as existing firms. In addition, they have a higher probability of exiting the market. Something other than chance could drive higher profitability of established firms relative to entrants. A small competitive advantage early on, perhaps from experience (as in Seru, Shumway, and Stoffman, 2010) or ability, could determine whether an HFT firm can consistently invest in ever more sophisticated technology and thus maintain a competitive advantage over rival firms. Alternatively, the higher profitability of established HFTs could be due to a survivorship bias: profitable firms remain while unprofitable firms exit; this process of selection results in established firms having a higher average profitability than entrants, who have not been selected out.

HFT profits exhibit large positive outliers – some firms strongly outperform. Why might the HFT industry exhibit this winners-take-all type concentration? A contributing factor may be speed. The fastest firm may be able to consistently enter and exit more favorable trading opportunities or cancel resting limit orders before they are picked off by faster traders. We measure both absolute speed and relative speed and show that speed does matter. Absolute Speed matters for Mixed HFTs and relative speed matters for Aggressive HFTs. For Aggressive HFTs competition for ever-increasing speed creates a "positional externality" (Frank, 2005), since attempting to be the fastest seems to come at the expense of other firms. While such an arms race, or rank-order tournament, can sometimes be socially positive such as by incentivizing effort in situations where effort cannot be directly observed (Lazear and Rosen, 1981) in the case of HFT, the positional externality may lead to a wasteful investment in technology and human capital. The inherent problems with an arms race for ever-increasing speed and technological sophistication thus raises questions about whether the speed of information incorporation into the market at the millisecond time horizon has social value.

This paper contributes mainly to two literatures: the growing body of work on HFT and the study of profitability by different groups of traders. In the first instance, researchers studying HFT must overcome data limitations. No publicly available dataset allows researchers to directly identify HFTs. Hasbrouck and Saar (2010) overcome this difficulty by using NASDAQ Total-ITCH order book runs, messages in the order book that change rapidly (in milliseconds) and interact with each other. They argue this activity comes from HFTs given the frequency of observations. However, with the Total-ITCH data it is not possible to rule out that these runs are coming from several anonymous slower traders or an institutional market participant using an algorithm to enter a position. Moreover, the public order book approach cannot be used to study HFTs' aggressive activity or the activity of individual firms.

A second approach to researching HFT has been to look at a small number of manually picked firms that appear to be HFT firms. This is done in the NASDAQ data set used in Brogaard, Hendershott, and Riordan (2011).[1] NASDAQ, with the assistance of Terrence Hendershott, designated 26 firms as HFTs and provided order book and trade data indicating activity by the 26 firms for 2008, 2009, and part of 2010. While valuable for understanding HFT on NASDAQ, given the fragmentation of securities trading, such data encompasses just a fraction of the total trading activity of HFTs in a given stock.[2]

We overcome these problems by taking an approach similar to Kirilenko, Kyle, Samadi, and Tuzun (2010) who define different trading groups based on a selection criteria. HFTs are identified as those firms with high volume, low intraday inventory and low overnight inventory. Like Kirilenko et al. (2010), we are able to cleanly identify trading firms as HFTs based on a well-defined selection algorithm described in the Data section. While all work done to date considers HFT to be a single type of trading activity, we show the wide heterogeneity of trading strategies, profits, and speed within the E-mini market. The data used in this paper consist of all the trades from the leading month contract of the E-mini S&P 500 futures contract from August 2010 to August 2012.[3] Our data allow us to study the strategies and profitability of HFT firms both cross-sectionally and in time-series over a two-year span.

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

[1] Hendershott and Riordan (2009) use a similar approach to categorize German DAX algorithmic traders; Hendershott, Jones, and Menkveld (2011) do the same for the NYSE.
[2] Menkveld (2011) studies one HFT, which seems to fit the HFT designation criteria used in this paper.
[3] We exclude the four months a year in which the leading contract expires in order to exclude rollover effects

The focus of this paper is the profitability of HFTs. A number of previous studies have looked into the profitability 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. They find SOES bandits on average earn a small profit per contract and that they do so over several hundreds of trades per day. HFTs also aim to trade often, thousands of times per day, and earn a small amount per trade. We find they earn $0.25 on average per contract traded. This equates to $18,799 per day for each HFT in the August 2010 E-mini S&P 500 contract alone. Unlike mutual funds (Carhart, 1997), but consistent with some of the literature on hedge funds (Jagannathan, Malakhov, and Novikov, 2010), HFTs consistently outperform the market.

HFTs act as short-term intermediaries, and competition among such intermediaries is a widely-used assumption in the market microstructure literature. This assumption is typically implemented as a zero economic profits condition for market intermediaries (Easley and O'Hara, 1987; Glosten and Milgrom, 1985; Kyle, 1985). Our findings question whether models built with zero-profit intermediaries capture important strategic interactions in high-frequency markets.

Previous studies have also documented that different types of traders often engage in different trading strategies. Like Ackermann, McEnally, and Ravenscraft (1999), who study the profitability of different hedge fund strategies, we study different trading strategies of HFTs. While other studies look into factors that induce different traders to trade (e.g. Grinblatt and Keloharju, 2001), we focus on different market conditions and firm characteristics that drive firms to be profitable and look at how the distribution of profits evolves over time.

The rest of the paper is as follows. Section II describes the data. Section III examines the profitability of HFTs. Section IV studies how HFTs earn their profits. Section V studies market concentration and entry/exit of firms within the HFT sector and Section VI concludes.

## II. Data

We use transaction-level data for the E-mini S&P 500 futures contract from August 2010 to August 2012. We only look at the front-month contract for each month - the contract with the nearest expiration date - which almost always has the highest volume and open interest of all open contracts, and exclude months in which the leading contract expires in order to exclude rollover effects. For select cross sectional analysis we focus on August 2010, which has a September 2010 expiration. For the rest of the analysis we look at the months from August 2010 to August 2012 (excluding the expiration months).

The data are trade-by-trade and contain common fields such as price, the number of contracts traded, and time of the trade in units of seconds (and in milliseconds for a few of the months we examine). In addition, the data contain a variable identifying the buyer and seller at the user-level and identifies which side initiated the trade. The data also allow us to group multiple transactions into an order. That is, if there is a market order for 10 contracts and three different market participants provide liquidity for the trade, we can observe the three different liquidity providers matched to the single trader's executable order, as well as determine that they were all related to one order.

Cancelled transactions and other irregular transactions can also be identified in our dataset and have been filtered out. Each contract has a multiplier of $50 times the value of the underlying S&P 500 index; thus a contract with an index value of 1000 indicates the futures contract is valued at $50,000. The tick size in the S&P 500 E-mini is .25 index points; thus, given the $50 multiplier, a one tick change is equivalent to $12.50. The contract is cash-settled against the value of the underlying S&P 500 index. The dollar value of trading volume is approximately $200 billion per day in August 2010.

The S&P 500 E-mini is a favorable setting for studying HFT as it is a highly liquid market with several different market participants regularly trading, including a high number of HFTs. Hasbrouck (2003) shows that the E-mini futures contract is the largest contributor to the price discovery process of the S&P 500 index. In addition, because the contract only trades on the Chicago Mercantile Exchange, there is no concern about unobserved trades occurring on other exchanges.[4]

In addition, only minimal requirements prevent entities from engaging in HFT and a HFT firm's operating costs are relatively low.[5] Given the low obstructions to participate as an intermediary in the E-mini market and the low costs to set up a HFT operation, we should find a market in which competitive forces drive down profits. The E-mini market has no designated market makers, no liquidity rebates, and no obligations for market participants (such as making prices continuous). There are no institutional barriers to entry to become an intermediary in this market and no duty to undertake trades, so that HFT trading activity is presumably in explicit pursuit of profits. The E-mini trading environment provides an appealing setting to test the efficiency of markets at the sub-second time interval.

The Globex matching engine stamps a unique matching ID on each transaction, which identifies the exact ordering of transactions. The contract is in zero net supply and buying and selling are symmetrical, so there are no short-selling constraints. 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. While the S&P E-mini futures contract trades almost continuously, we only use data during normal trading hours: 8:30 a.m. - 3:15 p.m. Central Standard Time.[6] Finally, trading in the E-mini is a zero-sum gain: one trader's profits come directly at the expense of another trader.

### a. Categorizing Traders

The categorization of traders used in this paper is based on capturing the common characteristics of a high frequency trader: a market participant who trades a large number of contracts, consistently maintains a low inventory level, and ends the day at or near a zero inventory position. We find 65 firms satisfy the HFT criteria in August 2010 and a similar number in the other months studied.

---

[4] Note that unlike many equity markets, the E-mini S&P 500 futures market does not have maker-taker fees for the front month contract.

[5] Such costs include co-located servers, data feeds, and exchange fees.

[6] The E-mini market only occurs on electronic markets. There is a short break in trading between 4:30 p.m. and 5:00 p.m. Central Standard Time.

The precise selection criteria are as follows. For each month, there are three categories a potential trader must satisfy to be considered a HFT: (1) Trade more than a median of 5,000 contracts in all the days that this trader is active; (2) have a median (across days) end-of-day inventory position, scaled by total contracts the firm traded that day, of no more than 5%; (3) have a median (across days) maximum variation in inventory that day (maximum position minus minimum position that day), scaled by total contracts the firm traded that day, of less than 10%.

We create three different subcategories of HFTs based on their aggressiveness, noting that the aggressiveness of a given HFT firm is highly persistent across days. The subcategories are Aggressive, Mixed, and Passive. The definition is based on how frequently the HFT firm initiates a transaction. To be considered an Aggressive HFT, a firm must meet the previously-discussed HFT requirements and must also initiate at least 60% of the trades it enters into; to be considered a Passive HFT a firm must initiate fewer than 20% of the trades it enters into; those HFTs that meet neither the Aggressive nor the Passive definition are labeled as Mixed HFTs. There are 14 Aggressive, 30 Mixed, and 21 Passive HFTs in August 2010 and similar numbers in the other months.

We classify non-HFT firms into four different subcategories: Non-HFT Market Maker, Fundamental, Small, and Opportunistic traders. We define a Non-HFT Market Maker as any non-HFT firm that in a particular month: (1) Provides liquidity in at least 80% of the trades it enters into; (2) has a median (across days) end-of-day inventory position, scaled by total contracts the firm traded that day of no more than 15%; and (3) trades a median of at least 20 contracts per day. We identify 737 Non-HFT Market Makers in our sample for the month of August 2010. The Non-HFT Market Maker category captures traditional market makers examined by Hasbrouck (1993) and Coughenour and Saad (2004).

Next, we define Fundamental traders and Small traders. The Fundamental trader category is meant to capture institutional traders (e.g. Anand, Irvine, Puckett, and Venkataraman, 2012; Puckett and Yan, 2011) while the Small trader category is more like retail traders (e.g. Kaniel, Saar, and Titman, 2008; Seasholes and Zhu, 2010). A Fundamental trader is defined as any firm which: (1) Trades a median of at least 1000 contracts per day (about $60 million in notional value); and (2) has a median (across days) end-of-day inventory position divided by total contracts the firm traded that day greater than 30%. Such firms generally represent traders who are interested in taking large directional positions and holding them overnight. There are 346 firms classified as Fundamental traders in August 2010.

Small traders are defined as firms that trade less than a median of 20 contracts a day of all the days that firm is active. This is the majority of traders, with 21,761 participants in August 2010. The remaining firms do not fit in the specified categories and are therefore grouped into the Opportunistic category. There are 8,494 such firms in August 2010. Traders in the Opportunistic category thus are medium-sized traders who either take large directional positions (but are not large enough to be classified as Fundamental traders) or who move in and out of positions throughout the day but with significantly larger fluctuations and persistence in their positions than HFTs and Non-HFT Market Makers. This group likely captures brokerage firms, hedgers, small institutional investors, hedge funds, and other hard-to-identify traders.

### b. Summary Statistics

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, four statistics are reported: The daily percent of market volume traded, the daily percent of liquidity-taking contracts (aggressive contracts by trader category / total market volume), the daily aggressiveness ratios (aggressive contracts by trader category / total contracts by trader category), and the average trade size per transaction.

Table 1 Row 8 shows that, on average, 3.2 million contracts are traded in the S&P 500 E-mini per day. This is a liquid market with on average about 70 contracts trading *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 17.8% 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). The contrast between the HFT types is stark: for example, Aggressive HFTs take 25.60% of market liquidity (Row 9), while Passive HFTs take only 2.19% (Row 11). In terms of their respective aggressiveness, that equates to Aggressive HFTs taking liquidity in 84.22% (Row 17) of the contracts they trade and Passive HFTs only taking liquidity in 12.35% (Row 19). The trade size between the categories also varies substantially: Aggressive HFTs' average trade size is 5.3 contracts (Row 25), compared to 2.3 for Passive HFTs (Row 27). The non-HFT categories also have a great deal of variation, with Fundamental traders having a 5.67 average trade size (Row 28) compared to Non-HFT Market Makers' 3.92 (Row 29).

Next, we turn to examining volume and positions of the different trader types across the two-year span. Figure 1, Panel A shows the average daily HFT volume of the HFT subgroups. The total market volume decreases over the two-year span from 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.

INSERT FIGURE 1 ABOUT HERE

Figure 1, Panel B looks at what percent of market volume each trader type comprises for the two year span. Surprisingly, although average daily market volume fluctuates considerably over the two-year span, from a high of over 3 million contracts in August 2011 to a low of 2,322,787 contracts in

August 2012, 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%; similarly, Opportunistic percentage volume starts in August 2010 at 31.93% and ends in August 2012 at 30.30%. 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%.[7]

Taken together, Figure 1 Panels A and B contradict the common assumption that HFT volume, both in absolute terms and as a percentage of the market, has been increasing in recent years; in the E-mini S&P 500 futures contract, it is in fact decreasing in absolute terms and holding relatively constant in percentage terms.

Figure 1 Panels C and D report the inventory dynamics of the three different types of HFTs. Panel C shows absolute value of end-of-day positions, first taking the median across trading days for each firm individually and then averaging across all HFT firms within each type. Panel C shows that HFTs carry little overnight positional risk by zeroing out their inventories at the end of each trading day: in our two-year sample, Aggressive HFTs carry an average of 25 contracts overnight, Mixed carry an average of 6 contracts overnight, and Passive HFTs carry an average of 5 contracts overnight.

Beyond managing end-of-day inventory, HFTs limit the positions they take intraday. Panel D reports average inventory range, defined as the maximum position taken on a day minus the minimum position taken on that same day, first taking the median across trading days for each firm individually and then averaging across all HFT firms within each type. Panel D shows that HFTs trade within modest inventory bounds: in our two-year sample, Aggressive HFTs carry an average intraday range of 737 contracts, Mixed carry an average intraday range of 388 contracts, and Passive HFTs carry an average intraday range of 208 contracts.

[7] This is not due to Mixed HFTs changing categories to Aggressive HFTs; in fact, no HFT that started off as Mixed or Passive changed to Aggressive during the two year span.

## III. The Profitability of High Frequency Traders

We document four key aspects of profitability. First focusing on HFT profits during August 2010, HFT profits vary across firms and across days. Aggressive HFTs have a right skew and large kurtosis. Second, a simple model demonstrates that the probability of default by a HFT firm is quite small. Third, HFT profits are level over the two-year span. Finally, the risk and return tradeoff of HFT firms using the Sharpe ratio shows that they generate large returns given the risk they undertake.

