Automation, Intermediation and The Flash Crash

ANDREI KIRILENKO, ALBERT S. KYLE, MEHRDAD SAMADI, and TUGKAN TUZUN*

ABSTRACT

The Flash Crash of May 6, 2010, shook the confidence of market participants and raised questions about the market structure of electronic markets. In these markets, intraday intermediation has been increasingly provided by market participants without formal obligations to do so. We examine intraday intermediation in the E-mini S&P 500 stock index futures market before and during the Flash Crash. We discuss the evolution of trading from human to electronic environments and the implications of our results for market design.

Keywords: High-Frequency, Automation, Volatility, Flash Crash, Intermediation, Market Making

*Kirilenko is with the Imperial College Business School, e-mail: a.kirilenko@imperial.ac.uk, Kyle is with the Smith School at the University of Maryland, e-mail: akyle@rhsmith.umd.edu, Samadi is with Southern Methodist University's Cox School of Business, e-mail: msamadi@smu.edu, and Tuzun is with the Board of Governors of the Federal Reserve, e-mail: tugkan.tuzun@frb.gov. The results and discussion in this paper are based on the analysis in the following article: Kirilenko, A., Kyle, A. S., Samadi, M. and Tuzun, T. (2017). "The Flash Crash: High-Frequency Trading in an Electronic Market," The Journal of Finance, 72, 3: 967—998.

Electronic copy available at: https://ssrn.com/abstract=3119363

In our article, "The Flash Crash: High-Frequency Trading in an Electronic Market" (Kirilenko, Kyle, Samadi, and Tuzun, 2017), we empirically examine intraday market intermediation in an electronic market before and during a systemic intraday event known as the "Flash Crash." The U.S. Commodity Futures Trading Commission (CFTC) and Securities and Exchange Commission (SEC) joint report (CFTC and SEC, 2010) described the Flash Crash as follows:

> "At 2:32 p.m. [CT], 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). [...] 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 [...]. By 3:08 p.m., [...] the E-mini prices [were] back to nearly their pre-drop level [...]."

Figure 1 presents end-of-minute transaction prices (solid line) and minute-by-minute trading volume (dashed line) of the S&P 500 E-mini stock index futures contract on May 6, 2010.

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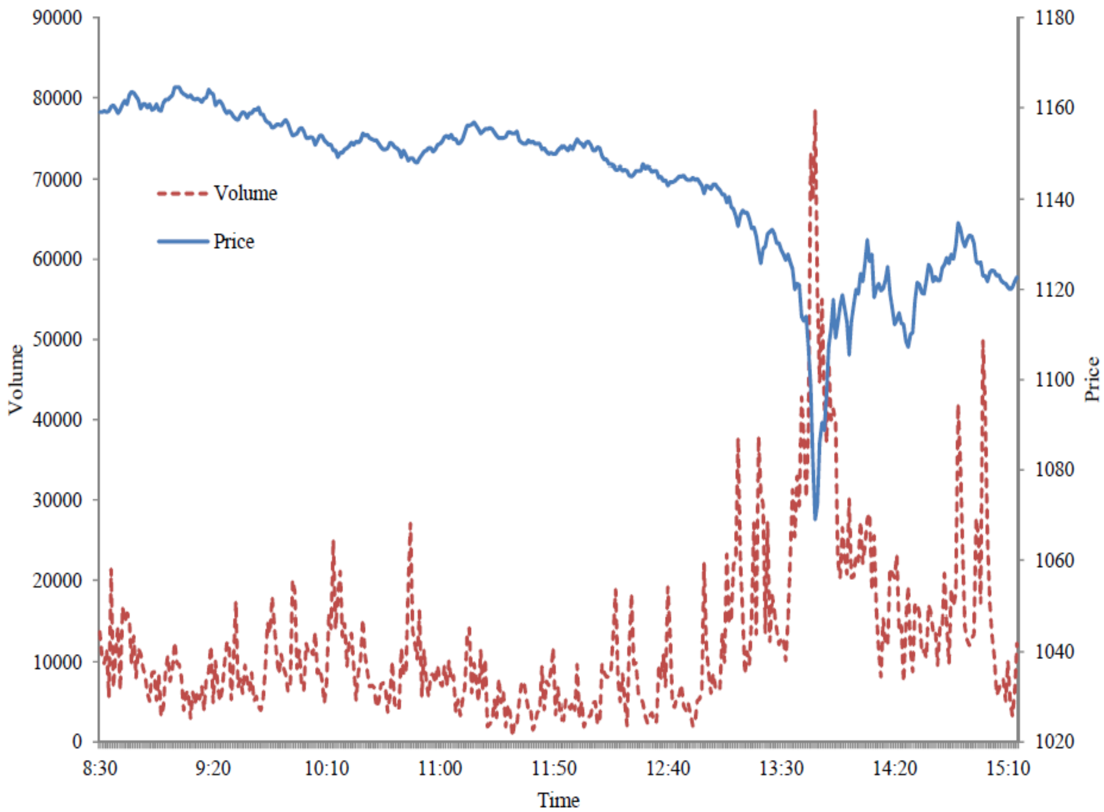

