High Frequency Trading in the Equity Markets During US Treasury POMO

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Abstract We analyze high frequency trading (HFT) activity in equities during US Treasury permanent open market (POMO) purchases by the Federal Reserve. We construct a model to study HFT quote and trade behavior when private information is released and confirm it empirically. We estimate that HFT firms reduce their inside quote participation by up to 8% during POMO auctions. HFT firms trade more aggressively, and they supply less passive liquidity to non-HFT firms. Market impact also rises during Treasury POMO. Aggressive HFT trading becomes more consistently profitable, and HFT firms earn a higher return per share. We also estimate that HFT firms earn profits of over $105 million during US Treasury POMO events.

JEL Classification G12, G21, G24

1 Introduction

High frequency trading (HFT) has grown since the adoption of the Regulation National Market System in 2005, and now represents the majority of equity trading volume in the USA. The impact of HFT on the equity markets has become a central question in the policy debate about market structure and in the academic literature on market microstructure.

HFT firms engage in a variety of strategies. Hagstromer and Norden (2013) divide these approaches into market making and opportunistic. Our work considers both aspects by looking at both liquidity provision and aggressive trading profits. Menkveld (2013) analyzes the arrival of the Chi-X high frequency platform in Europe and concludes that HFT firms act as market makers in the new market. Hasbrouck and Saar (2013) suggest that HFT activity improves traditional market

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quality measures such as short-term volatility, spreads, and displayed depth in the limit order book. Carrion (2013) studies a data set from Nasdaq that identifies HFT firms. He finds that HFT participants supply liquidity when it is low and take liquidity when it is high. Brogaard et al. (2014) analyze the same data set and argue that HFT increases price efficiency.

While HFT firms are often passive liquidity providers, this contribution asks whether their role changes during periods of market turbulence. This question is motivated in part by the "Flash Crash" of May 6, 2010 when over 200 stocks traded down to a penny bids before the market quickly rebounded. The U.S. Commodity Futures Trading Commission and Securities and Exchange Commission (2010) task force report analyzed HFT activity from the 12 largest firms during the crash. Half significantly curtailed their trading activity during the crash including two firms that stopped trading for the rest of the day. The "Flash Crash" helps to clarify why reporting the average effect of HFT firms on the market may provide a misleading portrait of their contribution to market quality. Analyzing their impact when the market is under stress or reacting to news needs to be isolated from their contribution during less turbulent periods.

Benos and Wetherilt (2012) note that HFT firms are in competition with designated market makers (DMMs). They emphasize that the HFT firms have no affirmative quoting obligations. This allows them to "compete with DMMs when market-making is profitable but withdraw altogether from the market when it is not..."

We examine this claim by looking at periods of potential market stress, the US Treasury purchases made by the Fed beginning in late 2008 as part of its quantitative easing program. The Federal Reserve's asset purchase program began in November 2008 with \$600 billion of GSE debt and mortgage backed securities. In March 2009, the Federal Open Market Committee enlarged these programs and authorized purchases of \$300 billion in long-term Treasuries. We examine 57 auctions between 2008 and 2010.

We develop a theoretical model in which HFT firms receive valuable private information before other market participants. This information will lead HFT firms to temporarily abandon their role as liquidity providers and trade aggressively in the direction of the news. Consistent with our model's prediction that HFT firms reduce their inside quoting activity, we find that during Treasury POMO auctions HFT firms reduce their inside bid participation by 8%. The model also predicts that HFT firms would trade more aggressively when obtaining valuable information. We do find that HFT firms buy more frequently in good news and sell more often in bad news using aggressive orders. We also find that HFT firms are less likely to supply liquidity to non-HFT firms that trade in the direction of news. These results are even stronger once we control for microstructure effects.

The ability of HFT firms to receive private information may create additional price impact. Zhang (2010) observes that HFT is positively correlated with stock price volatility and hinders the ability of the market prices to reflect fundamental information. Cvitanic and Kirilenko (2010) provide a theoretical perspective and show that HFT activity effects volume and the distribution of transaction prices.

Martinez and Roşu (2013) model HFT participants as informed traders who observe news stream and trade quickly. They find that HFT generates volatility and decreases liquidity.