### a. Distribution of Profits in August 2010

Throughout the paper, daily profits for each firm, $i$, is 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:

$$\pi_{i,t} = \sum_{n=1}^{N_{i,T}} p_n y_{i,n} + p_T y_{i,T} \ , \qquad (1)$$

where $n=1 \ldots N_{i,T}$ indexes the trades for trader $i$ between the start of the trading day ($t=0$) and the end of the trading day ($t=T$), $p_s$ is the price of the trade, $y_{i,n}$ is the quantity of the $n$-th trade by trader $i$, and $p_T y_{i,T}$ is the value of any end-of-day positions outstanding.[8]

Table 2 analyzes the distribution of profits for August 2010. Each observation in this table is a daily profit of a single HFT account (firm-day observations with trading quantity less than 1000 were removed). Summary statistics such as mean, median, skew, and kurtosis are reported here for both

[8] As Figure 1 Panel C shows, HFTs end the day near a zero inventory and so marking-to-market at the end of the trading day is relatively innocuous.

profit and profit-per-contract, in addition to total monthly profits, maximum daily loss of a firm, and maximum daily loss scaled by the average daily profit of that firm.

INSERT TABLE 2 ABOUT HERE

Aggressive HFTs earn a mean of $45,267 in gross trading profits in August 2010 (Column 2), while Mixed and Passive HFTs earn significantly less: only $19,466 and $2,460 per day, respectively. The P-value on the statistical significance of profits (Column 7) shows that these values differ statistically from zero. While the averages are all positive, there is a wide distribution of profitability. The standard deviation of the profits (Column 4) has Mixed HFTs realizing the highest variation in profits ($273,240) and Passive HFTs the lowest ($46,638). The 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, for Aggressive HFTs (positive skew) and in the lower tail for Mixed and Aggressive HFTs (negative skew). Additional data are reported in Panel A to emphasize the profit and risk of HFT. Column 8, *Total Monthly Profits*, shows the overall profits during August 2010 for the HFTs. The HFTs in August 2010 earn an aggregate of $23.6 million dollars in gross trading profits.[9] Annualized, this corresponds to a profit of over $280 million.

The lower part of the table reports the distribution of profits per contract. It generally has the same conclusion as the level of profitability results in Panel A: Passive HFTs are the least profitable of the HFT types.

The profits HFTs earn are not risk free. Columns 9 and 10 emphasize the losses HFTs can incur. Column 9, *Maximum Loss*, is the largest loss any HFT experiences on a day. Column 10, *Max Loss per Average Profit*, is the largest loss an HFT realizes (averaged across traders), scaled by that firm's average daily profit. The table shows that Mixed HFTs can lose over two million dollars in a single day, and the maximum loss is half a million for both Aggressive and Passive HFTs (Column 9). Across all

[9] We also calculate the total profits 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.

HFTs, the maximum loss per average profit is less for Aggressive HFTs than for Mixed and Passive HFTs. Aggressive HFTs can expect to have days where they lose $1.55 per dollar of average profit, whereas Mixed HFTs have days were they realize losses of $35.02 per dollar of average profit (Column 10).

The fact that Aggressive HFTs earn substantially higher profits than Passive HFTs suggests there is a strong profit motive for liquidity taking rather than liquidity providing. The existence and high profitability of Aggressive HFTs shows that, while on average HFTs are liquidity providers, many are not.

### b. Probability of Default

While HFT strategies are highly profitable, they are also risky on a day-to-day basis. As discussed above in Table 2, Panel A, the average daily profit for a given Aggressive HFT is $45,267 but the standard deviation is $167,411, almost four times the average. Thus, while it is possible for HFTs to earn substantial daily profits, it is also possible to lose large amounts. In Table 2, we see that Mixed HFTs even lose over two million dollars in a single day, and the maximum loss is half a million for both Aggressive and Passive HFTs.

However, simple calculations show that the downside risk for a HFT firm is quite negligible, despite the seemingly large standard deviation of daily profits. For example, if daily profits are independent and identically distributed and normally distributed with mean $\alpha$ = $45,000 and standard deviation $\sigma$ = $170,000, similar to what we find in Table 2,[10] and if each trader has initial capital, $V_0$ = $10 million that it can deploy on any given day[11], we can model the evolution of a trader's net worth as an arithmetic Brownian motion with constant drift $\alpha$ and constant volatility $\sigma$. Given that the trader has $V_0$ = $10 million net worth at time 0, based on the theory of hitting times we can calculate the

[10] These assumptions are approximately true. We construct an autocorrelogram across days which shows that the correlation decays rapidly (results available upon request).

[11] We can infer the initial capital based on the fact that the average HFT has a maximum inventory band of about 200 contacts, which valued at approximately $50,000 each, comes to $10 million. The $10 million assumes fully capitalized positions.

probability that the trader defaults at any finite time (i.e. $V_t = 0$) by the formula $P(default) = \exp\left(\frac{-2\,\alpha\,V_0}{\sigma^2}\right)$ (Karlin and Taylor, 1975 p. 361). Calibrating the formula to the values of $\alpha$, $\sigma^2$, and $V_0$ that we observe in the dataset, we find that *P(default)* < 0.0001. The trader's probability of defaulting is virtually zero. Also, simple calculations using the normal distribution show that the probability of an HFT at least breaking even (at $10 million) after a year (252 trading days) is >99.9%, and the probability of an HFT at least doubling its initial capital after a year is about 69.0%.

### c. HFT Profits over Time

We look at average daily HFT profits and profits per contract over the two-year span. To motivate the magnitude and distribution of HFT profits, we present Figure 2 which shows for each month the distribution of average daily profits (Panel A) and average daily profit per contract (Panel B) across firms. Figure 2 shows the time-series of average daily HFT profits (Panel A) and profits per contract (Panel B), broken down into Aggressive, Mixed, and Passive groups and with all firms aggregated together in their respective groups.

INSERT FIGURE 2 ABOUT HERE

Table 2, Panels B and C report the time series of profits. Panel B shows the monthly aggregate mean profitability per HFT firm, the standard deviation, the P-value of the mean, and the P-value of the median. Panel C reports the same but for the mean profitability per contract traded. The results are divided into groups based on the three subgroups of HFT, Aggressive, Mixed, and Passive.

The average monthly profits of HFTs vary substantially. Aggressive HFTs consistently earn positive average daily profit over the two-year span, with a mean of $395,875 per day over the two-year span, and with 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, and with a high of $890,828 per day in October 2010 and a low of $63,027 in January

2011; and Passive HFTs earn the lowest but still positive average daily profit over the two-year span, with a mean of $107,239 per day over the two-year span, and with a high of $403,259 per day in January 2012 and a low of -$22,499 in February 2011.

Panel C 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, and with a high of $2.01 in May 2011 and a low of $0.09 in January 2012; Mixed HFTs earn a less but still positive average daily profit per contract over the two-year span, with a mean of $0.52 per day over the two-year span, and with a high of $0.93 in May 2011 and a low of -$0.23 in January 2011; and Passive HFTs earn the lowest but still positive average daily profit per contract over the two-year span, with a mean of $0.46 over the two-year span, and with a high of $1.18 in January 2012 and a low of -$0.47 in February 2011.

Figure 3, plots the average daily profits of firms at the 10th, 25th, 50th, 75th and 90th percentiles. Each panel is broken down into three graphs for Aggressive, Mixed and Passive HFTs.

INSERT FIGURE 3 ABOUT HERE

Panel A shows that there is a wide distribution of profitability among Aggressive and Mixed HFT, but that it right skewed. Firms below the median earn small negative profits, while firms above the median earn large positive profits. The distribution of the Passive HFTs appears tighter.

Panel B shows the distribution across firms of average daily profit per contract. Looking across the 10th, 25th, 50th, 75th, and 90th percentiles, we see that in contrast to profit, profit per contract is approximately symmetrically distributed around the median.

In Table 2 Panels B and C, the Mean and Medians are tested each month for whether they differ from zero. (Columns 3 and 4 for Aggressive HFTs, 6 and 7 for Mixed, and 9 and 10 for Passive HFT.) Panel B shows that with Aggressive HFTs the median firm's monthly profit is always positive and statistically significant so at the five percent level. The mean is positive and statistically significant all but one month (January 2012, where the mean is negative). The results are similar for Mixed HFTs (except the mean is not stati stically significant in January 2011, November 2011, and July 2012) and Passive HFTs (where the mean is not significant for six of the months). Panel C's statistical significance for the profit per contract is less clear, especially with the means. The medians are statistically significant at the 5% level all but three months for the Aggressive, for all the Mixed, and for all but one of the Passive. The mean is only statistically significant for 4 months for the Aggressive, 3 months for the Mixed, and 2 months for the Passive.

Some have speculated that the profitability of HFT has decreased over time, perhaps due to increased competition. Given that it takes little capital to start an HFT firm, perhaps new entrants have driven down total profits for the average firm. Alternatively, it could be that competition decreases the profits for each firm, but the level of overall HFT profits remains the same. A third hypothesis is that while the per contract profit may be the same over time, overall profits would decrease (given the decrease in volume seen in Figure 1).

Performing a simple t-test on whether there is a mean difference between the average firm profit in August 2010 and August 2012 we find that Mixed HFTs have had no statistically significant change in their profits, while Aggressive and Passive HFTs have actually increased (P-value of .08 and .03, respectively). On a per contract basis, the same is true: Mixed HFT profits have remained the same, but Aggressive and Passive HFTs have experienced an increase (P-value of .08 for both).

### d. Risk and Return

Trading profits provide insight into the magnitude of HFTs' profits, but the variable of interest to financial economists is risk-adjusted performance. In an efficient market, returns above the risk-free rate should be proportional to risk. It may be that while the profits are high, the risks associated with generating them are also high, and so the risk adjusted returns are average or low. Next, we analyze this possibility.

We evaluate the Sharpe ratios of HFTs (Sharpe, 1966). The Sharpe ratio for each trader is calculated as:

$$SR_{i,t} = \frac{r_{i,t} - r_f}{\sigma_i} * \sqrt{252}\,, \tag{2}$$

where $r_{i,t}$ is the average daily return for trader $i$, calculated from the daily profit for trader $i$ and assuming the maximum inventory dollar value of trader $i$ is the amount of investable capital. σ is the standard deviation of trader $i$'s returns over the sample period.[12]

In Figure 4, we examine the Sharpe ratios of Aggressive, Mixed, and Passive HFTs, calculated by looking at daily returns. Menkveld (2011) calculates the Sharpe ratio of an HFT firm's trading in equities markets to be 9.35. Similarly, we find that on average Mixed HFTs have the highest risk-return tradeoff, generating a Sharpe ratio of over 10.46. Passive HFTs generate a Sharpe ratio of 8.56, and Aggressive HFTs 8.46. Yet even within these different types of HFTs, the Sharpe ratio for firms varies widely for example, 25% of Mixed HFTs have a Sharpe ratio greater than 17.11. The Sharpe ratios and their distributions are reported graphically in Figure 4.

INSERT FIGURE 4 ABOUT HERE

The risk-adjusted performance of the median Aggressive or Mixed HFT firm is 12 times higher than the Sharpe ratio of the S&P 500 (0.31) (Fama and French, 2002). The distribution is wide, with standard deviation of 10.0, 11.5, and 7.1 for Aggressive, Mixed, and Passive HFTs, respectively, in August 2012. Sharpe ratios at the top 10$^{th}$ percentile are 21.5, 19.3, and 12.7 for Aggressive, Mixed, and Passive HFTs, respectively, meaning that a subset of firms achieves risk-adjusted performance 40 to 70

[12] The risk-free rate is not subtracted from *r* as is normal because the time horizon is so short and the rate during August 2010 to August 2012 was so low as to make it an inconsequential value. The Effective Fed Funds Rate in August 2010 was 0.19% (research.stlouisfed.org).

times that of the S&P 500. We thus conclude that while HFTs bear some risk, their risk-adjusted returns are unusually high.

## IV. How do HFTs Make Profits?

Section III documents that HFTs earn high risk-adjusted returns, and they do not appear to be decreasing over time. Before exploring in detail these facts we further explore how HFTs earn these profits. We begin by tabulating the counterparties from which HFTs earn their profits to determine from whom HFTs earn their profits. Next we perform spectral analysis of the profits to analyze the time-scale over which HFTs earn their profits.

### a. HFT Profits by Counterparty

From whom do these profits come? In addition to HFTs, we divide the remaining universe of traders in the E-mini market into four categories of traders: Fundamental traders (likely institutional traders), Non-HFT Market Makers, Small traders (likely retail traders), and Opportunistic traders. We decompose what we call short-term profits into how much each category is earning from the others. As we will see, HFTs earn most of their profits from Opportunistic traders, but also earn profits from Fundamental traders, Small traders, and Non-HFT Market Makers. Small traders in particular suffer the highest short-term losses to HFTs on a per contract basis: $3.49 per contract to Aggressive HFTs compared to $1.92 for Fundamental traders and $2.49 for Opportunistic traders, for a contract valued at approximately $50,000.

Table 3 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. Fundamental traders capture institutional investors, who are generally considered informed (e.g.

Badrinath, Kale, and Noe, 1995; Boehmer and Wu, 2008; Boulatov, Hendershott, and Livdan, 2011; Hendershott, Livdan, and Schurhoff, 2012). Under the informed trader hypothesis we expect to see HFT profits being small, or even negative, when trading with Fundamental traders. However, a growing literature shows that Fundamental traders may trade in a way that makes their order flow noticeable (Hirschey, 2011). Heston, Korajczyk, and Sadka (2010) show that institutional traders leave a detectable pattern in their trading activity. Under the detectable patterns hypothesis we would expect HFT profits to be higher when trading with Fundamental traders than with others.

We have the opposite hypotheses for Small traders (retail investors). Retail investors are thought to be noise traders and so under the uninformed hypothesis we expect them to incur significant losses to HFTs (e.g. Hvidkjaer, 2008; Kaniel, Saar, and Titman, 2008; Barber, Odean, and Zhu, 2009). However, because retail traders are small and trade noisily they may not leave patterns in the data (due to their one-off orders) and consequently HFTs may have a more difficult time inferring information from the small traders' order flow. Under the undetectable patterns hypothesis we would expect Small firms to lose less to HFTs.

Whether HFTs will make profits from Non-HFT Market Makers is an empirical question: HFTs, especially Passive HFTs, compete for order flow with Non-HFT Market Makers. Thus, on balance, we do not expect that Passive HFTs earn profits by trading with Non-HFT Market Makers. However, Aggressive HFTs may earn profits from Non-HFT Market Makers by picking off stale quotes.

We construct Table 3 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. We do not take into account which of the two parties is the buyer or seller, or which is the aggressive party. Based on the remaining trades, for each day we calculate the daily profits for the HFTs and for Fundamental traders over the course of the month.

The profits calculated in Table 3 are the implied short-term profits: we calculate the marked-to-market profits of each trader on 1 minute frequencies and reset the inventory position of each trader to zero after each of these 1 minute intervals. Then, we sum up all the 1 minute interval profits to get a measure of daily profits. Therefore, we capture the short-term profits of traders and not gains and losses from longer-term holdings. Since the futures market is a zero-sum game, the resulting profits matrix is symmetrical and zero along the diagonals.[13]

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 market, 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 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.

INSERT TABLE 3 ABOUT HERE

On average 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. Row 2 of Panel A, Table 6 shows that on an average day, Aggressive HFTs (in aggregate) make $1,691,738 from Fundamental investors, $1,962,675 from Non-HFT Market Makers, $379,275 from Small traders, and $8,171,350 from Opportunistic traders. While Mixed HFTs make positive profits from all other (non-HFT) trader types, they lose money to more aggressive HFTs. In particular, Mixed HFTs lose money to Aggressive HFTs (Column 4, Row 4, $-7,190,140), and Passive HFTs lose money to both Aggressive HFTs (Column 4, Row 5, $-2,557,038) and Mixed HFTs (Column 5, Row 4, $-1,400,125).

