The Flash Crash: The Impact of High Frequency Trading on an Electronic Market*

Andrei Kirilenko—MIT Sloan School of Management
Albert S. Kyle—University of Maryland
Mehrdad Samadi—University of North Carolina
Tugkan Tuzun—Board of Governors of the Federal Reserve System

Original Version: October 1, 2010
Revised version: September 24, 2014

ABSTRACT

We present an empirical analysis of the Flash Crash – a systemic market event on May 6, 2010. The Flash Crash was blamed on high frequency traders (HFTs) – hyperactive trading algorithms operating inside automated markets. We use audit-trail data for the E-mini S&P 500 futures contract to show that HFTs did not cause the Flash Crash – a large sell program did – but exacerbated the price movement by absorbing immediacy ahead of others. We present novel findings on the trading behavior of HFTs as part of a market ecosystem and propose recommendations for making automated markets more resilient to large liquidity imbalances.

*We thank participants at numerous seminars and conferences for very helpful comments and suggestions. The views presented in this paper are our own and do not represent a position of any official agency, its management or staff.

A draft of this paper was originally authorized for public distribution by the U.S. Commodity Futures Trading Commission (CFTC) prior to the release of the joint report of the staffs of the CFTC and the U.S. Securities and Exchange Commission (SEC) entitled "Findings Regarding the Market Events of May 6, 2010". The CFTC-SEC report was issued to the public on September 30, 2010. Prior to the release, all matters related to the aggregation of data, presentation of results, and sharing the results with the public were reviewed by the CFTC Senior Staff, reviewers in the Office of the Chairman, the Division of Market Oversight, the Office of the General Counsel, the Division of Enforcement, as well as staff from other divisions of the CFTC. CFTC Chairman and Commissioners were briefed on the analysis and results of the paper prior to the public release of the report.

On February 21, 2014, after a lengthy review process, the CFTC re-authorized this paper for public distribution and stated that the following disclaimer must be used: The research presented in this paper was co-authored by Andrei Kirilenko, a former full-time CFTC employee, Albert Kyle, a former CFTC contractor who performed work under CFTC OCE contract (CFCE-09-CO-0147), Mehrdad Samadi, a former full-time CFTC employee and former CFTC contractor who performed work under CFTC OCE contracts (CFCE-11-CO-0122 and CFOCE-13-CO-0061), and Tugkan Tuzun, a former CFTC contractor who performed work under CFTC OCE contract (CFCE-10-CO-0175). The Office of the Chief Economist and CFTC economists produce original research on a broad range of topics relevant to the CFTC's mandate to regulate commodity futures markets, commodity options markets, and the expanded mandate to regulate the swaps markets pursuant to the Dodd-Frank Wall Street Reform and Consumer Protection Act. These papers are often presented at conferences and many of these papers are later published by peer-review and other scholarly outlets. The analyses and conclusions expressed in this paper are those of the authors and do not reflect the views of other members of the Office of the Chief Economist, other Commission staff, or the Commission itself.

On May 6, 2010, in the course of about 36 minutes starting at 2:32pm ET, U.S. financial markets experienced one of the most turbulent periods in their history. Broad stock market indices – the S&P 500, the Nasdaq 100, and the Russell 2000, collapsed and rebounded with extraordinary velocity. The Dow Jones Industrial Average (DJIA) experienced the biggest intraday point decline in its entire history. Stock index futures, options, and exchange-traded funds, as well as individual stocks experienced extraordinary price volatility often accompanied by spikes in trading volume. Because these dramatic events happened so quickly, the events of May 6, 2010, have become known as the "Flash Crash."

This paper uses audit trail data during May 3-6, 2010 to examine the ecosystem of the S&P 500 E-mini futures during these four days and the role of high frequency traders and other market participants in the Flash Crash. The audit trail dataset: (i) contains time stamps for all trades up to the second; (ii) sequences trades within each second; (iii) identifies the account numbers of the two participants for each trade; (iv) distinguishes between the buyer and a seller for each trade, and (v) distinguishes between the participant that originated the trade (aggressive side) and the participant whose order was executed against (passive side).

On September 30, 2010, the staffs of the Commodity Futures Trading Commission (CFTC) and Securities and Exchange Commission (SEC) issued a report on the events of May 6, 2010. The 104-page report described how an automated execution program to sell 75,000 contracts of the E-Mini S&P 500 futures, algorithmic trading activity, and obscure order submission practices all conspired to create the Flash Crash.[1]

In the aftermath of the Flash Crash, the media became particularly fascinated with the secretive blend of high-powered technology and hyperactive market activity known as high frequency trading (HFT).[2] To many investors and market commentators, high frequency trading has become the root cause of the unfairness and fragility of automated markets.[3] In response to public pressure, government regulators and self-regulatory organizations (e.g., securities and derivatives exchanges) around the world have come up with a variety of anti-HFT measures. These measures range from a tax on financial

[1]The CFTC-SEC report's narrative of the triggering event of the Flash Crash was based in part on the preliminary analysis contained in the original version of this paper (see footnote 22 of the CFTC-SEC report). The narrative (the report) and the analysis (the paper) were presented separately in part because the CFTC-SEC report was written for a very broad audience, while the methodology and preliminary results in the original paper were intended for peer review by research scientists and market experts. Both the report and the paper serve the same purpose of describing to the market participants, the research community, and the general public how unrelated trading algorithms activated across different parts of the financial marketplace can cascade into a systemic event for the entire U.S financial market. The original version of this paper has been cited by numerous academic, government-sponsored and industry-sponsored studies.

[2]See, "Disagreement on safe speed for HFT", Financial Times, June 3, 2010. See also, "A Second Is a Long Time in Finance", The Wall Street Journal, March 3, 2011.

[3]"Testimony on Computerized Trading: What Should the Rules of the Road Be?" The Committee on Banking, Housing, and Urban Affairs Subcommittee on Securities, Insurance and Investment, September 20, 2012.

transactions designed to make HFT prohibitively expensive and contribute to public revenue to "throttles" on the number of messages a trader is allowed to send to an exchange.[4]

This study offers an empirical analysis of trading at the time of market stress as evidenced by the events of May 6, 2010. We show that HFT did not cause the Flash Crash, but contributed to extraordinary market volatility experienced on May 6, 2010. We also show how high frequency trading contributes to flash-crash-type events by exploiting short-lived imbalances in market conditions. We argue that in the ordinary course of business, high frequency traders (HFTs) use their technological advantage to aggressively remove the last few contracts at the best bid or ask levels and then establish new best bids and asks at adjacent price levels. This type of trading activity accelerates, albeit for only a few milliseconds, the price move imposing an "immediacy absorption" cost on all other traders who are not fast enough to react to an imminent price move.

Under calm market conditions, this trading activity somewhat accelerates price changes and adds to trading volume but does not result in a directional price move. However, at times of market stress and elevated volatility, when prices are moving directionally due to an order flow imbalance, this trading activity can exacerbate a directional price move and contribute to volatility. Higher volatility further increases the speed at which the best bid and offer queues get depleted, which makes HFTs act faster, leading to a spike in trading volume and setting the stage for a flash-crash-type event. On May 6, HFTs exacerbated the Flash Crash by aggressively removing the last few contracts at best bids and demanding additional depth while liquidating inventories during key moments of dwindling market liquidity.

Flash-crash-type events temporarily shake the confidence of some market participants but probably have little impact on the ability of financial markets to allocate resources and risks. These events though raise a broader set of questions about the optimal market structure of automated markets. Grossman and Miller (1988) show that, in equilibrium, the market structure is determined by a tradeoff between (i) the costs borne by the *intermediaries* for supplying liquidity and maintaining a continuous market presence and (ii) the benefits accrued to liquidity-demanding *customers* for being able to execute trades as "immediately" as possible when they come to the market. The costs to the intermediaries are primarily fixed costs — the opportunity cost of being open for business – while the benefits to the customers are primarily marginal — lowering of the risk that prices would move against them if they have to wait to execute a particular transaction. In equilibrium, the intermediaries are compensated just enough to recover their fixed costs of maintaining continuous market presence, as well as adverse selection costs of trading with customers who come to the market at different times. There is also improved risk sharing among customers with different attitudes toward market risk – those who are comfortable to wait longer get a better deal, while those who dislike waiting pay for having their trades done sooner.

While the overall framework is still useful, advances in technology and infrastruc-

[4] "High-Speed Traders Race to Fend off Regulators", The Wall Street Journal, December 27, 2012.

ture have altered the cost-benefit balance in favor of the most technologically-advanced financial intermediaries with the smallest overhead per market – the very definition of high frequency traders. Because advanced trading technology can be deployed with little alteration across many automated markets, the cost of providing intermediation services per market has fallen drastically. As a result, the supply of immediacy provided by the HFTs has skyrocketed. At the same time, the benefits of immediacy accrue disproportionally to those who possess the technology to take advantage of it. As a result, HFTs have also become the main beneficiaries of immediacy, using it not only to lower their adverse selection costs, but also to take advantage of the customers who dislike adverse selection, but do not have the technology to be able to trade as quickly as they would like to. These market participants express their demands for immediacy in their trading orders, but are too slow to execute these orders compared to the HFTs. Consequently, HFTs can both increase their demand for immediacy and decrease their supply of immediacy just ahead of any slower immediacy-seeking customer. This immediacy-absorption activity makes prices move against all slower customers who seek immediacy, including more traditional intermediaries. This is different from the stylized Grossman-Miller framework in which intermediaries only provide immediacy, while customers only demand it. In the modified framework, a handful of technologically-advanced HFTs are not only able to provide immediacy and reduce their own cost of adverse selection, but also to demand immediacy and impose an immediacy-absorption "cost" on all non-HFT market participants, including the market makers. Thus, high frequency trading can make it both costlier and riskier for market makers to maintain continuous market presence.

Building on the Grossman-Miller framework, Huang and Wang (2008) develop an equilibrium model in which they link the cost of maintaining continuous market presence with market crashes even in the absence of fundamental shocks and perfectly offsetting idiosyncratic shocks. In their model, market crashes emerge endogenously when a sudden excess of sell orders overwhelms insufficient risk-bearing capacity of liquidity providers. The critical feature of the model is that the provision of continuous market presence is costly. As a result, market makers choose to maintain equilibrium risk exposures that are too low to offset temporary liquidity imbalances. In the event of a large enough sell order, the liquidity on the buy side can only be obtained after a price drop that is large enough to compensate increasingly reluctant market makers to take on additional risky inventory. These equilibrium crashes are accompanied by high trading volume and large price volatility as documented in the E-mini S&P 500 stock index futures contract on May 6, 2010.

If the immediacy absorption activity of HFTs makes it costlier for the market makers to maintain continuous market presence, then high frequency trading could be linked to greater market fragility. Unfortunately, we are unable to conduct a direct estimation of the cost that the immediacy absorption activity of HFTs imposes on the market makers, because after the publication of our initial results, academic access to relevant data was shut off by the CFTC. [5] Thus, we resort to documenting a number of empirical regularities, which we believe stem from the immediacy absorption activity of High Frequency Traders.

We show that HFTs are much more likely than market makers to aggressively execute the last 100 contracts before a price move in the direction of a trade. As they get wind of an imminent increase in net demand for immediacy on either the long or the short side of the market, HFTs quickly demand it ahead of slower investors and move the price to take advantage of it. We also show that HFTs trade aggressively in the direction of the price move while market makers get "run over" by a price move. Furthermore, we find that HFTs "scratch" — quickly buy and sell at the same price — more of their trades than Market Makers.

Based on our results, appropriate regulatory actions should aim to encourage HFTs to provide immediacy, while discouraging them from demanding it, especially at times of market stress. We believe that this should be accomplished through changes in market design rather than transaction taxes, limits or fees as the higher opportunity costs imposed on the HFTs would, at best, be passed on to other market participants, with the least technologically-savvy investors bearing the brunt of the cost.

For example, automated matching engines should include a number of functionalities to slow down or pause order matching and thus temporarily halt the demand for immediacy, especially if significant order flow imbalances are detected. These short pauses followed by auction-based re-opening procedures would, in the spirit of Huang and Wang (2010), force market participants to coordinate their liquidity supply responses in a pre-determined manner instead of seeking to execute ahead of others.[6] The five-second trading pause triggered at the bottom of the Flash Crash is one example of such a functionality. We believe that regulators should encourage significantly more effort towards developing and deploying other "forced coordination" measures that would serve as effective pre-trade safeguards in today's fast and interlinked markets.

The paper is organized as follows. A brief description of the events of May 6, 2010 are in Section I. Section II describes the activity of all traders (appropriately aggregated so it does not reveal individual transactions or business practices) in a stock index futures contract were the Flash Crash was triggered. Section III presents the analysis of the Flash Crash and concludes that HFTs did not cause it. Section IV presents the analysis of absorbing the large order flow imbalance that triggered the Flash Crash. An empirical analysis of the activity of High Frequency Traders on the day of the Flash Crash, as well as during three days prior to it are in Section V. In Section VI we summarize our findings and offer our views on the lessons we could learn from the traumatic events of May 6, 2010.

[5] "CME Group Sparked Shutdown of CFTC's Academic Research Program, Reuters, April 24, 2013.

[6] Huang and Wang (2010) develop an equilibrium model in which both liquidity demand and supply are determined endogenously and argue that forcing market participants to coordinate their liquidity responses in a pre-determined manner could increase welfare.

I. The Events of May 6, 2010.

The CFTC-SEC report describes the events of May 6, 2010 as follows:

> "At 2:32 p.m., against [a] backdrop of unusually high volatility and thinning liquidity, a large fundamental trader (a mutual fund complex) initiated a sell program to sell a total of 75,000 E-Mini [S&P 500 futures] contracts (valued at approximately $4.1 billion) as a hedge to an existing equity position. [. . .] This large fundamental trader chose to execute this sell program via an automated execution algorithm ("Sell Algorithm") that was programmed to feed orders into the June 2010 E-Mini market to target an execution rate set to 9% of the trading volume calculated over the previous minute, but without regard to price or time. The execution of this sell program resulted in the largest net change in daily position of any trader in the E-Mini since the beginning of the year (from January 1, 2010 through May 6, 2010). [. . .] This sell pressure was initially absorbed by: high frequency traders ("HFTs") and other intermediaries in the futures market; fundamental buyers in the futures market; and cross-market arbitrageurs who transferred this sell pressure to the equities markets by opportunistically buying E-Mini contracts and simultaneously selling products like SPY [(S&P 500 exchange-traded fund ("ETF"))], or selling individual equities in the S&P 500 Index. [. . .] Between 2:32 p.m. and 2:45 p.m., as prices of the E-Mini rapidly declined, the Sell Algorithm sold about 35,000 E-Mini contracts (valued at approximately $1.9 billion) of the 75,000 intended. [. . .] By 2:45:28 there were less than 1,050 contracts of buy-side resting orders in the E-Mini, representing less than 1% of buy-side market depth observed at the beginning of the day. [. . .] At 2:45:28 p.m., trading on the E-Mini was paused for five seconds when the Chicago Mercantile Exchange ("CME") Stop Logic Functionality was triggered in order to prevent a cascade of further price declines. [. . .] When trading resumed at 2:45:33 p.m., prices stabilized and shortly thereafter, the E-Mini began to recover, followed by the SPY. [. . .] Even though after 2:45 p.m. prices in the E-Mini and SPY were recovering from their severe declines, sell orders placed for some individual securities and ETFs (including many retail stop-loss orders, triggered by declines in prices of those securities) found reduced buying interest, which led to further price declines in those securities. [. . .] [B]etween 2:40 p.m. and 3:00 p.m., over 20,000 trades (many based on retail-customer orders) across more than 300 separate securities, including many ETFs, were executed at prices 60% or more away from their 2:40 p.m. prices. [. . .] By 3:08 p.m., [. . .] the E-Mini prices [were] back to nearly their pre-drop level [. . . and] most securities had reverted back to trading at prices reflecting true consensus values."

Figure 1 below shows just how extreme the intraday volatility in stock index and futures prices was on May 6, 2010. In the course of 13 minutes, between 2:32:00 ET and 2:45:28 ET, the front-month E-mini S&P 500 futures fell 5.1%; during the next 23 minutes, it rose 6.4 percent.

<Insert Figure 1>

The extreme volatility in the E-mini was accompanied by a rapid spike in trading volume, as illustrated in Figure 2. During the 36-minute period of the Flash Crash, trading volume per minute was nearly 8 times greater than trading volume per minute earlier in the day. A massive spike in trading volume is the critical distinguishing characteristic of the events of May 6, 2010.