Figure 1: Prices and trading volume of the E-mini S&P 500 stock index futures contract. Source: Kirilenko, Kyle, Samadi, and Tuzun (2017). This figure presents the minute-by-minute transaction prices and trading volume of the June 2010 E-mini S&P 500 futures contract on May 6, 2010, between 8:30 and 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.

The Flash Crash has raised questions about the resiliency of automated markets and the behavior of nondesignated intraday intermediaries during periods of large and temporary buying or selling pressure in electronic markets.

To answer these questions, we examine trading in the E-mini S&P 500 stock index futures from May 3, 2010, through May 6, 2010. We classify trading accounts that do not accumulate significant directional positions, and whose inventories display intraday mean reversion from May 3 through May 5 as intraday intermediaries. We further separate intraday intermediaries into high frequency traders (HFTs) and market makers. We find that that the combined net inventories of the accounts classified as intraday intermediaries, both HFTs and market makers, over the four days of our sample, including the day of the Flash Crash, did not exceed 6,000 E-mini contracts. This amount is significantly smaller than the large sell program of 75,000 contracts documented in the CFTC-SEC joint report (CFTC and SEC, 2010).

We find that during the period of large and temporary selling pressure on May 6, both categories of intraday intermediaries have accumulated net long inventory positions as prices declined. However, we also find that the trading activity of HFTs is distinct from that of a traditional market maker: the direction of HFT trading precedes price changes, while the activity of market makers does not. Furthermore, HFTs lift a disproportionate amount of the final best ask depth before an increase in the best ask level and provide a disproportionate proportion of depth first transacted against at the new price level.

Our findings regarding the behavior of HFTs have catalyzed a discussion regarding market design in the presence of traders that can use their relative speed advantage to extract rents from slower and less tech-savvy market participants.

The rest of the paper proceeds as follows. In Section I, we describe the data used in this study; in Section II, we summarize the empirical methodology and results. Section III contains a discussion on the evolution of trading and its implications for market design.

I. Data and Trader Categories

A. Data

We examine all regular transactions in the E-mini S&P 500 June 2010 futures contract occurring during the 405-minute period starting at 8:30 a.m. CT and ending at 3:15 p.m. CT (15 minutes after the close of trading in the underlying stocks) for the sample period from May 3, 2010, through May 6, 2010. The data contain (1) account identifiers for the buyer and the seller; (2) the price and quantity transacted; (3) the date and time (to the second) of each transaction; (4) a sequence identification number that sorts trades into chronological order within one second; (5) a field indicating whether the trade resulted from a marketable limit, nonmarketable limit, or market order; and (6) a precise "aggressiveness" flag that indicates whether the buyer or seller submitted a marketable order. For more information on the data, see Kirilenko, Kyle, Samadi, and Tuzun (2017).

