# The Trading Profits of High Frequency Traders

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**Abstract:** We examine the profitability of a specific class of intermediaries, high frequency traders (HFTs). Using transaction level data with user identifications, we find that high frequency trading (HFT) is highly profitable: 31 HFTs earn over $29 million in trading profits in one E-mini S&P 500 futures contract during one month. 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 an unusually high average Sharpe ratio of 9.2. These results provide insight into the efficiency of markets at high-frequency time scales and raise the question of why we don't see more competition among HFTs.

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## I. Introduction

In financial economics, a long-standing issue is how information finds its way into market prices and whether market prices are informationally efficient. Grossman and Stiglitz (1980) argue that markets must possess inefficiencies to compensate informed investors for the costs of gathering and trading on that information. According to their model informed investors earn excess returns as compensation for information acquisition and distribution. Campbell, Lo and Mackinlay (1997) assert that, "in a large and liquid market, informational costs are likely to justify only small abnormal returns, but it is difficult to say how small, even if such costs could be measured precisely."

In this paper, we study market efficiency by focusing on a particular type of investor, High Frequency Traders (HFTs). HFTs depend on speed, which is closely related to information – it is the ability to react to and incorporate information into market prices. Whether it is using expedited information to make an investment, reduce risk, or mitigate the costs of adverse selection, those quickest to react can capture informational rents.

We document that HFTs generate consistent and large excess returns in one of the most liquid and competitive financial markets - the E-mini S&P 500 futures market. These excess returns likely arise as a result of exploiting fleeting informational advantages at short time scales. We find that while HFTs bear some risk, they generate an unusually high average Sharpe ratio of 9.2. The concentration of profits among these few rapidly trading market participants - 31 out of over 31,403 traders – reveals deviations from market efficiency at very short intervals. Within these 31 firms, a small group of aggressive (liquidity-taking) HFTs are the most profitable.

We test and reject the null hypothesis that HFTs do not earn excess returns, as measured both by their gross profits and Sharpe ratios. While we are not able measure the net return to HFTs, returns after including the costs of computer systems, labor, overhead, risk management systems, etc, the magnitude of their gross trading profits suggests they also earn significant abnormal net returns.

Besides their role in price discovery, HFTs are often cited as central to liquidity provision in modern financial markets. We explore the heterogeneity in liquidity provision strategies and show that only a subgroup of HFTs are liquidity providers. In particular, some HFTs are almost 100% liquidity takers, and these firms trade the most and are the most profitable.

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.

This paper contributes mainly to two literatures: the growing body of work on HFT and the study of profitability by different groups of traders. Researchers studying HFT must overcome data limitations. No publicly available dataset allows researchers to directly identify HFTs. Hasbrouck and Saar (2010) overcome the 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 research HFT has been to look at one or a handful 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 natural 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 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 within the E-mini market.

The data used in this paper consist of all the trades in August 2010 for the September 2010-expiring E-mini S&P 500 futures contract. Analyzing one month of data has limitations. We are unable to study how profits vary over long intervals and we rely on the month to be representative of HFT profits. However, we do repeat the analysis for the month of May 2010 and discover qualitatively similar findings (in fact, we find marginally *larger* profits). Another 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.

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 time per day, and earn a small amount per trade. We find they earn $1.11 on average per contract traded. This equates to $46,039 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.

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. We find that the aggressiveness[3] of a given HFT firm is highly persistent across days and use this finding to classify HFTs into three categories: Aggressive, Mixed, and Passive. Although the average aggressiveness ratio of a high frequency trader is 42% - meaning HFTs are net liquidity providers - there is a wide variation across HFTs. We categorize HFT firms into three groups as follows: a firm is an Aggressive HFT if the proportion of aggressive executions they use exceeds 40%; a Mixed HFT if aggressive executions is between 20% and 40% of its trades; and Passive HFT if aggressive executions is less than 20% of the time. [4] These three groups exhibit distinct stylized features with regard to their trading strategies.

[3] The terms “aggressive” and “passive” in this paper refer to the party that executes the trade and is executed against, respectively (which is also equivalent to the terms “liquidity taker” and “liquidity provider”, respectively). This terminology does not refer to whether a given order is a market order or a limit order. In the E-mini market, almost all trades are limit orders, either limit orders that execute against other limit orders immediately upon placement or limit orders that are not matched and are placed on the order book to be canceled or executed against at a later time.

[4] Some HFTs have aggressive ratios very close to 100%, but due to data-use limitations we are unable to report more refined HFT sub-types.

We show the level of profits is significantly higher for Aggressive HFTs than for Passive and Mixed ones. However, on a per contract analysis, the disparity is smaller: Aggressive, Mixed, and Passive HFTs earn a median profit per contract traded of $0.98, $0.53, and $0.34, respectively. The profits for all groups include the profit (or loss) from the bid-ask spread.

We decompose trading profits over different time horizons using spectral analysis, following the methods of Hasbrouck and Sofianos (1993). The analysis is done in transaction time for technical reasons explained in Section III.d. There are approximately 10 transactions per second. We find that 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 less total market transactions) but gain money on longer time scales, those over 1,000 market transactions. Among the three sub-types of HFTs, Aggressive HFTs tend to incur most of their profits on holdings lasting between 11-1,000 total market transactions. In contrast, both Mixed and Passive HFTs tend to lose money at time horizons of 1,000 transactions or less, and instead make money over the slightly longer intervals.

In an efficient market, returns above the risk-free rate should be proportional to risk. Menkveld (2011) calculates one HFT firm's Sharpe ratio in the EU equities market 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 vary widely - for example 25% of Mixed HFTs have a Sharpe ratio greater than 17.11.

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), Non-HFT Market Makers, Small traders (likely retail), and Opportunistic traders. We decompose profits into how much each category is earning from the others. 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 loss to HFTs on a per contract basis: $4.42 per contract compared to $1.22 for Fundamental traders and $2.25 for Opportunistic traders, for a contract valued at approximately $50,000.

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. We find that factors associated with trading risk (such as market volatility and inventory holdings) tend to magnify both profits and losses, and thus on net increase profits. While HFTs have high Sharpe ratios, there is still a tradeoff between risk and reward. Perhaps not surprisingly, traders that trade more earn larger profits, though the relationship is one of diminishing returns. We also find that aggressiveness, both overall (permanent aggressiveness) and at a given time (transient aggressiveness), is important. Both permanent and transitory aggressiveness are associated with a positive shift in HFT profits.

The rest of the paper is as follows. Section II describes the data. Section III examines the univariate characteristics of HFTs' profits. Section IV studies the cross sectional and time series profitability of HFT. Section V discusses the findings and Section VI concludes.

## II. Data

We use transaction-level data for the September 2010 E-mini S&P 500 futures contract for the month of August 2010.[5] During August 2010, the September 2010 contract is the front-month contract - the contract with the nearest expiration date – and has the highest volume and open interest of all open contracts. 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. In addition, the data contain a variable identifying the buyer and seller at the user-level and identifies which

[5] It is possible that August 2010 is an anomaly and our results are specific to the month. Because of data limitations we cannot analyze a longer time series. However, we ran our analysis on May 2010 and in fact find *stronger* profitability results. However, we do not include these results due to the highly irregular market conditions of May 6, 2010.

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.[6]

In addition, minimal requirements exist that prevent entities from engaging in HFT and a HFT firm's operating costs are relatively low.[7] 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 their trading activity is in explicit pursuit of profits.

[6] 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.
[7] Such costs include co-located servers, data feeds, and exchange fees.

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; 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.[8] 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. This paper finds 31 firms that meet the definition.

The precise selection criteria are as follows. For each day there are three categories a potential trader must satisfy to be considered a HFT: (1) Trade more than 10,000 contracts; (2) have an end-of-day inventory position of no more than 2% of the total contracts the firm traded that day; (3) have a maximum variation in inventory scaled by total contracts traded of less than 15%. A firm must meet all three criteria on a given day to be considered engaging in HFT for that day. Furthermore, to be labeled an HFT firm for the purposes of this study, a firm must be labeled as engaging in HFT activity in at least 50% of the days it trades and must trade at least

[8] 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.

50% of possible trading days. So, for instance, if a firm meets all three criteria in 15 trading days in August and trades during 20 days, that firm will be deemed to be a HFT firm. However, if the firm meets all three HFT criteria for only 5 of its 20 trading days, it will not be labeled as a HFT firm.

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, must also initiate at least 40% of the trades it enters into, and must do so for at least 50% of the trading days in which it is active. To be considered a Passive HFT a firm must initiate fewer than 20% of the trades it enters into, and must do so for at least 50% of the trading days during which it is active. Those HFTs that meet neither the Aggressive nor the Passive definition are labeled as Mixed HFTs. There are 10 Aggressive, 11 Mixed, and 10 Passive HFTs.

We classify non-HFT firm in to 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 on a particular day: (1) provides liquidity in at least 80% of the trades it enters into, (2) has an end-of-day inventory position of no more than 15% of the total contracts the firm traded that day, and (3) trades at least 100 contracts per day. To be considered a Non-HFT Market Maker, a firm must trade at least one contract 50% of the days in the sample, and meet the above definition for at least 70% of the trading days during which it is active. We identify 47 Non-HFT Market Makers in our sample. The Non-HFT Market Maker category captures traditional market makers examined by Hasbrouck (1993) and Coughenour and Saad (2004).