<Insert Figure 2>

As the event spread through the entire U.S. financial market system with extraordinary velocity, it left a broad universe of market participants – from professional traders with decades of experience to small retail investors – with a realization that something was terribly wrong inside the shining new automated markets.

A survey conducted by Market Strategies International during June 23-29, 2010 reported that over 80 percent of U.S. retail advisors believed that "overreliance on computer systems and high-frequency trading" were the primary contributors to the volatility observed on May 6, 2010. Calls for stricter regulation or even an outright ban of high frequency trading quickly followed.

II. The Ecosystem of An Automated Market

In this section we describe the activity of all traders in the stock index futures contract that serves as the price discovery vehicle for the entire U.S. stock market.

A. The E-Mini S&P 500

The E-mini S&P 500 E-mini futures contract (E-mini) owes its geeky name to the fact that it is traded only electronically and in denominations 10 times smaller than the original, floor-traded S&P 500 index futures contract. The Chicago Mercantile Exchange (CME) introduced the E-mini contract in 1997. Since then it has become a popular instrument to hedge exposures to baskets of U.S. stocks or to speculate on the direction of the entire stock market. The E-mini contract attracts the highest dollar volume among U.S. equity index products – futures, options, stocks or exchange-traded funds.

The E-mini contract features a simple and robust design. The contracts are cash-settled against the value of the underlying S&P 500 equity index at expiration dates in

March, June, September, and December of each year. The contract with the nearest expiration date, which attracts the majority of trading activity, is called the "front-month" contract. In May 2010, the front-month contract was the contract expiring in June 2010. The notional value of one E-mini contract is $50 times the S&P 500 stock index. During May 3-6, 2010, the S&P 500 index fluctuated slightly above 1,000 points, making each E-mini contract be worth about $50,000. The minimum price increment, or "tick" size, of the E-mini is 0.25 index points, or $12.50; a price move of one tick represents a fluctuation of about 2.5 basis points.

The E-mini trades exclusively on the CME Globex trading platform, a fully electronic limit order market. Trading takes place 24 hours a day with the exception of one 15-minute technical maintenance break each day. The CME Globex matching algorithm for the E-mini follows a "price priority-time priority" rule in that orders offering more favorable prices are executed ahead of orders with less favorable prices, and orders with the same prices are executed in the order they were received and time-stamped by Globex.

The market for the E-mini features both pre-trade and post-trade transparency. Pre-trade transparency is provided by transmitting to the public in in real time the quantities and prices for buy and sell orders resting in the central limit order book up or down 10 tick levels from the last transaction price. Post-trade transparency is provided by transmitting to the public the prices and quantities of executed transactions. The identities of individual traders submitting, canceling or modifying bids and offers, as well those whose bids and offers have been executed, are not made available to the public.

Hasbrouck (2003) shows that the E-mini has become the price discovery market were the value of the S&P 500 stock index is first "discovered" because many different types of traders are able to simultaneously channel their demands into a single central limit order book for a single, front-month contract trading on a single electronic trading platform.

B. The Data

For the day of the Flash Crash and three days prior to that, May 3-6, 2010, we examine transaction-level, "audit-trail" data for all regular transactions in the front-month June 2010 E-mini S&P 500 futures contract. These data come from the Trade Capture Report (TCR) dataset, which the CME provides to the Commodity Futures Trading Commission (CFTC) — the U.S. federal regulator of futures, options, and swaps markets.

For each of the four days, we examine all transactions occurring during the 405 minute period starting at the opening of the market for the underlying stocks at 8:30 am CT (CME Globex is in the Central Time zone) or 9:30 am ET and ending at the time of the technical maintenance break at 3:15 pm CT, 15 minutes after the close of trading in the underlying stocks.

For each transaction, we utilize fields with the account numbers for the buyer and the seller, the price and quantity transacted, the date and time (to the nearest second), a sequence ID number which sorts trades into chronological order even within one second, order type (market order or limit order), and an "aggressiveness" indicator stamped by the CME Globex matching engine — "N" for the resting order and "Y" for the order that executed against a resting order.

The source data is confidential. This means that the results we present often provide a deliberately obscured illustration of what we have actually rigorously established and validated. Moreover, even though we have checked and re-checked our results, they are unlikely to be ever independently validated by other researchers. Even with these limitations though, we still believe that we owe the public the most informative analysis of the extraordinary stressful events that unfolded in the E-mini on May 6, 2010 and the lessons for market design that we can learn from these events.

Table I provides aggregate summary statistics for the June 2010 E-Mini S&P 500 futures contract during May 3-6, 2010. The first column reports average statistics for the three days prior to the Flash Crash, May 3-5, 2010, and the second column reports statistics for the day of the Flash Crash itself, May 6, 2010.

<Insert Table I>

Table I illustrates what an extraordinary day May, 6, 2010 was. On May 6, the log-difference between the high and low prices of the day — an estimate of intraday volatility — clocks at 9.82% or nearly 6.4 times higher than the 1.54% average during the previous three days. On May 6, 5,094,703 June E-mini contracts with a total value of more than $250 billion were traded – approximately twice the average volume of 2,397,639 contracts on the previous three days. On May 6, 15,422 accounts executed 1,030,204 trades. During the previous three days, 11,875 trading accounts executed on average 446,340 trades.

C. The Traders

The 15,422 trading accounts that traded during May 6, 2010 have drastically different holding horizons and levels of trading activity. Some traders hold positions overnight, while others take intra-day positions that may last hours, minutes, or seconds. Some traders trade thousands of contracts every day, while other traders trade just a handful of contracts once. To describe interactions among traders with different holding periods and different levels of trading activity, we group the trading accounts that traded on May 6, 2010, into six distinct categories: High Frequency Traders (16 accounts), Market Makers (179 accounts), Fundamental Buyers (1263 accounts), Fundamental Sellers (1276 accounts), Opportunistic Traders (5808 accounts), and Small Traders (6880 accounts).[7]

[7]Throughout the paper we use the following convention: we use capital letters whenever we refer to the categories we defined (e.g., Market Makers) and lower case letters whenever we refer to general type of activity (e.g., market making).

Our definition of both High Frequency Traders and Market Makers is designed to capture traders who consistently follow a strategy of buying and selling a large number of contracts while maintaining low levels of inventory. Specifically, an account is classified as a High Frequency Trader or Market Maker if and only if it satisfies the following three requirements:

- Volume: The account must have traded 10 contracts or more on at least one of the three days prior to the Flash Crash (May 3,4,5, 2010).

- End-of-day inventory balance: During the three days in which the account traded 10 contracts or more, the average of the absolute value of the end-of-day net position cannot exceed 5% of its total trading volume for that day. For example, if an account traded 100 contracts during the day, then by the end of the day, it cannot hold more than 5 contracts either net long or net short. An account that bought 52 contracts and sold 48 would satisfy this requirement, while an account that bought 55 contracts and sold 45 would not.

- Intraday inventory balance: During the three days in which the account traded 10 contracts or more, the square root of the sum of squared deviations of the net contract holdings for each of the 405 minutes from the net contract holdings at the end of the day cannot exceed 1.5% of its total trading volume for that day. For example, an account that either bought or sold one contract per minute throughout the entire trading day (405 minutes) and ended up with 5 contracts net long at the end of the day, would satisfy the requirement.

These three requirements separate trading accounts that hold small net intraday and end-of-day positions relative to their trading volume. Of the 195 accounts satisfying these three conditions, we further classify as High Frequency Traders 16 accounts with the highest average number of trades during May 3-5. The other 179 accounts, we classify as Market Makers. The 16 most active accounts are classified differently from the other 179 accounts due to a large gap in the number of trades between the 16th and 17th accounts. Thus, a High Frequency Trader is classified similarly to a Market Maker in all respects, except that the HFT participates in a significantly greater number of transactions.

If an account is classified as a High Frequency Trader or a Market Maker on any of the three days during May 3-5, 2010, we keep it within the same category during all four days, May 3-6, 2010. Importantly, this restriction does not require that a High Frequency Trader or a Marker Maker sticks with the low inventory relative to volume requirement on the day of the Flash Crash. On May 6, 2010, the trading behavior of an account classified as a High Frequency Trader or a Marker Maker based on its trading activity on the previous three days could have changed. We examine whether such a change did take place on May 6, 2010 and, if it did, whether it precipitated or contributed to the extraordinary price volatility, and a spike in trading volume observed on that day.

Unlike High Frequency Traders and Market Makers, the other four categories of traders (Small Traders, Fundamental Buyers, Fundamental Sellers, and Opportunistic Traders) are classified separately for each day based on their end-of-day inventory and trading activity on that specific day. We set the following volume/inventory thresholds for the four categories of traders. On each day, an account is classified as a Small Trader if it trades fewer than 10 contracts. On each day, an account is classified as a Fundamental Buyer if it trades 10 contracts or more and accumulates a net long end-of-day position equal to at least 15% of its total trading volume for the day. Similarly, an account is classified as a Fundamental Seller if it trades 10 contracts or more and its net short position at the end of the day is at least 15% of its total trading volume for the day. All remaining accounts are classified as Opportunistic Traders. Opportunistic Traders at times act like Market Makers (buying a selling around a given inventory target) and at other times act like Fundamental Traders (accumulating a directional position).

Traders categorized as Fundamental Buyers and Fundamental Sellers accumulate directional net positions. Each of them gets to its end-of-day inventory in a different way. Some acquire large net positions by executing many small-size orders throughout the day, while others choose to reach their inventory target by executing just a few large-size orders in the beginning and at the end of the day.

Traders categorized as Opportunistic Traders may follow a variety of arbitrage trading strategies, including cross-market arbitrage (e.g., long futures–short securities), statistical arbitrage (e.g., buy on statistically significant downside price movements–sell on statistically significant upside price movements), news arbitrage (buy if the news indicators are positive–sell if the news indicators are negative) and many other strategies.

Unlike accounts that are classified as High Frequency Traders and Market Makers, Fundamental, Opportunistic or Small accounts are determined based on their trading activity on each of the four days that we investigate.

D. The Market Ecosystem

Figure 3 provides a visual representation of the trading activity and end-of-day positions for all but the Small Traders, whose activity is negligible. Four panels correspond to each of the four trading days. The shaded areas are stylistically drawn to cover the areas populated by the individual trading accounts that fall into each of the categories based on their trading volume (vertical axis) and end-of-day position scaled by trading volume (horizontal axis).

<Insert Figure 3>

According to Figure 3, the ecosystem of the E-mini market consists of five fairly distinct clusters of traders – Fundamental Buyers, Fundamental Sellers, High Frequency Traders, Opportunistic Traders and Market Makers. In terms of their trading volume, High Frequency Traders stand out from all the other trading categories and are clearly separated from the Market Makers. By accumulating a significant negative inventory, the cloud of Fundamental Sellers spreads out to the left of the origin, while the cloud of Fundamental Buyers spreads out to the right. Opportunistic traders overlap to some extent with all the other categories of traders.

Average indicators of trading activity for all categories of traders are presented in Table II. Panel A presents averages for the three days prior to the Flash Crash, May 3-5, 2010, while panel B presents indicators for the day of the Flash Crash itself, May 6, 2010.

<Insert Table II>

According to Table II, during the three days prior to the Flash Crash, High Frequency Traders accounted for 34.22% of the total trading volume and Market Makers accounted for an additional 10.49% of the total trading volume. On the day of the Flash Crash, their respective shares of the total trading volume dropped to 28.57% and 9.00%.

Table II also presents trade-weighted and volume-weighted "Aggressiveness Ratios," defined as the percentage of trades or contracts in which a trade results from an executable (i.e., Aggressive) order as opposed to a non-executable (i.e., Passive or resting) order. During May 3-5, 2010, the volume-weighted proportion of Aggressive order executions by High Frequency Traders and Market Makers were 45.68% and 41.62%, respectively; on May 6, 2010, the proportions are only slightly different, 45.53% and 43.55%, respectively. Overall, however, the averages are not granular enough to be informative about how High Frequency Traders acted during the Flash Crash. The next section presents a more detailed look at their trading activity.

III. Did High Frequency Traders Trigger the Flash Crash?

In this section we examine whether High Frequency Traders changed their trading behavior on May 6, 2010 in a way that could have triggered the Flash Crash. We also conduct the same analysis for the Market Makers. Specifically, we analyze inventory dynamics of High Frequency Traders and Market Makers on the day of the Flash Crash and compare it to their inventory dynamics during the previous three days. Figure 4 presents end-of-minute E-mini prices and minute-by-minute total inventory of High Frequency Traders during each of the four days.

<Insert Figure 4>

The intra-day position of High Frequency Traders fluctuates around zero and rarely exceeds 4,000 contracts (about \$200 million). If the prices and dates on the four panels were to be removed, a reader would not be able to tell by looking at the inventory of High Frequency Traders which of the four days is May 6, 2010. The largest net intraday inventory level of Market Makers is even smaller — roughly half that of High Frequency Traders. During the early moments of the Flash Crash, HFTs accumulated inventories and proceeded to sell aggressively at key moments in order to liquidate their inventories

We regress second-by-second changes in inventory levels of High Frequency Traders on the level of their inventories the previous second, the change in their inventory levels the previous second, the change in prices during the current second, and lagged price changes for each of the previous 20 previous seconds. The regression equation is:

$$\Delta y_t = \alpha + \phi \cdot \Delta y_{t-1} + \delta \cdot y_{t-1} + \sum_{i=0}^{20} [\beta_i \cdot \Delta p_{t-i}/0.25] + \epsilon_t, \tag{1}$$

where y_t and Δy_t denote inventories and change in inventories of High Frequency Traders for each second of a trading day; $t = 0$ corresponds to the opening of stock trading on the NYSE at 8:30:00 a.m. CT (9:30:00 ET) and $t = 24,300$ denotes the close of Globex at 15:15:00 CT (4:15 p.m. ET); Δp_t denotes the price change in index point units between the high-low midpoint of second $t-1$ and the high-low midpoint of second t.

Table III presents coefficient estimates for this regression. Panel A reports the results for May 3-5 (where the data is pooled) and Panel B for May 6. The t-statistics are calculated using the White (1980) estimator. To test for robustness, we also estimated this regression using three alternative specifications: (i) we removed the current price from the regression; (ii) used longer lag structure for net holdings; and (iii) explicitly modeled the time-series error structure. Our results, which we plan to post in an online Statistical Appendix, remain qualitatively the same.[8]

<Insert Table III >

The first and second columns of Panel A present regression coefficients and t-statistics for High Frequency Traders and Market Makers during May 3-5.[9]

The coefficient estimate for the long-term mean reversion parameter for High Frequency Traders is $\delta = -0.005$ ($t = 11.77$), and the coefficient estimate for Market Makers is $\delta = -0.004$ ($t = 8.93$). These coefficients have the interpretation that High Frequency Traders liquidate 0.5% of their aggregate inventories on average each second and Market

[8]We thank an anonymous referee for recommending alternative model specifications.

[9]Dickey-Fuller tests verify that inventories of High Frequency Traders and Market Makers are stationary. Multicollinearity does not affect the reported results. Newey-West standard errors are very similar to White standard errors.

Makers liquidate 0.4% of their inventories each second, implying AR-1 half-lives for inventories of about 140 seconds for High Frequency Traders and 175 seconds for Market Makers.

For High Frequency Traders, the coefficient estimate for contemporaneous price changes $\beta_0 = 32.09$ ($t = 18.44$) has the interpretation that High Frequency Traders buy 32 more contracts in seconds when prices rise one tick than in seconds when prices do not change. The coefficient estimates for the first three lags in price changes $\beta_1 = 17.18$, $\beta_2 = 8.36$, $\beta_3 = 5.09$, and $\beta_4 = 3.62$ are all positive and statistically significant as well. These results are consistent with the interpretation that High Frequency Traders trade in the direction of the price movement up to 4 seconds prior to it and as it happens, contrary to traditional thinking about passive market making.

For Market Makers, the regression results are quite different. The coefficient for contemporary price changes $\beta_0 = -13.54$ ($t = -23.83$) is negative and statistically significant, and the coefficient for a one-second lag $\beta_1 = -1.22$ ($t = -2.71$) is negative and statistically significant also; for lags of 3 to 8 seconds, the coefficients become positive and statistically significant. These results are consistent with the interpretation that Market Makers engage in traditional passive market making by buying during the seconds when prices are falling. The positive coefficients at lags 3-8 suggest that market makers liquidate these inventories after holding them for 3-8 seconds. These regression results suggest that, possibly due to their slower speed or inability to anticipate possible changes in prices, Market Makers buy when the prices are already falling and sell when the prices are already rising.