[13] A limitation of the approach taken in Table 3 is that it can only measure profits from direct order flow.

Panel B of Table 3 expresses the trading profits between groups as a percentage of a group's total profit.[14] For example, Column 1, Row 2 is the percent of HFTs' profit derived from trading with Fundamental traders: Aggressive and Mixed HFTs earn 7.7% and 2.9% of their profits respectively from trading with Fundamental traders. For groups that have net losses (Non-HFT Market Makers, Small Trader, and Opportunistic), Panel B expresses the percent of total losses: For example Column 2, Row 5 shows that 68.7% of all Non-HFT Market Maker traders' losses are from trades with Aggressive HFTs.

Row 1 of the table shows that Aggressive HFTs make most of their profits from trading with Opportunistic (37.2%) and Mixed HFT (32.8%) market participants. Furthermore, the different sub-types of HFTs make profits from each other. There is a hierarchy among the HFTs: Aggressive HFTs earn profits from Mixed and Passive HFTs, while Mixed HFTs earn profits from Passive HFTs.

Lastly, Panel C 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. The empirical results support the first hypothesis that Fundamental (institutional) traders are generally informed traders able to evade leaving a detectable pattern in their trading activity from which HFTs glean information. The results also support the hypothesis that Small (retail) traders are noise traders who incur the largest effective transaction costs per contract.

Column 9 reports the effective transaction cost imposed on all other traders. Since Aggressive HFTs collect $2.04 per contract (Column 9, Row 2) over 15.2% of the volume (Table 1), while everyone else loses while trading 84.8% (=100% - 15.2%) of the volume, the effective Aggressive HFT imposed transaction cost on all other traders is $2.04*(0.152/0.848) = $0.36 per contract. Scaling this per-

[14] Note how each row sums to 100% when either only Column 2 (HFT) or Columns 3, 4, and 5 (the HFT types) are considered.

contract transaction cost by $50,000 the approximate price of a contract yields an estimated HFT-imposed transaction cost of 0.0007%.

### b. Spectral Analysis

To understand the investment horizon of HFTs, we follow Hasbrouck and Sofianos (1993) and decompose HFT profits in August 2010 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.

Spectral analysis treats marked-to-market profits as a function of two different time series: prices and inventory levels, which can vary at different frequencies. Fourier analysis is used to decompose prices and inventories into waves of varying frequencies: if the two time series, prices and inventories, are in phase (traders buy before the price is going up) they make profits, while if the two time series are out of phase (traders buy before the price goes down) they incur losses. We find that Aggressive HFTs as a whole lose money on shorter time scales (on round trip transactions that occur on a time scale of a 1,000 or fewer total market transactions) but gain money on longer time scales, those over 1,000 market transactions. In contrast, both Mixed and Passive HFTs tend to gain money at time horizons of 1,000 transactions or fewer, and instead lose money over the longer intervals.

Spectral analysis must be conducted in transaction time, as opposed to clock time, as several trades regularly occur within a second and, while we can order trades at the sub-second level, we are unable to determine the time between trades within a second due to the precision of the time stamp (second-by-second). Thus, our time variables $t$, $\tau$, and $T$ (defined below) refer to transaction time. There are approximately 10 transactions per second.

Mathematically, we express mark-to-market profits for any individual trader at time $\tau$ as:

$$\pi_\tau = \sum_{t=0}^{\tau} x_t (p_t - p_{t-1}) = \sum_{t=0}^{\tau} x_t \cdot \Delta p_t \tag{3}$$

where $x_t$ is the inventory holdings of that trader and $p_t$ is the price at time $t$. Spectral analysis requires us to assume that $x_t$ and $\Delta p_t$ are stationary processes, which is a valid assumption to make given that $x_t$, HFT firms' inventories, is a mean-reverting process and $\Delta p$, the first difference of the price process, is a martingale difference sequence.

We define the following functions:

$$\hat{x}(\omega) = \sum_{t=0}^{T} x_t e^{2\pi i t\omega/T} \tag{4}$$

$$\widehat{\Delta p}(\omega) = \sum_{t=0}^{T} \Delta p_{t+1} e^{2\pi i t\omega/T} \tag{5}$$

where the variable 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 $p_t$, respectively.

We can recover the original marked-to-markets profits formula in (3) using the following formula. (See Hasbrouck and Sofianos, 1993 for details regarding Fourier analysis):

$$\pi_T = \frac{1}{T}\sum_{\omega=1}^{\infty} \hat{x}(\omega)\overline{\widehat{\Delta p}(\omega)} = \frac{1}{T}\sum_{\omega=1}^{\infty} 2 * Real(\hat{x}(\omega)\overline{\widehat{\Delta p}(\omega)}), \tag{6}$$

where *Real* is the function that takes the real part of a complex number. The last equality in Equation (6) follows because the imaginary part of $\hat{x}(\omega)\overline{\widehat{\Delta p}(\omega)}$ sums to 0. 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.

We compute the spectral density of profits for each day and HFT firm using Equations (4) through (6). For each firm-day we decompose the summation in Equation (6) into the following intervals: 1-10, 11-100, 101-1,000, 1,001-10,000, 10,000-100,000, and 100,000+ market transactions. This decomposes the total daily profit for each firm into different components based on the time-horizon of the trading strategy. For each trader and each interval, we take the median profits over the course of the 22 days in our August 2010 sample. For each of the three sub-types we take the median and the 25th and 75th percentiles of profits across firms. The spectral analysis of profits results are reported in Table 5.

INSERT TABLE 4 ABOUT HERE

Row 1 in Table 7 shows that in August 2010 Aggressive HFTs tend to make positive profits at medium time scales, in the 1,001-10,000 and 10,001-100,000 transaction range (Columns 2 and 3), with negative profits at short ranges (11-100 and 101-1,000 transaction intervals) and the longest time scale of 100,000+ transactions (Column 4). In order for an aggressive trade to be profitable, a trader 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.

## V. Market Concentration and Entry/Exit of HFT Firms

So far we have documented that HFTs earn above average profits given the risks they assume, and we have analyzed the time horizon of holding and trading partners that contribute to these profits. In this section we analyze entry and exit of HFTs into the HFT market. Our results indicate that the industry lends itself to concentration. We first show that over time the Herfindahl index does not seem to be decreasing. Next we provide evidence of firm-level persistence in profitability. Focusing on new entrants, we find that new entrants at first perform in-line with other HFTs, eventually underperform and have a higher probability of exiting. Finally, we show that a defining factor of HFT, speed, plays an important role in determining the profitability of an HFT firm, particularly for Aggressive HFTs.

The Herfindahl index is a commonly used measure of concentration of market share or earnings within an industry. Table 5 calculates the Herfindahl index for each sub-group of HFTs, for each month in the data set.

INSERT TABLE 5 ABOUT HERE

We report a Profit-based Herfindahl index as well as a Volume-based one. The Profit Herfindahl index is calculated as:

$$Herfindahl_{i,t} = \sum_{i=1}^{N} \left[\frac{Profit_{i,t}}{HFT\ Profit_t}\right]^2 \quad (7)$$

where $N$ is the number of firms in the HFT subgroup 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 sub group of interest (Aggressive, Mixed, or Passive). The Volume Herfindahl 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].

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 6 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. A simple univariate regression of the Profit based and Volume based Herfindahl indices on time shows that concentration is not decreasing, and is increasing for Mixed and Passive HFTs. For both the Profits and Volume based measures, Herfindahl index increases over time for Mixed HFT (significant at the 10% level for Profits, and the 1% level for Volume), decreases over time for Passive HFT (significant at the 1% level for both), but is unchanged for Aggressive HFTs. HFT is a rather new industry, and so one might expect concentration to decrease as new entrants join the market. We observe the opposite.

### a. The Consistency of HFT Profits

The results in Section III show that both across time and across types, HFTs earn positive profits. However, the results do not provide an insight into whether it is the same traders earning profits over time. To examine the consistency at the individual firm level, we ask if HFTs that are profitable one day continue to be profitable in subsequent days. As suggestive evidence we produce a figure that addresses the question, Do HFT firms that outperformed or underperformed in August 2010 continue to out- or under-perform during the subsequent two-year span? We find this to be the case for Aggressive HFTs but not for Passive HFTs.

INSERT FIGURE 5 ABOUT HERE

Figure 5 shows the average daily profitability of HFTs in the August 2010-based over- and under-performing categories, in addition to all HFT firms. Within each of the three HFT types, Aggressive, Mixed and Passive, HFTs that were in the top tercile of profit earners in August 2010 were labeled "Top 3$^{rd}$", Those in the lowest tercile where labeled "Bottom 3$^{rd}$" We trace out the average daily profits of these groups and for all HFTs over the two-year span. The Figure shows whether firms that start out outperforming/underperforming other HFTs continue to outperform/underperform.

For Aggressive and Mixed HFTs, those that outperform/underperform other HFTs in August 2010 continue to do so in the subsequent two year span (conditional on these firms staying in the market). However, this is not true to Passive HFTs, demonstrating that outperforming or underperforming other HFTs in August 2010 was due to chance. Interestingly, all the Aggressive and Mixed HFTs in the bottom third exit the market by January 2012, and all the Passive HFTs in the bottom third exit by April 2012.

To formally analyze the persistence of HFT profits we look at the role that yesterday's profits have in predicting today's profits for an HFT. Persistent profits over time suggest that something other than luck is driving a firm's performance. Also, persistent performance may lead to concentration as strong performing firms will continue to perform well, but less successful firms will exit the industry.

To test persistence we run the following OLS regression:

$$Profit_{i,t} = \alpha + \beta_1 Profit_{i,t-1} + \beta_2 Aggressiveness_{i,t} + \beta_3 Volume_t + \beta_4 Volatility_5 + \epsilon_{i,t} \qquad (8)$$

where $Profit_{i,t}$ is a modified version of log profits, namely sign(profits)*log(1+|profits|) to allow for negative values, realized by firm $i$ on trading day t, $Volume_{i,s}$ is the log of each trader's trading volume for that day; $Volatility_s$ is the price volatility of that day defined as the (volume-weighted) standard deviation of the price process throughout that trading day; and $Aggressiveness_{i,s}$ is trader $i$'s average (volume-weighted) aggressiveness ratio. We include these regressors to control for both time-specific and firm-specific effects.

The results are reported in Table 6, Panel A.

INSERT TABLE 6 ABOUT HERE

Columns 1, 3, and 5 are coefficients with the standard errors in the column to the right. Columns 1 – 3 are univariate regressions, while Columns 4 – 6 include the control variables. The univariate results for each type of HFT show that one-day lagged performance is a predictor of today's performance. Similarly, the specification with control variables maintains the statistical significance, demonstrating that profitability is persistent even after controlling for time effects.

It may be that persistence is strongest for the best performing firms, the idea being that the best performing firms not only are the best in that they earn the highest profits, but also that they do so regularly. To test this we rerun the OLS regression specified in Equation 8, but include a dummy variable $\mathbf{1}_{Top\ 3rd\ i,t-1}$ to capture top performing firms. $\mathbf{1}_{Top\ 3rd\ i,t-1}$ is a dummy variable taking the value one if firm *i* on day *t-1* was in the top one-third of its profitability among its subgroup of HFT firms. We thus repeat the OLS analysis and report the results in Table 6, Panel A, Columns 7 – 9. The coefficient on the top one-third dummy is not statistically significant. Thus, we conclude that persistence in profits is a common feature among HFT firms, it is not being driven only by the best performing firms.

We repeat the OLS analysis and report the results in Table 6, Panel A, Columns 7 – 9. The coefficient on the top one-third dummy is not statistically significant. Thus, we conclude that persistence in profits is a common feature among HFT firms, it is not being driven only by the best performing firms.

Panel A tests whether a firm's profits yesterday predict its profits today. Panel B does the same but at longer horizons, from one month up to one year. Panel B repeats the analysis in the last specification but replaces the 1-day lag value of profits and the 1-day lag top one-third dummy with the profit from an earlier period: one-month earlier, two months earlier, six months earlier, and one year earlier. Each coefficient is obtained by running the full specification regression from Panel A (Columns 7 – 9) but replace the lag of profitability from 1 day to longer horizons, between 30 days and one year. Each Column in Panel A is a different regression. The dependent variability is Profitability of firm i on day t, and the HFT firms are analyzed in separate subcategories: Aggressive, Mixed, and Passive.

The results show that persistence in Aggressive HFT dies out quickly; after 30-days it is no longer statistically significant. However, for Mixed and Passive the persistence lasts, for half a year for Mixed firms and for two months for Passive firms.

### b. New HFT Firms

Persistent profit is one piece of evidence suggesting that HFT profits are gained by more than just luck. However, the persistence of profits cannot distinguish what drives the high profits. We consider two factors that may influence profitability: newness and speed. We expect, given the high Sharpe ratios observed in Section III that new entrants would try and capture market share. If success in HFT is independent of ability or newness, we would expect new firms to perform in line with more experience firms. To analyze this hypothesis we look at trading profits again, but focus now on new entrants. We repeat a similar regression as in Equation 8:

$$Profit_{i,t} = \alpha + \beta_1 \mathbf{1}_{New\ Entrant\ i,t} + \beta_2 Aggressiveness_{i,t} + \beta_3 Volume_t + \beta_4 Volatility_5 + \epsilon_{i,t}. \quad (9)$$

The control variables are the same as in Table 6. Lagged Profits is excluded as a control as it may confound with the variable of interest, the dummy variable, *New Entrant* $_{i,t}$, which takes the value 1 during a period after a new HFT firm participates in the market. We consider four different time periods for a firm to be considered a new entrant: 1 month, 2, 3, and 4 months after first appearing as an HFT. So the < *1 month old* dummy variable will take the value one for firm *i* during t to t + 30 if firm *i* began trading on day *t-1*, otherwise it will take the value zero. We exclude the observations in 2010 as this is when we first observe any firm. Every two rows represent three regressions for a subgroup of HFT: Aggressive, Mixed, and Passive. The two, three, and four month dummy variables are similarly defined. The results are reported in Table 7, Panel A.

INSERT TABLE 7 ABOUT HERE

The coefficients are reported in Columns 1, 3, and 5; their robust standard errors are reported in Columns 2, 4, and 6. Each regression includes the full set of control variables identified above. The Adjusted R-square is reported below the coefficient.

The regressions for the new entrants for less than one month are statistically insignificant except for Mixed HFT, which has a positive coefficient, suggesting that new Mixed HFT entrants earn more profits than HFTs with a longer track record. When looking longer, at 2-months, the Mixed HFT statistical significance disappears, but Passive HFT new entrants now have a positive coefficient. However, the three and four month definition show that new Aggressive HFTs and new Passive HFTs underperform. These results suggest that, immediately, new HFT entrants are not at a disadvantage, and may outperform, but that after their initial entry, as soon as three or four months after, they began to underperform. If HFTs need to continually adapt and update their algorithms, it could be that new entrants start with competitive algorithms but are less able to keep up with technological change.

The limitation of the above analysis is that it does not take into account exit. That is, a new HFT firm that is performing poorly may choose to exit trading, and hence the data set. Thus we may have survival bias - if a firm drops out of the dataset, it will likely do so because of poor performance, but then we are missing observations that would suggest that new entrants underperform even more.