Fundamental traders and Small traders are defined on a daily basis. A firm may be considered a Fundamental trader one day but not the next. 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 at least 5,000 contracts (about $300 million), and (2) accumulates a net end-of-day position of at least 15% of the total daily volume traded by that firm. Such firms generally represent traders who are interested in taking large directional positions and holding them overnight. There are 157 firms classified as Fundamental traders on at least one day.

Small traders are defined as firms that trade less than 10 contracts a day. This is the majority of traders, with 25,150 participants. The remaining 6,008 firms do not fit in the specified categories and are therefore grouped into the Opportunistic category. 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

We designate each of the 31,403 trading firms into one of seven categories: Aggressive HFT (10), Mixed HFT (11), Passive HFT (10), Non-HFT Market Maker (47), Fundamental (157), Small (25,150), and Opportunistic (6,008). Table 1 presents a summary of trading behavior for different traders.

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 / market volume), the daily aggressiveness ratios (aggressive contracts by trader category / total contracts by type), 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 46.8% of the double-counted trading volume $\left(\frac{Buys_{HFT} + Sells_{HFT}}{2 * MktVolume}\right)$, or 1.49 million contracts daily (Row 1+2+3). The largest category is Opportunistic, with 42.6% of contract volume by its 6,008 participants (Row 7). The variation within the HFT categories over different days is considerable. For example, Aggressive HFTs range from 20.5% to 30.2% of market volume across days, and they have the smallest variation of the three HFT categories (Row 1).

Passive HFTs make up a significantly smaller portion of HFT volume (6.18%, Row 3) than Aggressive HFTs (25%, Row 1). The contrast between the HFT types is large: for example, Aggressive HFTs take 33.8% of market liquidity (Row 9), while Passive HFTs take only 1.55% (Row 11). In terms of their respective aggressiveness, that equates to Aggressive HFTs taking liquidity in 67.7% (Row 17) of the contracts they trade and Passive HFTs only taking liquidity in 12.6% (Row 19). The trade size between the categories also varies substantially: Aggressive HFTs' average trade size is 5.51 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 5.5 average trade size (Row 28) compared to Non-HFT Market Makers' 2.9 (Row 29).

Table 2 presents the fraction of trading between different market participants.

INSERT TABLE 2 ABOUT HERE

The rows represent the aggressive market participant of a trade and the columns represent the passive market participant. The reported statistics are the percent of trades between the respective aggressive-passive parties as identified in the rows and columns. The statistic underneath is the expected amount of trading between the two parties if trading were independent (i.e. calculated by multiplying their marginal frequencies). The *Total* row is the percent of trades in which the column-identified market participant participates.[9] The *Total* column is the same for the row-identified market participant. Column 8 Row 8 shows that in August 2010 35,057,121 contracts were traded.

A notable regularity appears: Aggressive and Mixed HFTs trade with non-HFTs *more* often than they should if trading pairs were unconditionally independent, and trade with each other less than expected.[10] For example, Column 1 Row 1 shows that Aggressive HFTs trade with Aggressive HFTs 4.16% of the time, while the expected amount of trading between two Aggressive HFTs is 5.35% if traders were matched independently. Across types it is true as well. Column 1 Row 3 shows Aggressive HFTs trade with Passive HFTs 3.33% of the time while independent matching would result in 3.64%. At the same time, HFTs trade more with non-HFTs. For instance, Column 6 Row 1 shows Aggressive HFTs initiate trades with Opportunistic traders 14.53% of the time, when we expected them to do so 12.6% of the time. Column 1 Row 6 shows that Aggressive HFTs supply liquidity to Opportunistic traders 8.68% of the time when we expect them to do so 7.57% of the time. While in this market, traders are not allowed to choose the counterparties of their trades, Table 2 shows that HFTs indirectly prefer to trade with some participants more than others. This phenomenon is not due to the fact that HFTs are less aggressive as a whole than the average trader: our scheme of placing the aggressive trades on the rows and the passive trades the on column controls for differences in aggressiveness.

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[9] Note that these row totals for aggressive trading are slightly different from the corresponding numbers in Table 1, Panel B. The reason is that the numbers in Table 1, Panel B are means across days, where each day is given equal weighting, whereas these numbers are computed for the month as a whole.
[10] This is true for all HFT-HFT pairs, except for when Passive HFTs are the aggressive party (Row 3).

Table 2 also shows that together, HFTs participate on the aggressive side of trades 49.05% percent of the time (Column 8 Rows 1+2+3). They are on the passive side of trades 44.18% percent of the time (Column 1+2+3 Row 8). HFTs are thus involved on one or both sides of a traded contract 74.6% of the time (Total aggressive side HFT + Total passive side HFT - HFT-to-HFT trading [18.62%]). The double-counted volume from HFTs is 46.62%. To emphasize, 46.62% of trading volume comes from a mere 31 trading firms: 31/31,403 or 0.09% of trading firms make up almost half of all the trading volume seen in the E-mini S&P 500.

### c. HFT Inventory Management and Risk Characteristics

To generate trading profits a trader must enter into a position in an asset and hold it for a period of time. Table 3 focuses on how HFTs manage their inventory. Panel A reports the end-of-day level of inventory held by HFT firms. Panel B reports the maximum daily deviation from zero a HFT firm holds in inventory, scaled by its activity for that day.

INSERT TABLE 3 ABOUT HERE

Each variable is calculated at the day level. Panel A Column 5 provides evidence of a notable characteristic of HFTs –the median HFT firm has *zero* overnight inventory and this is true regardless of the type of HFT. Column 2 Row 4 shows that the average HFT holds a -9.8 inventory position over night. The mean varies slightly among the different HFT types. Column 3 shows that the distribution of *End of Day Inventory* is much wider – overall a one standard deviation is 414 contracts. Passive HFTs take the least risk – with a standard deviation of only 141 contracts. Mixed HFTs take on the most inventory risk with a standard deviation in overnight inventory of 639 contracts. While these values are relatively large, they should be put in perspective. From Table 1 (Row 3) a Passive HFT firm trades on average of 19,696

(6.18%*3,187,011/10) contracts per day and (Row 2) a Mixed HFT firm trade 45,169 (15.59%*3,187,011/11) contracts. The *End of Day Inventory* size is minimal in comparison.[11]

Whereas Panel A in Table 3 shows that HFTs rarely hold risk overnight, Panel B provides insight into the risk management of HFTs during the trading day. The reported statistic is the maximum daily inventory position (in absolute terms) accumulated by any HFT, scaled by the trader's total trading that day. Beyond managing inventory at the end of the day, HFTs actively limit the positions they take intraday. Column 3, Row 4 shows HFTs on average carry an inventory of 2% of their total trading volume. From Table 1, that equates to 963 contracts. Like their end-of-day inventory, HFTs tightly regulate their intraday inventory risk. The rank order of risk management is the same intraday as it is in Panel A: Passive HFTs have the strictest average inventory limit (1.1%) and Mixed HFTs have the least stringent (2.6%). While most trader-days experience low inventory positions, occasionally HFTs (except Passive HFTs) take on a directional position with their trades.

## III. The Profitability of High Frequency Traders

We consider four key aspects of profitability. First we show that HFT profits are on average positive and that firm-day profits have a wide distribution. This finding raises three questions that we address in the rest of the section. First, whether these profits are persistent or whether they occur sporadically. Second, whether, after taking into account risk, HFTs generate abnormal returns. Finally, what types of trades are profitable, in particular over what investment horizon do HFTs realize their profits? We find strong evidence consistent with HFTs earning persistent profits that result in high Sharpe ratios, and these profits mainly come from very short term positions.

[11] One of the requirements to be categorized as a HFT firm is that the trader have an end-of-day position of less than 2% of that firm's total daily volume. Panel A of Table 3 shows this restriction is rarely binding.

## a. The Distribution of HFT Profits

Average daily profits of HFTs are reported in Panel A of Table 4. Profits, $\pi_{i,t}$ , for each HFT firm $i$ are calculated for each trading day $t$ according to marked-to-market accounting, assuming that each trader starts each day with a zero inventory position. More precisely, for each trader, we calculate the end-of-day profits as the cumulative cash received from selling short positions minus the cash paid from buying long positions, plus the value of any outstanding positions at the end-of-day, marked to the market price at close:

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

Where $n=1...N_i$ indexes the trades for trader $i$ between the start of the trading day ($s=0$) and the end of the trading day ($s=T$), $p_s$ 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.[12]

INSERT TABLE 4 ABOUT HERE

On average, an HFT makes $46,039 per day in gross trading profits (Column 2). However, the aggregated average HFT profitability masks the heterogeneity in profitability across the three sub-types: a Passive HFT earns only $5,484 per day, while a Mixed HFT earns $35,562. The average Aggressive HFT though performs significantly better than both of the other two types, earning $95,508. 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

[12] As exhibited in Table 3 Panel A, on a median day, HFTs end the day with zero inventory and so the marking-to-market at the end of the trading day is relatively innocuous.

is a wide distribution of profitability. The standard deviation of the profits (Column 4) is 237,608, with Mixed HFTs realizing the highest variation in profits and Passive HFTs the lowest. 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, especially in the upper tail.