B. Trader Categories

Over 15,000 accounts traded in the E-mini market during our sample period. Unlike U.S. equity and corporate bond markets, traders in the E-mini market do not have formal designations, such as market maker, dealer, or specialist. Therefore, to classify accounts as intraday market intermediaries, we use a data-driven approach based on trading activity and inventory patterns. An account is classified as an intraday intermediary if it holds small intraday and end-of-day net positions relative to its daily trading volume from May 3, 2010, through May 5, 2010, irrespective of its trading behavior on May 6,

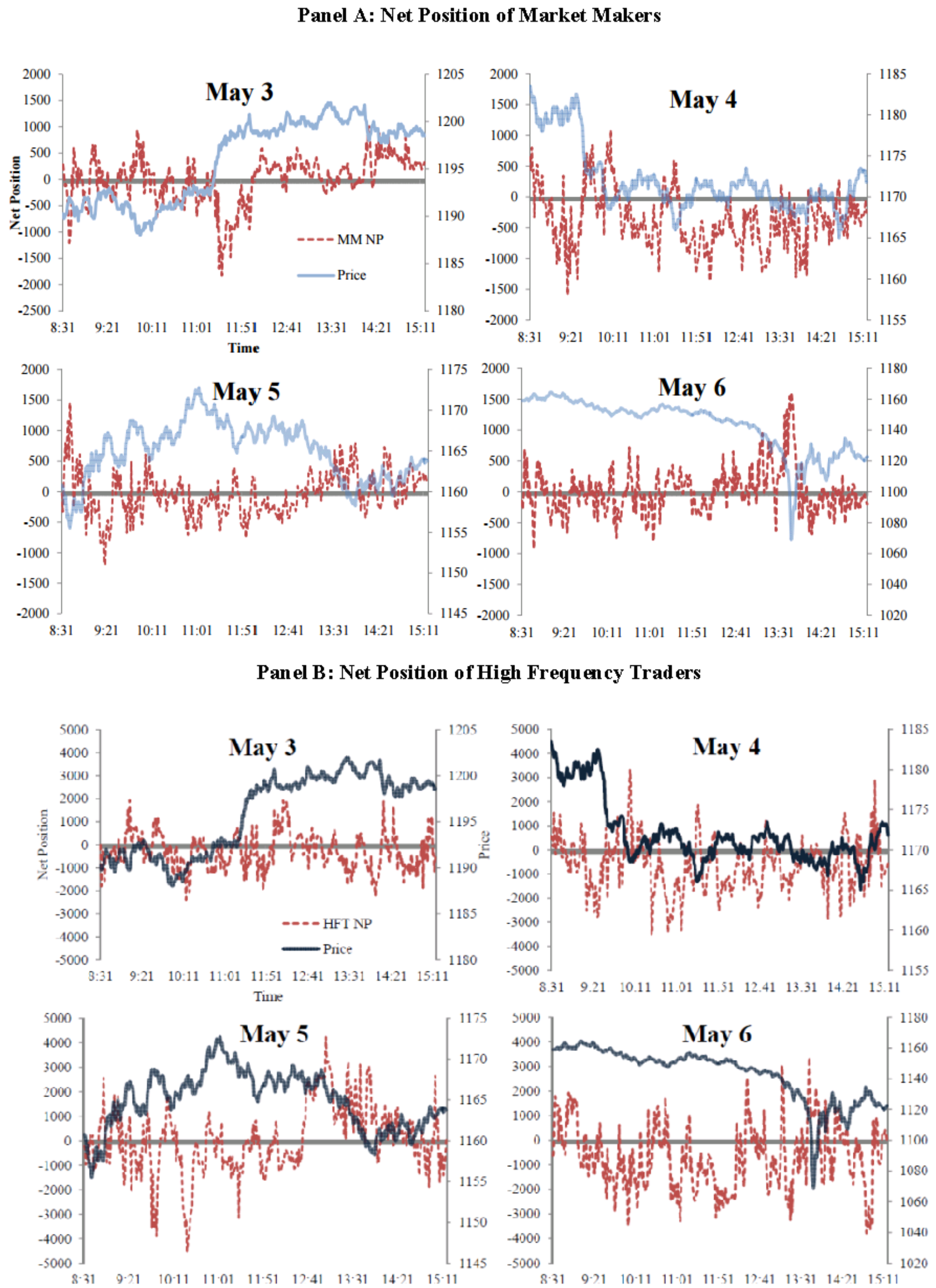

Figure 2: Net position of Market Makers and High Frequency Traders. Source: Kirilenko, Kyle, Samadi, and Tuzun (2017). This figure presents the net position (left vertical axis) of market makers and HFTs and market transaction prices (right vertical axis) for the June 2010 S&P 500 E-mini futures contract over one-minute intervals on May 3, May 4, May 5, and May 6, 2010, between 8:30 and 15:15 CT. Net position is calculated as the difference between the total open long and total open short positions of market makers and HFTs at the end of each minute. Transaction price is the last market transaction price each minute. The top panel presents the net positions of market makers and the bottom panel presents the net positions of HFTs.

2010. We classify 204 traders as intraday market intermediaries. Of these 204 accounts, we further classify the 16 most active accounts (that is, those with the highest number of trades from May 3 through May 5) as HFTs. The remaining intraday intermediary accounts are classified as market makers. For specifics, see Kirilenko, Kyle, Samadi, and Tuzun (2017).

While HFTs comprise a small proportion of the number of trading accounts active during our sample, they are responsible for 34.22% of the trading volume from May 3 through May 6. Furthermore, approximately half of HFT trading volume results from marketable orders, a departure from the classic stock market specialist who would passively provide quotes.

II. Intermediation and the Flash Crash

Liquidity crashes can emerge if a sudden excess of sell orders overwhelms the insufficient risk-bearing capacity of intermediaries. The risk-bearing capacity of intermediaries can be empirically measured by the observed bounds of their intraday net positions. Figure 2 presents the end-of-minute net inventories of market makers and HFTs alongside the price level of the E-mini. The dashed lines plot the net (inventory) positions of market makers and HFTs, while the solid lines plot the price level of the S&P 500 E-mini futures contract.

<Insert Figure 2>

On each of the four days in our sample, HFTs never accumulated inventories greater than approximately 4,000 contracts, which is much smaller than the 75,000-contract sell program documented in the CFTC-SEC joint statement (CFTC and SEC, 2010).