Consistent with these studies, we find that the release of auction bidding information raises market impact. A 1000 share order from a HFT firm moves the market on average \$0.0318, but on POMO days this rises to \$0.0341. This is evidence that high frequency traders appear to have superior information.

Whether they are at the active or passive side, HFT trades are more profitable when the counterpart is a non-HFT firm rather than a HFT firm. High frequency traders are able to generate the most profit from private information because of their ability to trade quickly. Baron et al. (2017) study the profitability of HFT in the E-mini futures contract and find that HFT firms make high and persistent profits from all categories of non-HFT participants. Hirschey (2013) provides evidence that HFT firms anticipate the order flow from non-HFT investors and their aggressive trades are highly correlated with future returns.

We find that HFT firms are consistently profitable trading during POMO events. They are profitable 88% of the time on aggressive trades and 100% of the time on passive trades. We estimate a daily average profit per stock of \$1300.35 which rises to \$1895.37 on POMO days. The profits per share from aggressive trading rise 300%. Extrapolating these results to the market as a whole, we estimate profits of more than \$105 million.

The chapter is organized as follows. We develop a theoretical model in Sect. 2 to study HFT behavior when private information is released. Section 3 describes the HFT data set. Section 4 describes the POMO purchases by the Federal Reserve. In Sect. 5, we analyze HFT quote and trade activities during POMO and provide empirical support for our model. Additional empirical results on market impact and profits of HFT are presented in Sect. 6. We perform robustness checks in Sect. 7, and Sect. 8 concludes.

2 The Model

2.1 Model Setup

Consider a risky security, with the terminal value V, that changes from its initial value V_0 based on random innovations $\varepsilon \sim N(0, \sigma^2)$ and fundamental information,

$$V = V_0 + \varepsilon + \eta. \tag{1}$$

η is the expected change in the fundamental value due to the information arrival of POMO auctions. η is assumed to be independent from ε and can take three values: $\eta = +\delta > 0$ if the news is positive, $\eta = -\delta$ if the news is negative, and $\eta = 0$ if no information arrives.

There are three types of traders in our model: noise traders (NTs), limit order traders (LOTs), and high frequency traders (HFTs). NTs submit orders for liquidity reasons and use market orders that hit the bid or offer on the limit order book. We assume that a noise trader arrives exogenously with probability θ, and will submit a buy order with probability γ or a sell order with probability $1-\gamma$.

LOTs provide liquidity by placing bid and offer quotes competitively. HFTs are profit maximizing. They trade either passively to earn the bid-ask spread by submitting limit orders or aggressively to realize a positioning profit using marketable limit orders. We assume in our model that HFTs trade faster than NTs and LOTs in the sense that they are more quickly informed of the value of η than noise traders and limit order traders.

To simplify the analysis we assume that all orders by each type of traders are for one unit of the security. Because the order flow of noise traders is exogenous, we only need to focus on two players: LOTs and HFTs. We then analyze their decision problems under different market conditions.

2.2 Limit Order Traders

LOTs do not observe the value of η, but they infer its value based on trading activity. Their conjecture about the probability distribution of η: $\eta = +\delta$ with probability α, $\eta = -\delta$ with probability β, and therefore $\eta = 0$ with probability $1-\alpha-\beta$. The unconditional expectation of η is calculated as $\overline{\eta} = \delta(\alpha-\beta)$. LOTs post bid and offer quotes at B and A respectively, and are aware that HFTs have superior information about η. Following Glosten and Milgrom (1985), we consider buys and sells separately. Given that other traders buy, the expected profit of LOTs is

$$\mathrm{E}\left[\pi_{\mathrm{LOT}}|\mathrm{Buy}\right] = A - \mathrm{E}\left[V|\mathrm{Buy}\right] = A - V_0 - \mathrm{E}\left[\eta|\mathrm{Buy}\right]. \qquad (2)$$

To calculate the expectation of η given that the trade is a buy, we first compute the conditional probabilities of η.