The top graph in Figure 1 presents the trader-day distribution of profits overall and for the three types of HFTs.[13] The figure complements Table 4 by depicting the non-normality of the profit distribution of HFTs.[14] In particular, it shows both the magnitude of HFT profits, as well as their variability. Aggressive and Mixed HFTs contain a significant mass in the upper tail of their profit distribution. However, all HFT types also experience days with large losses.

INSERT FIGURE 1 ABOUT HERE

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 show that while some HFTs may be providing liquidity and making markets, others are not.

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 31 HFTs in August 2010 earn an aggregate of $29.3 million dollars in gross trading profits.[15] Annually, this corresponds to a profit of over $350 million.

While HFT strategies are highly profitable, they are also risky on a day-to-day basis. As discussed above, Table 4, Panel A, Row 4 shows the average daily profit for a given HFT is

[13] If a trader's profits are greater than $250,000 or less than -$250,000 the extreme values are placed in the > *$250,000* or < *-$250,000* bin, respectively.
[14] The Shapiro-Wilk normality test statistic shows that the distributions of all the different profitability distributions are highly non-normal.
[15] We also calculate the total profits of these 31 HFT firms 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. Their total monthly profits calculated this way is slightly higher at $30,140,078.

$46,039 but the standard deviation is $237,608, almost five times the average. Thus, while it is possible for HFTs to earn substantial daily profits, it is also possible to lose large amounts. Figure 1 shows that, while on average HFTs are profitable, there are a number of trader-days in which they lose money. In Table 4, we see that several HFTs even lose over a million dollars in a single day.

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 $\sigma$ = $250,000, similar to what we find in Table 4,[16] and if each trader has initial capital, $V_0$ = $10 million that it can deploy on any given day[17], 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 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 > 99.8%, and the probability of an HFT at least doubling its initial capital after a year is about 63%.

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. Mixed HFTs can lose over one million dollars on a bad

[16] These assumptions are approximately true. We construct an autocorrelogram across days which shows that the correlation decays rapidly (results available upon request).
[17] 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.

day (Column 9). Across all 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 $6.9 per dollar of average profit, whereas Mixed and Passive HFTs have days were they realize losses of $35.61 and $29.92 per dollar of average profit, respectively (Column 10).

Table 4, Panel B 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. All HFT types make statistically significant non-zero profits per contract, and there is a wide distribution of profits. The lower graph in Figure 1 shows the daily profits of HFTs, scaled by the number of contracts traded.

### b. Persistence of profits

The previous results 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. Table 5 reports the trader-level consistency of HFT profitability over time.

INSERT TABLE 5 ABOUT HERE

Column 2, *% Profitability*, reports the percent of firm-days that are profitable. HFTs are profitable more often than not. In 74% of firm-days, HFTs earn positive gross trading profits. Aggressive HFTs are the least frequently profitable at 68% of the firm-days. Passive HFTs are profitable slightly less often than Mixed HFTs at 71% compared to 76%.

The consistency of the HFTs' profitability across time varies. Columns 3, 4 and 5 capture this variation. The third Column, *% Profitable ≥ 90%*, measures the fraction of traders profitable more than 90% of the time. 13% of HFTs are profitable at least nine out of every ten trading days. Aggressive HFTs are the most likely to exhibit this level of consistency. The fourth Column, *% Profitable ≥ 75%* measures the fraction of traders profitable greater than 75% of the trading days. 55% of HFTs are profitable within this range. Passive HFTs are the most likely to be in this category. Column 5, *% Profitable ≥ 50%,* measures the fraction of traders profitable greater than 50% of the trading days. Only 13% of HFTs lose money on more days than they make it.

### c. Sharpe Ratios

Trading profits provide insight into the magnitude of HFTs' profits, but the variable of interest to financial economists is risk-adjusted performance. We now evaluate the Sharpe ratios of HFTs. Table 6, Panel A reports the Sharpe ratio based on daily profits (Sharpe, 1966). The Sharpe ratio for each trader is calculated as:

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

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.[18]

INSERT TABLE 6 ABOUT HERE

[18] 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 was so low as to make it an inconsequential value. The Effective Fed Funds Rate in August 2010 was 0.19% (research.stlouisfed.org).

According to Table 6, HFTs earn above-average gross rates of return for the amount of risk they take. This is true overall and for each type. Column 1 reports the average annualized Sharpe ratio statistics. Overall, the average annualized Sharpe ratio for an HFT is 9.2.[19] Among the subcategories, Aggressive HFTs (8.46) exhibit the lowest risk-return tradeoff, while Passive HFTs do slightly better (8.56) and Mixed HFTs achieve the best performance (10.46). Column 2 and 4 report the 25$^{th}$ and 75$^{th}$ percentile of Sharpe ratios. The distribution is wide, with an inter-quartile range of 2.23 to 13.89 for all HFTs. Nonetheless, even the low end of HFT risk-adjusted performance is seven times higher than the Sharpe ratio of the S&P 500 (0.31) (Fama and French, 2002).

Panel B of Table 6 calculates the Sharpe ratio using day profit-per-contract-traded as the measure of return. The results could change dramatically, in either direction, depending on whether number of contracts traded increases or decreases with profitability. Suppose that some HFTs have better signals and are able to more precisely determine whether a trade will be profitable. It could be that such a trader trades *more* as it receives a more accurate signal. On the other hand, the trader could trade *less* as fewer trades meet its signal criteria. In the first scenario we would expect the Sharpe ratio to increase whereas in the second scenario it would decrease. The average results remain high (8.88) like in Panel A, as does the distribution. While we do not test for statistical significance the Aggressive and Mixed HFTs' results are consistent with more profitable traders trading more, as demonstrated by the higher Sharpe ratios (this shows up in the average result (Column 1) and especially the 75$^{th}$ percentile (Column 4)). The reverse is true for the Passive HFTs.

### d. Spectral Analysis

[19] We also calculate Sharpe ratios over hourly intervals rather than daily intervals and find qualitatively similar results.

To understand the investment horizon of HFTs, we follow Hasbrouck and Sofianos (1993) and decompose HFT profits over different time horizons using spectral analysis. The time-horizon over which HFTs make their profits provides insight into their trading strategies and allows us to further examine the differences between the types of HFTs. 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. If the two time series 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.

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.

Mathematically, we express mark-to-market profits for any individual trader at time τ 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):

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

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 frequency ω. For example, if a HFT firm cycles in and out of a position every 100 market transactions, then $2 * Real\left(\hat{x}(\omega)\overline{\widehat{\Delta p}(\omega)}\right)$ is the magnitude of those profits with ω=100.

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+ 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 sample. Also, for each trader and day, we calculate profits per contract traded. For HFT as a whole and for each of its sub-types we take the median and the 25th and 75th percentiles across firms of both profits and profits per contract. The profits results are in Table 7 Panel A and the profits per contract results are in Panel B.

INSERT TABLE 7 ABOUT HERE

Row 1 in Table 7 Panel A shows that Aggressive HFTs tend to make positive profits at short time scales, in the 11-100 and 101-1000 transaction range (Columns 2 and 3), with negative profits at the extremely short range (Column 1, 1-10 transaction interval) and longer time scales of 1,001-10,000 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 for this reason Aggressive HFTs fail to make money at the shortest time intervals. While Aggressive HFTs also tend to make positive profits at the 10,000+ transactions interval, the size of these profits are small. The spectral analysis results are consistent with the notion that Aggressive HFTs make money by entering into short-lived profit opportunities and quickly unwinding their positions.

In contrast, both Mixed and Passive HFTs tend to lose money at short time scales (1-10, 11-100, and 101-1,000 transactions). While making money on longer time scales (1,001-10,000 and 10,000+ transactions). These results are consistent with the idea that Mixed and Passive HFTs do not generally aggressively unload their positions but wait until they can passively sell off their inventory. The losses on a shorter time scale could reflect Mixed and Passive HFTs being adversely selected during short horizons. However, these losses are compensated for by their longer holdings.

## IV. How do HFTs make profits?

Taking the above results as given, we now study how and when HFTs earn their profits. We begin by tabulating the counterparties from which HFTs earn their profits. We then test a variety of hypotheses regarding HFT profits at 10 second intervals.

### a. HFT Profits by Counterparty

Table 8 breaks down the trading profits by trading pairs: 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.

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) losses 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.

We construct Table 8 by considering *only* the trades between two groups and calculating the profit flows that result from those trades. To illustrate, we calculate the HFT-Fundamental profit flows by removing all trades except those for which one party was an 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 8 are the implied short-term profits: we 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. Table 8 reports the average daily trading profits over August 2010. Since the futures market is a zero-sum game, the resulting profits matrix is symmetrical and zero along the diagonals.[20]

INSERT TABLE 8 ABOUT HERE

On average HFTs make positive profits from *all* other types of traders. Row 2 of Panel A, Table 8 shows that on an average day, HFTs (in aggregate) make $146,005 from Fundamental investors, $89,874 from Non-HFT Market Makers, $50,328 from Small traders, and $1,616,219

[20] A limitation of the approach taken in Table 8 is that it can only measure profits from direct order flow.

from Opportunistic traders.[21] While Mixed and Passive 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, $-212,463), and Passive HFTs lose money to both Aggressive HFTs (Column 4, Row 5, $-114,028) and Mixed HFTs (Column 5, Row 4, $-1,907).