Similarly, market makers do not take on net inventories that exceed 1,500 contracts in either direction. These findings are consistent with the limited risk-bearing capacity of intermediaries during a liquidity crash, as intraday intermediaries did not take on larger inventories compared with their pre-May 6 inventories.

We further examine how the behavior of HFTs is different than that of traditional market makers, particularly the notion that HFTs can snipe stale quotes of slower market participants using superior trading technology. In a centralized limit order book market, a pattern consistent with stale quote sniping involves lifting posted depth just prior to a price change and then offsetting the position immediately at the new price level. Despite not directly examining limit order book data, the exact sequence of transactions and an aggressive-passive flag allow us to infer trader activity around price change events in the centralized E-mini order book in trade and volume time. Results are presented in Table 1.

Table 1
Shares of Passive and Aggressive Trading Volume Around Price Increase and Price Decrease Events

Source: Kirilenko, Kyle, Samadi, and Tuzun (2017). This table presents the share of aggressive and passive trading volume in each trader category for the last 100 contracts traded before a price increase or price decrease event and the first 100 contracts traded at the new price (higher or lower) after a price increase or decrease event. For comparison purposes, this table also presents the unconditional share of aggressive and passive trading volume in each trader category. Trader categories are as follows: 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.

Panel A: Trading at the Best Ask Around Price Increase Events, May 3–5, 2010

	Last 100 Contracts		First 100 Contracts		Volume at Best Ask	
	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: Trading at the Best Bid Around Price Decrease Events, May 3–5, 2010

	Last 100 Contracts		First 100 Contracts		All Volume at Best Bid	
	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: Trading at the Best Ask Around Price Increase Events, May 6, 2010

	Last 100 Contracts		First 100 Contracts		All Volume at Best Ask	
	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: Trading at the Best Bid Around Price Decrease Events, May 6, 2010

	Last 100 Contracts		First 100 Contracts		All Volume at Best Bid	
	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%

Table 1 has four panels. Panel A presents price increase events from May 3 through May 5. Panel B presents price decrease events from May 3 through May 5. Panels C and D present price increase and decrease events on May 6, respectively. In each panel, the last column presents the volume participation of different categories of traders without conditioning on price changes.