Consequently we may be over-estimating the performance of new entrants. To address the survival issue, we perform a Logit regression to determine whether new entrants are more likely to exit:

$$Exit_{i,t} = \alpha + \beta_1 \mathbf{1}_{New\ Entrant\ i,t} + \beta_2 Aggressiveness_{i,t} + \beta_3 Volume_t + \beta_4 Volatility_5 + \epsilon_{i,t} \qquad (10)$$

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, *New Entrant i,t*, defined as above. 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. The control variables are as defined above. The results are reported in Table 7, Panel B. The coefficients are reported in Columns 1, 3, and 5; their robust standard errors are reported in Columns 2, 4, and 6. Each regression includes the full set of control variables identified above. The Pseudo R-square is reported below the coefficient.

For Aggressive and Mixed HFT new entrants, regardless of the time horizon of the definition, are much more likely to stop trading than their more experienced competitors. We speculate that new entrants having a difficult time surviving will limit the degree to which competitive forces may drive down the profits of existing HFTs.

We are careful not to conclude that experience drives profitability. Alternatively, the higher profitability of established HFTs could be due to a survivorship bias: profitable firms remain while unprofitable firms exit; this process of selection results in established firms having a higher average profitability than entrants, who have not been selected out. Thus, we can conclude that something other than chance determines firms' profits, but cannot say whether it is experience or a survivorship bias.

### c. Speed

Finally, we look at the relationship between speed and profits and show that there is an association between the two. Our measures of latency and *Speed* are those developed by Weller (2012), who previously studied the latency of HFTs in metal markets: 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 suitable 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, this latency measure aims to capture a firm's reaction speed to market events given its technological constraint.

We sort Aggressive/Mixed HFTs' and Passive HFTs' firm-day observations into decile bins corresponding to their latency, and then take the average of both the latency and the profits over all firm-day observations within each decile bin.[15] *Speed* is the reciprocal of the average latency (plus 1 millisecond, to ensure we do not divide by zero). Figure 6 plots *Speed* vs. average profits for each decile bin.

INSERT FIGURE 6 ABOUT HERE

[15] Firm-day profit observations which resulted in gains or losses of over $100,000 were considered outliers and excluded in producing Figure 6.

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).[16] Figure 6 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 decile increases from approximately 0.4 to 0.75 to 1; similarly, 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. That HFT speed increases over time while the distribution of profits is relatively stable leads us to ask whether HFT profitability is associated with relative or absolute profits.

Weller (2012) estimates a similar regression for HFTs in metal markets, looking at the relationship between profits and relative speed (rank ordering of firms in terms of speed), and finds that a 10-rank improvement in speed is associated with a growth of 34% in profits. Using a similar framework, we estimate the regression specified in Equation 11 using firm-day observations of HFT profitability in the E-mini S&P 500 futures contract. Extending his work, we differentiate between the three types of HFTs (Aggressive, Mixed, and Passive) to examine whether speed matters for different types of HFTs; we also place both Absolute and Relative (rank ordered) Speed in the same regression equation to examine which is more important in determining the profitability of HFTs. Unlike in Weller, which looks at speed of traders at a fixed point in time (four consecutive days in December

[16] Because millisecond time stamps were needed for this analysis, we were limited to which months we could look at.

2011), we exploit the time-series dimension of our data to overcome the multicollinearity problem inherent in including both Absolute and Relative Speed as regressors[17].

$$Profits_{i,t} = \alpha + \beta_1 AbsoluteSpeed_{i,t} + \beta_2 RelativeSpeed_{i,t} + controls + \epsilon_{i,t} \tag{11}$$

where $Profits_{,i,t}$ is again a modified version of log profits, namely sign(profits)*log(1+|profits|) as suggested by Weller (2012) to allow for negative values, $AbsoluteSpeed_{i,t}$ is Weller's speed measure described above, $RelativeSpeed_{i,t}$ 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. The control variables used are the same as before: the HFT's aggressiveness, the day's total trading volume, and the day's price volatility. The results are reported in Table 8.

INSERT TABLE 8 ABOUT HERE

Table 8 shows that for all three sub-types of HFTs, profits are increasing in both in absolute speed, with statistically significant coefficients of 14.44, 12.72 and 6.15 for Aggressive, Mixed, and Passive HFTs respectively, and in relative speed, 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 increasing with absolute speed but decreasing in relative speed (higher relative rank means higher profits). However, after combining the two regressors together and adding controls, only Absolute Speed is statistically significant for Aggressive HFTs, only Relative Speed is statistically significant for Mixed HFTs, and neither of the regressors is statistically significant for Passive HFTs.

[17] For example, if two HFTs both increase in absolute speed over time but maintain the same rank ordering, we can examine how their profitability changes.

## VI. Conclusion

Using data that identify individual firms, this paper examines the profitability of HFTs. This paper has three key findings. First, HFT is highly profitable (before incorporating operating and trading costs) but not without risks. The magnitude and consistency of their profits as well as their risk-return tradeoff demonstrate unusually strong performance. Second, HFTs are a heterogeneous set of firms that have different trading and profit characteristics. Third, we describe different market conditions and firm characteristics that are associated with profitability, such as aggressiveness, speed, and newness. Our findings shed light on the competitiveness of the HFT industry and provide insight into the determinants of HFT profitability.

## References


Ackermann, C., R. McEnally, and D. Ravenscraft, 1999. The performance of hedge funds: Risk, return, and incentives, *Journal of Finance*, 54 (3), 833-874.

Anand, A., P. Irvine, A. Puckett, and K. Venkataraman, 2012, Performance of institutional trading desks: An analysis of persistence in trading costs, *Review of Financial Studies*, 25 (2), 557-598.

Badrinath, S., J. Kale, and T. Noe, 1995, Of shepherds, sheep, and the cross-autocorrelations in equity returns, *Review of Financial Studies*, 8 (2), 401-430.

Barber, B., T. Odean, and N. Zhu, 2009, Do retail trades move markets? *Review of Financial Studies*, 22 (1), 151-186.

Boehmer, E. and J. Wu, 2008. Order flow and prices. *Working Paper*.

Boulatov, A., T. Hendershott, and D. Livdan, 2011, Informed trading and portfolio returns, *Review of Economic Studies*, Forthcoming.

Brogaard, J., T. Hendershott, and R. Riordan, 2011, High frequency trading and price discovery, *Working Paper*.

Carhart, M., 1997, On persistence in mutual fund performance, *Journal of Finance*, 52 (1), 57-82.

Coughenour, J. and M. Saad, 2004, Common market makers and commonality in liquidity, *Journal of Financial Economics*, 73 (1), 37-69.

Easley, D. and M. O'Hara, 1987, Price, trade size, and information in securities markets, *Journal of Financial Economics*, 19 (1), 69-90.

Fama, E. and K. French, 2002, The equity premium, *Journal of Finance*, 57 (2), 637-659.

Frank, R., 2005, Positional externalities cause large and preventable welfare losses, *American Economic Review*, 95 (2), 137–141.

Glosten, L., and P. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics*, 14 (1), 71-100.

Grinblatt, M. and M. Keloharju, 2001, What makes investors trade?, *Journal of Finance*, 56 (2), 589-616.

Grinblatt, M., M. Keloharju, and J. Linnainmaa, 2011, IQ, trading behavior, and performance, *Journal of Financial Economics*, 104 (2), 339-362.

Grossman, S. and J. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review*, 70 (3), 393-408.

Harris, J. and P. Schultz, 1998, The trading profits of soes bandits, *Journal of Financial Economics*, 50 (1), 39-62.

Hasbrouck, J., 2003, Intraday price formation in US equity index markets, *Journal of Finance*, 58 (6), 2375-2400.

Hasbrouck, J. and G. Saar, 2010, Low-latency trading, *Working Paper*.

Hasbrouck, J. and G. Sofianos, 1993, The trades of market makers: An empirical analysis of NYSE specialists, *Journal of Finance*, 48 (5), 1565-1593.

Hendershott, T., D. Livdan, and N. Schurhoff, 2012, Are institutions informed about news?, *Working Paper*.

Hendershott, T., and R. Riordan, 2009, Algorithmic trading and information, *Working Paper*.

Hirshleifer, J., 1971, The private and social value of information and the reward to inventive activity, *American Economic Review*, 61 (4), 561-574.

Heston, S., R. Korajczyk, and R. Sadka, 2010, Intraday patterns in the cross-section of stock returns, *Journal of Finance*, 65 (4), 1369-1407.

Hirschey, N., 2011, Do high-frequency traders anticipate buying and selling pressure?, *Working Paper*.

Hvidkjaer, S., 2008, Small trades and the cross-section of stock returns, *Review of Financial Studies*, 21 (3), 1123-1151.

Jagannathan, R., A. Malakhov, and D. Novikov, 2010, Do hot hands exist among hedge fund managers? an empirical evaluation, *Journal of Finance*, 65 (1), 217-255.

Kaniel, R., G. Saar, and S. Titman, 2008, Individual investor trading and stock returns, *Journal of Finance*, 63 (1), 273-310.

Karlin and Taylor, 1975. *A first course in stochastic processes*, 2nd edition New York: Academic Press.

Kirilenko, A., A. Kyle, M. Samadi, and T. Tuzun, 2010, The flash crash: The impact of high frequency trading on an electronic market, *Working Paper*.

Kyle, A., 1985, Continuous auctions and insider trading, *Econometrica*, 53 (6), 1315-1335.

Lazear, E., and S. Rosen, 1981, Rank-order tournaments as optimum labor contracts, *Journal of Political Economy*, 89 (5), 841-64,

Menkveld, A., 2011, High frequency trading and the new-market makers, *Working Paper*.

Puckett, A., and X. Yan, 2011, The interim trading skills of institutional investors, *Journal of Finance*, 66 (2), 601-633.

Seasholes, M., and N. Zhu, 2010, Individual investors and local bias, *Journal of Finance*, 65 (5), 1987-2010.

Sharpe, W,. 1966, Mutual fund performance, *Journal of Business*, 39 (1), 119-138.

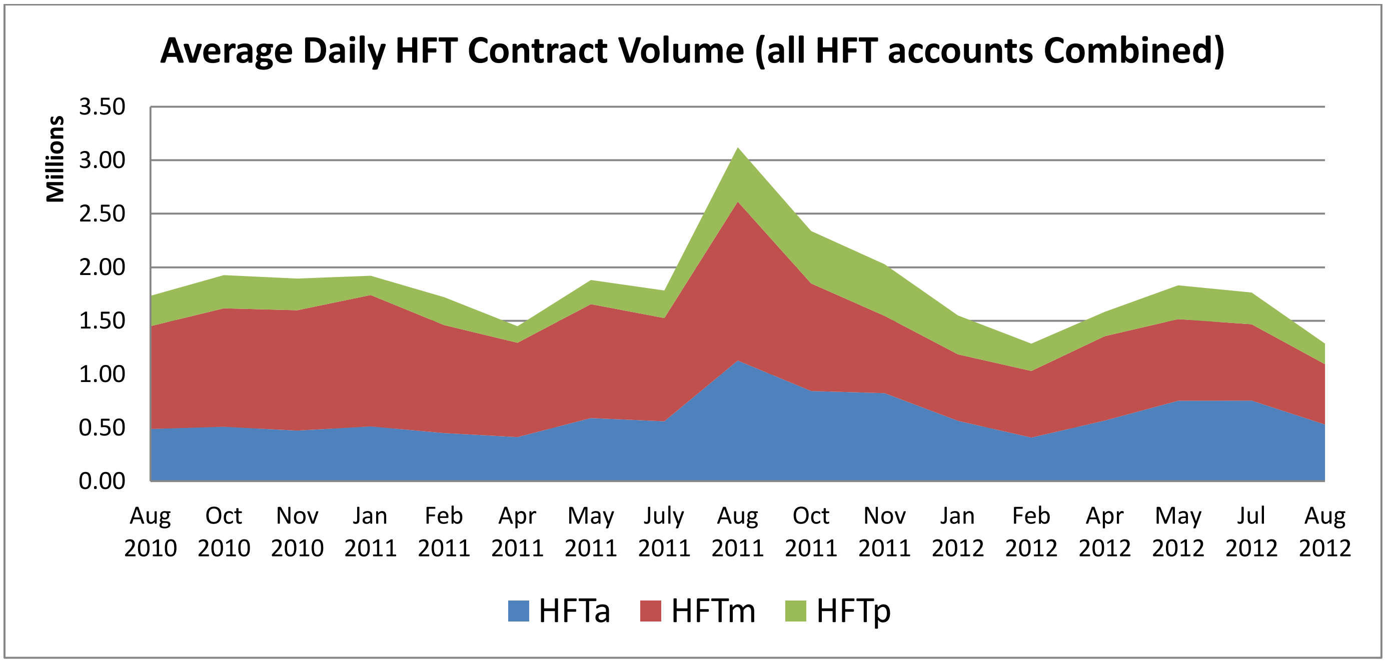
Seru, A., T. Shumway, and N. Stoffman, 2010, Learning by trading, *Review of Financial Studies*, 23 (2), 705-739.

Weller, B., 2012, Liquidity and High Frequency Trading, *Working Paper*.

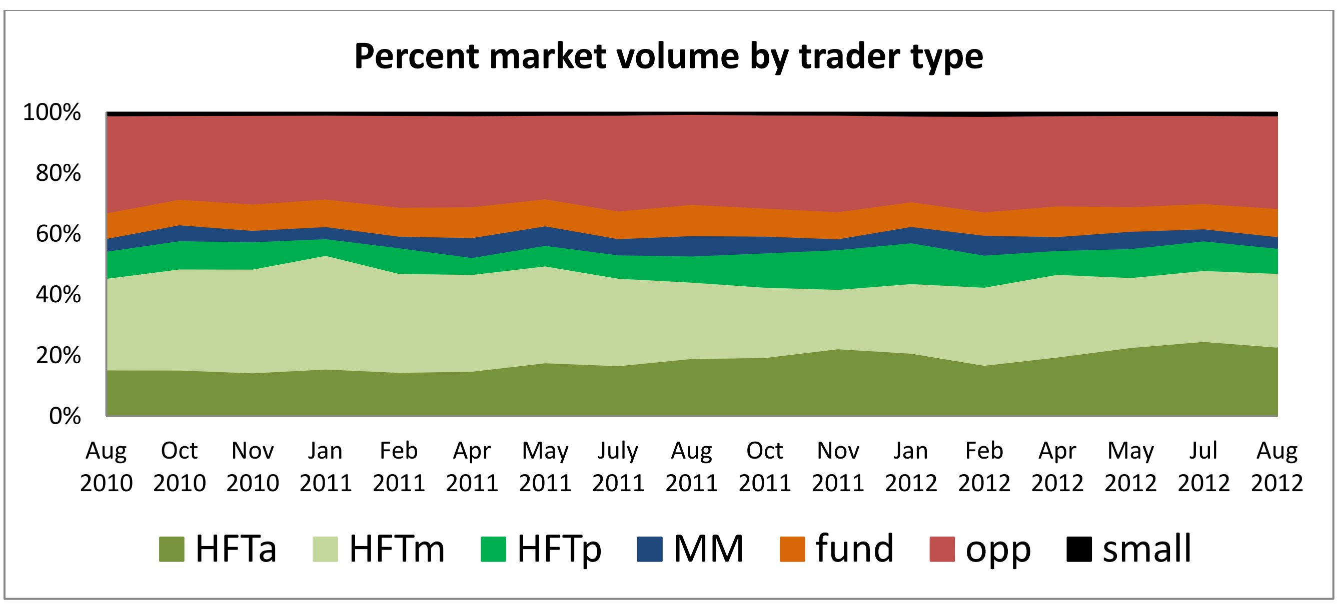
## Figure 1 HFT Activity

Panel A shows the average daily HFT volume of all HFT accounts combined. Panel B looks at what percent of market volume each trader type comprises. Panel C looks at the absolute value end-of-day position averaged across firms. Panel D looks at the intraday inventory range (max intraday position – min intraday position) averaged across firms.