Panel B of Table 8 expresses the trading profits between groups as a percentage of a group's total profit.[22] For example, Column 1, Row 2 is the percent of HFTs' profit derived from trading with Fundamental traders: HFTs earn 7.67% of their profits from trading with Fundamental traders. For groups that have net losses (Fundamental, Passive HFTs, Non-HFT Market Makers, Small Trader, and Opportunistic), Panel B expresses the percent of total losses: For example Column 2, Row 6 shows that 60.21% of all Fundamental traders' loses are from trades with HFTs.

Row 1 of the table shows that HFTs make most of their profits from trading with Opportunistic (84.96%) and Fundamental (7.67%) 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 HFTs normally close their positions at the end of the trading day, their profits can be interpreted as transaction costs extracted from the rest of the market, not gains from long-term directional positions. For example, Fundamental traders incur a loss of -$1.22 (Column 2, Row 1) when trading with HFTs, while Small traders experience a much larger loss of -$4.42 (Column

[21] Note that the profit/trade results in Table 8 deviate slightly from the results of Table 4. The reason is that in Table 4 each day's value is equally weighted. Here the analysis is volume weighted and we are evaluating implied short-term profits.
[22] Note, each row sums to 100% when either only Column 2 (HFT) or Columns 3, 4, and 5 (the HFT types) are considered.

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 HFTs collect $0.91 per contract (Column 9, Row 2) over 47% of the volume (Table 2), while everyone else loses while trading 53% (=100% - 47%) of the volume, the effective HFT imposed transaction cost on non-HFT traders is $0.91*(0.53/0.47) = $1.03 per contract. Scaling this per-contract transaction cost by $50,000 - the approximate price of a contract - yields an estimated HFT-imposed transaction cost of 0.002%.

### b. Analysis of Intraday HFT Profits

Having examined from *whom* HFTs earn their profits we address in further detail how and when HFTs accumulate their profits. We examine HFT profits using 10-second windows.[23] The advantage of this 10-second intraday approach is the fine temporal resolution of the determinants of profits; the disadvantage is that over 10 seconds profits have to be valued using marked-to-market accounting, so the reported profits will be a mix of realized and unrealized profits. However, since the holding time for positions by HFTs are short, on the order of seconds, 10 seconds captures a significant portion of realized profits and not unrealized profits.

To perform intra-day profit analysis, we divide up the standard trading day into 10-second time intervals and calculate characteristics of the market and of individual HFTs based on each 10-second interval. The analysis is performed on log profits. Consequently, non-positive profits must be handled separately. We separate profits and losses into two groups and perform

[23] We perform the same analysis on 1-, 2-, and 5-second windows and get qualitatively similar results.

regressions on the two separately using the logarithm of the absolute value of the profit or loss. While this resolves a technical issue it also allows for the comparison of profit and loss dynamics.

We estimate the following log-linear regression equation for HFTs:

$$\begin{gathered} Log(\pi_{i,s}) = \alpha + Log\big(AccountVolume_{i,s}\big)\beta_1 + Log(Volatility_s)\beta_2 + FirmAggr_{i,s}\beta_3 \\ +FirmAvgAggr_i\beta_4 + FirmInvRange_{i,s}\beta_5 + Log(|FirmNetPosition_{i,s}|)\beta_6 \\ + Log(MktVolume_s)\beta_7 + \varepsilon_{i,s}, \end{gathered} \tag{7}$$

where $s$ indexes 10-second intervals and $i$ indexes the HFTs.[24] The dependent variable is the log of the absolute value of HFT profits or losses, $Log(\pi_{i,s})$, calculated according to Equation 1, that trader $i$ generates within 10-second interval $s$. The regressors are: $Log(FirmVolume_{i,s})$ the log of each trader's trading volume within the interval; $Volatility_s$ , the price volatility within the interval, defined as the (volume-weighted) standard deviation of the price process within the interval; $FirmAggr_{i,s}$ , trader $i$'s aggressiveness ratio within the 10-second interval; $FirmAvgAgg_i$, trader $i$'s aggressiveness ratio over the entire month; $FirmInvRange_{i,s}$, the (volume-weighted) standard deviation of the trader's inventory position within the interval, scaled by $10^{-3}$; $Log(FirmNetPosition_{i,s})$, the absolute value of the trader's net position at the start of the interval; and $Log(MktVolume_s)$, the log of the total market trading volume within the interval. Table 9 reports the results. Standard errors are clustered by day.

INSERT TABLE 9 ABOUT HERE

### Profit Scalability

[24] As a notational convention, we use $t$ to index time in days and $s$ to index 10-second intervals.

To test whether the trading strategies of HFTs are scalable we include two variables in the regression: *Log(FirmVolume$_{i,s}$)* and *Log(MktVolume$_{s}$)*. These variables capture two types of scalability – trader-level activity scalability and market-level activity scalability. If HFT strategies are scalable we expect the coefficients on one or both of these coefficients to be near one. While we do not have strong priors on which type of HFTs may be more competitive, the lower profit results in Table 4 Panel B for Passive HFTs may be indicative of a more competitive environment.

For HFTs as a whole and among the three sub-types, higher profits and higher losses are associated both with increased trading on the part of the trader and by the market as a whole. Market and firm trading volume has a magnifying effect on profits and losses. A 1% increase in firm volume and total market volume is associated with a 0.13% and 0.057% increase in profits, respectively, and a 0.114% and 0.0187% increase in losses, respectively. The coefficient on *Log(FirmVolume$_{i,s}$)* shows profits exhibit decreasing returns to scale with volume - profit per contract decreases with increasing trading volume. The most profitable firms trade higher volume, but at a lower profit per contract. For HFTs as a whole the coefficient on *Log(MktVolume$_{s}$)* is 0.057, implying that profits also scale sub-linearly with market trading volume.

Among the sub-types of HFT, Passive HFTs exhibit a slightly more scalable trading strategy than Aggressive HFTs (0.2 compared to 0.0994). The opposite is true for overall market value (0.0397 compared to 0.0622). However this is not the case for losses.

### Aggressiveness

A firm's strategy likely dictates the types of orders it places. Aggressive HFTs need to overcome the bid-ask spread to be profitable, but can choose precisely when to execute a trade. Passive HFTs have the opposite tradeoff – they capture the bid-ask spread, but make themselves available to trade over the life of the limit order and are subject to being adversely selected by other traders. We capture permanent aggressiveness with $FirmAvgAggr_i$ and transient aggressiveness with $FirmAggr_{i,s}$.

The $FirmAggr_{i,s}$ coefficients in Table 9 show that for HFTs as a whole higher transient aggressiveness is associated with higher profits with a coefficient of 0.404 for profits (Column 1) and -0.393 for losses (Column 5). High transient aggressiveness is associated with higher profitability (higher profits, smaller losses). Columns 2 – 4 and 6 – 8 show a similar qualitative story for the three sub-types – transitory aggressiveness is profitable. This suggests that HFTs, as a whole and within each sub-type, aggressively act on profitable opportunities, regardless of their normal behavior.

Unlike transient aggressiveness, permanent aggressiveness, captured by $FirmAvgAggr_i$, magnifies profits and losses (Coefficient of 0.589 and 0.351 in Columns 1 and 5, respectively). The sub-type matters. Within Aggressive HFTs, aggressiveness tends to decrease profits and increase losses (-0.114 and 1.16 for profits and losses, respectively), while more aggressive Mixed HFTs are less profitable (-1.24) and have smaller losses (-0.221). More aggressive Passive HFTs are more profitable (0.742) but also have larger losses (0.119).

**Risk**

Section III.c addresses the risk-reward tradeoff using the Sharpe ratio. The Sharpe ratio measures the riskiness of the realized outcomes. This section extends the analysis of the riskiness of HFT trading strategies by looking at their exposure to potentially detrimental price movements. Risk is measured in three ways: (i) $FirmInvRange_{i,s}$, to capture a HFT firm's willingness to take over a high-frequency time-scale. Larger positions mean more risk. (ii) $Log(FirmNetPosition_{i,s})$ to highlight whether HFTs are compensated for holding longer-term directional positions – positions across 10-second intervals. The longer a holding period the more risk associated with it, and so expect a positive association with higher profits. (iii) $Volatility_s$, to identify the role of exposure to market riskiness.

Taking on more risk through higher inventory positions ($FirmInvRange_{i,s}$) amplifies profits and losses (Coefficients in Columns 1 of 0.315 and Column 5 of 0.609). Note that the definition of $FirmInvRange_{i,s}$ is scaled by $10^{-3}$, so the interpretation is that a 1000-contract increase for an HFT's inventory range is associated with a 31.5% increase in a HFT firm's profitability and 60.9% increase in losses during that interval. While HFTs are highly profitable, there is still a risk-reward tradeoff measuring risk by inventory range. We do not have a clear hypothesis why the risk-reward tradeoff might be higher for some HFTs than others but do document a wide variation among the sub-types: Mixed HFTs experience a relatively low relation (0.0474 and statistically insignificant for profits and 0.258 for losses), Aggressive HFTs a moderate one (0.596 for profits and .808 for losses), and Passive HFTs an unusually large relationship (2.8 for profits and 2.15 for losses).