At lags $i = 10, \ldots, 20$ seconds, the coefficients β_i turn negative and statistically significant for High Frequency Traders but are not statistically different from zero for Market Makers. These results are consistent with the interpretation that High Frequency Traders liquidate inventories acquired through trading for 5 seconds in the direction of the price movement by liquidating the positions 10-20 seconds later. Thus, the actual half-life of positions of High Frequency Traders is probably less than the 140 seconds implied by interpreting δ as an AR-1 coefficient, without regard to the coefficients associated with price dynamics.

Panel B presents coefficient estimates for Equation 1 on May 6. The first column of Panel B shows the results for High Frequency Traders and the second column the results for Market Makers. For High Frequency Traders, the coefficient for the level of inventories is $\delta = -0.005$ ($t = -6.76$), the same coefficient as for May 3-5, implying a half-life of about 140 seconds. For Market Makers, the coefficient is $\delta = -0.008$ ($t = -7.79$), implying a decrease in the half-life of inventories from about 175 seconds during May 3-5 to about 90 seconds on May 6. This decrease is consistent with the high velocity of prices during May 6.

For High Frequency Traders and Market Makers, the estimated coefficient for contemporaneous price changes are $\beta_0 = 10.81$ ($t = 6.05$) and $\beta_0 = -8.16$ ($t = -12.09$), respectively. Similar to May 3-5, the coefficient for High Frequency Traders is positive and the coefficient for Market Makers is negative. The absolute values of the coefficients are, however, smaller. The smaller absolute values are consistent with the interpretation that the high volatility on May 6 implied many tick changes occurring at more closely spaced periods of time, reduced market liquidity, and therefore reduced trading volume at each tick.

To test whether or not HFTs and Market Makers changed their behavior on the day of the Flash Crash, we interact dummy variables for the Up phase and the Down phase of the Flash Crash with the regression coefficients in equation 2. Letting D_t^D denote a dummy variable for the Down phase (13:32:00 to 13:45:28 CT) and D_t^U a dummy variable for the Up phase (13:45:33 to 14:08:00 CT), the regression specification becomes:

$$\begin{aligned}\Delta y_t = \alpha &+ \phi\Delta y_{t-1} + \delta y_{t-1} + \Sigma_{i=0}^{20}[\beta_i \times p_{t-i}/0.25] \\ &+ D_t^D\{\alpha^D + \phi^D\Delta y_{t-1} + \delta^D y_{t-1} + \Sigma_{i=0}^{20}[\beta_i^D \times p_{t-i}/0.25]\} \\ &+ D_t^U\{\alpha^U + \phi^U\Delta y_{t-1} + \delta^U y_{t-1} + \Sigma_{i=0}^{20}[\beta_i^U \times p_{t-i}/0.25]\} + \epsilon_t,\end{aligned}$$

We stack observations from May 3, May 4, May 5, and May 6 (excluding only the observations after 14:08:00 (CT)). By creating two sets of dummy variables for the down and up periods of the Flash Crash, we test for a change in trading behavior relative to the rest of the sample period. With this approach, we are able to estimate any change of behavior by HFTs and Market Makers during the Flash Crash. Results are presented in the table below.

<Insert Table IV >

For HFTs, during the Down Phase, all coefficients except for one are statistically insignificant. We interpret this as evidence that HFTs did not (either economically or statistically) significantly change their trading behavior during the Down phase, i.e. the time when the prices were rapidly falling. We also find that during the Up phase which commenced after a 5 second pause in trading, the coefficients for the contemporaneous price change as well as two seconds prior to it are negative and significant for HFTs. This suggests that during the Up phase, HFTs reduced their inventory 2 seconds prior to and contemporaneously with price increases. In summary, during the critical 36 minutes of the Flash Crash, HFTs are not changing their behavior when prices are falling and seem to be selling as prices are rising relative to the rest of the sample.

In contrast, Market Makers, increase their inventory during several seconds in the Down phase and then reduce their inventory 1 second prior to and contemporaneously with price decreases relative to the rest of the sample. Furthermore, Market Makers reduce their inventory between the 10th and the 3rd second in the Up phase and then turn around and increase their inventory 1 second prior to and contemporaneously with price increases relative to the rest of the sample. This empirical pattern suggests that

Market Makers accumulated inventories on the way down, temporarily got run over my the fall in prices, then kept buying in the up period. This is consistent with liquidity provision leading up to and during a market dislocation. However, Market Makers are simply being overwhelmed by a very large liquidity imbalance that we examine in the next section.

IV. Absorbing a Large Order Flow Imbalance

There are strong theoretical reasons to believe that a large order flow imbalance can trigger a market crash even in the absence of any fundamental shock by overwhelming the limited risk-bearing capacity of the intermediaries.[10] The important aspect of the Flash Crash is how quickly the prices in the E-mini have recovered to the pre-crash levels as liquidity rushed into the market attracted by lower prices. Which traders supplied the liquidity in response to an order flow imbalance merely an hour before the stock market closes, when and how did it happen, and why did the trading volume spike up?

To empirically investigate these questions, we divide the 36-minute Flash Crash into two phases – 13 minutes of rapidly declining prices (from 2:32 p.m. to 2:45 p.m. ET) followed by 23 minutes of rapidly increasing prices (from 2:45 p.m. to 3:08 p.m. ET). Figure 5 plots minute-by-minute net purchases and sales by Fundamental Buyers, Fundamental Sellers, and Opportunistic Traders from the period starting 15 minutes before the down phase of the Flash Crash until the end of the up phase.

<Insert Figure 5 >

During the down phase of the Flash Crash, Fundamental Sellers were frequently selling more than 5,000 contracts per minute ($250 million). In the minutes surrounding the bottom of the Flash Crash, sales by Fundamental Sellers reached 10,000 to 20,000 contracts per minute ($500 million to $1 billion). At the same time, purchases by Fundamental Buyers were significantly smaller than sales by Fundamental Sellers with the balance being acquired by the Opportunistic Traders. At the beginning of the up phase, Fundamental Sellers continued to sell heavily. Fundamental Buyers absorbed some of the selling pressure with remainder going again to Opportunistic Traders. Towards the end of the up phase, Opportunistic Traders both bought and sold in different minutes, on average liquidating some of the purchases they had made earlier.

Table V presents total purchases and sales by the six trader categories during the down- and up-phases of the Flash Crash on May 6 (panel A) with average quantities for the three previous days May 3-5 (panel B).

<Insert Table V >

[10]See, for example, Huang and Wang (2008).

During the down phase, Fundamental Sellers made gross sales of 94,101 contracts (net sales of 83,599 contracts), while Fundamental Buyers made gross purchases of 78,359 contracts (net purchases of 49,665 contracts). These quantities are 10 to 15 time larger than the gross sales of 8,428 and gross purchases of 7,958 made by Fundamental Sellers and Fundamental Buyers during the same period of May 3-5. During the down phase, gross purchases and sales by Opportunistic Traders increased from 20,552 and 20,049 contracts during May 3-5 to 221,236 and 189,790 contracts on May 6.

During the up phase, Fundamental Sellers made gross sales of 145,396 contracts (net sales of 110,177), while Fundamental Buyers made gross purchases of 165,612 contracts (net purchases of 110,369 contracts). These quantities also exceed the average gross sales of 15,585 contracts and gross purchases of 14,910 contracts by similar multiples during the same time interval of May 3-5. During the up phase, gross purchases and sales by Opportunistic Traders increased from 39,535 and 37,317 contracts during May 3-5 to 306,326 and 302,417 contracts

As the table shows, the process by which the modern automated market is able to absorb order flow imbalances of such magnitude is a confluence of different responses from all six groups of traders. Together, these responses resulted in a 14-fold increase in trading volume compared to the size of the 75,000 contract sell program. This massive increase in trading volume indicates how automated markets typically digest order flow imbalances. A small order flow imbalance might generate a tiny increase in intermediation trades, perhaps a few trades by a High Frequency trader or a Market Maker. In contrast, a large buy or sell program generates many intermediation trades leading to significant price adjustments and an increase in trading volume many times the size of the order that triggered the imbalance. This occurs because different types of traders have different strategies: some follow trends while others trade on mean reversion; some hold inventory for mere seconds, while others hold it for minutes, hours, or days. As a result, contracts are passed around from trader to trader before the order flow imbalance plays itself out and the price adjustment is completed.

During the down phase of the Flash Crash, High Frequency Traders traded faster than all other traders, and by doing so have amplified downward price momentum as prices approached intraday lows. After buying 3,000 contracts in a falling market in the first ten minutes of the Flash Crash, some High Frequency Traders began to aggressively hit the bids in the limit order book. Especially in the last minute of the down phase, many of the contracts sold by High Frequency Traders looking to aggressively reduce inventories were executed against other High Frequency Traders, generating a "hot potato" effect and a rapid spike in trading volume. This is consistent with the fact that High Frequency Traders as a group did not significantly change their total inventory even as the prices were rapidly falling.

Figure 6 shows the magnitude of the hot potato effect. The figure presents the 5 second moving average of the ratio of the absolute value of the net position change of High Frequency Traders to their trading volume.

<Insert Figure 6>

We find that compared to the previous three days, HFT "hot potato" trading on May 6 was extremely high. The hot potato effect was especially pronounced between 13:45:13 and 13:45:27 CT, when prices were plunging with a tremendous velocity. During this time, the HFTs traded over 27,000 contracts or about 49% of the total trading volume, but their net position changed by a mere 200 contracts.

The downward spiral in prices and the spike in trading volume were interrupted by a five-second trading pause triggered by the "stop-logic" functionality built into the CME's Globex trading system.[11] A few seconds after the 5-second pause, transaction prices first stabilized and then rebounded rapidly, as Fundamental Buyers and Opportunistic Trader lifted offers. By 2:08 p.m. CT, 36 minutes after the Flash Crash began, prices of E-mini futures had recovered to their pre-Flash-Crash levels.

Note that the process of absorbing large order flow imbalances in automated markets is quite different from that in open outcry markets. In open outcry markets, market makers were actively discouraged from trading with each other and a single trader wishing to accumulate a large inventory over a short period of time would be directed my market surveillance to trade "upstairs" so as not to destabilize the market. In contrast, in automated markets, trading is anonymous and safeguards are designed to police for individual order imbalances (e.g., price limits and quantity bands for each order), but not for large order imbalances or market disruptions that might be caused by a trading program consisting of many individual orders that individually satisfy the safeguards in place (as was the case with the 75,000 trading program). As a result, open outcry markets did not need to employ market-wide stop-logic type functionality to detect and deal with significant order flow imbalances.

This leads us to suggest that automated exchanges should consider including a number of different functionalities to slow down or pause order matching, especially if significant order flow imbalances are detected. These short pauses followed by auction-based re-opening procedures would, in the spirit of Huang and Wang (2010), force market participants to coordinate their liquidity supply responses in a pre-determined manner instead of seeking to execute ahead of others. We believe that more diligent use of trading pauses of short duration and coordinated re-opening protocols can be an effective

[11]The CME's Globex stop-logic functionality is an automated pre-trade safeguard procedure designed to prevent the execution of cascading stop orders that would cause "excessive" declines or increases in prices due to lack of sufficient depth in the central limit order book. In the context of this functionality, "excessive" is defined as being outside of a pre-determined 'no bust' range. The 'no bust range' varies from contract to contract; for the E-mini it was set at 6 index points–24 ticks–in either direction for the E-mini. After the stop-logic functionality is triggered, the trading is paused for a certain period of time as the matching engine goes in what's called a 'reserve state'. The length of the trading pause varies between 5 and 20 seconds from contract to contract; it was set at 5 seconds for the E-mini. During the 'reserve state', orders can be submitted, modified or cancelled, but no executions can take place. The matching engine exits the reserve state by initiating the same auction opening procedure as it does in the beginning of each trading day. After the starting price is determined by the re-opening auction, the matching engine goes back into the standard continuous matching protocol.

pre-trade safeguard in today's fast automated markets. The five-second trading pause triggered at the bottom of the Flash Crash followed by a re-opening auction procedure is one example of such a functionality. The five-second trading pause triggered at the bottom of the Flash Crash followed by a re-opening auction procedure is one example of such a functionality. Many more such "forced coordination" measures could be designed and implemented in today's fast and interlinked markets.

V. What Do High Frequency Traders Do?

So far, we have established that High Frequency Traders did not trigger the Flash Crash, but have exacerbated the price movement and fueled a spike in the total trading volume during the time when the E-mini prices were falling rapidly in response to large order flow imbalance. What kind of trading activity would make the HFTs contribute this way to a flash-crash-type event?

We believe that in the ordinary course of business, HFTs use their technological advantage to profit from aggressively removing the last few contracts at the best bid and ask levels and then establishing new best bids and asks at adjacent price levels ahead of an immediacy-demanding customer. As an illustration of this "immediacy absorption" activity, consider the following stylized example, presented in Figure 7 and described below.

<Insert Figure 7>

Suppose that we observe the central limit order book for a stock index futures contract. The notional value of one stock index futures contract is $50. The market is very liquid – on average there are hundreds of resting limit orders to buy or sell multiple contracts at either the best bid or the best offer. At some point during the day, due to temporary selling pressure, there is a total of just 100 contracts left at the best bid price of 1000.00. Recognizing that the queue at the best bid is about to be depleted, HFTs submit executable limit orders to aggressively sell a total of 100 contracts, thus completely depleting the queue at the best bid, and very quickly submit sequences of new limit orders to buy a total of 100 contracts at the new best bid price of 999.75, as well as to sell 100 contracts at the new best offer of 1000.00. If the selling pressure continues, then HFTs are able to buy 100 contracts at 999.75 and make a profit of $1,250 dollars among them. If, however, the selling pressure stops and the new best offer price of 1000.00 attracts buyers, then HFTs would very quickly sell 100 contracts (which are at the very front of the new best offer queue), "scratching" the trade at the same price as they bought, and getting rid of the risky inventory in a few milliseconds.

This type of trading activity reduces, albeit for only a few milliseconds, the latency of a price move. Under normal market conditions, this trading activity somewhat accelerates price changes and adds to the trading volume, but does not result in a significant directional price move. In effect, this activity imparts a small "immediacy absorption" cost on all traders, including the market makers, who are not fast enough to cancel the last remaining orders before an imminent price move.

This activity, however, makes it both costlier and riskier for the slower market makers to maintain continuous market presence. In response to the additional cost and risk, market makers lower their acceptable inventory bounds to levels that are too small to offset temporary liquidity imbalances of any significant size. When the diminished liquidity buffer of the market makers is pierced by a sudden order flow imbalance, they begin to demand a progressively greater compensation for maintaining continuous market presence, and prices start to move directionally. Just as the prices are moving directionally and volatility is elevated, immediacy absorption activity of HFTs can exacerbate a directional price move and amplify volatility. Higher volatility further increases the speed at which the best bid and offer queues are being depleted, inducing HFT algorithms to demand immediacy even more, fueling a spike in trading volume, and making it more costly for the market makers to maintain continuous market presence. This forces more risk averse market makers to withdraw from the market, which results in a full-blown market crash.

Empirically, immediacy absorption activity of the HFTs should manifest itself in the data very differently from the liquidity provision activity of the Market Makers. To establish the presence of these differences in the data, we test the following hypotheses:

Hypothesis H1: HFTs are more likely than Market Makers to aggressively execute the last 100 contracts at the best bid or offer before a price move in the direction of the trade. Market Makers are more likely than HFTs to have the last 100 resting contracts against which aggressive orders are executed.

Hypothesis H2: HFTs trade aggressively in the direction of the price move, then reverse position with passive trade. Market Makers get run over by a price move.

Hypothesis H3: Both HFTs and Market Makers scratch trades, but HFTs scratch more.

To statistically test our "immediacy absorption" hypotheses against the "liquidity provision" hypotheses, we divide all of the trades during the 405 minute trading day into two subsets: Aggressive Buy trades and Aggressive Sell trades. A specific trade is often not a standalone event, but a part of a sequence of transactions associated with the execution of a particular trading strategy. Looking at the sequence of trades rather than the individual trades allows us to make inferences about the strategies of traders.