$$\Pr(\eta = +\delta|\mathrm{Buy}) = \frac{\Pr(\eta = +\delta, \mathrm{Buy})}{\Pr(\mathrm{Buy})} = \frac{\alpha(1+\theta\gamma)}{\alpha+\theta\gamma}, \qquad (3)$$

$$\Pr(\eta = -\delta|\mathrm{Buy}) = \frac{\Pr(\eta = -\delta, \mathrm{Buy})}{\Pr(\mathrm{Buy})} = \frac{\beta\theta\gamma}{\alpha+\theta\gamma}.$$

We assume that competition among LOTs drives their expected profit to a positive amount c_{LOT}. Therefore, the best offer is set as

$$A = V_0 + \mathrm{E}\left[\eta|\mathrm{Buy}\right] + c_{\mathrm{LOT}} = V_0 + \overline{\eta} + \frac{\delta\alpha\left(1-\alpha+\beta\right)}{\alpha+\theta\gamma} + c_{\mathrm{LOT}}. \qquad (4)$$

Similarly, we can obtain the best bid by LOTs. The conditional probabilities of η given that other traders sell is

$$\Pr(\eta = +\delta|\text{Sell}) = \frac{\Pr(\eta = +\delta, \text{Sell})}{\Pr(\text{Sell})} = \frac{\alpha\theta(1-\gamma)}{\beta + \theta(1-\gamma)}, \tag{5}$$
$$\Pr(\eta = -\delta|\text{Sell}) = \frac{\Pr(\eta = -\delta, \text{Sell})}{\Pr(\text{Sell})} = \frac{\beta(1+\theta(1-\gamma))}{\beta + \theta(1-\gamma)}.$$

If the expected profit is driven to c_{LOT} by competition, the best bid is set as

$$B = V_0 + \text{E}[\eta|\text{Sell}] - c_{\text{LOT}} = V_0 + \overline{\eta} - \frac{\delta\beta(1+\alpha-\beta)}{\beta + \theta(1-\gamma)} - c_{\text{LOT}}. \tag{6}$$

The bid-ask spread is

$$A - B = \frac{\delta[2\alpha\beta + \theta(\alpha(1-\gamma)(1+\beta-\alpha) + \beta\gamma(1+\alpha-\beta))]}{(\alpha+\theta\gamma)(\beta+\theta(1-\gamma))} + 2c_{\text{LOT}}. \tag{7}$$

It is not hard to show that the spread is always positive. As seen in (7), the bid-ask spread can be decomposed into two components for LOTs. The first term captures the adverse selection risk and the second one covers the inventory cost.

In the symmetric case that LOTs' conjecture on positive or negative news has equal probability, i.e. $0 \le \alpha = \beta \le \frac{1}{2}$, the bid-ask spread reduces to

$$A - B = \frac{\delta\alpha(2\alpha + \theta)}{(\alpha+\theta\gamma)(\alpha+\theta(1-\gamma))} + 2c_{\text{LOT}}. \tag{8}$$

2.3 High Frequency Traders

HFTs maximize their profit using either limit orders or marketable limit orders. They can expect to earn the bid-ask spread on passive trades by placing limit orders. By using marketable limit orders HFTs must pay the spread. A trader may want to do so because valuable limit orders can disappear quickly given the competition from other HFTs and the cancellation of limit orders. In this way they expect to gain trading profits. We assume that HFTs are informed of the value of η under news release and have the same conjecture as LOTs about the distribution of η when no information arrives. We then study the optimal order placement decision of HFTs based on different market conditions.

When there is no news expected on POMO auctions, HFTs' conjecture about the terminal security value is

$$\text{E}[V|\text{non}-\text{POMO}] = V_0 + \overline{\eta}. \tag{9}$$

Since it lies between the best bid and offer quotes by LOTs, they could expect a loss if they submit marketable limit orders by crossing the spread. For example, the expected profit for a buy marketable limit order would be

$$\mathrm{E}\left[V|\mathrm{non}-\mathrm{POMO}\right]-A=-\frac{\delta\alpha\left(1-\alpha+\beta\right)}{\alpha+\theta\gamma}-c_{\mathrm{LOT}}<0. \tag{10}$$

Instead, HFTs are better off under no expected news if they provide liquidity by posting bid and offer quotes and earn the bid-ask spread on passive trades.