A firm's willingness to hold longer positions, $Log(FirmNetPosition_{i,s})$, is also strongly related to profitability with a coefficient of 0.639 for profits and 0.761 for losses. Again, risk amplifies the profits and losses. Among the different sub-types there is little variation in the coefficient size.

Finally market variability, $Volatility_s$, magnifies profits and losses. Since profits depend on the size of price changes, one might expect profits and losses to scale linearly with the size of price changes and hence the volatility. However, For HFTs as a whole, the coefficients are 0.201 for profits (Column 1) and 0.163 for losses (Column 5). The sub-types behave similarly.

## V. Discussion

The analysis in this paper touch on three important economic questions: 1) Are HFTs liquidity providers? 2) Are financial markets efficient at high frequencies? 3) Is the market for HFT competitive? We discuss these questions one by one.

**Are HFTs liquidity providers?**

HFTs assert that they enhance market quality through their liquidity provision. While our paper finds that the majority of HFT firms are liquidity providers and that HFTs more often than not (60%) provide liquidity, many HFTs in our sample (i.e. most of the Aggressive HFTs) are on net liquidity takers. Some of these HFTs are almost 100% liquidity takers, and these firms are also the most profitable and active on the markets.

For exchanges and regulators, it is important to recognize the heterogeneity in liquidity provision and design rules to target different HFT strategies accordingly: it could be, for example, that Mixed and Passive HFTs play an important market role by competing to provide liquidity, while Aggressive HFTs could add or subtract to market quality in other ways. Aggressive HFTs could be predatory and extract rents from slower or less informed traders, or they may provide value by correcting transient price deviations and thus leading to lower volatility and better price discovery. They could also facilitate the rapid execution of passive limit orders placed by fundamental traders: some fundamental traders may prefer to place limit orders passively in order to capture the spread. Nevertheless, we find wide variation in the activities of HFTs, which should be taken into consideration for future research and policy implementation.

**Are financial markets efficient at high frequencies?**

The semi-strong form of the efficient market hypothesis (EMH) asserts that the current market price reflects all public information, so that no group of investors should be able to consistently earn excess returns on the basis of these two pieces of information alone. Following

Grossman and Stiglitz (1980), the EMH does allow for certain classes of investors who can establish a cost-advantage (either in better information collection, lower transaction costs or faster trading speed) to earn excess returns over investors who do not possess such an advantage. However, under this scenario, the EMH dictates that the excess returns should be equal to the cost of the technology (this assumes perfect competition, which according to our third point below may not be the case) – so that the net excess returns of high-frequency trading (after factoring in these costs) should be zero.

HFTs earn large gross profits that appear to be above the market rate for risk taking: their average Sharpe ratio is over 25 times that of the S&P 500 index. These findings are inconsistent with the EMH. Besides investing in speed-reducing technologies to capture profits, the data show HFTs carefully manage inventory to reduce risk, which results in high Sharpe ratios by reducing risk. While we are unable measure the net returns of HFTs (including computer systems, labor, overhead, risk management systems, etc), the magnitude of their profits suggests that HFTs still earn significant excess returns even after accounting for their costs. The magnitude of their profits brings into question the efficiency of markets at high-frequency time scales.

**Is the HFT market competitive?**

A high level of market competition among HFTs and other intermediaries is important as it is believed to lead to better price discovery, faster execution, and lower trading costs for all market participants. In a competitive environment revenue from intermediation would be pushed down, as hypothesized by Grossman and Stiglitz (1980), to the marginal cost of extracting and reacting to information. However, in the August 2010 E-mini S&P 500 futures market a small number of HFTs seems to earn unusually high profits, and their revenues are not commensurate to their level of risk taking.

How can HFTs maintain consistently high profits without having their profits driven down by competition? Note that while Passive HFTs have high Sharpe ratios, their magnitude of profits are relatively small, suggesting that competition for liquidity provision may be driving down profits. In contrast, Aggressive HFTs, who earn the highest profits, seem to be unaffected by competitive forces. It may be that the profitability of Aggressive HFTs depends on their relative speed: in a winner-takes-all market, profits accrue almost entirely to the fastest. The speed and technological sophistication needed to compete with the most profitable firms may represent a barrier to entry in the HFT market. Perhaps a small competitive advantage early on, be it from experience (Seru, Shumway, and Stoffman, 2010) or intelligence (Grinblatt, Keloharju, and Linnainmaa, 2011), can be the difference in whether an HFT can consistently invest in ever more sophisticated technology and thus maintain a competitive advantage over rival firms. This hypothesis may explain the heavy upper tail in the distribution of profits observed in Section III.a.

An arms race for ever-increasing speed and technological sophistication raises questions about whether the speed of information incorporation into the market at the millisecond time horizon has social value. Hirshleifer (1971) argues that for markets in general there is probably over-investment in information collection, since there are often large private gains from investment in information collection when there are little or no social gains. This observation might be especially true in a market where traders invest in technologies to compete on speed, since it is the rank ordering of firms (in terms of speed and technological sophistication) that determines who receives the bulk of the profits. Competition for ever-increasing speed creates a "positional externality" (see Robert H. Frank, 2005), since attempting to be the fastest can only 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, see Lazear and Rosen, 1981), in the case of HFT, the positional externality may lead to a wasteful investment in technology and human capital.

## 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 trading risk (such as market volatility and inventory holdings), trading volume, and aggressiveness. Our findings shed light on the competitiveness of the HFT industry and provide insight into the efficiency of markets in very short periods.

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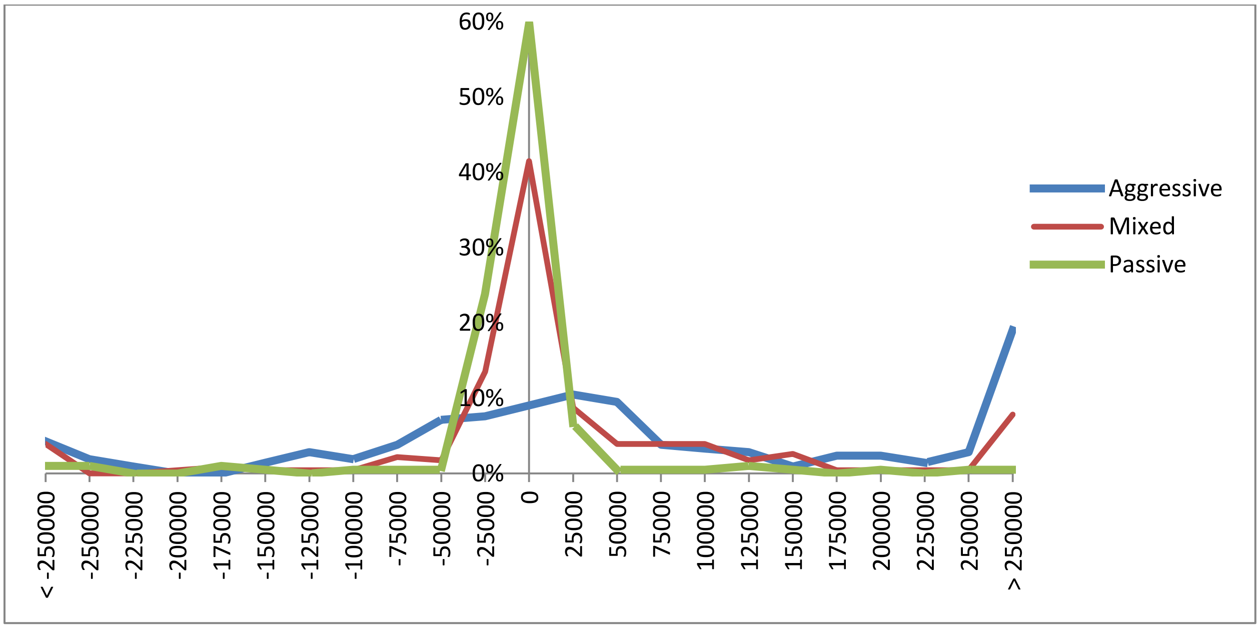
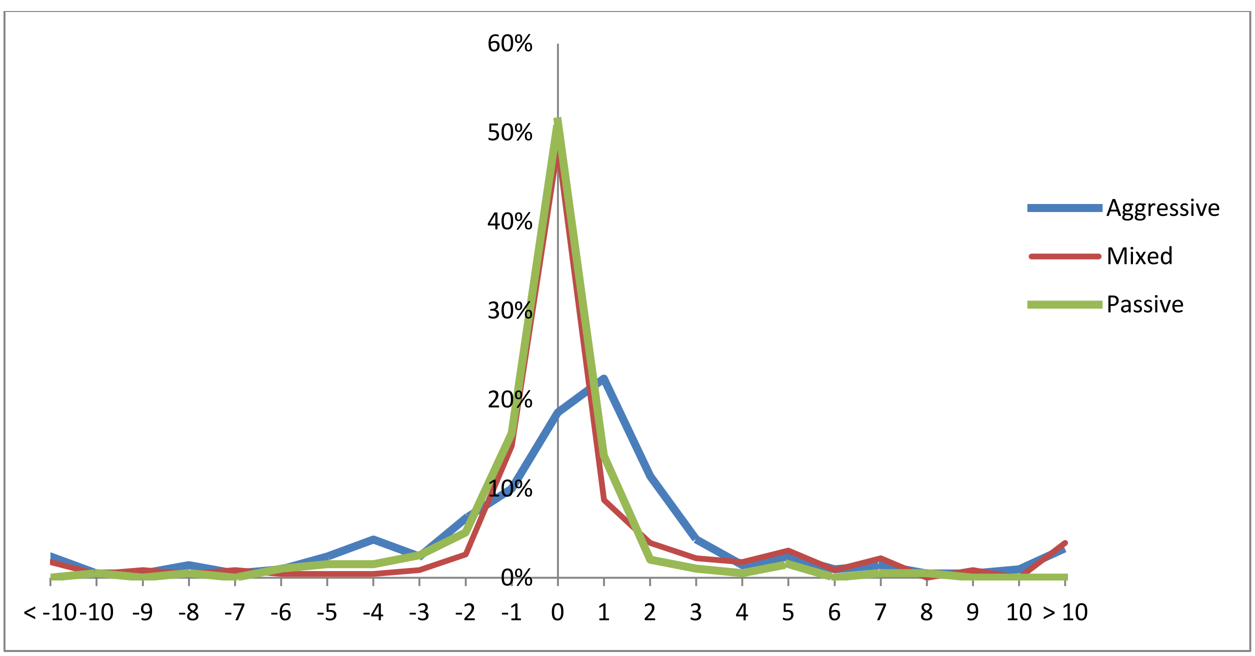
## Figure 1 Distribution of HFT day total profitability