Testing Hypothesis H1. Aggressive removal of the last 100 contracts by HFTs; passive provision of the last 100 resting contracts by the Market Makers. Using the Aggressive Buy sequences, we label as a "price increase event" all occurrences of trading sequences in which at least 100 contracts consecutively executed at the same price are followed by some number of contracts at a higher price. To examine indications of low latency, we focus on the last 100 contracts traded before the price increase and the first 100 contracts at the next higher price (or fewer if the price changes again before 100 contracts are executed). Although we do not look directly at the limit order book data, price increase events are defined to capture occasions where traders use executable buy orders to lift the last remaining best offers in the limit order book. Using Aggressive sell trades, we define "price decrease events" symmetrically as occurrences of sequences of trades in which 100 contracts executed at the same price are followed by executions at lower prices. These events are intended to capture occasions where traders use executable sell orders to hit the last few best bids in the limit order book. The results are presented in Table VI.

<Insert Table VI>

Table VI has four panels covering (A) price increase events on May 3-5, (B) price decrease events on May 3-5, (C) price increase events on May 6, and (D) price decrease events on May 6. In each panel there are six rows of data, one row for each trader category. Relative to panels A and C, the rows for Fundamental Buyers (BUYER) and Fundamental Sellers (SELLER) are reversed in panels B and D to emphasize the symmetry between buying during price increase events and selling during price decrease events. The first two columns report the percentage shares of Aggressive and Passive contract volume for up to the last 100 contracts before the price change; the next two columns report the percentage shares of Aggressive and Passive volume for up to the next 100 contracts after the price change. For comparison, the last two columns report the "unconditional" market shares of Aggressive and Passive sides of all Aggressive buy volume or sell volume. For May 3-5, the data are based on volume pooled across the three days.

During May 3-5, there were 4100 price increase events and 4062 price decrease events. On May 6 alone, there were 4101 price increase events and 4377 price decrease events. Similarity in the number of price events is consistent with our treating the period of May 3-5 as a "single day" when comparing it to May 6.

The percentage share of Aggressive and Passive contract volume for up to the last 100 contracts before the price change is calculated as follows: starting at a price change event, we count backwards the number of contracts traded at the "old" price preceding the price event; when we get to 100 contracts and there was not another price event, we stop; if there is another price event fewer than 100 contracts back, we also stop; we then attribute each contract traded either Aggressively or Passively to one of our six categories of traders, add up the contracts for each category, and calculate the percentage share of Aggressive and Passive contract volume for up to the last 100 contracts traded at the "old" price before the price change. We then compute averages for each category over all price increase and all price decrease events for May 3-5 and May 6, respectively.

Similarly, we calculate the percentage shares of Aggressive and Passive volume for up to the next 100 contracts after the price change by counting forward the number of contracts traded at the "new" price following the price event. Again, if there no subsequent price event, we stop at 100 contracts; if there is another price event fewer that 100 contracts forward, we stop at whatever the number contracts (less than 100) was traded at the "new" price. We then attribute each contract traded either Aggressively or Passively to one of our six categories of traders, add up the contracts for each category, and calculate the percentage share of Aggressive and Passive contract volume for up to the next 100 contracts traded at the "new" price after the price change. We then compute averages for each category over all price increase and all price decrease events for May 3-5 and May 6, respectively.

For robustness, we conducted the same analysis for 20 and 50 contracts, as well as for 10, 25, and 50 transactions (on average there are [4] contracts are traded per transaction) and came up with qualitatively similar results. Furthermore, standard errors associated with the averages for "up to the last 100" or "up to the next 100" contracts are always less than 1%. For that reason, we do not report them in the table.

Consider panel A of Table VI, which describes price increase events associated with Aggressive buy trades on May 3-5, 2010. High Frequency Traders participated on the Aggressive side of 34.04% of all aggressive buy volume. Strongly consistent with our immediacy absorption hypothesis, the participation rate rises to 57.70% of the Aggressive side of trades on the last 100 contracts of Aggressive buy volume before price increase events and falls to 14.84% of the Aggressive side of trades on the first 100 contracts of Aggressive buy volume after price increase events.

High Frequency Traders participated on the Passive side of 34.33% of all aggressive buy volume. Consistent with our hypothesis, the participation rate on the Passive side of Aggressive buy volume falls to 28.72% of the last 100 contracts before a price increase event. It rises to 37.93% of the first 100 contracts after a price increase event.

These results are inconsistent with the notion that High Frequency Traders behave like textbook market makers, suffering adverse selection losses associated with being picked off by informed traders. Instead, when the price is about to move to a new level, HFTs tend to avoid being run over and take the price to the new level with Aggressive trades of their own.

Market Makers follow a noticeably more passive trading strategy than High Frequency Traders. According to panel A or Table VI, Market Makers are 13.48% of the Passive side of all Aggressive trades, but they are only 7.27% of the Aggressive side of all Aggressive trades. On the last 100 contracts at the old price, Market Makers' share of volume increases only modestly, from 7.27% to 8.78% of trades. Their share of Passive volume at the old price increases, from 13.48% to 15.80%. These facts are consistent with the interpretation that Market Makers, unlike High Frequency Traders, do engage in a strategy similar to traditional passive market making, buying at the bid price, selling at the offer price, and suffering losses when the price moves against them. These facts are also consistent with our hypothesis that High Frequency Traders have lower latency than Market Makers.

Intuition might suggest that Fundamental Buyers would tend to place the Aggressive trades which move prices up from one tick level to the next. This intuition does not seem to be corroborated by the data. According to panel A of Table VI, Fundamental Buyers are 21.53% of all Aggressive trades but only 11.61% of the last 100 Aggressive contracts traded at the old price. Instead, Fundamental Buyers increase their share of Aggressive buy volume to 26.17% of the first 100 contracts at the new price.

Taking into account symmetry between buying and selling, panel B of Table VI shows the results for Aggressive sell trades during May 3-5, 2010, are almost the same as the results for Aggressive buy trades. High Frequency Traders are 34.17% of all Aggressive sell volume, increase their share to 55.20% of the last 100 Aggressive sell contracts at the old price, and decrease their share to 15.04% of the last 100 Aggressive sell contracts at the new price. Market Makers are 7.45% of all Aggressive sell contracts, increase their share to only 8.57% of the last 100 Aggressive sell trades at the old price, and decrease their share to 6.58% of the last 100 Aggressive sell contracts at the new price. Fundamental Sellers' shares of Aggressive sell trades behave similarly to Fundamental Buyers' shares of Aggressive Buy trades. Fundamental Sellers are 20.91% of all Aggressive sell contracts, decrease their share to 11.96% of the last 100 Aggressive sell contracts at the old price, and increase their share to 24.87% of the first 100 Aggressive sell contracts at the new price.

Panels C and D of Table VI report results for Aggressive Buy trades and Aggressive Sell trades for May 6, 2010. Taking into account symmetry between buying and selling, the results for Aggressive buy trades in panel C are very similar to the results for Aggressive sell trades in panel D. For example, Aggressive sell trades by Fundamental Sellers were 17.55% of Aggressive sell volume on May 6, while Aggressive buy trades by Fundamental Buyers were 20.12% of Aggressive buy volume on May 6. In comparison with the share of Fundamental Buyers and in comparison with May 3-5, the Flash Crash of May 6 is associated with a slightly lower—not higher—share of Aggressive sell trades by Fundamental Sellers.

A comparison of May 6 with May 3-5 reveals that the share of Aggressive trades by High Frequency Traders drops from 34.04% of Aggressive buys and 34.17% of Aggressive sells on May 3-5 to 26.98% of Aggressive buy trades and 26.29% of Aggressive sell trades on May 6. The share of Aggressive trades for the last 100 contracts at the old price declines by even more. High Frequency Traders' participation rate on the Aggressive side of Aggressive buy trades drops from 57.70% on May 3-5 to only 38.86% on May 6. Similarly, the participation rate on the Aggressive side of Aggressive sell trades drops from and 55.20% to 38.67%. These declines are largely mimicked by increases in the participation rate by Opportunistic Traders on the Aggressive side of trades. For example, Opportunistic Traders' share of the Aggressive side of the last 100 contracts traded at the old price rises from 19.21% to 34.26% for Aggressive buys and from 20.99% to 33.86% for Aggressive sells. These results likely come about because Opportunistic Traders engaged in cross-market arbitrage strategies (e.g., trading the E-mini against the SPY - S&P 500 ETF) were extremely active during the Flash Crash as evidenced by the propagation of the shock from the E-mini to the SPY (which is what made the Flash Crash a systemic event).

Testing Hypothesis H2. HFTs trade aggressively in the direction of the price move, then reverse position with a passive trade; Market Makers get run over by a price move. To examine this hypothesis, we analyze whether High Frequency Traders use Aggressive trades to trade in the direction of contemporaneous price changes, while Market Makers use Passive trades to trade in the opposite direction from price changes. To this end, we estimate the regression Equation 1 for Passive and Aggressive inventory changes separately.

<Insert Table VII >

Table VII presents the regression results of the two components of change in holdings on lagged inventory, lagged change in holdings and lagged price changes over one second intervals. Panel A and Panel B report the results for May 3-5 and May 6, respectively. Each panel has four columns, reporting estimated coefficients where the dependent variables are net Aggressive volume (Aggressive buys minus Aggressive sells) by High Frequency Traders ($\Delta AHFT$), net Passive volume by High Frequency Traders ($\Delta PHFT$), net Aggressive volume by Market Makers (ΔAMM), and net Passive volume by Market Makers (ΔPMM).

We observe that for lagged inventories ($NPHFT_{t-1}$), the estimated coefficients for Aggressive and Passive trades by High Frequency Traders are $\delta_{AHFT} = -0.005$ ($t = -9.55$) and $\delta_{PHFT} = -0.001$ ($t = -3.13$), respectively. These coefficient estimates have the interpretation that High Frequency Traders use Aggressive trades to liquidate inventories more intensively than passive trades. In contrast, the results for Market Makers are very different. For lagged inventories ($NPMM_{t-1}$), the estimated coefficients for Aggressive and Passive volume by Market Makers are $\delta_{AMM} = -0.002$ ($t = -6.73$) and $\delta_{PMM} = -0.002$ ($t = -5.26$), respectively. The similarity of these coefficients estimates has the interpretation that Market Makers favor neither Aggressive trades nor Passive trades when liquidating inventories.

For contemporaneous price changes (in the current second) (ΔP_{t-1}), the estimated coefficient Aggressive and Passive volume by High Frequency Traders are $\beta_0 = 57.78$ ($t = 31.94$) and $\beta_0 = -25.69$ ($t = -28.61$), respectively. For Market Makers, the estimated coefficients for Aggressive and Passive trades are $\beta_0 = 6.38$ ($t = 18.51$) and $\beta_0 = -19.92$ ($t = -37.68$). These estimated coefficients have the interpretation that in seconds in which prices move up one tick, High Frequency Traders are net buyers of about 58 contracts with Aggressive trades and net sellers of about 26 contracts with Passive trades in that same second, while Market Makers are net buyers of about 6 contracts with Aggressive trades and net sellers of about 20 contracts with Passive trades. High Frequency Traders and Market Makers are similar in that they both use Aggressive trades to trade in the direction of price changes, and both use Passive trades to trade against the direction of price changes. High Frequency Traders and Market Makers are different in that Aggressive net purchases by High Frequency Traders are greater in magnitude than the Passive net purchases, while the reverse is true for Market Makers.

For lagged price changes, coefficient estimates for Aggressive trades by High Frequency Traders and Market Makers are positive and statistically significant at lags 1-4 and lags 1-10, respectively. These results have the interpretation that both High Frequency Traders' and Market Makers' trade on recent price momentum, but the trading is compressed into a shorter time frame for High Frequency Traders than for Market Makers.

For lagged price changes, coefficient estimates for Passive volume by High Frequency Traders and Market Makers are negative and statistically significant at lags 1 and lags 1-3, respectively.[12]

Panel B of Table VII presents results for May 6. Similar to May 3-5, High Frequency Traders tend to use Aggressive trades more actively than Passive trades to liquidate inventories, while Market Makers do not show this pattern. Also similar to May 3-5, High Frequency Trades and Market Makers use Aggressive trades to trade in the contemporaneous direction of price changes and use Passive trades to trade in the direction opposite price changes, with Aggressive trading greater than Passive trading for High Frequency Traders and the reverse for Market Makers. In comparison with May 3-5, the coefficients are smaller in magnitude on May 6, indicating reduced liquidity at each tick. For lagged price changes, the coefficients associated with Aggressive trading by High Frequency Traders change from positive to negative at lags 1-4, and the positive coefficients associated with Aggressive trading by Market Makers change from being positive and statistically significant at lags 1-10 to being positive and statistically significant only at lags 1-3. These results illustrate accelerated trading velocity in the volatile market conditions of May 6.

We further examine how high frequency trading activity is related to market prices. Figure 8 illustrates how prices change after HFT trading activity in a given second. The upper-left panel presents results for buy trades for May 3-5, the upper right panel presents results for buy trades on May 6, and the lower-left and lower-right present corresponding results for sell trades. For an "event" second in which High Frequency Traders are net buyers, net Aggressive Buyers, and net Passive Buyers, value-weighted average prices paid by the High Frequency Traders in that second are subtracted from the value-weighted average prices for all trades in the same second and each of the following 20 seconds. The results are averaged across event seconds, weighted by the magnitude of High Frequency Traders' net position change in the event second. Price differences on the vertical axis are scaled so that one unit equals one tick ($12.50 per one E-mini contract).

[12] We also introduce lead price changes up to 10 seconds into this regression framework. Price change coefficients are positive and significant for the net aggressive volume of High Frequency Traders before May 6. Coefficients are very similar when we include longer lags of prices and holdings changes. Newey-West standard errors are very close to White standard errors. Results are available upon request.

<Insert Figure 8>

When High Frequency Traders are net buyers during May 3-5, prices rise by 17% of a tick in the next second, then begin to gradually fall; 20 seconds after a net buy by HFTs, process remain 15 % of a tick higher. The total effect of net buy HFT trades can be separated into net aggressive and net passive buy trades. When HFTs buy aggressively, prices rise by 20% of a tick in the next second, continue rising into the next second, stabilize at about 23

On May 6, the effects of an aggressive HFT buy trade and a passive HFT sell trade are qualitatively the same as during May 3-5. However, the permanent price effects of HFT trading on that day are much more pronounced for an aggressive HFT sell or a passive HFT buy. Following an aggressive HFT sell, prices continue to drift down for the next 20 seconds (when they reach over half a tick); similarly, prices continue to drift upward after a passive HFT buy until they stabilize at stay at about half a tick 20 seconds later.

These charts illustrate how profitable the "immediacy removal" trading strategy is for HFTs. During May 3-5, HFTs make about a quarter of a tick per contract within seconds by either aggressively selling and then passively buying (before a price move) or by aggressively buying and then passively selling (when the price comes to their resting orders). During the times of fast changing prices and very high volatility, HFTs make a full tick per contract in a matter of seconds.

Testing Hypothesis H3. Both HFTs and Market Makers scratch trades; HFTs scratch more. A textbook market maker will try to buy at the bid price, sell at the offer price, and capture the bid-ask spread as a profit. Sometimes, after buying at the bid price, market prices begin to fall before the market maker can make a one tick profit by selling his inventory at the best offer price. To avoid taking losses in this situation, one component of a traditional market making strategy is to "scratch trades in the presence of changing market conditions by quickly liquidating a position at the same price at which it was acquired. These scratched trades represent inventory management trades designed to lower the cost of adverse selection. Since many competing market makers may try to scratch trades at the same time, traders with the lowest latency will tend to be more successful in their attempts to scratch trades and thus more successful in their ability to avoid losses when market conditions change.

To examine whether and to what extent traders engage in trade scratching, we sequence each trader's trades for the day using audit trail sequence numbers which not only sort trades by second but also sort trades chronologically within each second. We define an "immediately scratched trade" as a trade with the properties that the next trade in the sorted sequence (1) occurred in the same second, (2) was executed at the same price, (3) was in the opposite direction, i.e., buy followed by sell or sell followed by buy. For each of the trading accounts in our sample, we calculate the number of immediately scratched trades, then compare the number of scratched trades across the six trader categories.

The results of this analysis are presented in the table below. Panel A provides results for May 3-5 and panel B for May 6. In each panel, there are five rows of data, one for each trader category. The first three columns report the total number of trades, the total number of immediately scratched trades, and the percentage of trades that are immediately scratched by traders in five categories. Small trader category results are not reported for confidentiality reasons. For May 3-6, the reported numbers are from the pooled data.