As shown in the last column of Panel A, when not conditioning on price changes, HFTs account for 34.04% of aggressive trading at the best ask price level. The share of the HFTs' aggressive volume rises to 57.70% at the best ask price level before price increase events and falls to 14.84% at the new best ask price level after price increase events. On the passive side, HFTs account for 34.33% of the total passive volume at the best ask price level. However, the share of HFTs' passive volume at the best ask falls to 28.72% before a price increase event and rises to 37.93% at the new best ask price level after a price increase event. For price decrease events, as shown in Panel B, the results are essentially symmetric.

In contrast, market makers follow a noticeably more passive trading strategy than HFTs. According to Panel A, market makers account for 13.48% of the passive volume at the ask and only 7.27% of the aggressive volume at the ask. For the last 100 contracts at the old ask, the market makers' share of volume increases relatively modestly, from 7.27% to 8.78% of aggressive volume at the old best ask price level. However, the market makers' share of passive volume at the old best ask price also increases, from 13.48% to 15.80%.

We also examine the association between HFTs' trading and price fluctuations up to 20 seconds after HFTs trade. Figure 3 illustrates the results. The upper-left panel presents results for HFT buy events from May 3 through May 5, the upper-right panel presents results for HFT buy events on May 6, and the lower-left and lower-right panels present corresponding results for HFT sell events. For an "event-second" in which HFTs are net buyers, net aggressive buyers, or net passive buyers, value-weighted average prices paid by HFTs 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 the net position change of HFTs in the event-second. Price differences on the vertical axis are given in the number of ticks ($12.50 per one E-mini contract).