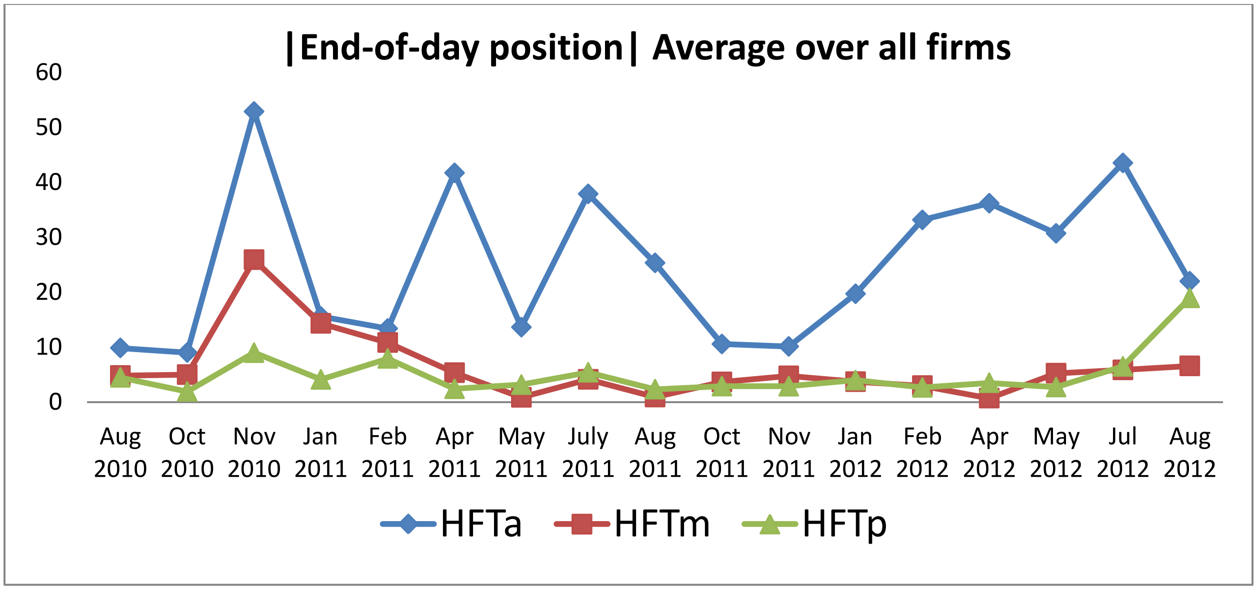
**Panel A: Percent market volume of all trader types**




**Panel B: HFT average daily volume**




**Panel C: Absolute value end-of-day position averaged over all firms**




**Panel D: Intraday inventory range (max intraday position – min intraday position) averaged over all firms**

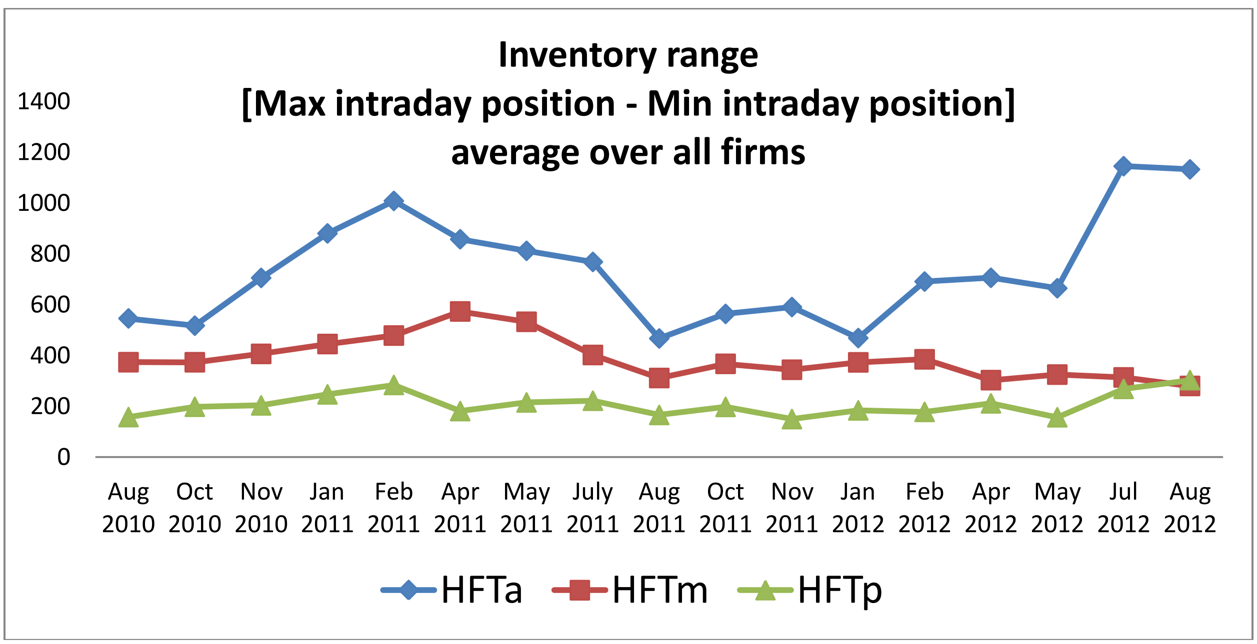
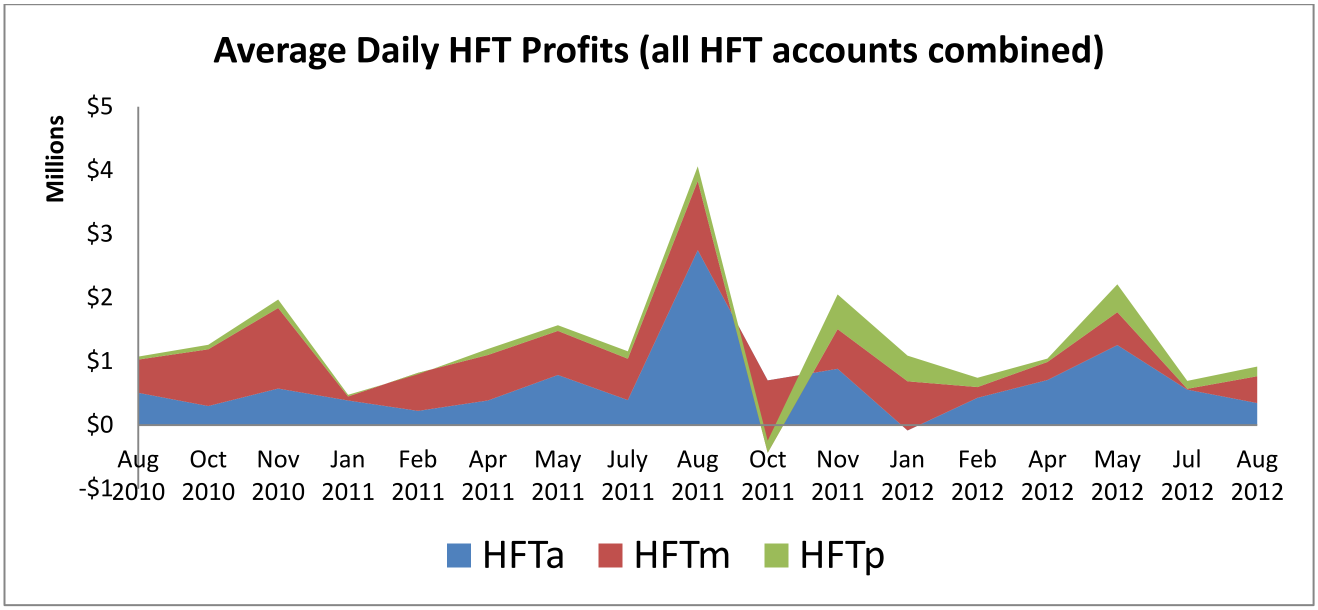


**Figure 2. Profits – Time Series**

This Figure shows the time-series of average daily HFT profits (Panel A) and profits per contract (Panel B), broken down into Aggressive, Mixed and Passive groups and with all firms aggregated together in their respective groups.

**Panel A: Profits**




**Panel B: Profits per Contract**

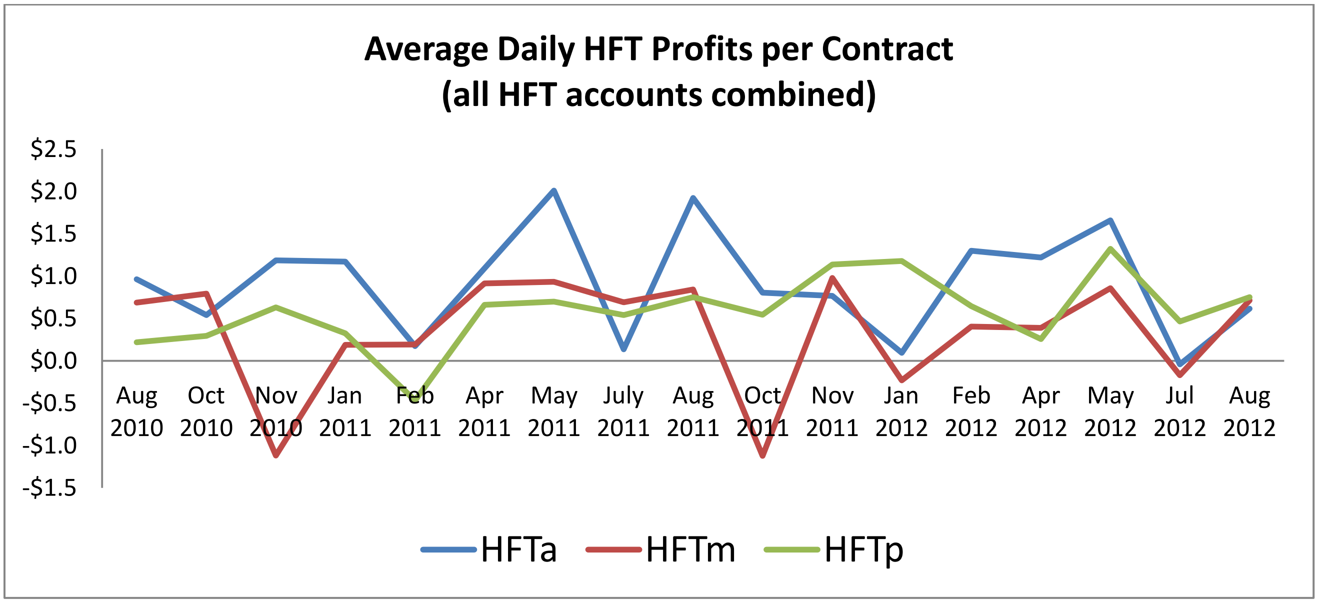
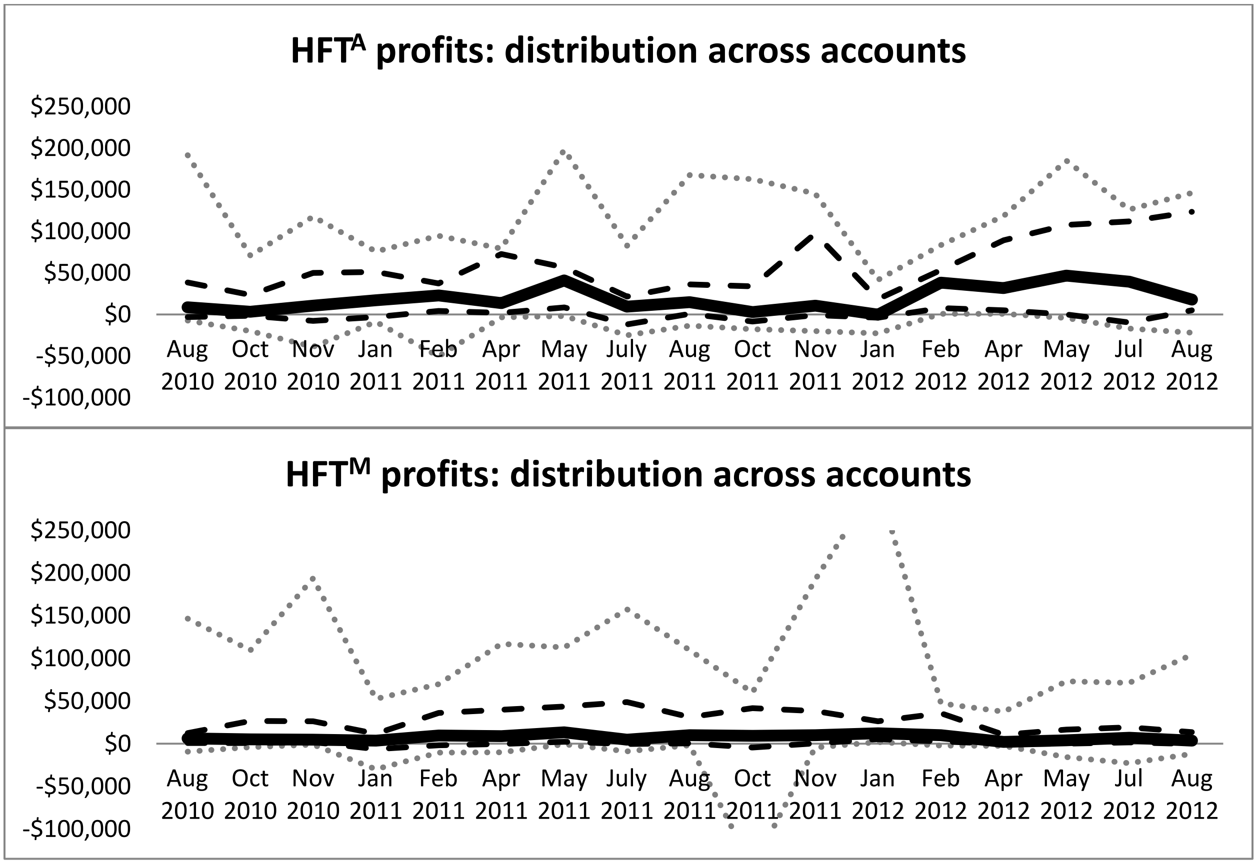
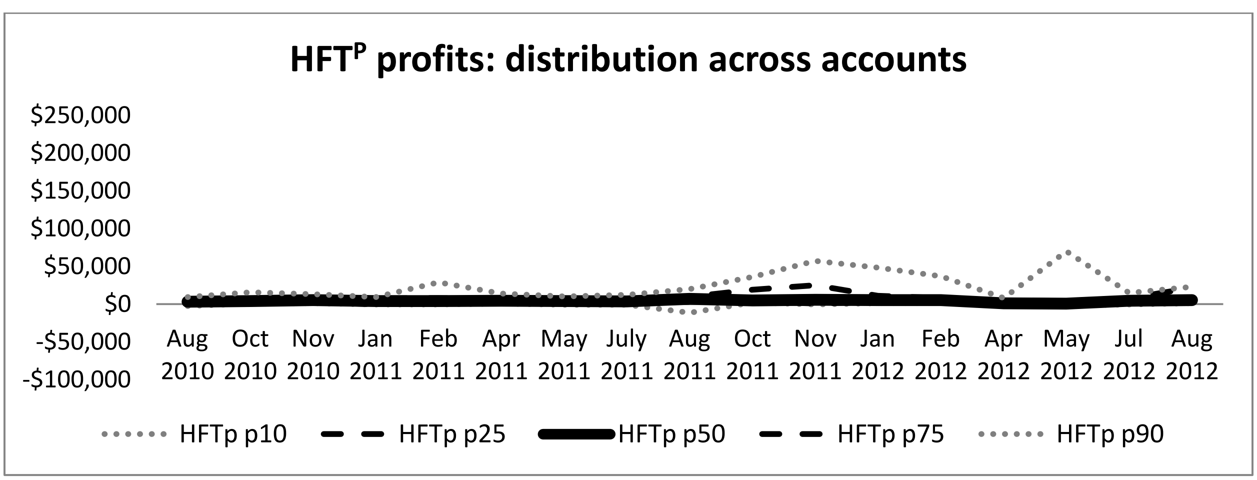