<Insert Table VIII>

This table shows that High Frequency Traders scratched 2.84 % of trades on May 3-5 and 4.26 % on May 6; Market Makers scratched 2.49 % of trades on May 3-5 and 5.53 % of trades on May 6. While the percentages of immediately scratched trades by Market Makers is slightly higher than that for High Frequency Traders on May 6, the percentages for both groups are very similar.

The fourth, fifth, and sixth columns of Table VIII report the mean, standard deviation, and median of the number of scratched trades for the traders in each category.

Although the percentages of scratched trades are similar, the mean number of immediately scratched trades by High Frequency Traders is much greater than for Market Makers: 540.56 per day on May 3-5 and 1610.75 on May 6 for High Frequency Traders versus 13.35 and 72.92 for Market Makers. The differences between High Frequency Traders and Market Makers reflect differences in volume traded. Table VIII shows that High Frequency Traders and Market Makers scratch a significantly larger percentage of their trades than other trader categories.

VI. Concluding Remarks

More than 40 years ago, stock exchanges began to think about switching from face-to-face human trading to fully automated trading platforms. Fischer Black (1971) surmised that, regardless of whether markets were human or automated, liquid markets would exhibit price continuity only if trading is characterized by a large volume of small individual trades. As electronic central limit order books have replaced human trading, Black's insights have proven to be correct. Black (1995) also predicted that, to reduce impact costs, electronic markets would induce institutions to shift from executing large trades as blocks with "upstairs" human dealers to using "order shredding" strategies in which computer algorithms submit many small trades over time into electronic trading platforms. This insight has also proven to be correct.

Black did not foresee, however, how dramatically advances in the computing and telecommunication technology would favor the most technologically-advanced financial intermediaries known as high frequency traders or HFTs. We find that these traders engage in immediacy absorption activity just ahead of any slower immediacy-seeking market participant. This immediacy absorption activity makes prices move against all slower customers who seek immediacy and, thus, imposes an immediacy absorption cost on all slower traders, including the traditional market makers.

As suggested by Huang and Wang (2008), even a small cost of maintaining continuous market presence makes market makers choose to maintain risk exposures that are too low to offset temporary liquidity imbalances. In the event of large enough sell order, the liquidity on the buy side could only be obtained after a price drop that is large enough to compensate increasingly reluctant market makers to take on additional risky inventory. These liquidity-based crashes are accompanied by high trading volume and large price volatility as documented during a series of events that took place on May 6, 2010 that collectively became known as the Flash Crash.

The events of May 6, 2010 were extremely traumatic to many market participants. Was the Flash Crash caused by the high frequency traders? What have we learned from this event? How do we make sure that events like that are less likely to happen in the future?

In this paper, we show that HFTs did not cause the Flash Crash, but accelerated a price movement due to a large order imbalance caused by an automated execution program to sell E-mini S&P 500 futures contracts. We also show that HFTs contributed to the Flash Crash by engaging in their typical immediacy-absorption practice of aggressively removing the last few contracts at the best bid or ask levels and then establishing new best bids and asks at adjacent price levels.

Under calm market conditions, this trading activity accelerates, albeit for only a few milliseconds, the price movement and adds to trading volume, but does not result in a directional price move. At times of market stress, when prices are moving directionally, due to an order flow imbalance and the volatility is already elevated, this trading activity can amplify a directional price move and significantly add to volatility. Higher volatility further increases the speed at which the best bid and offer queues get depleted, inducing HFTs to act faster, leading to a spike in trading volume, and setting the stage for a flash-crash-type event.

The Flash Crash has forced regulators and self-regulatory organizations to re-visit the intricacies of market design and to contemplate policies that prevent these events from happening in the future. The proposed responses vary from a tax on all financial transactions to imposing delays on the cancellation or modification of resting orders or restricting directional changes in prices on a security-by-security basis.

Based on our results, appropriate regulatory actions should aim to encourage HFTs to provide immediacy, while discouraging them from demanding it. We believe that this can be accomplished through changes in market design rather than taxes, limits or restrictions as higher opportunity costs imposed on the technologically-advanced intermediaries would, at best, be passed on to other market participants. For example, a more diligent use of market-wide trading pauses of short duration, which give slower algorithms a few much needed seconds to decide on what terms they are willing to replenish liquidity in the central limit order book, can be a highly effective pre-trade safeguard in today's fast and interlinked markets.

We acknowledge that in markets for individual securities, fragmentation of order flow across competing trading venues makes the coordination of brief trading pauses difficult. We also acknowledge that the task of coordinating responses across competing markets overseen by different regulators with contradictory objectives is even more difficult. This paper is our call to rise to these challenges.

References

Black, Fischer, 1971, Towards a Fully Automated Exchange, Part I, *Financial Analysts Journal* 27, 29-34.

Black, Fischer, 1995, Equilibrium Exchanges, *Financial Analysts Journal* 51, 23-29.

CFTC-SEC Staff Report, Preliminary Findings Regarding the Market Events of May 6, 2010.

CFTC-SEC Staff Report, Findings Regarding the Market Events of May 6, 2010.

Grossman, Sanford J., and Miller, Merton H., 1988, Liquidity and Market Structure, *Journal of Finance* 43,3,617–633.

Hasbrouck, Joel, 2003, Intraday Price Formation in U.S. Equity Index Markets, *Journal of Finance* 58, 2375–2400.

Huang, Jennifer. and Jiang Wang, 2008, Liquidity and market crashes, *Review of Financial Studies*, 2607-2643.

Huang, Jennifer and Jiang Wang, 2010, Market Liquidity, Asset Prices, and Welfare, *Journal of Financial Economics*, 95, 107-127.

White, Halbert, 1980, A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity, *Econometrica* 48, 817–838.

Table I: Market Descriptive Statistics

	May 3-5	May 6th
Daily Trading Volume	2,397,639	5,094,703
# of Trades	446,340	1,030,204
# of Traders	11,875	15,422
Trade Size	5.41	4.99
Order Size	10.83	9.76
Limit Orders % Volume	95.45%	92.44%
Limit Orders % Trades	94.36%	91.75%
Log High-Low Range	1.54%	9.82%
Return	-0.02%	-3.05%

This table presents summary statistics for the June 2010 E-Mini S&P 500 futures contract. The first column presents averages calculated for May 3-5, 2010 between 8:30 and 15:15 CT. The second column presents statistics for May 6, 2010 between 8:30 to 15:15 CT. Volume is the number of contracts traded. The number of traders is the number of trading accounts that traded at least once during a trading day. Order size and trade sizes are measured in the number of contracts. The use of limit orders is presented both in percent of the number of transactions and trading volume. Volatility is calculated as range, the natural logarithm of maximum price over minimum price within a trading day.

Table II: Summary Statistics of Trader Categories

Panel A: May 3-5 3 Day Average

Trader Type	% Volume	% of Trades	# Traders	Trade Size (Avg.)	Order Size (Avg.)	Limit Orders % Volume	Limit Orders % Trades	Agg Ratio Trade-Weighted	Agg Ratio Vol-Weighted
High Frequency Traders	34.22%	32.56%	15	5.69	14.75	100.000%	100.000%	49.91%	45.68%
Market Makers	10.49%	11.63%	189	4.88	7.92	99.614%	98.939%	43.10%	41.62%
Fundamental Buyers	11.89%	10.15%	1,013	6.34	14.09	91.258%	91.273%	66.04%	64.09%
Fundamental Sellers	12.11%	10.10%	1,088	6.50	14.20	92.176%	91.360%	62.87%	61.13%
Opportunistic Traders	30.79%	33.34%	3,504	4.98	8.80	92.137%	90.549%	55.98%	54.71%
Small Traders	0.50%	2.22%	6,065	1.22	1.25	70.092%	71.205%	59.04%	59.06%
	Volume	# of Trades	# Traders	Trade Size (Avg.)	Order Size (Avg.)	Limit Orders % Volume	Limit Orders % Trades	Volatility	Return
All	2,397,639	446,340	11,875	5.41	10.83	95.45%	94.36%	1.54%	-0.02%

Panel B: May 6th

Trader Type	% Volume	% of Trades	# Traders	Trade Size (Avg.)	Order Size (Avg.)	Limit Orders % Volume	Limit Orders % Trades	Agg Ratio Trade-Weighted	Agg Ratio Vol-Weighted
High Frequency Traders	28.57%	29.35%	16	4.85	9.86	99.997%	99.997%	50.38%	45.53%
Market Makers	9.00%	11.48%	179	3.89	5.88	99.639%	99.237%	45.18%	43.55%
Fundamental Buyers	12.01%	11.54%	1,263	5.15	10.43	88.841%	89.589%	64.39%	61.08%
Fundamental Sellers	10.04%	6.95%	1,276	7.19	21.29	89.985%	88.966%	68.42%	65.68%
Opportunistic Traders	40.13%	39.64%	5,808	5.05	10.06	87.385%	85.352%	61.92%	60.28%
Small Traders	0.25%	1.04%	6,880	1.20	1.24	63.609%	64.879%	63.49%	63.53%
	Volume	# of Trades	# Traders	Trade Size (Avg.)	Order Size (Avg.)	Limit Orders % Volume	Limit Orders % Trades	Volatility	Return
All	5,094,703	1,030,204	15,422	4.99	9.76	92.443%	91.750%	9.82%	-3.05%

This table presents summary statistics for trader categories and the overall market. The first column presents statistics prior to May 6 as the average over three trading days, May 3-5, 2010 from 8:30 to 15:15 CT. The second column presents statistics for May 6 from 8:30 to 15:15 CT.

Table III: HFTs and Market Makers: Net Holdings and Prices

Panel A: May 3-5			Panel B: May 6		
	Δ NP HFT	**Δ NP MM**		**Δ NP HFT**	**Δ NP MM**
Intercept	-1.64	-0.53	**Intercept**	-3.22	0.04
	(-3.54)	**(-3.33)**		**(-3.38)**	(0.13)
$\Delta NPHFT_{t-1}$	-0.006		$\Delta NPHFT_{t-1}$	0.011	
	(-0.69)			(1.19)	
$NPHFT_{t-1}$	-0.005		$NPHFT_{t-1}$	-0.005	
	(-11.77)			**(-6.76)**	
$\Delta NPMM_{t-1}$		-0.006	$\Delta NPMM_{t-1}$		-0.035
		(-0.79)			**(-2.69)**
$NPMM_{t-1}$		-0.004	$NPMM_{t-1}$		-0.008
		(-8.93)			**(-7.79)**
ΔP_t	32.09	-13.54	ΔP_t	10.81	-8.16
	(18.44)	**(-23.83)**		**(6.05)**	**(-12.09)**
ΔP_{t-1}	17.18	-1.22	ΔP_{t-1}	4.63	6.64
	(12.58)	**(-2.71)**		**(3.39)**	**(13.88)**
ΔP_{t-2}	8.36	2.16	ΔP_{t-2}	-1.52	2.73
	(7.15)	**(4.99)**		(-1.25)	**(4.44)**
ΔP_{t-3}	5.09	2.53	ΔP_{t-3}	-1.36	1.14
	(4.93)	**(5.97)**		(-1.06)	**(2.84)**
ΔP_{t-4}	3.91	2.65	ΔP_{t-4}	-1.82	0.49
	(3.62)	**(6.54)**		(-1.48)	(1.11)
ΔP_{t-5}	1.81	2.50	ΔP_{t-5}	-0.23	-0.77
	(1.56)	**(5.91)**		(-1.17)	(-1.68)
ΔP_{t-6}	-0.08	2.16	ΔP_{t-6}	-0.31	-0.31
	(-0.07)	**(5.42)**		(-0.23)	(-0.78)
ΔP_{t-7}	-1.00	1.84	ΔP_{t-7}	-5.04	-0.62
	(-0.97)	**(4.96)**		**(-3.62)**	(-1.33)
ΔP_{t-8}	-1.76	1.47	ΔP_{t-8}	-1.78	-0.36
	(-1.56)	**(3.83)**		(-1.41)	(-0.93)
ΔP_{t-9}	-1.81	0.45	ΔP_{t-9}	-1.68	-1.11
	(-1.70)	(1.19)		(-1.35)	**(-2.45)**
ΔP_{t-10}	-3.90	0.52	ΔP_{t-10}	-1.65	-0.39
	(-3.78)	(1.37)		(-1.13)	(-0.84)
ΔP_{t-11}	-4.73	-0.03	ΔP_{t-11}	-1.08	-0.63
	(-4.70)	(-0.07)		(-0.74)	(-1.28)
ΔP_{t-12}	-3.46	0.15	ΔP_{t-12}	0.71	-1.17
	(-3.33)	(0.41)		(0.43)	**(-2.58)**
ΔP_{t-13}	-3.80	0.27	ΔP_{t-13}	2.26	-0.62
	(-3.74)	(0.72)		(1.43)	(-1.49)
ΔP_{t-14}	-4.77	0.32	ΔP_{t-14}	-2.66	-0.27
	(-4.70)	(0.86)		**(-1.85)**	(-0.71)
ΔP_{t-15}	-2.74	-0.19	ΔP_{t-15}	0.43	-0.83
	(-2.63)	(-0.53)		(0.34)	**(-2.19)**
ΔP_{t-16}	-2.21	-0.64	ΔP_{t-16}	-0.68	0.23
	(-2.09)	(-1.72)		(-0.41)	(0.61)
ΔP_{t-17}	-2.52	-0.10	ΔP_{t-17}	-0.66	0.29
	(-2.45)	(-0.26)		(-0.45)	(0.73)
ΔP_{t-18}	-4.36	0.04	ΔP_{t-18}	0.45	-0.77
	(-3.96	(0.12)		(0.29)	**(-2.04)**
ΔP_{t-19}	-4.21	0.57	ΔP_{t-19}	-2.63	-0.30
	(-4.16)	(1.51)		**(-1.87)**	(-0.76)
ΔP_{t-20}	-5.86	-0.12	ΔP_{t-20}	-1.07	-0.71
	(-5.86)	(-0.33)		(-0.79)	(-1.65)
#obs	72837	72837	**#obs**	24275	24275
$Adj-R^2$	0.019	0.026	$Adj-R^2$	0.010	0.039

This table displays estimated coefficients of the following regression: $\Delta y_t = \alpha + \phi \Delta y_{t-1} + \delta y_{t-1} + \sum_{i=0}^{20} [\beta_i \times \Delta p_{t-i}/0.25] + \epsilon_t$. The dependent variable is changes in holdings of High Frequency Traders and Market Makers, respectively. Both changes in holdings, Δy_t, and lagged holdings, y_{t-1}, are in the number of contracts. Price changes, Δp_{t-i}, are in ticks. Estimates are computed for second-by-second observations. The t-statistics are calculated using the White (1980) estimator. t values reported in parentheses are in bold if the coefficients are statistically significant at the 5% level. Observations are stacked for May 3-5.