HFTs place their quotes at the same bid and offer prices as the limit order traders. They are not adversely selected by other traders, so they would earn a higher expected profit than LOTs at the bid and offer quotes specified in (6) and (4). At the bid side HFTs expect to have a profit of

$$c_{\mathrm{HFT}}^{B}=\frac{\delta\beta\left(1+\alpha-\beta\right)}{\beta+\theta(1-\gamma)}+c_{\mathrm{LOT}}, \tag{11}$$

and their expected profit at the offer side would be

$$c_{\mathrm{HFT}}^{A}=\frac{\delta\alpha\left(1-\alpha+\beta\right)}{\alpha+\theta\gamma}+c_{\mathrm{LOT}}. \tag{12}$$

When a positive information of POMO auctions is expected, HFTs' conjecture about the terminal security value is

$$\mathrm{E}\left[V|\mathrm{positive}\right]=V_0+\delta. \tag{13}$$

For a marketable limit order purchase, their expected profit is

$$\mathrm{E}\left[\pi_{\mathrm{HFT}}|\mathrm{positive}\right]=V_0+\delta-A=\delta\left(1-\alpha+\beta\right)-c_{\mathrm{HFT}}^{A}. \tag{14}$$

It is positive when $\delta>c_{\mathrm{HFT}}^{A}/\left(1-\alpha+\beta\right)$. This suggests that HFTs would take the profitable opportunity to buy the security at the offer quote A by LOTs when they are informed of a good news with a relatively big rise of the equity value. Although they pay the spread in this way, HFTs can earn trading profits because of their superior information about the news.

It also indicates that in this situation HFTs would withdraw their liquidity provision at the inside offer and then post a higher offer quote at $V_0+\delta+c_{\mathrm{HFT}}^{A}$.

The analysis for HFTs' order strategy with a negative expected information is similar. Their expected profit for a sell marketable limit order is

$$\mathrm{E}\left[\pi_{\mathrm{HFT}}|\mathrm{negative}\right]=B-\left(V_0-\delta\right)=\delta\left(1+\alpha-\beta\right)-c_{\mathrm{HFT}}^{B}, \tag{15}$$

which is greater than zero when $\delta>c_{\mathrm{HFT}}^{B}/\left(1+\alpha-\beta\right)$. It suggests that HFTs would sell the security to LOTs at the bid quote B when they expect a bid drop of the equity value. In this case they would choose to scale back from the inside bid and then post a lower bid at $V_0 - \delta - c^B_{\text{HFT}}$. We then validate these theoretical implications by analyzing their quoting and trading activities during the period of Treasury POMO auctions.

3 HFT Data Set

We utilize a data set from Nasdaq that identifies HFT firms. This is the same data set used by Carrion (2013) and Brogaard et al. (2014). The data tracks 120 stocks, listed in Table 1, and has information at different intervals and samples about quotes and trades from 26 HFT firms.

The trade information is most complete. It includes all trades on the Nasdaq exchange during regular market hours, apart from the opening and closing crosses, from January 2008 to December 2009, plus the week of February 22–26, 2010. We begin our analysis in December 2008 with the onset of POMO activity by the Federal Reserve. This sample covers the entire first round of asset purchases by the Federal Reserve. The data set tells whether a HFT firm initiated or filled a trade. These 26 firms are involved in 76% of all the trading activity during the period January 2008 through February 2010.

There are detailed Nasdaq order book data snapshots sampled from the first week of each quarter from January 2008 to December 2009, and then February 22–26, 2010. We observe whether a HFT firm is providing liquidity at each tier of the order book. To supplement the HFT data for our market impact analysis, we make