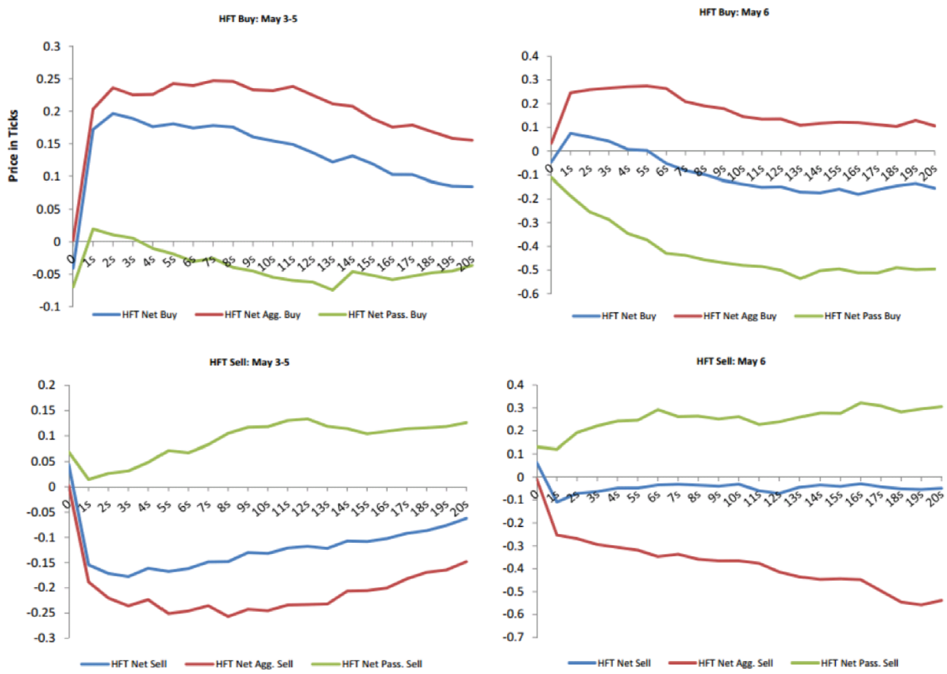

Figure 3: High Frequency Traders' trading and prices. Source: Kirilenko, Kyle, Samadi, and Tuzun (2017). This figure illustrates how prices change after HFT' trading activity for a given second. The upper-left panel presents results for buy trades for May 3 through May 5, 2010, the upper-right panel presents results for buy trades on May 6, 2010, and the lower-left and lower-right panels present corresponding results for sell trades. For an "event-second" in which HFTs are net buyers, net aggressive buyers, and net passive buyers, value-weighted average prices paid by HFTs 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 HFTs' net position change in the event-second. The upper-left panel presents results for May 3 through May 5, 2010, the upper-right panel presents results for May 6, 2010, 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).

When HFTs are net buyers from May 3 through May 5, prices rise but then eventually begin to revert. However, 20 seconds after a net buy by HFTs, prices remain 15% of a tick higher. Results are symmetric for HFTs' net selling and on May 6, though prices appear to have a larger and more persistent response after sales by HFTs.

These results suggest that High Frequency Traders behave differently than traditional market makers. The behavior of High Frequency Traders is empirically more consistent with quote sniping than traditional market making.

III. Discussion

A. From Human to Electronic Trading

The Flash Crash of May 6, 2010, shook the confidence of market participants and raised questions about the market structure of electronic markets. Since the October 1987 crash, the market structure has evolved as technological advances have enabled participants to trade using algorithms with little or no human intervention. This section contains a discussion on how moving from a purely human environment of pit trading to an anonymous electronic trading environment has changed the economics of trading. For expositional purposes, this section is restricted to the trading practices in the S&P 500 E-mini futures market, one of the first exclusively automated markets.

Priority Rules In face-to-face pit trading, the concept of "first acceptance" did not mean the time priority was respected. Instead, it meant that when a trader made an offer that was accepted by several other traders at approximately the same time, the trader making the offer had to give the trade to the trader who accepted it first. This method did not require a trader to accept an offer at a given price from the trader who made the offer at that price first. As a result of this absence of time priority, human floor traders who traded on their own accounts on the floor of an exchange are often able to have bids and offers accepted even though other floor brokers, trying to execute orders for customers not on the floor, have already made offers at the same price first.

In contrast, when trading S&P 500 E-mini futures contracts on the Globex electronic trading platform, both price and time priority are rigidly respected 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.

Anonymity In human markets, brokers did not disclose the identities of the traders on behalf of whom they were executing orders; however, human traders on the floor of an exchange developed some idea of their counterparties from what happened on the floor. For example, some floor traders always traded for themselves as de facto market makers, while others always executed customer orders as brokers. A floor trader trading with another specialized floor trader thus knows something about the identity of his counterparty from observing who he is trading with. For example, local traders who make markets may avoid trading with one another because they are trying to make money from similar strategies and thus should not be trading in the opposite direction from one another unless there is a good reason to do so. Human floor traders also promptly tell their counterparty the name of the clearing firm for their customer orders. While not giving up the identity of the counterparty, floor brokers can guess, based on the clearing firm, something about the identity of the counterparty.

The market for the E-mini features both pre-trade and post-trade transparency. Pre-trade transparency is achieved by transmitting to the public 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 obtained by transmitting the prices and quantities of executed transactions to the public. While the market as a whole is transparent, the identities of individual traders submitting, canceling, or modifying bids and offers as well those whose bids and offers have been executed are anonymous. Therefore, unlike human trading, electronic traders following similar strategies can end up trading with each other. Indeed, both the CFTC-SEC joint report (CFTC and SEC, 2010) and a joint staff report by the U.S. Department of the Treasury, Board of Governors of the Federal Reserve, Federal Reserve Bank of New York, SEC, and CFTC (U.S. Treasury and others, 2015) document that high-frequency market intermediaries frequently trade against one another during each market dislocation.