**Figure 3. Profits – Distribution**

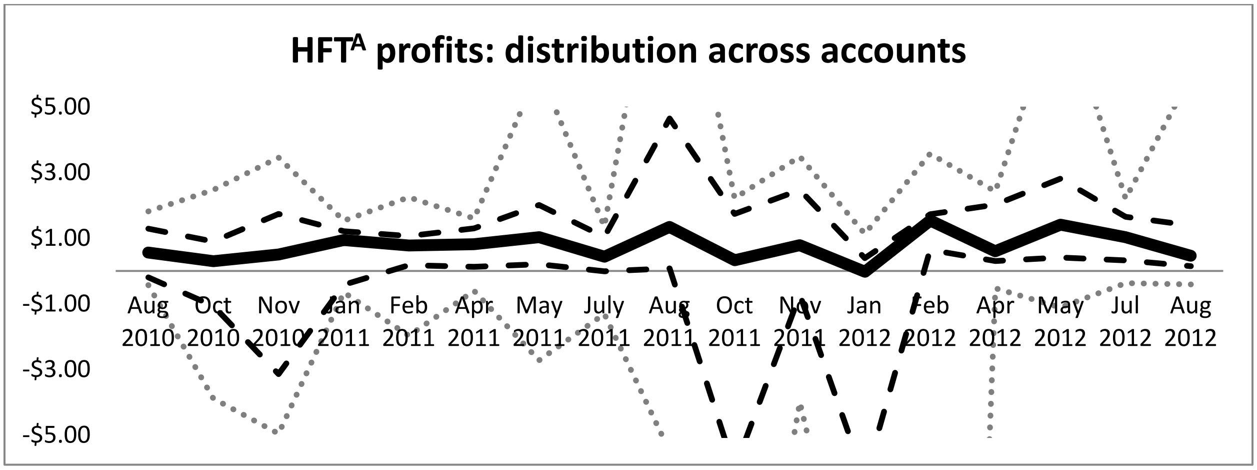
This Figure plots the average daily profits of firms at the 10th, 25th, 50th, 75th and 90th percentiles. Each panel is broken down into three graphs for Aggressive, Mixed and Passive HFTs.

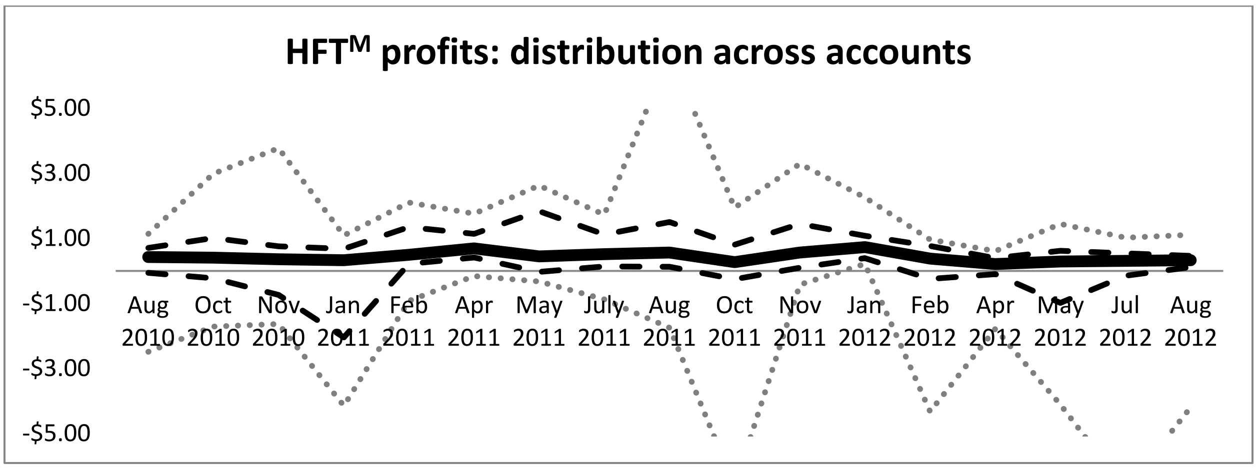
**Panel A: Profits**



**Panel B: Profits per Contract**



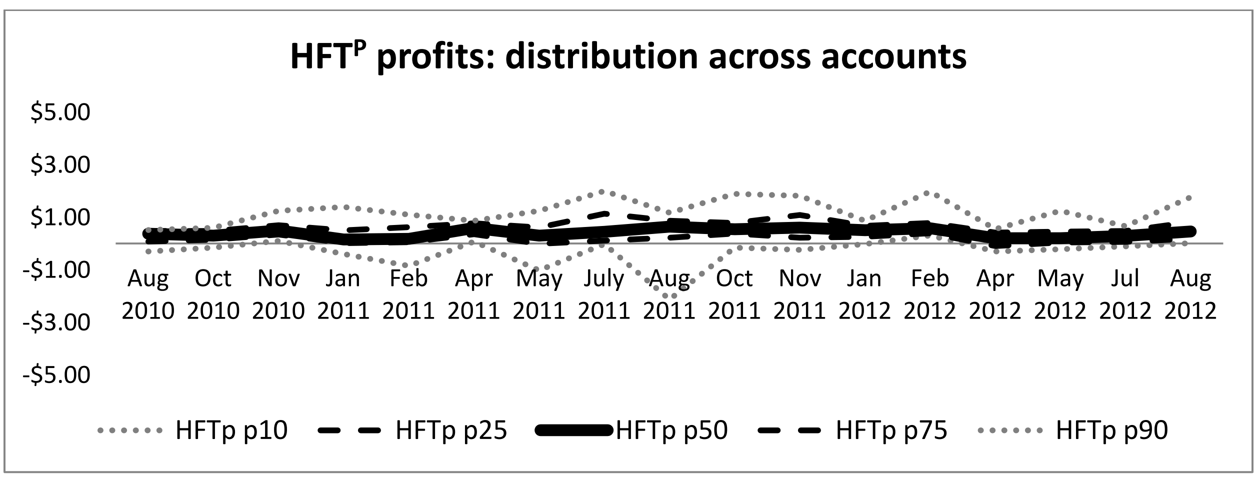



**Figure 4. Sharpe Ratios**

This Figure plots the monthly Sharpe ratios of firms at the 10th, 25th, 50th, 75th and 90th percentiles. Each panel is broken down into three graphs for Aggressive, Mixed and Passive HFTs.

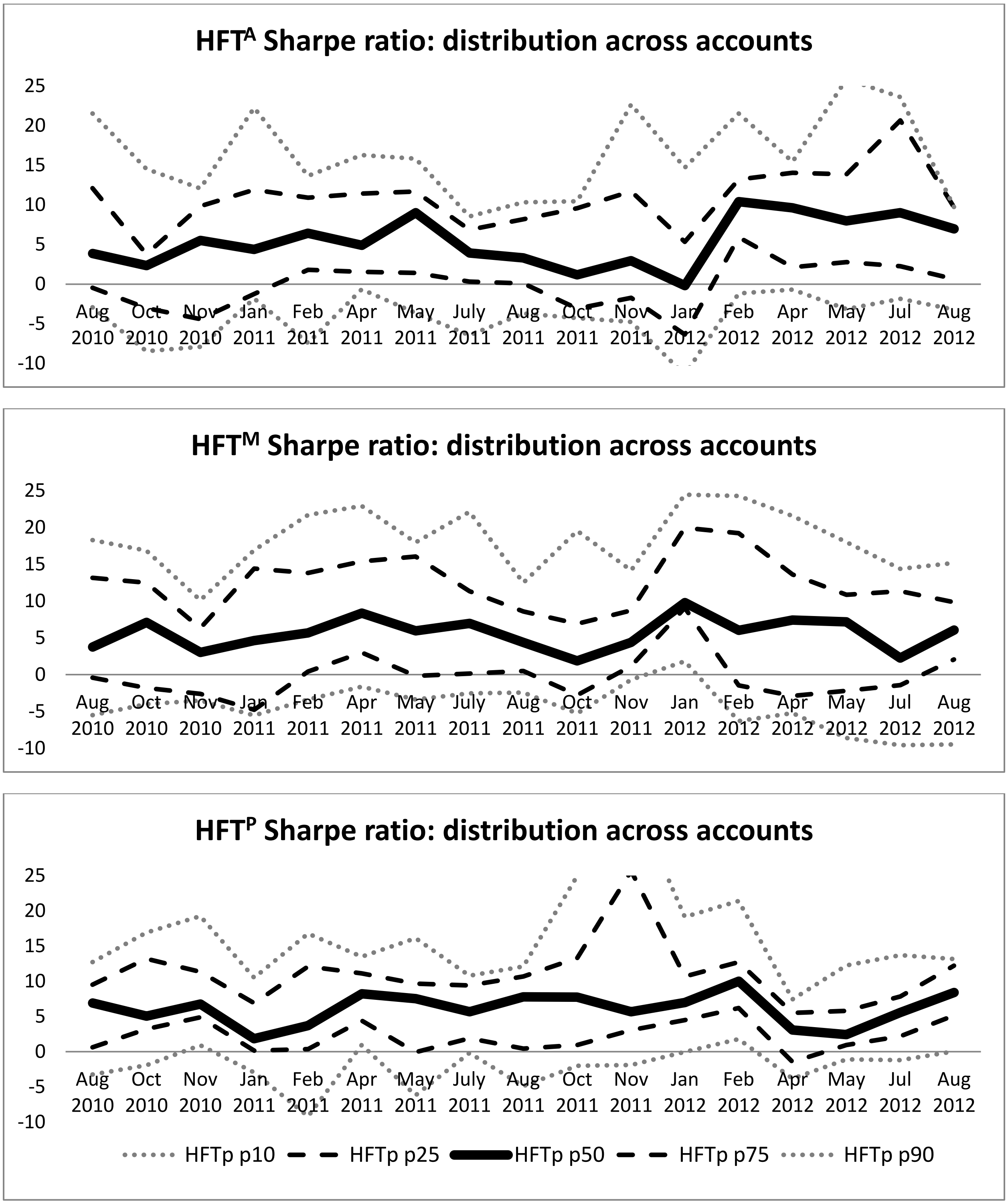


**Figure 5. Profit Consistency**

This Figure shows the average daily profits over time of three groups of HFTs based on their relative performance in August 2010. Outperformance is defined as being in the top third of firm profitability in August 2010, underperformance is defined as being in the bottom third of profitability in August 2010.

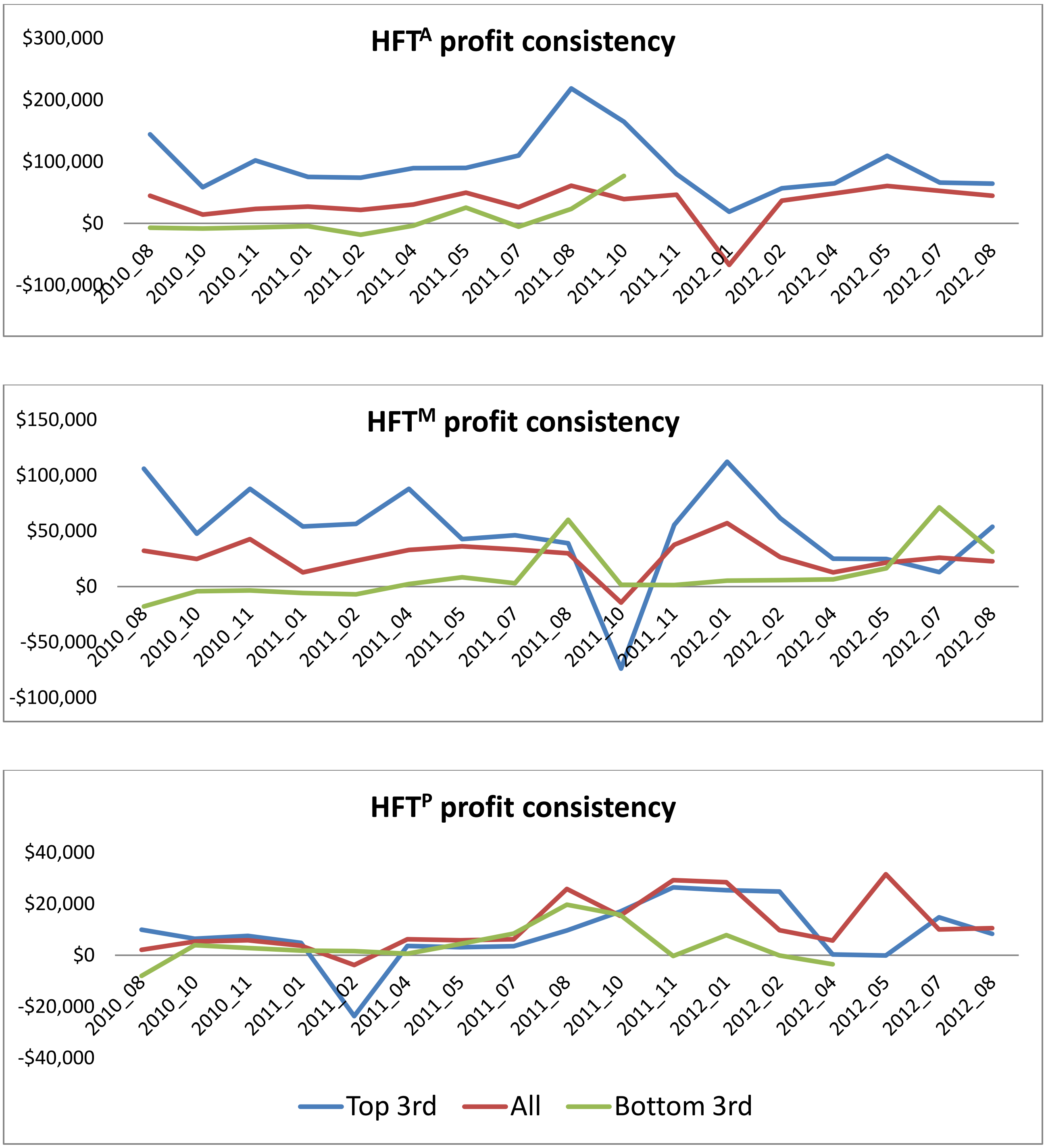
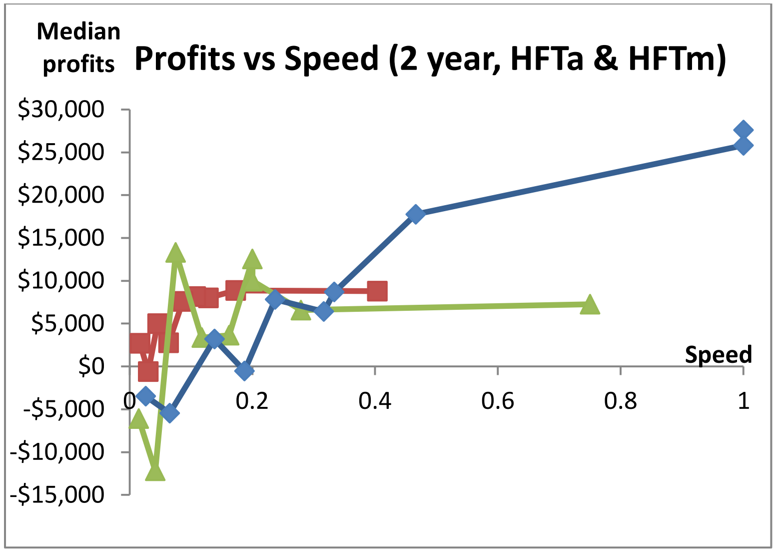


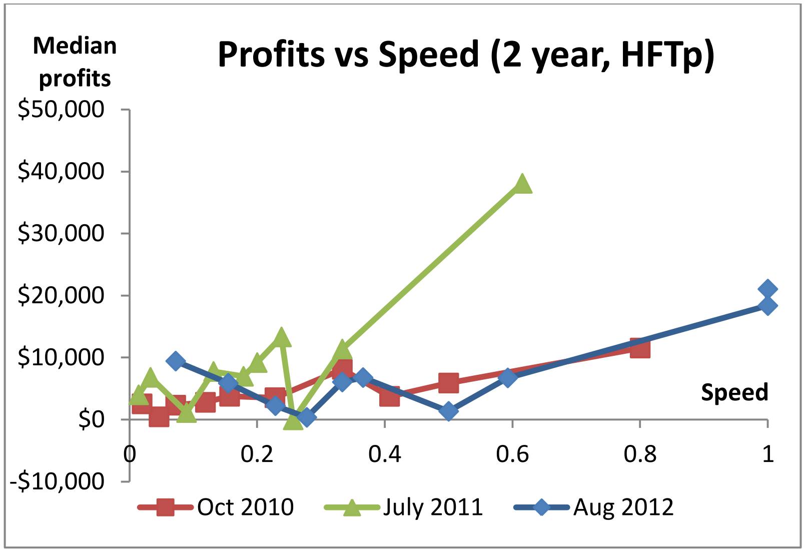
**Figure 6. Speed**

This Figure shows the relationship between speed and profits. Speed is defined as the time in milliseconds between successive trades that switch from a passive trade to an aggressive trade and is measured for each firm-day. The Speed measure uses the 5th percentile of this measure. For all days, and for all Aggressive and Mixed HFTs (which we group together) and Passive HFTs, we put the firm-day observations into one of 10 decile bins corresponding to their latency and take the average of both the speed and the profits across both days and firms.