Table IV: HFTs and Market Makers: The Flash Crash

Variable	Δ NP HFT	Δ NP MM	Variable (cont)	Δ NP HFT	Δ NP MM	Variable (cont)	Δ NP HFT	Δ NP MM
Intercept	-2.04	-0.48	**Intercept**^{D}	9.22	9.15	**Intercept**^{U}	2.27	0.49
	(-4.78)	**(-3.34)**		(1.19)	**(2.41)**		(0.55)	(0.33)
ΔNP_{t-1}	-0.005	-0.024	ΔNP^D_{t-1}	-0.031	-0.024	ΔNP^U_{t-1}	0.004	0.085
	(-0.69)	**(-3.31)**		(-0.80)	(-0.63)		(0.10)	**(2.74)**
NP_{t-1}	-0.005	-0.005	NP^D_{t-1}	-0.002	-0.007	NP^U_{t-1}	-0.001	0.000
	(-12.95)	**(-10.78)**		(-0.38)	(-1.62)		(-0.21)	(-0.17)
ΔP_t	31.47	-15.48	ΔP^D_t	1.29	14.13	ΔP^U_t	-40.83	14.29
	(16.89)	**(-21.96)**		(0.18)	**(6.73)**		**(-12.18)**	**(13.68)**
ΔP_{t-1}	14.96	-0.54	ΔP^D_{t-1}	-3.02	11.44	ΔP^U_{t-1}	-9.60	5.63
	(12.17)	(-1.23)		(-0.57)	**(5.11)**		**(-3.44)**	**(7.12)**
ΔP_{t-2}	6.24	2.69	ΔP^D_{t-2}	-6.84	1.87	ΔP^U_{t-2}	-9.72	-1.83
	(5.36)	**(5.99)**		(-1.26)	(0.81)		**(-3.57)**	**(-2.20)**
ΔP_{t-3}	3.02	2.65	ΔP^D_{t-3}	-4.16	-2.03	ΔP^U_{t-3}	-3.97	-2.47
	(3.31)	**(7.14)**		(-0.69)	(-1.22)		(-1.61)	**(-3.75)**
ΔP_{t-4}	1.92	2.74	ΔP^D_{t-4}	-9.74	-4.91	ΔP^U_{t-4}	-1.12	-2.51
	(2.04)	**(7.78)**		**(-1.98)**	**(-3.11)**		(-0.49)	**(-3.70)**
ΔP_{t-5}	0.63	2.21	ΔP^D_{t-5}	-10.94	-3.45	ΔP^U_{t-5}	1.86	-2.86
	(0.64)	**(5.99)**		(-1.57)	**(-2.25)**		(0.75)	**(-4.36)**
ΔP_{t-6}	-1.89	1.99	ΔP^D_{t-6}	0.59	-2.91	ΔP^U_{t-6}	4.27	-2.45
	(-2.03)	**(5.72)**		(0.11)	(-1.86)		(1.78)	**(-3.71)**
ΔP_{t-7}	-2.85	1.92	ΔP^D_{t-7}	-1.66	-2.71	ΔP^U_{t-7}	-4.54	-3.38
	(-2.89)	**(5.18)**		(-0.31)	(-1.59)		(-1.73)	**(-5.05)**
ΔP_{t-8}	-2.52	1.43	ΔP^D_{t-8}	2.45	-2.97	ΔP^U_{t-8}	1.79	-1.65
	(-2.68)	**(4.33)**		(0.44)	(-1.92)		(0.76)	**(-2.76)**
ΔP_{t-9}	-2.59	0.48	ΔP^D_{t-9}	-4.32	-2.98	ΔP^U_{t-9}	2.69	-1.64
	(-2.76)	(1.44)		(-0.61)	(-1.70)		(1.12)	**(-2.54)**
ΔP_{t-10}	-5.18	0.91	ΔP^D_{t-10}	3.93	-3.40	ΔP^U_{t-10}	4.41	-1.52
	(-4.66)	**(2.12)**		(0.50)	(-1.78)		(1.76)	**(-2.22)**
ΔP_{t-11}	-5.07	-0.05	ΔP^D_{t-11}	9.84	-6.35	ΔP^U_{t-11}	6.01	-0.36
	(-5.76)	(-0.16)		(1.30)	**(-2.96)**		**(2.27)**	(-0.51)
ΔP_{t-12}	-4.05	-0.10	ΔP^D_{t-12}	8.38	-0.73	ΔP^U_{t-12}	4.37	-0.79
	(-4.46)	(-0.31)		(1.07)	(-0.37)		(1.34)	(-1.26)
ΔP_{t-13}	-3.86	-0.07	ΔP^D_{t-13}	11.92	-4.69	ΔP^U_{t-13}	10.02	0.28
	(-4.27)	(-0.20)		(1.64)	**(-2.10)**		**(3.34)**	(0.43)
ΔP_{t-14}	-4.36	0.28	ΔP^D_{t-14}	-8.56	0.79	ΔP^U_{t-14}	1.64	-0.59
	(-5.01)	(0.84)		(-1.29)	(0.41)		(0.62)	(-0.98)
ΔP_{t-15}	-2.05	-0.17	ΔP^D_{t-15}	8.46	-5.41	ΔP^U_{t-15}	1.47	-0.09
	(-2.27)	(-0.50)		(1.17)	**(-2.55)**		(0.64)	(-0.15)
ΔP_{t-16}	-2.01	-0.39	ΔP^D_{t-16}	-3.25	3.92	ΔP^U_{t-16}	1.07	0.99
	(-2.10)	(-1.11)		(-0.41)	(1.80)		(0.37)	(1.56)
ΔP_{t-17}	-2.67	0.01	ΔP^D_{t-17}	6.24	-1.57	ΔP^U_{t-17}	5.19	0.48
	(-3.05)	(0.02)		(0.81)	(-0.69)		**(2.13)**	(0.75)
ΔP_{t-18}	-3.89	0.19	ΔP^D_{t-18}	-8.62	0.86	ΔP^U_{t-18}	7.37	-0.69
	(-4.10)	(0.58)		(-1.05)	(0.42)		**(2.58)**	(-1.12)
ΔP_{t-19}	-3.50	0.70	ΔP^D_{t-19}	-1.05	-3.07	ΔP^U_{t-19}	-0.75	-0.88
	(-3.88)	**(2.08)**		(-0.12)	(-1.39)		(-0.30)	(-1.44)
ΔP_{t-20}	-5.30	-0.33	ΔP^D_{t-20}	-2.32	3.13	ΔP^U_{t-20}	4.88	-0.06
	(-5.82)	(-1.00)		(-0.30)	(1.36)		**(2.14)**	(-0.09)
			# of Obs	93092	93092			
			Adjusted R2	0.021	0.036			

This table displays estimated coefficients of the following regression: $\Delta y_t = \alpha + \phi \Delta y_{t-1} + \Delta y_{t-1} + \Sigma_{i=0}^{20}[\beta_i \times p_{t-i}/0.25] + D_t^D\{\alpha^D + \phi^D \Delta y_{t-1} + \delta^D y_{t-1} + \Sigma_{i=0}^{20}[\beta_i^D \times p_{t-i}/0.25]\} + D_t^U\{\alpha^U + \phi^U \Delta y_{t-1} + \delta^U y_{t-1} + \Sigma_{i=0}^{20}[\beta_i^U \times p_{t-i}/0.25]\} + \epsilon_t$ during May 3-6 with dummy variables D_t^D and D_t^U included to interact with observations during the Down (from 13:32:00 CT to 13:45:28 CT) and Up (from 13:45:33 CT to 14:08:00 CT) phases of the Flash Crash, respectively. The period between 13:45:28 CT and 13:45:33 CT corresponds to the 5 second pause in trading; there are no changes in prices or inventory during the 5 second pause. The cutoff for observations on May 6, 2010 is 14:08:00 CT. The dependent variable is changes in holdings of High Frequency Traders and Market Makers, respectively. Both changes in holdings, Δy_t, and lagged holdings, y_{t-1}, are in the number of contracts. Price changes, Δp_{t-i}, are in ticks. Estimates are computed for second-by-second observations. The t-statistics are calculated using the White (1980) estimator. The t-statistics reported in parentheses are in bold if the coefficients are statistically significant at the 5% level.

Table V: Trading Volume During the Flash Crash

Panel A: May 3-5						
	DOWN			UP		
	Sell	Buy	Net	Sell	Buy	Net
High Frequency Traders	23,746	23,791	45	40,524	40,021	-503
Market Makers	6,484	6,328	-156	11,469	11,468	-1
Fundamental Buyers	3,064	7,958	4,894	6,127	14,910	8,783
Fundamental Sellers	8,428	3,118	-5,310	15,855	5,282	-10,573
Opportunistic Traders	20,049	20,552	503	37,317	39,535	2,218
Small Traders	232	256	24	428	504	76
Total	62,003	62,003	0	111,720	111,720	0

Panel B: May 6th						
	DOWN			UP		
	Sell	Buy	Net	Sell	Buy	Net
High Frequency Traders	152,436	153,804	1,368	191,490	189,013	-2,477
Market Makers	32,489	33,694	1,205	47,348	45,782	-1,566
Fundamental Buyers	28,694	78,359	49,665	55,243	165,612	110,369
Fundamental Sellers	94,101	10,502	-83,599	145,396	35,219	-110,177
Opportunistic Traders	189,790	221,236	31,446	302,417	306,326	3,909
Small Traders	1,032	947	-85	1,531	1,473	-58
Total	498,542	498,542	0	743,425	743,425	0

This table presents the number of contracts sold and bought by trader categories during DOWN and UP periods. DOWN period is defined as the interval between 13:32:00 and 13:45:28 CT. UP period is defined as the interval between 13:45:33 and 14:08:00 CT. Panel A reports the average number of contracts bought and sold between May 3 and May 5, 2010 during the DOWN and UP periods in the day. Panel B reports the number of contracts bought and sold on May 6, 2010 during the DOWN and UP periods.

Table VI: Shares of Passive and Aggressive Trading Volume Around Price Increase and Price Decrease Events

Panel A: Aggressive Buy Trades, Price Increase Events, May 3-5, 2010

	Last 100 Contracts		First 100 Contracts		All Aggressive Buy Trades	
	Passive	Aggressive	Passive	Aggressive	Passive	Aggressive
HFT	28.72%	57.70%	37.93%	14.84%	34.33%	34.04%
MM	15.80%	8.78%	19.58%	7.04%	13.48%	7.27%
BUYER	6.70%	11.61%	4.38%	26.17%	4.57%	21.53%
SELLER	16.00%	2.65%	11.82%	7.09%	16.29%	5.50%
OPP	32.27%	19.21%	25.95%	43.39%	30.90%	31.08%
SMALL	0.51%	0.04%	0.34%	1.46%	0.44%	0.58%

Panel B: Aggressive Sell Trades, Price Decrease Events, May 3-5, 2010

	Last 100 Contracts		First 100 Contracts		All Aggressive Sell Trades	
	Passive	Aggressive	Passive	Aggressive	Passive	Aggressive
HFT	27.41%	55.20%	38.31%	15.04%	34.45%	34.17%
MM	15.49%	8.57%	20.64%	6.58%	13.79%	7.45%
SELLER	5.88%	11.96%	3.83%	24.87%	5.67%	20.91%
BUYER	17.98%	3.22%	12.71%	8.78%	15.40%	6.00%
OPP	32.77%	20.99%	24.18%	43.41%	30.30%	30.89%
SMALL	0.47%	0.06%	0.34%	1.32%	0.39%	0.58%

Panel C: Aggressive Buy Trades, Price Increase Events, May 6, 2010

	Last 100 Contracts		First 100 Contracts		All Aggressive Buy Trades	
	Passive	Aggressive	Passive	Aggressive	Passive	Aggressive
HFT	28.46%	38.86%	30.55%	14.84%	30.94%	26.98%
MM	12.95%	5.50%	13.88%	5.45%	12.26%	5.82%
BUYER	6.31%	17.49%	5.19%	21.76%	5.45%	20.12%
SELLER	13.84%	3.84%	14.30%	5.71%	14.34%	4.40%
OPP	38.26%	34.26%	35.94%	51.87%	36.86%	42.37%
SMALL	0.19%	0.06%	0.16%	0.37%	0.16%	0.31%

Panel D: Aggressive Sell Trades, Price Decrease Events, May 6, 2010

	Last 100 Contracts		First 100 Contracts		All Aggressive Sell Trades	
	Passive	Aggressive	Passive	Aggressive	Passive	Aggressive
HFT	28.38%	38.67%	30.13%	14.59%	30.09%	26.29%
MM	12.27%	5.04%	14.85%	5.64%	12.05%	5.88%
SELLER	4.19%	16.46%	3.77%	21.21%	3.82%	17.55%
BUYER	15.83%	5.90%	13.89%	6.97%	15.27%	7.26%
OPP	39.12%	33.86%	37.15%	51.10%	38.56%	42.68%
SMALL	0.21%	0.08%	0.21%	0.48%	0.21%	0.34%

This table presents each trader category's share of aggressive and passive trading volume for the last 100 contracts traded before a price increase event or price decrease event and the first 100 contracts traded at the new higher price after a price increase event or the new lower price after a price decrease event. For comparison purposes, this Table also presents the unconditional share of aggressive and passive trading volume of each trader category. Trading categories are High Frequency Traders (HFT), Market Makers (MM), Fundamental Buyers (BUYER), Fundamental Sellers (SELLER), Opportunistic Traders (OPP), and Small Traders (SMALL). To emphasize the symmetry between buying and selling, the rows for BUYER and SELLER in panels B and D have been reversed relative to panels A and C.

Table VII: HFTs and Market Makers: Liquidity Provision/Removal

	Panel A: May 3-5				Panel B: May 6			
	Δ A HFT	**Δ P HFT**	**Δ A MM**	**Δ P MM**	**Δ A HFT**	**Δ P HFT**	**Δ A MM**	**Δ P MM**
Intercept	-1.29	-0.35	-0.34	-0.19	-2.86	-0.36	-0.25	0.28
	(-2.64)	(-1.24)	**(-3.15)**	(-1.36)	**(-3.22)**	(-0.65)	(-1.40)	(1.15)
$\Delta NPHFT_{t-1}$	-0.042	0.036			-0.003	0.014		
	(-4.67)	**(6.95)**			(-0.29)	(1.76)		
$NPHFT_{t-1}$	-0.005	-0.001			-0.004	-0.001		
	(-9.55)	**(-3.13)**			**(-5.24)**	**(-2.73)**		
$\Delta NPMM_{t-1}$			0.007	-0.013			-0.003	-0.032
			(1.71)	(-1.91)			(-0.56)	**(-2.60)**
$NPMM_{t-1}$			-0.002	-0.002			-0.003	-0.004
			(-6.73)	**(-5.26)**			**(-5.60)**	**(-4.80)**
ΔP_t	57.78	-25.69	6.38	-19.92	23.70	-12.89	4.94	-13.10
	(31.94)	**(-28.61)**	**(18.51)**	**(-37.68)**	**(12.72)**	**(-8.26)**	**(11.20)**	**(-15.73)**
ΔP_{t-1}	22.55	-5.37	5.79	-7.01	-1.12	5.74	3.91	2.73
	(15.88)	**(-7.33)**	**(18.79)**	**(-17.44)**	(-0.91)	**(4.71)**	**(11.09)**	**(6.33)**
ΔP_{t-2}	9.61	-1.26	4.75	-2.59	-2.66	1.14	1.66	1.08
	(7.80)	(-1.82)	**(15.87)**	**(-7.04)**	**(-2.26)**	(1.05)	**(5.65)**	**(1.86)**
ΔP_{t-3}	5.44	-0.36	3.64	-1.12	-1.15	-0.21	0.54	0.60
	(4.91)	(-0.56)	**(12.86)**	**(-3.16)**	(-0.89)	(-0.16)	**(1.98)**	(1.41)
ΔP_{t-4}	3.29	0.62	3.11	-0.46	-2.81	1.00	0.23	0.26
	(2.84)	(0.92)	**(11.11)**	(-1.36)	**(-2.54)**	(0.94)	(0.90)	(0.65)
ΔP_{t-5}	1.93	-0.12	2.59	-0.09	-0.69	0.46	0.16	-0.93
	(1.63)	(-0.17)	**(8.90)**	(-0.26)	(-0.55)	(0.42)	(0.61)	(-1.86)
ΔP_{t-6}	-0.99	0.91	2.04	0.13	-1.82	1.51	0.05	-0.37
	(-0.85)	(1.37)	**(7.21)**	(0.38)	(-1.58)	(1.44)	(0.21)	(-1.02)
ΔP_{t-7}	-0.29	-0.71	2.10	-0.26	-2.69	-2.35	-0.52	-0.10
	(-0.26)	(-1.07)	**(8.46)**	(-0.81)	**(-2.22)**	(-1.85)	**(-1.90)**	(-0.21)
ΔP_{t-8}	-0.98	-0.79	1.74	-0.27	-2.22	0.44	-0.63	0.27
	(-0.80)	(-1.16)	**(6.61)**	(-0.82)	(-1.90)	(0.48)	**(-2.35)**	(0.69)
ΔP_{t-9}	-0.73	-1.08	1.16	-0.71	-0.80	-0.88	-0.10	-1.01
	(-0.64)	(-1.68)	**(4.59)**	**(-2.15)**	(-0.71)	(-0.83)	(-0.35)	**(-2.20)**
ΔP_{t-10}	-2.54	-1.36	1.01	-0.48	-2.96	1.30	-0.51	0.13
	(-2.33)	**(-2.20)**	**(3.89)**	(-1.48)	**(-2.03)**	(1.19)	(-1.70)	(0.24)
ΔP_{t-11}	-3.54	-1.19	0.43	-0.45	-1.10	0.02	-0.87	0.24
	(-3.32)	**(-1.91)**	(1.67)	(-1.44)	(-0.91)	(0.02)	**(-3.16)**	(0.51)
ΔP_{t-12}	-2.52	-0.93	0.21	-0.05	0.97	-0.27	-0.40	-0.78
	(-2.31)	(-1.44)	(0.81)	(-0.17)	(0.82)	(-0.19)	(-1.48)	(-1.85)
ΔP_{t-13}	-2.13	-1.67	0.50	-0.24	1.17	1.09	-0.29	-0.32
	(-1.98)	**(-2.71)**	(1.91)	(-0.77)	(0.92)	(0.83)	(-1.13)	(-0.85)
ΔP_{t-14}	-4.39	-0.38	0.11	0.21	-1.25	-1.42	-0.45	0.18
	(-4.08)	(-0.61)	(0.40)	(0.65)	(-1.16)	(-1.27)	(-1.84)	(0.53)
ΔP_{t-15}	-1.97	-0.77	0.10	-0.29	1.01	-0.58	-0.54	-0.30
	(-1.83)	(-1.21)	(0.38)	(-0.93)	(0.77)	(-0.63)	**(-2.03)**	(-0.77)
ΔP_{t-16}	-2.43	0.23	-0.18	-0.46	-1.30	0.62	0.22	0.01
	(-2.19)	(0.37)	(-0.67)	(-1.44)	(-1.06)	(0.54)	(0.82)	(0.04)
ΔP_{t-17}	-2.19	-0.33	0.24	-0.34	-1.71	1.05	-0.24	0.53
	(-2.01)	(-0.52)	(0.89)	(-1.04)	(-1.35)	(1.03)	(-0.87)	(1.29)
ΔP_{t-18}	-3.26	-1.10	0.31	-0.27	0.48	-0.04	0.05	-0.82
	(-2.87)	(-1.75)	(1.25)	(-0.84)	(0.44)	(-0.03)	(0.19)	**(-2.32)**
ΔP_{t-19}	-3.59	-0.63	0.54	0.02	-0.75	-1.88	-0.27	-0.031
	(-3.31)	(-1.03)	**(2.09)**	(0.08)	(-0.61)	(-1.78)	(-0.97)	(-0.08)
ΔP_{t-20}	-4.62	-1.24	0.21	-0.33	-0.54	-0.54	-0.50	-0.21
	(-4.42)	**(-2.11)**	(0.86)	(-1.09)	(-0.46)	(-0.66)	(-1.95)	(-0.53)
#obs	72837	72837	72837	72837	24275	24275	24275	24275
$Adj-R^2$	0.043	0.026	0.020	0.063	0.025	0.027	0.046	0.070