Digital Representation and Accuracy In human markets, when traders record information about trades by hand, they frequently make mistakes, and mistakes become more common in hectic markets. These mistakes often lead to mismatches between quantities, prices, and counterparty information, and, as a result, trades do not clear immediately. Moreover, quickly clearing up such "out-trades" has traditionally absorbed large quantities of resources at clearing firms. For floor brokers who are executing the orders of customers, the costs associated with errors resulting from out-trades can be large compared with the small brokerage commissions they earn from executing such orders. In contrast, electronic markets are intrinsically much less prone to error due to multiple automated safeguards that electronic trading instructions (messages) must go through before an order is entered into an order book.

Speed and Latency When trading takes place face-to-face, floor brokers execute orders at a pace dictated by the speed with which humans process information. A floor broker executing a large order for a customer might question the accuracy of the quantity of the order before executing it in the pit. This might involve a phone call to the customer to confirm the order. After entering the pit with a large executable limit or market order, the floor broker might execute the trade cautiously. After taking out all the bids available at the best price, the broker might offer at the previously best bid several times before taking out bids one tick lower.

In the Globex system, limit orders and market orders are executed immediately according to the rules by which the system operates. Executable orders are generally executed in tens of microseconds, including orders for thousands of contracts, except for cases where the large executable limit or market orders would immediately move prices outside predefined safeguard bands.

High Frequency Traders and Quote Sniping The quote-sniping behavior we document can be related to the scalpers of the future pits, but on a much larger scale. In human markets, the lack of anonymity in trading, the costs associated with out-trades, and the lack of time and price priority has led to a profitable practice called "scalping." Scalping occurs when a "local" floor trader trading for a personal account on the floor of the exchange observes several floor brokers bid at the same price in an effort to execute customer orders and joins in the bidding. After buying from a floor broker, the scalper then tries to sell at a price tick higher. If successful, the scalper makes a one tick profit. If, however, the scalper senses that prices are about to move against him or her, the scalper will cut potential losses by selling to the bidders he or she was trying to scalp. If successful, the loss is zero. Thus, the scalper makes a tick when prices do not move against him or her and often avoids losing a tick when prices do move against him or her because the scalper can frequently hit the bids of the "paper" representing customer limit orders bidding at the same price at which the scalper bought.

Although brokers are not supposed to disclose orders to other traders, the scalper can infer from the fact that a given floor broker always executes customer orders that the bid represents an order from a customer. The scalper knows that the order will probably take a few seconds, and the scalper may be able to guess the clearing firm handling the customer order from the knowledge of the clearing firm on behalf of which the floor broker has executed orders previously.

Frequently, brokers wanting to sell will accept the bids and offers of scalpers rather than the bids and offers of other brokers bidding at the same price on behalf of customers. One traditional reason for this is that scalpers may be more accommodating when negotiating losses made due to errors.

Altogether, the profitability of scalping is enhanced by the lack of anonymity, the tendency for errors, the lack of time, and the price priority in human face-to-face markets. In order to execute a scalping strategy in a human market, it is economically necessary for the scalper to be physically present on the floor of the exchange and to execute his or her own trades personally. Otherwise, the time lags required to implement the strategy would be too large for it to be profitable. Physical presence requires that the scalper either own or rent a seat on the exchange. To the extent scalping is profitable, seats on the exchange become more valuable.

The Globex system has several differences from pit trading in terms of scalping strategies. First, trading on Globex is anonymous, making it harder for scalpers to know who is making bids and offers. Second, the Globex system respects time and price priority, making it impossible for scalpers to trade at the same price in front of resting orders. Third, the electronic trading environment of Globex tends to make out-trades far less common, eliminating a reason for brokers to prefer to trade with scalpers over other brokers.

Given that the electronic Globex environment has leveled the playing field in many ways (for example, anonymity, accuracy, and priority), we must ask whether certain traders can use their speed in order to gain an advantage over other traders. This paper provides empirical evidence consistent with the notion that accounts classified as HFTs snipe stale quotes of other market participants. The success of this strategy depends critically on the speed at which it can be executed. For our purposes, high speed (or low latency) means the ability to receive and process market information as well as the ability to submit, modify, or cancel orders at superior speeds.