Table 1 Stocks in HFT database

AA	AZZ	CDR	CSE	FFIC	IMGN	MANT	PFE
AAPL	BARE	CELG	CSL	FL	INTC	MDCO	PG
ABD	BAS	CETV	CTRN	FMER	IPAR	MELI	PNC
ADBE	BHI	CHTT	CTSH	FPO	ISIL	MFB	PNY
AGN	BIIB	CKH	DCOM	FRED	ISRG	MIG	PPD
AINV	BRCM	CMCSA	DELL	FULT	JKHY	MMM	PTP
AMAT	BRE	CNQR	DIS	GAS	KMB	MOD	RIGL
AMED	BW	COO	DK	GE	KNOL	MOS	ROC
AMGN	BXS	COST	DOW	GENZ	KR	MRTN	ROCK
AMZN	BZ	CPSI	EBAY	GILD	KTII	MXWL	ROG
ANGO	CB	CPWR	EBF	GLW	LANC	NC	RVI
APOG	CBEY	CR	ERIE	GOOG	LECO	NSR	SF
ARCC	CBT	CRI	ESRX	GPS	LPNT	NUS	SFG
AXP	CBZ	CRVL	EWBC	HON	LSTR	NXTM	SJW
AYI	CCO	CSCO	FCN	HPQ	MAKO	PBH	SWN

The table lists the 120 ticker symbols in the HFT database provided by Nasdaq

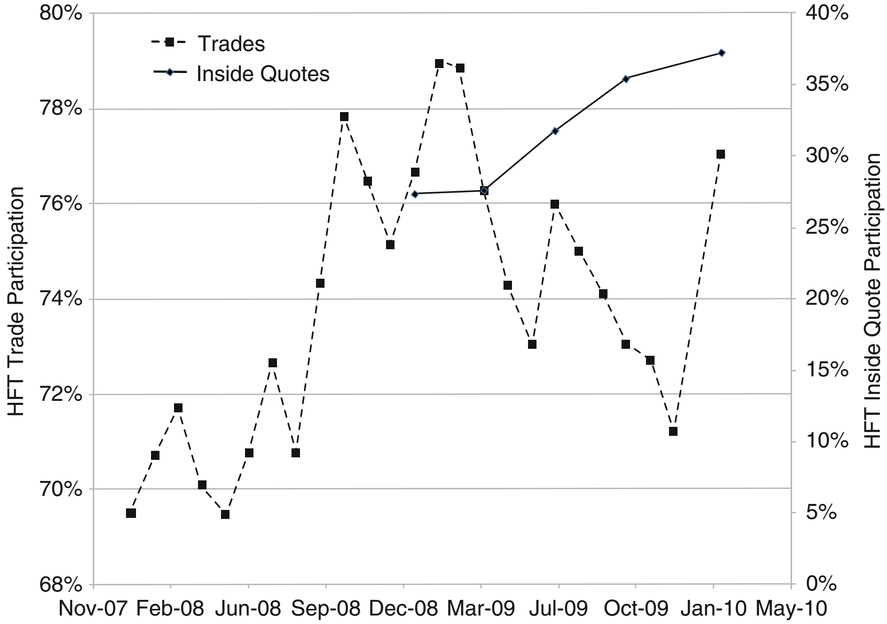

Fig. 1 Trade and inside quote activity due to HFT firms. This figure presents the percentage of trades and inside quote participation by HFT firms

use of the ITCH data set. ITCH provides full order book level detail for the Nasdaq market, but it does not provide any HFT information. We only analyze inside quote activity in both data sets though.

Market participants[1] and regulators[2] have been concerned about the size and scope of HFT activity in recent years. Our data set documents a growing role for HFT activity. Figure 1 plots the monthly average percentage of HFT trades. HFT trading activity appears to trend up in 2008, back down in 2009, before stabilizing in early 2010.

Another measure of HFT liquidity is the extent to which HFT firms make up the inside quote. We also graph this frequency in Fig. 1. Inside quote activity continues to uptrend in 2009, unlike the trade series. We will control for these trends in our analysis of the Federal Reserve auctions.

[1]See, e.g., Christopher Matthews, "High Frequency Trading: Wall Street's Doomsday Machine?", *Time Magazine*, August 8, 2012.

[2]SEC Chairman Mary Jo White, in testimony before the Senate Banking Committee on March 13, 2013, noted "..high frequency trading, complex trading algorithms, dark pools, and intricate new order types raise many questions and concerns."