This table presents estimated coefficients of the following regression: $\Delta y_t = \alpha + \phi \Delta y_{t-1} + \Delta y_{t-1} + \sum_{i=0}^{20} [\beta_i \times \Delta p_{t-i}/0.25] + \epsilon_t$. Dependent variables are changes in Aggressive and Passive holdings of High Frequency Traders and Market Makers. Changes in holdings, Δy_t, and lagged holdings, y_{t-1}, are in the number of contracts. Price changes, Δp_{t-i}, are in ticks. Estimates are computed for second-by-second observations. The t-statistics are calculated using the White (1980) estimator. t-statistics reported in parentheses are in bold if the coefficients are statistically significant at the 5% level. Observations are stacked for May 3-5.

Table VIII: Immediately Scratched Trades

Panel A: May 3-5

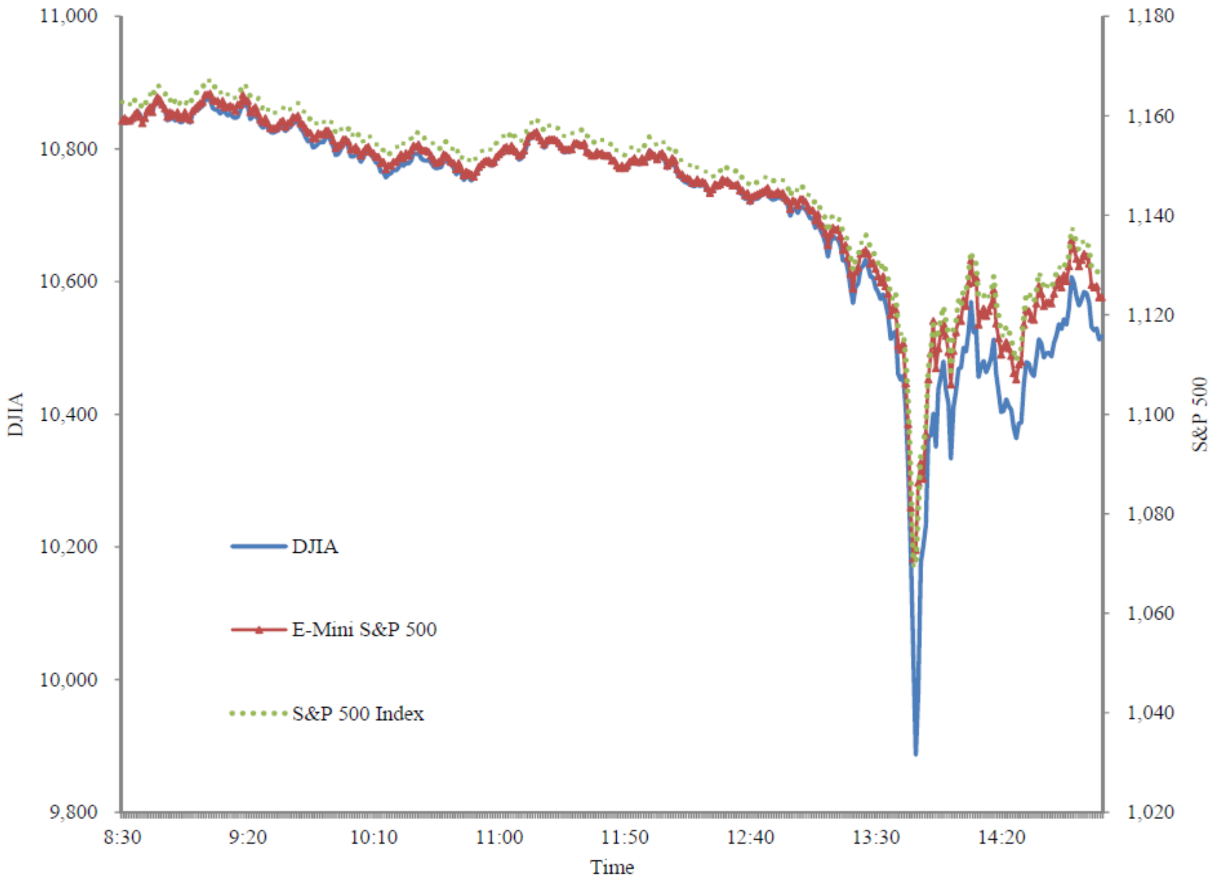
	All Trades	Scratched Trades	% of All Trades	Mean	Std	Median
HFT	871,177	24,781	2.84	540.56	768.32	218.50
Market Maker	314,780	7,847	2.49	13.35	54.44	0.00
Buyer	268,808	977	0.38	0.30	6.22	0.00
Seller	257,637	816	3.2	0.25	4.92	0.00
Opportunistic	893,262	15,980	1.79	1.45	39.97	0.00

Panel B: May 6

	All Trades	Scratched Trades	% of All Trades	Mean	Std	Median
HFT	604,659	25,772	4.26	1610.75	2218.86	553.00
Market Maker	236,434	13,064	5.53	72.98	422.19	0.00
Buyer	236,501	2,715	1.15	2.15	30.86	0.00
Seller	141,853	295	0.21	0.23	7.18	0.00
Opportunistic	810,901	11,571	1.43	1.99	71.94	0.00

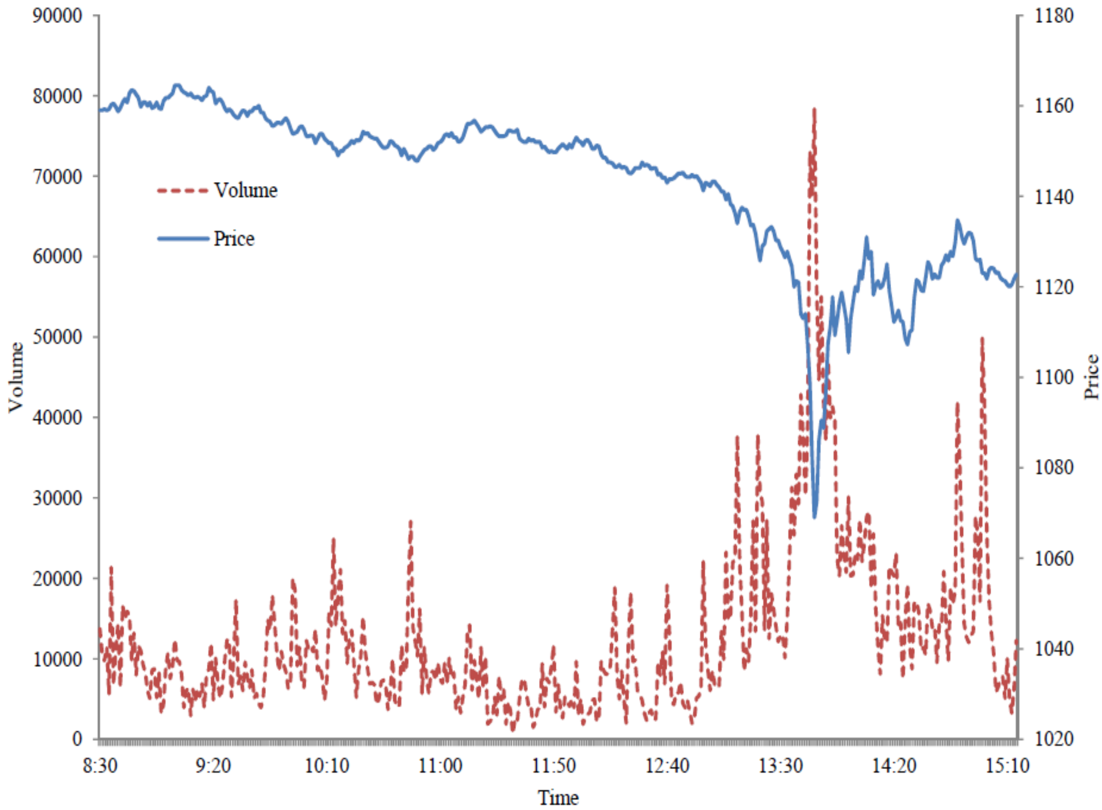
This table presents statistics for immediate trade scratching which measures how many times a trader changes his/her direction of trading in a second aggregated over a day. We define a trade direction change as a buy trade right after a sell trade or vice versa at the same price level in the same second. These statistics are taken across the 3 day sample period for May 3-5.

Figure 1: U. S. Equity Indices on May 6, 2010



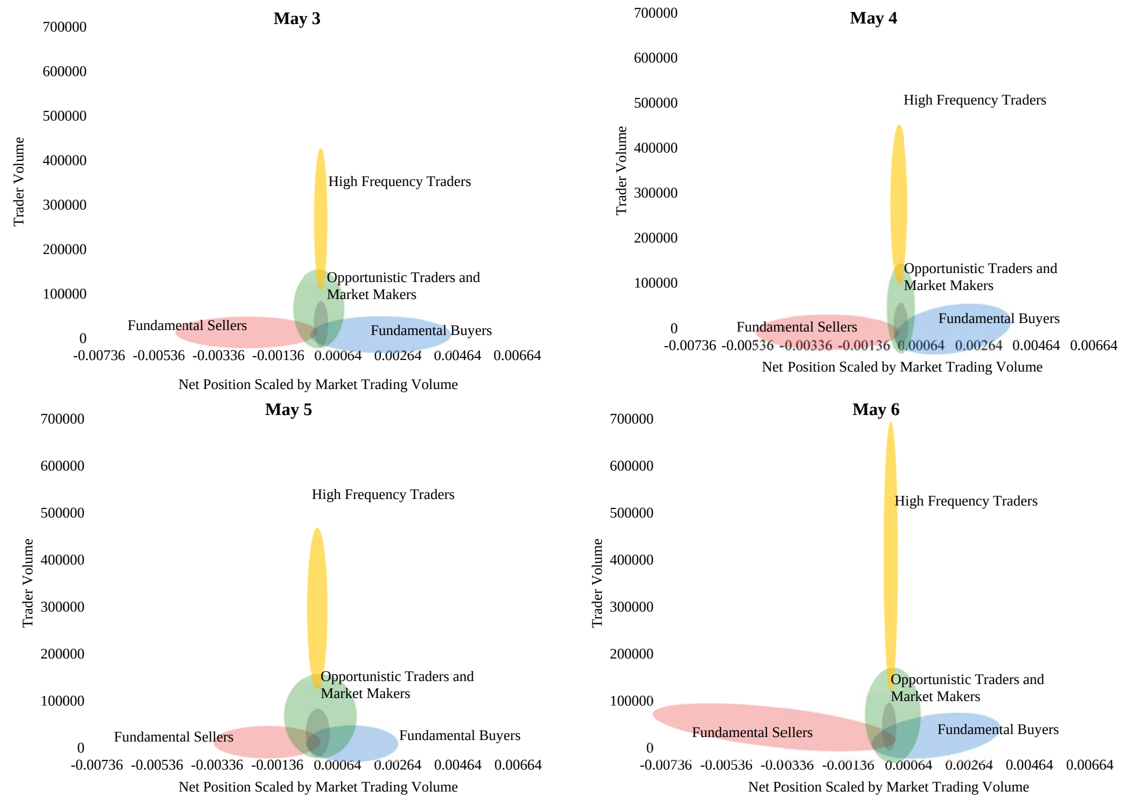
Source: "Preliminary Findings Regarding the Market Events of May 6, 2010". This figure presents end-of-minute transaction prices of the Dow Jones Industrial Average (DJIA), S&P 500 Index, and the June 2010 E-Mini S&P 500 futures contract on May 6, 2010 between 8:30 and 15:15 CT.

Figure 2: Prices and Trading Volume of the E-Mini S&P 500 Stock Index Futures Contract



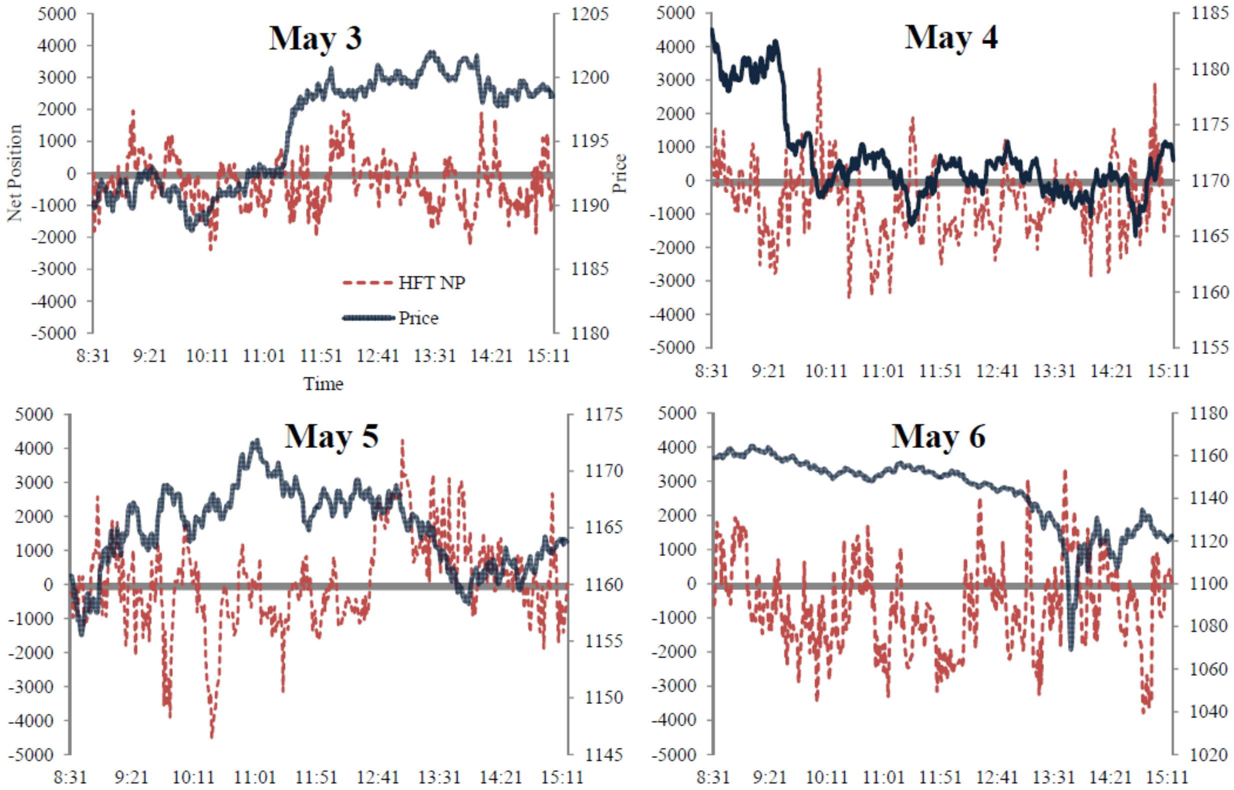
Source: "Preliminary Findings Regarding the Market Events of May 6, 2010". This figure presents minute-by-minute transaction prices and trading volume of the June 2010 E-Mini S&P futures contract on May 6, 2010 between 8:30 and 15:15 CT. Trading volume is calculated as the number of contracts traded during each minute. Transaction price is the last transaction price of each minute.