**Panel A: Aggressive and Mixed HFT**




**Panel B: Passive HFT**



## Table 1 Summary statistics of S&P 500 E-mini market

The mean, standard deviation, minimum, median, and maximum of the daily trading activity of seven different trader types' trading activity are reported: HFT-Aggressive ($HFT^A$), HFT-Mixed ($HFT^M$), HFT-Passive ($HFT^P$), Fundamental, Small Trader, Non-HFT Market Maker, and Opportunistic. Four different statistics are reported: *Daily % Market Volume* is the daily percent of market volume traded, *Daily Aggressive Quantity* is the daily percent of liquidity taking contracts, *Daily Aggressive Ratio* is the daily fraction of contracts that were liquidity taking, and *Daily Trade Size* is the average trade size. The label column for *Daily % Market Volume* reports the number of traders in each trader-type category.

**Panel A: Summary Statistics**

| **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 Quantity** | | | | | |
| $HFT^A$ | 25.60% | 2.90% | 16.69% | 26.36% | 29.55% |
| $HFT^M$ | 22.47% | 1.25% | 6.87% | 9.09% | 11.49% |
| $HFT^P$ | 2.19% | 0.33% | 1.73% | 2.06% | 3.10% |
| Fundamental | 9.72% | 1.25% | 6.87% | 9.09% | 11.49% |
| Small Trader | 1.20% | 0.13% | 0.97% | 1.19% | 1.40% |
| Non-HFT Market Maker | 1.10% | 1.25% | 6.87% | 9.09% | 11.49% |
| Opportunistic | 37.73% | 1.83% | 34.67% | 37.47% | 40.94% |
| Total | 1,593,506 | 409,710 | 826,026 | 1,540,508 | 2,232,787 |
| **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% |
| **Daily Trade Size** | | | | | |
| $HFT^A$ | 5.26 | 0.32 | 4.72 | 5.19 | 5.96 |
| $HFT^M$ | 4.42 | 0.29 | 3.79 | 4.46 | 4.92 |
| $HFT^P$ | 2.31 | 0.21 | 1.93 | 2.32 | 2.66 |
| Fundamental | 5.67 | 0.42 | 5.00 | 5.62 | 6.60 |
| Small Trader | 1.25 | 0.01 | 1.24 | 1.25 | 1.30 |
| Non-HFT Market Maker | 3.92 | 0.24 | 3.50 | 3.91 | 4.34 |
| Opportunistic | 4.66 | 0.24 | 4.11 | 4.67 | 5.09 |

## Table 2 Distribution of HFT Profits

Table reports the daily profits by each HFT firm. Panel A shows the day level profits of HFTs. *Daily Profit* is calculated as the difference between the prices at which firms bought and sold shares. While most of the time HFTs end the day with zero inventory, when that is not the case the inventory is marked-to-market at the end-of-day price. There are three rows: $HFT^A$, $HFT^M$, and $HFT^P$, which analyze Aggressive, Mixed, and Passive HFT, respectively. Table A focuses in detail on the distribution HFT profits in August 2010. The top portion of the table, *Daily Profit*, reports the number of observations, the Mean, Median, Standard Deviation, Skewness, and Kurtosis for each of the profit measures. In addition, the P-value for whether the mean profit value is statistically significantly different from zero is reported. *Total Monthly Profits* is the overall profits during August 2010 for the HFTs. *Max Loss* is the largest loss a HFT experiences on a day. *Max Loss Per Average Profit* is the average across firms of the largest loss a firm realizes, scaled by its average daily trading profits. The lower half of Panel A *Daily Profit Per Contract*, scales *Daily Profit* by the number of trades by the HFT firm for that day. Panel B and C report the time series profitability of HFT. Panel B shows the monthly aggregate mean profitability per HFT firm, the standard deviation, the P-value of the mean and the P-value of the median. Panel C reports the same but for the mean profitability per contract traded.

**Panel A: Daily Profit**

| | N | Mean | Median | Std. Dev. | Skew. | Kurt. | P-Value | Total Monthly Profits | Max Loss | Max Loss Per Average Profit |
|---|---|---|---|---|---|---|---|---|---|---|
| **$HFT^A$** | 245 | $45,267 | $14,538 | $167,411 | 3.593 | 26.57 | <.001 | $11,090,376 | $-428,825 | -$1.55 |
| **$HFT^M$** | 591 | $19,466 | $5,387.5 | $273,240 | -2.35 | 30.25 | <0.01 | $11,504,625 | $-2,661,600 | -$35.02 |
| **$HFT^P$** | 421 | $2,460.6 | $3,875 | $46,638.3 | -3.4 | 34.77 | <0.01 | $1,035,913 | $-411,962.5 | N.A. |

**Daily Profit Per Contract**

| | N | Mean | Median | Std. Dev. | Skew. | Kurt. | P-Value |
|---|---|---|---|---|---|---|---|
| **$HFT^A$** | 245 | $1.91 | $0.75 | $21.21 | -10.6 | 137.3 | <.001 |
| **$HFT^M$** | 591 | $-0.60 | $0.47 | $42.63 | -13.6 | 310.7 | <0.01 |
| **$HFT^P$** | 421 | $0.47 | $0.37 | $6.48 | 2.309 | 86.8 | <0.01 |

## Table 2 Continued

### Panel B: Profits Over Time

| | Daily Profit (in thousands) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | HFT Aggressive | | | | HFT Mixed | | | | HFT Passive | | | |
| | Mean | S.D | P-value of Mean | P-value of Median | Mean | S.D | P-value of Mean | P-value of Median | Mean | S.D | P-value of Mean | P-value of Median |
| **Aug-10** | 504 | 605 | <.01 | <.01 | 523 | 2,522 | 0.08 | <.01 | 47 | 227 | 0.28 | <.01 |
| **Oct-10** | 297 | 473 | <.01 | <.01 | 891 | 1,619 | <.01 | <.01 | 71 | 164 | 0.02 | <.01 |
| **Nov-10** | 572 | 1,073 | <.01 | <.01 | 1,265 | 1,736 | <.01 | <.01 | 133 | 179 | <.01 | <.01 |
| **Jan-11** | 384 | 552 | 0.05 | <.01 | 63 | 852 | 0.78 | <.01 | 27 | 113 | 0.27 | 0.01 |
| **Feb-11** | 221 | 661 | 0.12 | <.01 | 598 | 610 | <.01 | <.01 | -22 | 409 | 0.77 | <.01 |
| **Apr-11** | 384 | 401 | <.01 | <.01 | 714 | 753 | <.01 | <.01 | 95 | 75 | <.01 | <.01 |
| **May-11** | 785 | 662 | <.01 | <.01 | 692 | 1,202 | <.01 | <.01 | 89 | 146 | <.01 | <.01 |
| **Jul-11** | 391 | 1,061 | 0.04 | <.01 | 649 | 1,194 | <.01 | <.01 | 117 | 146 | <.01 | <.01 |
| **Aug-11** | 2,746 | 4,513 | <.01 | <.01 | 1,087 | 3,174 | 0.03 | <.01 | 230 | 2,374 | 0.64 | <.01 |
| **Oct-11** | 699 | 1,095 | <.01 | <.01 | -1,137 | 3,428 | 0.05 | <.01 | 190 | 908 | 0.36 | <.01 |
| **Nov-11** | 882 | 1,060 | <.01 | <.01 | 623 | 2,405 | 0.09 | <.01 | 546 | 717 | <.01 | <.01 |
| **Jan-12** | -86 | 534 | 0.50 | <.01 | 772 | 574 | <.01 | <.01 | 403 | 624 | <.01 | <.01 |
| **Feb-12** | 426 | 401 | <.01 | <.01 | 168 | 569 | 0.14 | <.01 | 147 | 143 | <.01 | <.01 |
| **Apr-12** | 705 | 736 | <.01 | <.01 | 284 | 247 | <.01 | <.01 | 53 | 191 | 0.08 | 0.01 |
| **May-12** | 1,255 | 1,138 | <.01 | <.01 | 517 | 616 | <.01 | <.01 | 438 | 813 | 0.02 | <.01 |
| **Jul-12** | 554 | 843 | <.01 | <.01 | 13 | 1,324 | 0.95 | <.01 | 125 | 183 | <.01 | <.01 |
| **Aug-12** | 343 | 683 | <.01 | <.01 | 421 | 436 | <.01 | <.01 | 153 | 220 | <.01 | <.01 |

## Table 2 Continued

### Panel C: Profits Per Contract Over Time

| | Daily Profit per Contract | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | HFT Aggressive | | | | HFT Mixed | | | | HFT Passive | | | |
| | Mean | S.D | P-value of Mean | P-value of Median | Mean | S.D | P-value of Mean | P-value of Median | Mean | S.D | P-value of Mean | P-value of Median |
| **Aug-10** | $0.96 | $1.07 | 0.16 | 0.01 | $0.69 | $2.73 | 0.73 | <.01 | $0.22 | $0.73 | 0.14 | <.01 |
| **Oct-10** | $0.54 | $0.83 | 0.04 | <.01 | $0.79 | $1.31 | 0.03 | <.01 | $0.29 | $0.54 | 0.31 | <.01 |
| **Nov-10** | $1.19 | $2.21 | 0.04 | <.01 | -$1.12 | $8.76 | 0.50 | <.01 | $0.63 | $1.02 | <.01 | <.01 |
| **Jan-11** | $1.17 | $1.78 | 0.52 | 0.06 | $0.19 | $0.82 | 0.70 | 0.02 | $0.33 | $0.87 | 0.97 | <.01 |
| **Feb-11** | $0.17 | $1.94 | 0.54 | <.01 | $0.19 | $2.15 | 0.84 | <.01 | -$0.47 | $2.88 | 0.83 | <.01 |
| **Apr-11** | $1.09 | $1.23 | 0.60 | <.01 | $0.92 | $0.90 | <.01 | <.01 | $0.66 | $0.52 | <.01 | <.01 |
| **May-11** | $2.01 | $3.27 | <.01 | <.01 | $0.93 | $1.62 | 0.47 | <.01 | $0.70 | $1.49 | 0.25 | <.01 |
| **Jul-11** | $0.14 | $2.88 | 0.22 | 0.01 | $0.69 | $1.20 | 0.92 | <.01 | $0.54 | $0.60 | 0.13 | <.01 |
| **Aug-11** | $1.92 | $3.15 | 0.41 | <.01 | $0.84 | $2.36 | 0.25 | <.01 | $0.75 | $3.95 | 0.76 | <.01 |
| **Oct-11** | $0.81 | $1.14 | 0.10 | 0.14 | -$1.12 | $3.13 | 0.34 | <.01 | $0.54 | $1.57 | 0.07 | <.01 |
| **Nov-11** | $0.77 | $1.45 | 0.34 | <.01 | $0.98 | $2.74 | 0.60 | <.01 | $1.14 | $1.25 | 0.45 | <.01 |
| **Jan-12** | $0.09 | $1.76 | 0.31 | 0.86 | -$0.23 | $7.03 | <.01 | <.01 | $1.18 | $1.82 | 0.06 | <.01 |
| **Feb-12** | $1.30 | $1.71 | 0.51 | <.01 | $0.40 | $0.89 | 0.85 | <.01 | $0.65 | $0.60 | 0.13 | <.01 |
| **Apr-12** | $1.22 | $1.09 | 0.41 | <.01 | $0.39 | $0.32 | 0.26 | <.01 | $0.26 | $0.82 | 0.26 | 0.09 |
| **May-12** | $1.66 | $1.89 | <.01 | <.01 | $0.86 | $1.03 | 0.79 | <.01 | $1.32 | $2.73 | 0.03 | <.01 |
| **Jul-12** | -$0.04 | $3.67 | 0.67 | <.01 | -$0.17 | $1.97 | 0.15 | 0.01 | $0.47 | $0.60 | 0.15 | <.01 |
| **Aug-12** | $0.62 | $1.19 | <.01 | <.01 | $0.71 | $0.74 | 0.80 | <.01 | $0.75 | $1.10 | 0.18 | <.01 |

## Table 3 Profit Breakdown

The table analyzes the decomposition of average daily short-term profits among different traders. 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 implied short-term profits: we first calculate the marked-to-market profits of each trader on a 10-second frequency and reset the inventory position of each trader to zero after each of these 10-second intervals. Then we sum up all the 10-second intervals to get a measure of daily profits. Therefore, we capture the short-term profits of traders and not gains and losses from longer-term holdings. Eight different trader types' trading activity are reported: HFT-Aggressive ($HFT^A$), HFT-Mixed ($HFT^M$), HFT-Passive ($HFT^P$), HFT-All (HFT), Fundamental, Small Trader, Non-HFT Market Maker, and Opportunistic. The HFT results are the sum of the $HFT^A$, $HFT^M$, and $HFT^P$ results and are reported for convenience. The rows identify who receives the profits, whereas the different columns represent from whom the profits are being derived. The *Total* column is the percent of trades in which the column-identified market participant participates. The *Total* column is the same for the row-identified market participant. Panel A analyzes the average daily trading type pairs' profits. For each trade, the type pair is identified and the profit is calculated as the mark-to-market profit 10-seconds after the trade occurred. Profits for each type pair are summed for the full 22 trading days in August 2010 and divided by 22 to obtain an average per day trading profit for each type pair. Panel B expresses the trading profits between groups as a percentage of a group's total profit. For groups that have net losses, Panel B expresses the percent of total losses. Panel C describes the profits and losses on a per contract basis, dividing the summed profit for a given type pair and dividing by the number of contracts exchanged between that type pair.