4 Permanent Open Market Operations (POMO)

After the federal funds rate reached the zero lower bound in December 2008, the Federal Reserve began its large scale asset purchases in March 2009. The Fed increased reserve bank credit from $893 billion on September 4, 2008 to $2298 billion on March 25, 2010 during (what turned out to be) the first round of quantitative easing (QE1). The Federal Reserve not only purchased US Treasuries as it normally would, it also bought GSE mortgage backed securities and debt. Because these assets were intended to remain on the balance sheet for an extended period, they were called "permanent" open market operations (POMO).[3]

We focus on US Treasury purchases because Treasury securities play a unique role in the asset markets. We are motivated by the work of Lou, Yan and Zhang (LYZ, 2013) who find that regularly scheduled Treasury auctions have price impacts on the Treasury, repo and equity markets. They link these effects to the limited risk bearing capacity of the primary dealers and fund flows influenced by temporary price distortions. Krishnamurthy and Vissing-Jorgensen (2012) highlight the unique role of Treasuries and note that changes in their supply effect the equilibrium price of liquidity and safety.

4.1 *Announcement Effects*

Gagnon et al. (2011) isolate five critical days in the evolution of the Fed's unconventional monetary policy. The days include the announcement of the program on November 25, 2008, the extension of asset purchases to the Treasury market on December 16, 2008, and the enlargement of the program on March 18, 2009. Gagnon et al. (2011) note that the Treasury market fell a cumulative 107 basis points on those 5 days.

The stock market reactions are in Table 2. On these 5 days, the CRSP value weighted index rose 5.03%. Between November 24, 2008 and March 24, 2010, the S&P 500 index rose from 851.81 to 1167.72, a gain of 37%. The belief that QE benefited equities is widely held and led to the view that Bernanke has placed a "put" under the market.[4]

4.2 *Details of the Auctions*

US Treasury security purchases began in March 2009. The Fed purchased $295.4 billion in 57 auctions in which dealers offered $1137 billion for sale. Maturities

[3]The history and motivation of the Federal Reserve program is analyzed in Gagnon et al. (2011).

[4]See, e.g., David Tepper, manager of the Apaloosa Hedge Fund, in the *Financial Times* of October 8, 2010.

Table 2 Stocks and bonds on POMO announcement days

Date	Stocks	10Y bond	Event
25-Nov-2008	4.83%	−36	LSAP announced
01-Dec-2008	−5.21%	−25	Bernanke speech
16-Dec-2008	3.90%	−33	LSAP extended to treasuries
01-Jan-2009	0.09%	28	Fed stands ready to buy more
18-Mar-2009	1.42%	−41	LSAPs enlarged
Event sum	5.03%	−107	

The table reports the 2-day changes ($t - 1$ to $t + 1$) in the CRSP value weighted stock index and the 10-year bond yield on the five event days

ranged from 2 to 30 years for 160 different CUSIPs. This represented about 3% of the outstanding Treasury debt, and about 8% of the available Treasury supply.[5]

D'Amico and King (2013) provide details on the implementation of the Treasury purchases. On every other Wednesday, the Open Market Desk at the Federal Reserve Bank of New York would announce the range of the yield curve they were purchasing and the dates on which bids could be submitted. At 10:15 AM on each auction day, the Fed would publish a list of CUSIPs that it would consider purchasing. Most days, the bidding would commence at 10:30 AM. Shortly after bidding closed at 11:00 AM, the Fed used a confidential algorithm to determine which bids to accept.

Table 3 provides details on the first Treasury purchase on March 25, 2009. The Federal Reserve announced that it would consider purchasing securities with maturities between February 29, 2016 and February 15, 2019.

It listed 18 CUSIPs in this maturity range, but excluded one security, the 5.125% note, maturing on June 15, 2016. On March 25, they accepted bids on 13 of the securities, buying $7.5 billion overall. This was 31% of the $21.9 billion submitted. We find below that the ratio of accepted bids to those submitted captures the liquidity effect of the auctions on the equity market.

4.3 Effect of POMO Flows on the Equity Market

Lou, Yan and Zhang's (LYZ, 2013) work suggests that dealers have a limited risk bearing capacity, and that following US Treasury auctions, capital returns to other markets, raising equities by nearly 50 basis points. LYZ suggest that this effect on the stock market operates through asset reallocations by hedge funds and mutual funds.