Figure 3: Trading Accounts Trading Volume and Net Position Scaled by Market Trading Volume



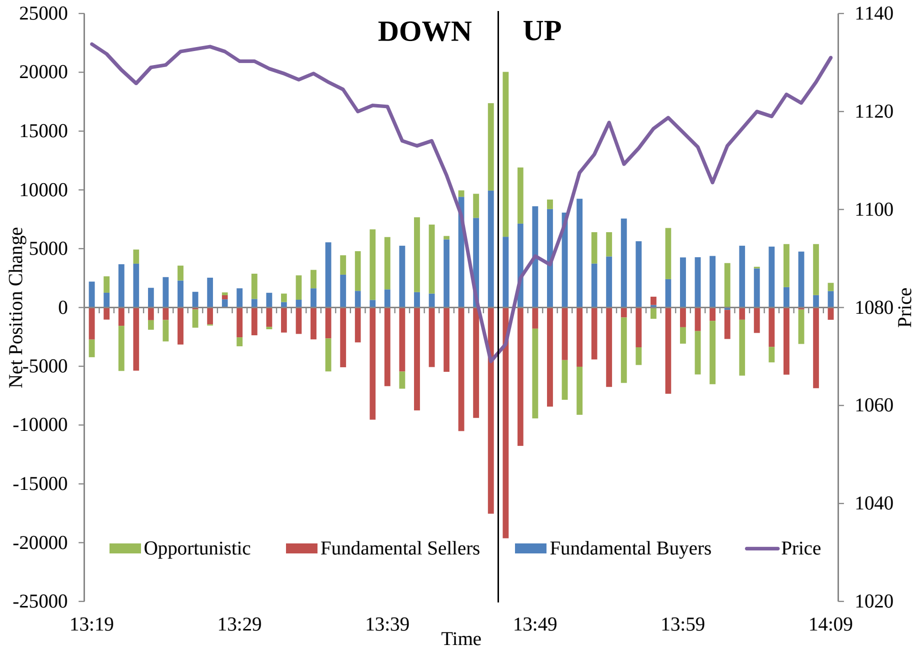
This figure presents trader categories superimposed (as shaded areas) over all individual trading accounts ranked by their trading volume and net position scaled by market trading volume. The figures reflect trading activity in the June 2010 E-Mini S&P 500 futures contract for May 3-6, 2010.

Figure 4: Net Position of High Frequency Traders



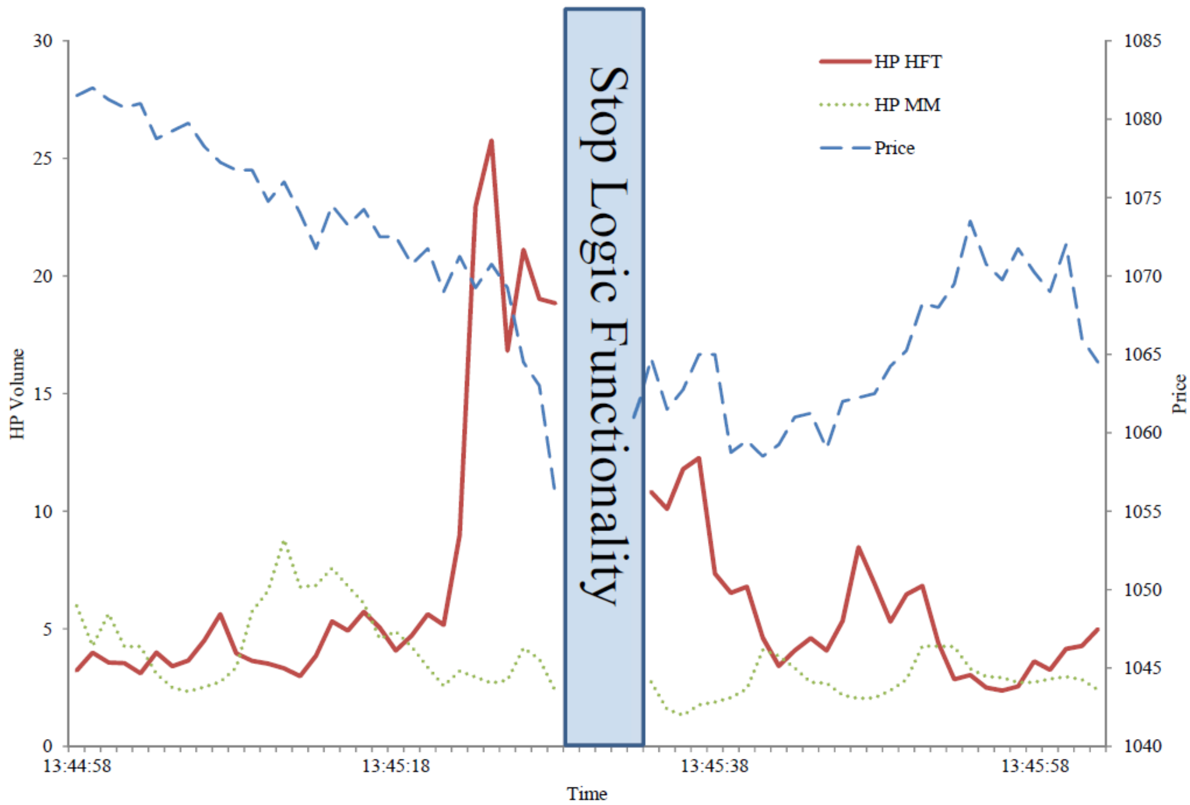
This figure presents the net position of High Frequency Traders (left vertical axis) and transaction prices (right vertical axis) in the June 2010 E-Mini S&P 500 futures contract over one minute intervals during May 3, 4, 5, and 6 between 8:30 to 15:15 CT. Net position is calculated as the difference between total open long and total open short positions of High Frequency Traders at the end of each minute. Transaction price is the last transaction price of each minute.

Figure 5: Change in Net Position of Fundamental and Opportunistic Traders



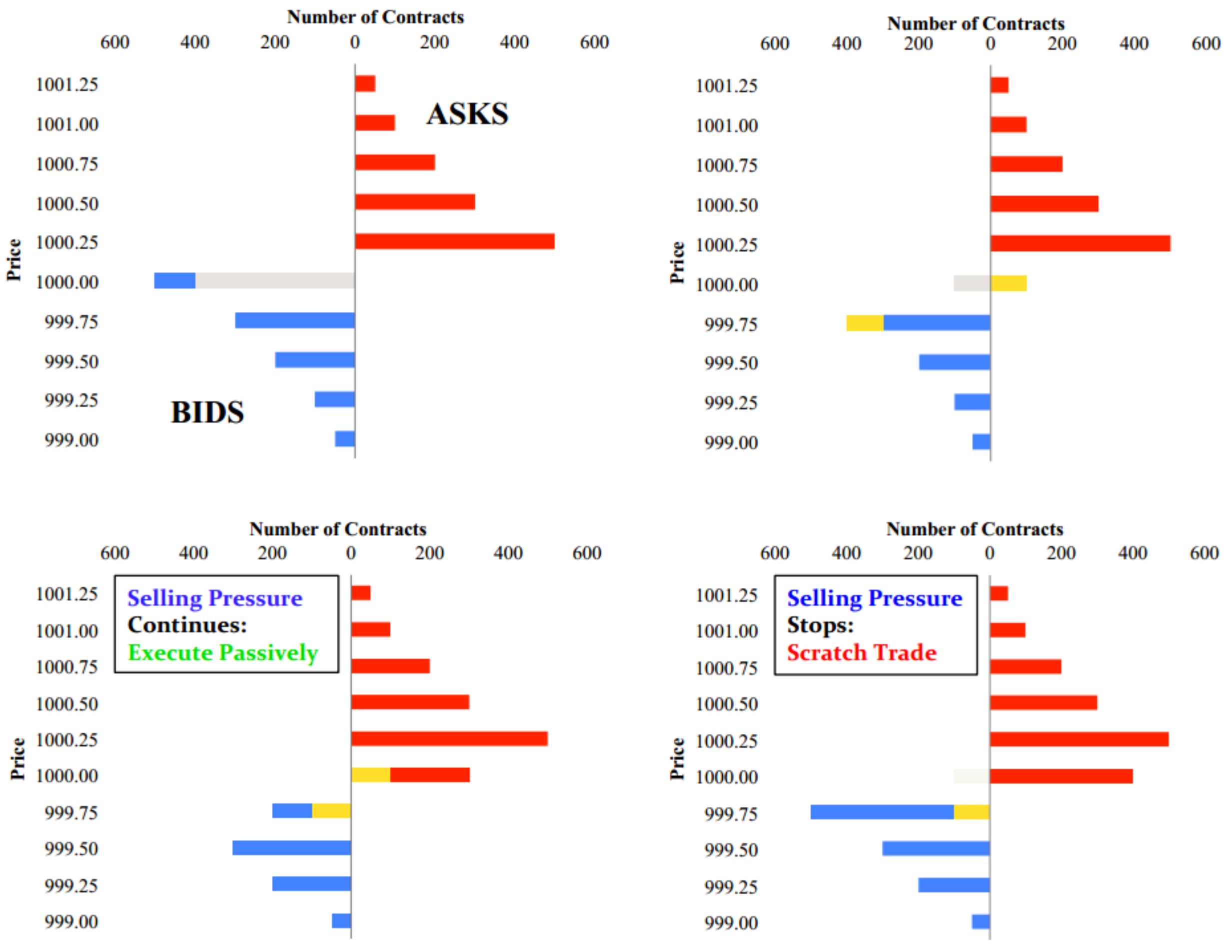
This figure presents the change in net position of Fundamental and Opportunistic Traders (left vertical axis) and transaction prices (right vertical axis) in the June 2010 E-Mini S&P 500 futures contract over one minute intervals on 6 between 13:19 to 14:09 CT. Net position is calculated as the difference between total open long and total open short positions of Opportunistic Traders at the end of each minute. Transaction price is the last transaction price of each minute.

Figure 6: Hot Potato Volume



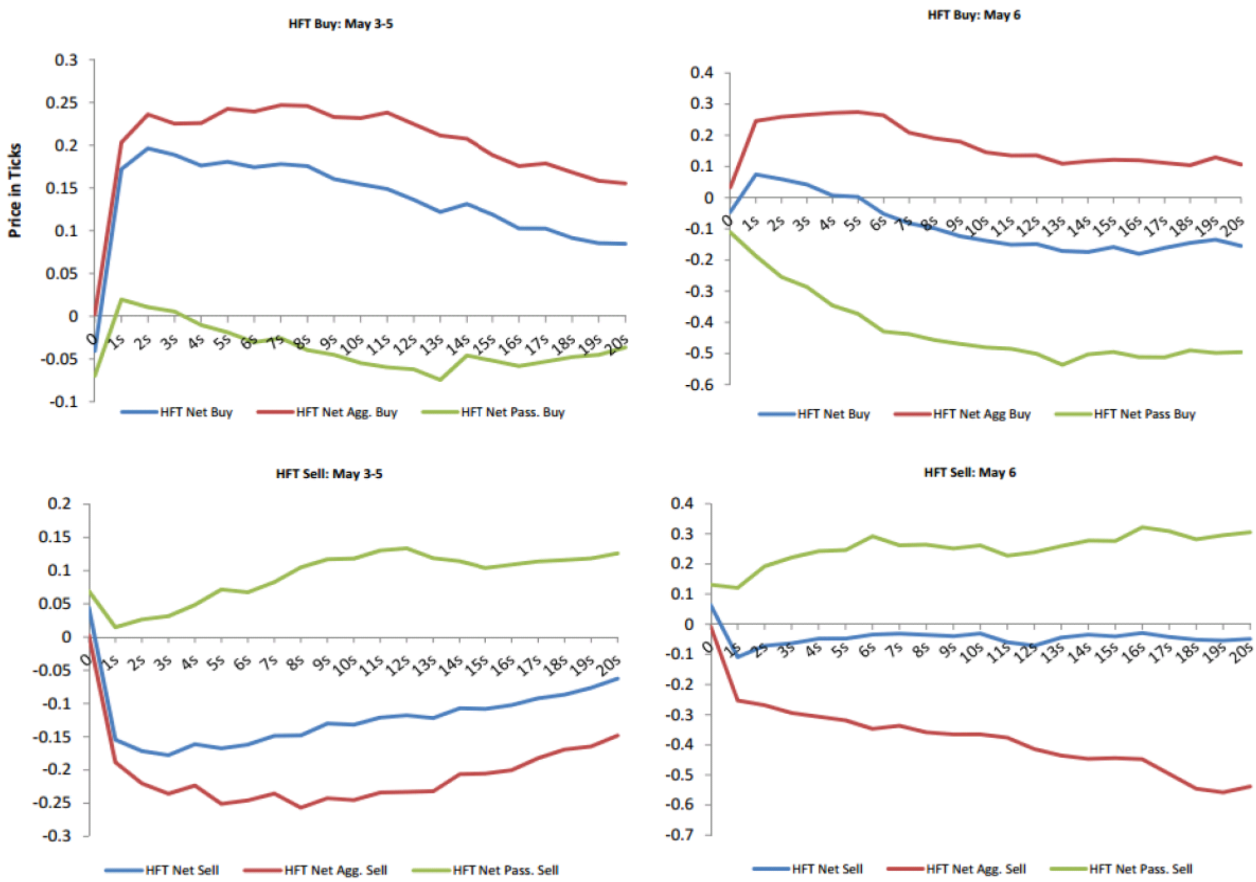
This figure shows the price and the scaled trading volume by HFTs and Market Makers over one second intervals. Scaled trading volume is calculated as the 5 second moving average of contracts traded over absolute value net holdings. Price reflects the last transaction price during an interval. Prices and scaled trading volumes are reported from 13:44 to 13:46 CT.

Figure 7: An Illustration of Immediacy Absorption Activity of High Frequency Traders



This figure presents an illustration of the "immediacy absorption" activity of HFTs. The top left panel illustrates a starting liquidity event – temporary selling pressure that results in an erosion of depth at best bid to a total of just 100 contracts (in deep blue) at the best bid price of 1000.00. The top right panel illustrates the response of HFTs: (i) absorbing immediacy by aggressively selling a total of 100 contracts at the best bid, thus completely depleting the queue at the best bid, and (ii) very quickly submitting sequences of new limit orders to buy a total of 100 contracts at the new best bid price of 999.75, as well as (iii) submitting orders to sell 100 contracts at the new best offer of 1000.00. The two bottom panels illustrate alternative scenarios. The bottom left panel illustrates a scenario of continuing selling pressure. Under this scenario, the market comes to the HFTs, enabling them to buy 100 contracts at 999.75 and pocket 1,250 dollars among them (the notional value of one contract is set at $50). The bottom right panel illustrates a scenario when the selling pressure stops. Under this scenario, HFTs quickly buy 100 contracts which are offered at the new best ask price of 1000.00, "scratching" their initial aggressive sell trade by buying at the same price, and getting rid of risky inventory.

Figure 8: HFT Trading and Prices



This figure illustrates how prices change after HFT trading activity in a given second. The upper-left panel presents results for buy trades for May 3-5, the upper right panel presents results for buy trades on May 6, and the lower-left and lower-right present corresponding results for sell trades. For an "event" second in which High Frequency Traders are net buyers, net Aggressive Buyers, and net Passive Buyers value-weighted average prices paid by the High Frequency Traders in that second are subtracted from the value-weighted average prices for all trades in the same second and each of the following 20 seconds. The results are averaged across event seconds, weighted by the magnitude of High Frequency Traders' net position change in the event second. The upper-left panel presents results for May 3-5, the upper-right panel presents results for May 6, and the lower two panels present results for sell trades calculated analogously. Price differences on the vertical axis are scaled so that one unit equals one tick ($12.50 per contract).