**Panel A: Profits**

| | **Counterparty** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Profits to:** | **$HFT^A$** | **$HFT^M$** | **$HFT^P$** | **Non-HFT Market Maker** | **Fundamental** | **Opportunistic** | **Small** | **Total** |
| **$HFT^A$** | $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 M. M.** | -$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 |

## Table 3 Continued

### Panel B: Percent Profits

| | Counterparty | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $\text{HFT}^{A}$ | $\text{HFT}^{M}$ | $\text{HFT}^{P}$ | Non-HFT Market Maker | Funda-mental | Opport-unistic | Small | Total |
| **Percent Profits to:** | | | | | | | | |
| $\text{HFT}^{A}$ | 0.0% | 32.8% | 11.6% | 8.9% | 7.7% | 37.2% | 1.7% | $21,952,215 |
| $\text{HFT}^{M}$ | -56.3% | 0.0% | 11.0% | 12.6% | 2.9% | 120.3% | 9.5% | $12,771,060 |
| $\text{HFT}^{P}$ | -509.0% | -278.7% | 0.0% | 16.8% | -74.3% | 860.6% | 84.7% | $502,338 |
| Fundamental | -149.8% | -33.3% | 33.1% | 33.9% | 0.0% | 205.6% | 10.6% | $1,129,413 |
| **Percent Losses to:** | | | | | | | | |
| Non-HFT M. M. | 68.7% | 56.3% | 3.0% | 0.0% | 13.4% | -37.1% | -4.2% | -$2,856,538 |
| Opportunistic | 26.4% | 49.7% | 14.0% | 3.4% | 7.5% | 0.0% | -1.1% | -$30,895,400 |
| Small Trader | 14.6% | 46.8% | 16.3% | 4.6% | 4.6% | 13.0% | 0.0% | -$2,603,088 |

### Panel C: Profit/Loss Per Trade

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $\text{HFT}^{A}$ | $0.00 | $2.02 | $1.93 | $2.64 | $1.92 | $2.49 | $3.49 | $2.04 |
| $\text{HFT}^{M}$ | -$2.02 | $0.00 | $0.94 | $1.95 | $0.18 | $1.92 | $4.42 | $0.60 |
| $\text{HFT}^{P}$ | -$1.93 | -$0.94 | $0.00 | $0.75 | -$0.62 | $1.79 | $5.05 | $0.08 |
| Non-HFT M. M. | -$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 4 Spectral Analysis

This table analyzes trading profits over different time horizons using spectral analysis, following the methods of Hasbrouck and Sofianos (1993). We first computed the spectral decomposition of profits for each individual HFT firm and each trading day, aggregating over the following intervals: 1-10, 11-100, 101-1,000, 1,001-10,000, 10,000-100,000 and 100,000+ market transactions. Then, for each HFT firm, we take the median profit for each firm over the course of the 22 days in our sample, and then take the median and the 25th and 75th percentiles across firms.

| | **Transaction Interval** | | | | | |
|---|---|---|---|---|---|---|
| | **1-10** | **11-100** | **101-1000** | **1001-10000** | **10000- 100000** | **100000+** |
| **$HFT^A$** | $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 5 : Herfindahl Concentration of HFT

This table calculates the Herfindahl index for each sub-group of HFTs, for each month in the data set. We report a Profit-based Herfindahl Index as well as a Volume-based one. The Profit Herfindahl index is calculated as: $Herfindahl_{i,t} = \sum_{i=1}^{N}\left[\frac{Profit_{i,t}}{HFT\ Profit_t}\right]^2$ . where $N$ is the number of firms in the HFT subgroup 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 sub group of interest (Aggressive, Mixed, or Passive). The Volume Herfindahl is calculated using the same forma but considering the number of contracts traded instead of trading profits. The Herfindahl index range of (0,1]. 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.

| | **Profit Herfindahl Index** | | | **Volume Herfindahl Index** | | |
|---|---|---|---|---|---|---|
| | **HFT A** | **HFT M** | **HFT P** | **HFT A** | **HFT M** | **HFT P** |
| **Aug-10** | 0.316 | 0.251 | 0.116 | 0.160 | 0.159 | 0.082 |
| **Oct-10** | 0.161 | 0.154 | 0.085 | 0.166 | 0.226 | 0.061 |
| **Nov-10** | 0.200 | 0.153 | 0.071 | 0.146 | 0.217 | 0.068 |
| **Jan-11** | 0.189 | 0.223 | 0.160 | 0.145 | 0.242 | 0.187 |
| **Feb-11** | 0.236 | 0.156 | 0.108 | 0.162 | 0.184 | 0.094 |
| **Apr-11** | 0.197 | 0.180 | 0.228 | 0.178 | 0.191 | 0.161 |
| **May-11** | 0.172 | 0.125 | 0.211 | 0.136 | 0.163 | 0.149 |
| **Jul-11** | 0.345 | 0.128 | 0.194 | 0.176 | 0.134 | 0.148 |
| **Aug-11** | 0.151 | 0.088 | 0.130 | 0.126 | 0.098 | 0.204 |
| **Oct-11** | 0.170 | 0.118 | 0.165 | 0.163 | 0.105 | 0.211 |
| **Nov-11** | 0.157 | 0.114 | 0.269 | 0.150 | 0.123 | 0.203 |
| **Jan-12** | 0.233 | 0.318 | 0.323 | 0.187 | 0.319 | 0.125 |
| **Feb-12** | 0.149 | 0.226 | 0.156 | 0.157 | 0.299 | 0.149 |
| **Apr-12** | 0.205 | 0.246 | 0.374 | 0.161 | 0.146 | 0.361 |
| **May-12** | 0.157 | 0.311 | 0.601 | 0.152 | 0.123 | 0.246 |
| **Jul-12** | 0.157 | 0.222 | 0.367 | 0.179 | 0.187 | 0.200 |
| **Aug-12** | 0.205 | 0.322 | 0.261 | 0.172 | 0.233 | 0.236 |

## Table 6 Consistency

This table looks at the consistency of HFT profits. Panel A tests whether a firm's profits yesterday predict its profits today. Panel B does the same but at longer horizons, from one-month up to one-year. Each Column in Panel A is a different regression. The dependent variability is Profitability of firm i on day t, and the HFT firms are analyzed in separate subcategories: Aggressive, Mixed, and Passive. The OLS regression is: $Profit_{i,t} = \alpha + \beta_1 Profit_{i,t-1} + \beta_2 \mathbf{1}_{top\ 3rd\ i,t-1} + \beta_3 Aggressiveness_{i,t} + \beta_4 Volume_t + \beta_5 Volatility_5 + \epsilon_{i,t}$ where $Profits_{,i,t}$ is the signed log of profits for firm i on day t. $Profit_{i,t-1}$ is the signed logged profits for firm i on day t-1. $\mathbf{1}_{Top\ 3rd\ i,t}$ is a dummy variable taking the value one if firm *i* on day *t-1* was in the top one-third of its profitability among its subgroup of HFT firms, $Volume_{i,s}$ is the log of each trader's trading volume for that day; $Volatility_s$ , is the log of the price volatility of that day defined as the (volume-weighted) standard deviation of the price process throughout that trading day; and $Aggressiveness_{i,s}$ is trader *i*'s average (volume-weighted) aggressiveness ratio. We include these regressors to control for both time-specific and firm-specific effects. Panel B Columns 1, 3 and 5 are coefficients with the standard errors in the column to the right. Each coefficient is obtained by running the full specification regression from Panel A (Columns 7 – 9) but replace the lag of Profitability from 1 day to longer horizons, between 30 days and one year. * represents *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

**Panel A: 1 Day Persistence**

| | HFT A | HFT M | HFT P | HFT A | HFT M | HFT P | HFT A | HFT M | HFT P |
|---|---|---|---|---|---|---|---|---|---|
| $Profit_{t-1}$ | 0.13*** | 0.15*** | 0.096*** | 0.0977*** | 0.107*** | 0.0721*** | 0.0737*** | 0.110*** | 0.0659*** |
| | (0.02) | (0.01) | (0.01) | (0.02) | (0.01) | (0.01) | (0.02) | (0.01) | (0.01) |
| Top 3rd $Dummy_{i,t-1}$ | | | | | | | 0.674 | -0.117 | 0.353 |
| | | | | | | | (0.48) | (0.28) | (0.32) |
| $Aggressiveness_{i,t}$ | | | | -2.835*** | -9.918*** | -3.893** | -2.825*** | -9.878*** | -3.935** |
| | | | | (0.85) | (0.89) | (1.56) | (0.84) | (0.89) | (1.56) |
| $Volume_t$ | | | | 0.997*** | 1.215*** | 1.087*** | 0.966*** | 1.225*** | 1.059*** |
| | | | | (0.08) | (0.07) | (0.09) | (0.08) | (0.07) | (0.09) |
| $Volatility_t$ | | | | 0.284 | -0.815*** | -1.414*** | 0.293 | -0.819*** | -1.402*** |
| | | | | (0.27) | (0.20) | (0.21) | (0.27) | (0.20) | (0.21) |
| N | 4406 | 7609 | 5706 | 4406 | 7609 | 5706 | 4406 | 7609 | 5706 |
| Adj-R^2 | 0.018 | 0.025 | 0.009 | 0.05 | 0.076 | 0.043 | 0.05 | 0.076 | 0.043 |

**Panel B: Longer Persistence**

| | HFT A | Std. Err | HFT M | Std. Err | HFT P | Std. Err |
|---|---|---|---|---|---|---|
| $Profit_{t-30}$ | 0.0137 | (0.02) | 0.0497*** | (0.01) | 0.0548*** | (0.02) |
| $Profit_{t-60}$ | 0.0256 | (0.02) | 0.0669*** | (0.02) | 0.0707*** | (0.02) |
| $Profit_{t-180}$ | 0.0334 | (0.03) | 0.0828*** | (0.02) | 0.0431 | (0.03) |
| $Profit_{t-360}$ | 0.0667 | (0.04) | 0.0179 | (0.03) | -0.047 | (0.06) |

## Table 7 New HFT Entrants

This table analyzes the performance of new HFT entrants. Panel A reports the results of the following OLS regression: $Profit_{i,t} = \alpha + \beta_1 \mathbf{1}_{New\ Entrant\ i,t} + \beta_2 Aggressiveness_{i,t} + \beta_3 Volume_t + \beta_4 Volatility_5 + \epsilon_{i,t}$. The control variables are the same as in Table 7. Lagged Profits is excluded as a control as it may confound with the variable of interest, the dummy variable, *New Entrant i,t*, which takes the value 1 during a period after a new HFT firm participates in the market. So the *< 1 month old* dummy variable will take the value one for firm *i* during t to t +30 if firm *i* began trading on day *t-1*, otherwise it will take the value zero. The two, three, and four month dummy variables are similarly defined. We exclude the observations in 2010 as this is when we first observe any firm. Each two rows represent three regressions for a subgroup of HFT: Aggressive, Mixed, and Passive. The coefficients are reported in Columns 1, 3, and 5; their robust standard errors are reported in Columns 2, 4, and 6. Each regression includes the full set of control variables identified above. The Adjusted R-square is reported below the coefficient. Panel B reports the results of the logit regression: $Exit_{i,t} = \alpha + \beta_1 \mathbf{1}_{New\ Entrant\ i,t} + \beta_2 Aggressiveness_{i,t} + \beta_3 Volume_t + \beta_4 Volatility_5 + \epsilon_{i,t}$ 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, *New Entrant i,t*, defined as above. 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. * represents *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

### Panel A: Profitability of New Entrants

| | HFT A | Std. Err | HFT M | Std. Err | HFT P | Std. Err |
|---|---|---|---|---|---|---|
| < 1 month old dummy | -0.718 | (0.48) | 1.046** | (0.41) | 0.229 | (0.35) |
| Adj-R^2 | 0.042 | | 0.065 | | 0.042 | |
| < 2 month old dummy | -0.618 | (0.42) | 0.0472 | (0.35) | 0.607** | (0.28) |
| Adj-R^2 | 0.042 | | 0.064 | | 0.043 | |
| < 3 month old dummy | -0.858** | (0.41) | 0.297 | (0.30) | 0.25 | (0.26) |
| Adj-R^2 | 0.043 | | 0.064 | | 0.042 | |
| < 4 month old dummy | -1.333*** | (0.39) | 0.0713 | (0.26) | -0.420* | (0.25) |
| Adj-R^2 | 0.045 | | 0.064 | | 0.042 | |

### Panel B: Probability of Exit

| | HFT A | Std. Err | HFT M | Std. Err | HFT P | Std. Err |
|---|---|---|---|---|---|---|
| < 1 month old dummy | 1.120*** | (0.32) | 1.075*** | (0.33) | 0.0106 | (0.39) |
| Pseudo R^2 | 0.0329 | | 0.0276 | | 0.0009 | |
| < 2 month old dummy | 1.375*** | (0.32) | 1.787*** | (0.30) | 0.169 | (0.31) |
| Pseudo R^2 | 0.0474 | | 0.0733 | | 0.0015 | |
| < 3 month old dummy | 1.375*** | (0.32) | 1.787*** | (0.30) | 0.169 | (0.31) |
| Pseudo R^2 | 0.0442 | | 0.056 | | 0.0016 | |
| < 4 month old dummy | 1.583*** | (0.40) | 1.420*** | (0.32) | 0.0559 | (0.29) |
| Pseudo R^2 | 0.049 | | 0.0504 | | 0.001 | |

## Table 8 Speed and Profits

This table reports the OLS regression coefficients for the following regression $Profits_{i,t} = \alpha + \beta_1 AbsoluteSpeed_{i,t} + \beta_2 RelativeSpeed_{i,t} + controls + \epsilon_{i,t}$ where Profits$_{,i,t}$ is a modified version of log profits, namely sign(profits)*log(1+|profits|) to allow for negative values, *AbsoluteSpeed*$_{i,t}$ is the speed measure described above, *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. The control variables used are the same as in Equation (9) and (10) Aggressiveness, Volume, and Volatility. Panel A presents the results for Aggressive HFTs, Panel B for Mixed HFTs, Panel C for Passive HFTs. * represents *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

**Panel A: Speed and Profits: HFT A**

| | (1) | (2) | (3) |
|---|---|---|---|
| Absolute Speed | 14.44** | | -1.11 |
| | (6.61) | | (6.03) |
| Relative Speed | | -6.72*** | -5.39*** |
| | | (1.30) | (1.94) |
| Controls | N | N | Y |
| N | 713 | 730 | 713 |
| Adj-R^2 | 0.0139 | 0.035 | 0.0638 |

**Panel C: HFT P**

| | (1) | (2) | (3) |
|---|---|---|---|
| Absolute Speed | 6.15*** | | 1.26 |
| | (1.51) | | (1.97) |
| Relative Speed | | -2.62*** | -1.68 |
| | | (0.77) | (1.29) |
| Controls | N | N | Y |
| N | 1128 | 1334 | 1128 |
| Adj-R^2 | 0.0118 | 0.0085 | 0.0447 |

**Panel B: HFT M**

| | (1) | (2) | (3) |
|---|---|---|---|
| Absolute Speed | 12.72*** | | 4.3** |
| | (1.86) | | (2.15) |
| Relative Speed | | -4.44*** | -0.23 |
| | | (0.73) | (1.03) |
| Controls | N | N | Y |
| N | 1598 | 1693 | 1598 |
| Adj-R^2 | 0.0188 | 0.0198 | 0.1164 |