Market Crashes and Intermediation In addition to their own capital, human intermediaries (for example, specialists and locals) can use external capital to provide intermediation. During market crashes, access to costly funding markets is crucial for human traders to continue to provide intermediation. Automated intermediaries, on the other hand, almost exclusively use their own capital for providing intermediation. As we show in Figure 2, the bounds of inventory positions are very small, suggesting that they do not have large operating capital. Automated intermediaries are disciplined to keep their inventories within their risk bounds even during market crashes. Furthermore, automated intermediaries hold inventories for a few minutes, whereas human intermediaries have been known to hold inventories for days. While it is unlikely that market intermediaries can directly cause a market crash, certain characteristics they possess could amplify or lessen the impact of market crashes. For example, smaller inventory positions and shorter holding periods of automated traders could make liquidity gaps more likely in the event of a large imbalance between buyers and sellers.

Tick Size The minimum tick size is an important institutional detail in the context of a transition from human to electronic markets. The minimum tick size is set by the rules that govern trading. For example, the minimum tick size for the E-mini S&P 500 contract is 0.25 S&P points. This means, for example, that a trade can be priced at 1,050.00 or 1,050.25 points but not at a price in between. Since the E-mini contract is defined as a multiple of 50 times the value of the index, one tick is worth \$12.50 per contract. At an S&P level of 1,000, one contract represents \$50,000 of shares underlying the index, and one tick represents about 2.5 basis points, that is, 0.025% of the face value of the contract.

The tick size of the E-mini S&P 500 contract is large relative to the liquidity and volatility of the market. In general, the tick size is expected to be smaller when the volatility is lower and trading volume is higher. After the decimalization of the U.S. equity market in 2001, the minimum tick size was reduced to one penny. For a typically priced \$40 stock, this implies a tick size of 2.5 basis points, about the same as the E-mini contract. The volatility of an individual stock is typically higher than the volatility of a stock index because portfolio diversification reduces idiosyncratic risk in baskets of stocks relative to individual stocks. Furthermore, the volume of trading in the E-mini is far greater than the trading volume of any stock. Indeed, the dollar trading volume of the E-mini futures contracts is of similar magnitude to the dollar trading volume of the entire stock market. Thus, based on the idea that low volatility and high dollar volume should be associated with a low tick size, we can conclude that the tick size for th E-mini S&P 500 contract is quite large relative to the tick size for individual stocks.

Except in exceptional circumstances, the bid–ask spread for the E-mini S&P 500 contract is one tick. Traditionally, tick size has been an important consideration when determining the profitability of scalping. On a typical trading day, it is common to find dozens of traders bidding and offering in aggregate for hundreds of contracts at the best bid and best offer.

B. Implications

Pre-trade Safeguards As electronic trading has facilitated the use of algorithmic trading strategies, the pace of trading is no longer dictated by the speed with which humans process information. The circuit breakers implemented after the stock market crash of October 19, 1987, were post-trade safeguards designed to respond to market declines. Now that automated trading has surpassed the speed of human cognition, there is a need for well-designed automated pre-trade safeguards to prevent flash crashes. However, when designing a pre-trade safeguard, a trade-off between allowing for price discovery and preventing a liquidity gap arises. The optimal calibration of pre-trade safeguards should vary by market and potentially even through time as the CME Stop-Logic Functionality was never triggered during the U.S. Treasury "Flash Rally" (U.S. Treasury, 2015).

Market Design and Competition on Speed Our findings regarding the behavior of the accounts we classify as HFTs have already in part started a discussion regarding market design in the presence of certain traders using their speed advantage in order to extract rents from other market participants. Studies have attributed this behavior to the standard limit order book market design and certain allocation rules in the event of excess supply or demand (for example, time priority). In light of this behavior, several alternative market designs have been proposed to limit competition based on speed or relative latency.

ACKNOWLEDGMENTS

The research presented in this paper was coauthored 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 CFCE-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 and commodity options markets, and its expanded mandate to regulate the swaps markets pursuant to the Dodd-Frank Wall Street Reform and Consumer Protection Act.The analyses and conclusions expressed in this paper are those of the authors and do not reflect the views of the Federal Reserve Board, the Federal Reserve System, the CFTC, nor their respective staffs.

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