The top graph, Profits, shows the distribution of day level profits of all HFTs and its three sub categories. The bottom graph, Profits per Contract, shows the distribution of day level profits per contract. If an HFT's profits are greater than $250,000 or less than -$250,000 the extreme values are placed in $250,000 or -$250,000 bin, respectively. The same winsorizing process is done in the Profits per Contract graph, but at the -$10 and $10 values.

### Profits




### Profits Per Contract



## 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. For each trader type 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 I each of the trader-type categories.

| **Daily % Market Volume** | **Mean** | **Std. Dev.** | **Min.** | **Median** | **Max** |
|---|---|---|---|---|---|
| $HFT^A$ (n=10) | 25.00% | 2.40% | 20.45% | 25.53% | 30.19% |
| $HFT^M$ (n=11) | 15.59% | 1.56% | 12.92% | 15.50% | 18.24% |
| $HFT^P$(n=10) | 6.18% | 0.86% | 4.52% | 6.17% | 7.77% |
| Fundamental (n=157) | 6.95% | 2.49% | 2.44% | 6.09% | 12.24% |
| Small Trader (n=25150) | 0.65% | 0.14% | 0.47% | 0.63% | 1.01% |
| Non-HFT Market Maker (n=47) | 3.05% | 0.34% | 2.26% | 3.04% | 3.62% |
| Opportunistic (n=6008) | 42.58% | 2.92% | 38.58% | 41.96% | 48.92% |
| Total (n=31403) | 3,187,011 | 819,419 | 1,652,052 | 3,081,016 | 4,465,574 |
| **Daily Aggressive Quantity** | | | | | |
| $HFT^A$ | 33.80% | 3.00% | 27.80% | 34.01% | 40.27% |
| $HFT^M$ | 9.06% | 1.25% | 6.87% | 9.09% | 11.49% |
| $HFT^P$ | 1.55% | 0.28% | 1.15% | 1.54% | 2.24% |
| Fundamental | 6.95% | 2.26% | 2.66% | 6.68% | 12.17% |
| Small Trader | 0.75% | 0.15% | 0.55% | 0.74% | 1.12% |
| Non-HFT Market Maker | 0.56% | 0.09% | 0.41% | 0.54% | 0.73% |
| Opportunistic | 47.34% | 2.80% | 41.98% | 47.37% | 52.97% |
| Total | 1,593,506 | 409,710 | 826,026 | 1,540,508 | 2,232,787 |
| **Daily Aggressive Ratio** | | | | | |
| $HFT^A$ | 67.70% | 2.10% | 62.30% | 67.90% | 71.60% |
| $HFT^M$ | 29.00% | 1.90% | 26.20% | 28.60% | 31.90% |
| $HFT^P$ | 12.60% | 2.00% | 9.80% | 11.80% | 16.70% |
| Fundamental | 51.10% | 6.60% | 38.20% | 49.90% | 63.60% |
| Small Trader | 57.90% | 1.10% | 55.40% | 57.70% | 60.00% |
| Non-HFT Market Maker | 9.10% | 0.90% | 7.30% | 9.10% | 10.60% |
| Opportunistic | 55.60% | 1.20% | 53.10% | 55.70% | 57.50% |
| **Daily Trade Size** | | | | | |
| $HFT^A$ | 5.51 | 0.34 | 5 | 5.45 | 6.19 |
| $HFT^M$ | 4.03 | 0.36 | 3.55 | 4.02 | 4.94 |
| $HFT^P$ | 2.31 | 0.23 | 1.81 | 2.32 | 2.78 |
| Fundamental | 5.51 | 0.98 | 4.28 | 5.44 | 8.14 |
| Small Trader | 1.2 | 0.01 | 1.18 | 1.2 | 1.22 |
| Non-HFT Market Maker | 2.9 | 0.32 | 2.28 | 2.89 | 3.65 |
| Opportunistic | 4.31 | 0.2 | 3.8 | 4.33 | 4.6 |

## Table 2 Trading Partners

The table tabulates the fraction of trading between different market participants. The different rows represent the aggressive market participant of a trade (the liquidity taker) and the columns represent the passive market participant (the liquidity supplier). The different trading type categories are HFT-Aggressive ($HFT^A$), HFT-Mixed ($HFT^M$), HFT-Passive ($HFT^P$), Fundamental, Small Trader, Non-HFT Market Maker, and Opportunistic. The reported statistics on top are the percent of trades between the respective aggressive-passive parties as identified in the rows and columns. The statistic in parenthesis is the expected amount of trading between the two parties if trading were independent (the row marginal frequency multiplied by the column marginal frequency). The *Total* row 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.

| | **Passive** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Aggressive** | **$HFT^A$** | **$HFT^M$** | **$HFT^P$** | **Fundamental** | **Non-HFT Market Maker** | **Opportunistic** | **Small Trader** | **Total** |
| **$HFT^A$** | 4.16% | 6.67% | 3.33% | 2.71% | 1.83% | 14.53% | 0.21% | 33.43% |
| | (5.35%) | (7.41%) | (3.64%) | (2.41%) | (1.84%) | (12.60%) | (0.17%) | |
| **$HFT^M$** | 1.25% | 1.52% | 0.90% | 0.79% | 0.54% | 4.12% | 0.07% | 9.20% |
| | (1.47%) | (2.04%) | (1.00%) | (0.66%) | (0.51%) | (3.47%) | (0.05%) | |
| **$HFT^P$** | 0.26% | 0.35% | 0.17% | 0.12% | 0.07% | 0.58% | 0.01% | 1.55% |
| | (0.25%) | (0.34%) | (0.17%) | (0.11%) | (0.09%) | (0.58%) | (0.01%) | |
| **Fundamental** | 1.41% | 1.66% | 0.81% | 0.53% | 0.37% | 2.39% | 0.03% | 7.20% |
| | (1.15%) | (1.59%) | (0.78%) | (0.52%) | (0.40%) | (2.71%) | (0.04%) | |
| **Non-HFT M.M** | 0.12% | 0.16% | 0.07% | 0.03% | 0.02% | 0.16% | 0.00% | 0.56% |
| | (0.09%) | (0.12%) | (0.06%) | (0.04%) | (0.03%) | (0.21%) | (0.00%) | |
| **Opportunistic** | 8.68% | 11.56% | 5.51% | 3.00% | 2.65% | 15.73% | 0.21% | 47.35% |
| | (7.57%) | (10.49%) | (5.16%) | (3.41%) | (2.61%) | (17.85%) | (0.25%) | |
| **Small Trader** | 0.12% | 0.22% | 0.10% | 0.03% | 0.04% | 0.20% | 0.00% | 0.71% |
| | (0.11%) | (0.16%) | (0.08%) | (0.05%) | (0.04%) | (0.27%) | (0.00%) | |
| **Total** | 16.00% | 22.16% | 10.90% | 7.21% | 5.52% | 37.70% | 0.52% | 35,057,121 |

## Table 3 Distribution of Risk Variables

Table reports key variables surrounding the level of risk HFTs incur. Panel A investigates the end-of-day level of inventory held by a HFT. Panel B reports the maximum daily deviation from zero a HFT holds in inventory, scaled by its activity for that day. Each variable is calculated at the day level. Within each panel there are four rows: $HFT^{A}$, $HFT^{M}$, $HFT^{P}$, and HFT, which analyzes Aggressive, Mixed, Passive, and All HFT respectively. The table reports the number of observations, mean, standard deviation, minimum, median, and maximum of the variable of interest.

**Panel A: End of Day Inventory**

| | N | Mean | Std. Dev. | Min. | Median | Max. |
|---|---|---|---|---|---|---|
| **$HFT^{A}$** | 210 | -12.2 | 237 | -1015 | 0 | 1016 |
| **$HFT^{M}$** | 229 | -12.4 | 639 | -3818 | 0 | 4312 |
| **$HFT^{P}$** | 197 | -4.3 | 141 | -799 | 0 | 814 |
| **HFT** | 636 | -9.8 | 414 | -3818 | 0 | 4312 |

**Panel B: Max. Inv. from 0 / Total Trades**

| | N | Mean | Std. Dev. | Min. | Median | Max. |
|---|---|---|---|---|---|---|
| **$HFT^{A}$** | 210 | 2.20% | 3.90% | 0.30% | 1.20% | 50% |
| **$HFT^{M}$** | 229 | 2.60% | 7.00% | 0.10% | 1.20% | 100% |
| **$HFT^{P}$** | 197 | 1.10% | 1.20% | 0.20% | 0.70% | 7.60% |
| **HFT** | 636 | 2.00% | 4.80% | 0.10% | 1.00% | 100% |

## Table 4 Distribution of HFT Daily Profits

Table reports the distribution of 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 four rows: $HFT^A$, $HFT^M$, $HFT^P$, and HFT, which analyzes Aggressive, Mixed, Passive, and All HFT respectively. The table 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 Panel B measure, *Daily Profit Per Contract*, scales *Daily Profit* by the number of trades by the HFT firm for that day.

**Panel A: Daily Profit**

| | N | Mean | Median | Std. Dev. | Skew. | Kurt. | P-Value | Total Monthly Profits | Max Loss | Max Loss Per Average Profit |
|---|---|---|---|---|---|---|---|---|---|---|
| **$HFT^A$** | 210 | $95,508 | $46,262 | $258,991 | 0.52 | 4.06 | <.0001 | $20,056,713 | -$876,938 | -$6.92 |
| **$HFT^M$** | 229 | $35,562 | $13,825 | $298,187 | -2.8 | 35.3 | 0.03 | $8,143,800 | -$2,661,600 | -$35.61 |
| **$HFT^P$** | 197 | $5,484 | $6,437 | $59,580 | -0.73 | 14.14 | 0.09 | $1,080,388 | -$323,163 | -$29.92 |
| **HFT** | 636 | $46,039 | $12,331 | $237,608 | -1.6 | 34.48 | <.0001 | $29,280,900 | -$2,661,600 | -$35.61 |

**Panel B: Daily Profit Per Trade**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **$HFT^A$** | 210 | $0.89 | $0.98 | 5.94 | 0.32 | 10.52 | 0.016 |
| **$HFT^M$** | 229 | $2.08 | $0.53 | 18.8 | 13.48 | 196.9 | 0.047 |
| **$HFT^P$** | 197 | $0.22 | $0.34 | 1.9 | -0.6 | 8.09 | 0.05 |
| **HFT** | 636 | $1.11 | $0.53 | 11.84 | 19.49 | 452 | 0.009 |

## Table 5 Consistency of HFT Profitability

The table reports the firm-level consistency of HFTs profitability over time. There are four rows: $HFT^A$, $HFT^M$, $HFT^P$, and HFT, which analyzes Aggressive, Mixed, Passive, and All HFT respectively. *# of Firm-Obs* is the number of observations; *% Firm-Obs Profitable* is the percent of firm-trading observations that are profitable. We measure the firm-trading profitability at the day level. Whether a firm is profitable, earning a positive amount in its trading activity, 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. *% Profitable ≥ 90%* is the fraction of firms profitable more than 90% of the time. *% Firms Profitable ≥ 75%* is the fraction of firms profitable greater than 75% of the time. *% Profitable ≥ 50%* is the fraction of firms profitable greater than 50% of the time.

| | **# of Firms-Obs** | **% Firm-Obs Profitable** | **% Firms Profitable ≥ 90%** | **% Firms Profitable ≥ 75%** | **% Firms Profitable ≥ 50%** |
|---|---|---|---|---|---|
| **$HFT^A$** | 210 | 68% | 20% | 40% | 80% |
| **$HFT^M$** | 229 | 76% | 9% | 54% | 100% |
| **$HFT^P$** | 197 | 71% | 10% | 70% | 80% |
| **HFT** | 636 | 74% | 13% | 55% | 87% |

## Table 6 Risk-Return Analysis (Sharpe Ratio)

The table analyzes HFTs risk-adjusted rate of return using the Sharpe ratio. The Sharpe ratio for each Panel is calculated as $SR_i = (r_i / \sigma_i) * \sqrt{252}$, where r is the average daily profit for firm *i* scaled by the maximum inventory dollar value of firm *i*, σ is the standard deviation of firm *i*'s profits, scaled by the maximum inventory dollar value of firm *i*. The maximum inventory dollar value captures the investable capital required by a firm and hence we can estimate returns. Note though, that since both the numerator and denominator are scaled accordingly, the values cancel. The risk-free rate is not subtracted from r as is normal because the time horizon (1-day) and the rate during August 2010 was so low as to make it an inconsequential value. Panel A calculates the Sharpe ratio using daily data; Panel B measures it using daily profit-per-trade as the measure of return. Within each Panel there are four rows: $HFT^A$, $HFT^M$, $HFT^P$, and HFT, which analyzes Aggressive, Mixed, Passive, and All HFT respectively. For each row the Mean, 25%, Median, and 75% levels of the HFTs' Sharpe ratios are reported.

**Panel A: Daily Profit**

| | **Mean** | **25%** | **Median** | **75%** |
|---|---|---|---|---|
| **$HFT^A$** | 8.46 | 2.3 | 8.08 | 13.89 |
| **$HFT^M$** | 10.46 | 2.23 | 13.23 | 17.11 |
| **$HFT^P$** | 8.56 | 1.27 | 9.47 | 13.22 |
| **HFT** | 9.2 | 2.23 | 9.7 | 13.89 |

**Panel B: Daily Profit per Trade**

| | **Mean** | **25%** | **Median** | **75%** |
|---|---|---|---|---|
| **$HFT^A$** | 8.82 | 1.02 | 6.24 | 18.11 |
| **$HFT^M$** | 11.08 | 2.21 | 14.04 | 20.92 |
| **$HFT^P$** | 6.51 | 1.16 | 7.72 | 9.87 |
| **HFT** | 8.88 | 1.16 | 7.49 | 17.7 |

## Table 7 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+ 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 25$^{th}$ and 75$^{th}$ percentiles across firms. In addition to decomposing gross trading profits (shown in Panel A), we do the same for profits per contract traded (Panel B), also taking each firm and day as a separate observation. The table shows that HFTs (column 1)as a whole lose money on shorter time scales (1-10, 11-100, and 101-1,000 transactions) but gain money on longer time scales (1001-10000 and 10000+ transactions). Among the three sub-types of HFTs, Aggressive HFTs tend to make positive profits at short time scales (11-100 and 101-1,000 transactions), with negative profits at the extremely short (1-10 transactions) range and small positive profits at the long time scale (10,000+ transactions). In contrast, both Mixed and Passive HFTs tend to lose money at short time scales (1-10, 11-100, and 101-1000 transactions), while making money on longer time scales (1,001-10,000 and 10,000+ transactions).

**Panel A: Total Daily Profit**

| | **Transaction Interval** | | | | |
|---|---|---|---|---|---|
| | **1-10** | **11-100** | **101-1000** | **1001-10000** | **10000+** |
| **HFT$^{A}$** | -$13,612 | $20,578 | $9,232 | -$7,024 | $2,354 |
| | [-28,025, -2,547] | [10,167, 55,683] | [-5,536, 40,474] | [-29,005, 2,061] | [-10,085, 11,402] |
| **HFT$^{M}$** | $250 | -$9,641 | -$27,823 | $13,729 | $24,802 |
| | [-4,452, 1,710] | [-20,233, -1,659] | [-31,094, 2,062] | [-2,552, 33,625] | [20,037, 43,011] |
| **HFT$^{P}$** | -$7,006 | -$12,183 | -$2,312 | $17,517 | $12,393 |
| | [-11,412, -4,825] | [-14,902, -7,538] | [-6,553, -848] | [11,797, 21,317] | [10,972, 18,125] |
| **HFT** | -$4,669 | -$7,930 | -$2,290 | $7,985 | $12,991 |
| | [-14,160, -662] | [-16,825, 14,617] | [-22,801, 11,490] | [-5,716, 21,129] | [9,212, 28,536] |

**Panel B: Profit Per Contract**

| | | | | | |
|---|---|---|---|---|---|
| **HFT$^{A}$** | -$0.32 | $0.86 | $0.26 | -$0.22 | $0.11 |
| | [-0.59, -0.06] | [0.6, $1.01] | [-0.41, 0.43] | [-0.4, -0.01] | [-0.29, 0.4] |
| **HFT$^{M}$** | $0.01 | | -$0.72 | $0.75 | $1.09 |
| | [-0.27, 0.07] | [-0.65, -0.21] | [-1.04, 0.11] | [-0.07, 1.21] | [0.74, 1.15] |
| **HFT$^{P}$** | -$0.48 | -$0.77 | -$0.15 | $0.90 | $0.82 |
| | [-0.54, -0.32] | [-1.01, -0.46] | [-0.47, -0.05] | [0.74, 1.2] | [0.73, 0.94] |
| **HFT** | -$0.29 | -$0.43 | -$0.15 | $0.55 | $0.75 |
| | [-0.53, -0.01] | [-0.77, 0.86] | [-0.71, 0.4] | [-0.24, 0.94] | [0.37, 1.04] |

## Table 8 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. For example, to calculate the HFT-fundamental profit flows, we only keep trades between HFTs and fundamental traders. We don't care which of the two parties is the buyer or seller, or which one is the aggressive party. 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 21 trading days in August 2010 and divided by 21 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:** | **Fundamental** | **HFT** | **$HFT^A$** | **$HFT^M$** | **$HFT^P$** | **Non-HFT Market Maker** | **Small Trader** | **Opportunistic** | **Total** |
| **Fundamental** | $0 | -$146,005 | -$124,356 | -$21,569 | -$81 | $2,232 | $3,035 | $44,238 | -$242,506 |
| **HFT** | $146,005 | $0 | -$326,491 | $210,555 | $115,936 | $89,874 | $50,328 | $1,616,219 | $1,902,427 |
| **$HFT^A$** | $124,356 | $326,491 | $0 | $212,463 | $114,028 | $79,594 | $23,528 | $1,059,606 | $1,940,066 |
| **$HFT^M$** | $21,569 | -$210,555 | -$212,463 | $0 | $1,907 | $8,041 | $18,846 | $429,914 | $57,260 |
| **$HFT^P$** | $81 | -$115,936 | -$114,028 | -$1,907 | $0 | $2,240 | $7,953 | $126,699 | -$94,898 |
| **Non-HFT M. M.** | -$2,232 | -$89,874 | -$79,594 | -$8,041 | -$2,240 | $0 | $3,714 | $62,428 | -$115,839 |
| **Small Trader** | -$3,035 | -$50,328 | -$23,528 | -$18,846 | -$7,953 | -$3,714 | $0 | -$15,790 | -$123,195 |
| **Opportunistic** | -$44,238 | -$1,616,219 | -$1,059,606 | -$429,914 | -$126,699 | -$62,428 | $15,790 | $0 | -$3,323,314 |

## Table 8 Continued

**Panel B: Percent Profits**

| | Counterparty | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Fundamental** | **HFT** | **$HFT^A$** | **$HFT^M$** | **$HFT^P$** | **Non-HFT Market Maker** | **Small Trader** | **Opportunistic** | **Total** |
| **Percent Profits to:** | | | | | | | | | |
| **HFT** | 7.67% | 0.00% | -17.16% | 11.07% | 6.09% | 4.72% | 2.65% | 84.96% | $1,902,427 |
| **$HFT^A$** | 6.41% | 16.83% | 0.00% | 10.95% | 5.88% | 4.10% | 1.21% | 54.62% | $1,940,066 |
| **$HFT^M$** | 37.67% | -367.72% | -371.05% | 0.00% | 3.33% | 14.04% | 32.91% | 750.81% | $57,260 |
| **Percent Losses to:** | | | | | | | | | |
| **Fundamental** | 0.00% | 60.21% | 51.28% | 8.89% | 0.03% | -0.92% | -1.25% | -18.24% | -$242,506 |
| **$HFT^P$** | -0.09% | 122.17% | 120.16% | 2.01% | 0.00% | -2.36% | -8.38% | -133.51% | -$94,898 |
| **Non-HFT M. M.** | 1.93% | 77.59% | 68.71% | 6.94% | 1.93% | 0.00% | -3.21% | -53.89% | -$115,839 |
| **Small Trader** | 2.46% | 40.85% | 19.10% | 15.30% | 6.46% | 3.01% | 0.00% | 12.82% | -$123,195 |
| **Opportunistic** | 1.33% | 48.63% | 31.88% | 12.94% | 3.81% | 1.88% | -0.48% | 0.00% | -$3,323,314 |

**Panel C: Profit/Loss Per Trade**

| | Fundamental | HFT | $HFT^A$ | $HFT^M$ | $HFT^P$ | Non-HFT Market Maker | Small Trader | Opportunistic | Total |
|---|---|---|---|---|---|---|---|---|---|
| **Fundamental** | $0.00 | -$1.22 | -$1.89 | -$0.55 | -$0.01 | $0.35 | $3.08 | $0.51 | -$0.69 |
| **HFT** | $1.22 | $0.00 | -$1.03 | $1.08 | $1.41 | $2.02 | $4.42 | $2.25 | $0.91 |
| **$HFT^A$** | $1.89 | $1.03 | $0.00 | $1.68 | $2.00 | $2.57 | $4.59 | $2.87 | $1.76 |
| **$HFT^M$** | $0.55 | -$1.08 | -$1.68 | $0.00 | $0.10 | $0.72 | $4.11 | $1.72 | $0.08 |
| **$HFT^P$** | $0.01 | -$1.41 | -$2.00 | -$0.10 | $0.00 | $1.01 | $4.73 | $1.30 | -$0.34 |
| **Non-HFT M. M.** | -$0.35 | -$2.02 | -$2.57 | -$0.72 | -$1.01 | $0.00 | $5.12 | $1.39 | -$0.82 |
| **Small Trader** | -$3.08 | -$4.42 | -$4.59 | -$4.11 | -$4.73 | -$5.12 | $0.00 | -$2.46 | -$3.97 |
| **Opportunistic** | -$0.51 | -$2.25 | -$2.87 | -$1.72 | -$1.30 | -$1.39 | $2.46 | $0.00 | -$1.60 |

## Table 9 Intraday HFT Profit Determinants

To perform intra-day profit analysis, we partition the day into 10-second time intervals and calculate characteristics of the market and of individual HFTs at the end of each 10-second interval. We estimate Equation (7) in the text using linear panel regression. Note, *Account Inventory Range* is scaled by $10^{-3}$. * p<0.05, ** p<0.01, *** p<0.001.

| | Log(Profits) | | | | Log(Losses) | | | |
|---|---|---|---|---|---|---|---|---|
| | **HFT** | **$HFT^A$** | **$HFT^M$** | **$HFT^P$** | **HFT** | **$HFT^A$** | **$HFT^M$** | **$HFT^P$** |
| **α** | -.856*** | -.158* | -.34*** | -.865*** | -.637*** | -.981*** | -.52*** | -.57*** |
| | (.033) | (.0664) | (.0621) | (.0465) | (.0312) | (.0714) | (.0497) | (.0415) |
| **Log(Account Volume$_{i,s}$)** | .13*** | .0994*** | .146*** | .2*** | .114*** | .154*** | .0486*** | .0864*** |
| | (.0023) | (.0036) | (.0042) | (.0051) | (.0023) | (.0039) | (.0034) | (.0049) |
| **Log(Volatility$_s$)** | .201*** | .223*** | .235*** | .124*** | .163*** | .191*** | .156*** | .134*** |
| | (.0036) | (.0069) | (.0063) | (.0049) | (.0035) | (.0073) | (.0051) | (.0047) |
| **Account Aggressiveness$_{i,s}$** | .404*** | .563*** | .209*** | .302*** | -.393*** | -.608*** | -.21*** | -.137*** |
| | (.0092) | (.0135) | (.0166) | (.0184) | (.0094) | (.015) | (.0148) | (.0165) |
| **Account Avg Aggressiveness$_i$** | .589*** | -.114*** | -1.24*** | .742*** | .351*** | 1.16*** | -.221** | .119 |
| | (.0142) | (.0311) | (.0877) | (.0648) | (.0131) | (.0306) | (.0691) | (.0658) |
| **Account Inventory Range$_i$** | .315*** | .596*** | .0474 | 2.8*** | .609*** | .808*** | .258*** | 2.15*** |
| | (.0188) | (.0266) | (.0267) | (.0696) | (.0168) | (.0282) | (.0224) | (.0659) |
| **Log(\|Account net position$_{i,s}$\|)** | .639*** | .6*** | .671*** | .518*** | .761*** | .698*** | .846*** | .716*** |
| | (.0023) | (.0044) | (.0037) | (.0039) | (.0025) | (.0051) | (.0035) | (.0047) |
| **Log(Market volume$_s$)** | .057*** | .0622*** | .0464*** | .0397*** | .0187*** | .0284*** | .0078 | .0245*** |
| | (.0038) | (.0073) | (.0066) | (.0056) | (.0036) | (.0075) | (.0051) | (.005) |
| **Adj-$R^2$** | 0.547 | 0.407 | 0.518 | 0.497 | 0.657 | 0.468 | 0.748 | 0.640 |
| **N** | 248521 | 72174 | 101411 | 74936 | 198768 | 66549 | 77123 | 55096 |