[5]There are three purchases of Treasury Inflation Protected securities (TIPS) totaling $4.5 billion, but we did not include them in our analysis.

Table 3 US Treasury purchase detail for March 25, 2009

Release time:		10:30
Close time:		11:00
Settlement date:		March 26, 2009
Maturity/call date range:		02/29/2016–02/15/2019
Total par amt $	Submitted	21,937,000,000
	Accepted	7,500,000,000

CUSIP	Coupon	Maturity	Par amt accepted ($)
912828KS8	2.6250	2/29/2016	2,836,000,000
912810DW5	7.2500	5/15/2016	115,000,000
912828FQ8	4.8750	8/15/2016	1,031,000,000
912828FY1	4.6250	11/15/2016	739,000,000
912810DX3	7.5000	11/15/2016	147,000,000
912828GH7	4.6250	2/15/2017	35,000,000
912828GS3	4.5000	5/15/2017	950,000,000
912810DY1	8.7500	5/15/2017	238,000,000
912828HA1	4.7500	8/15/2017	702,000,000
912810DZ8	8.8750	8/15/2017	159,000,000
912828HH6	4.2500	11/15/2017	0
912828HR4	3.5000	2/15/2018	0
912828HZ6	3.8750	5/15/2018	0
912810EA2	9.1250	5/15/2018	23,000,000
912828JH4	4.0000	8/15/2018	0
912828JR2	3.7500	11/15/2018	0
912810EB0	9.0000	11/15/2018	193,000,000
912828KD1	2.7500	2/15/2019	0
912810EC8	8.8750	2/15/2019	332,000,000
Exclusions			
912828FF2	5.125	6/15/2016	0

This is the first of 214 Treasury purchases between March 2009 and June 2011. Details can be found on the New York Federal Reserve web site, http://www.newyorkfed.org/markets/pomo/display/index.cfm

We are able to identify a channel from the POMO auctions into equities at an intra-daily frequency. We regress the 15-min CRSP value weighted return[6] on the accepted/submitted ratio of bids in the POMO auctions. A high ratio here indicates that firms may be freeing up more capital to redeploy elsewhere.

The empirical estimates in Table 4 support a POMO liquidity channel into stocks. The average accepted/submitted ratio in the sample is 27.62%. When this ratio rises to 43.75%, stocks rise 0.50%. More than 13% of 15-min returns are explained by

[6]This effect is present from 1-min up to 30-min after the auction. The peak impact on equity returns is at the 15-min horizon.

Table 4 POMO stock liquidity model

Dep. variable: 15-min value weighted return	
Intercept	−0.0028
	(0.001)
Accepted/submitted bid ratio	0.0114
	(3.097)
$\overline{R}^2$	0.1330

t-statistics in parentheses
The table reports the regression model estimate for the 15-min value weighted CRSP return on the 57 Treasury POMO days between November 2008 and March 2010

this ratio. This use of weighted averages is similar to the results in Abou and Prat (2000).

These auctions results show that while the total amount of assets to be purchased was known prior to the auction, the amount of buying and selling interest did provide news to the market. We then try to model in the next section how HFT firms might alter their trading activity upon receipt of this news.

The goal of the large-scale asset purchases was "an effort to drive down private borrowing rates, particularly at longer maturities." Using an event study, Gagnon et al. (2011) conclude that 10-year Treasury bond yields fell 91 basis points and that 10-year agency debt yields declined 156 basis points. Joyce et al. (2011) find that a program of similar scale in the UK lowered gilt yields by 100 basis points.

Central bank asset purchases can also have impact on related asset markets. Neely (2010) and Joyce et al. (2011) have both emphasized the portfolio balance channel in which declining exposure to Treasury also raises other asset prices. Neely (2010) shows that announcements related to the US asset purchase program also lowered 10-year government bond yields in Australia, Canada, Germany, Japan and the UK between 19 and 78 basis points. Krishnamurthy and Vissing-Jorgensen (2011) estimate that US corporate bond yields fell between 43 and 130 basis points. Neely (2010) also finds evidence for reallocation into the US stock market: the S&P 500 index rises a cumulative 3.42%.

Even though the size of Fed's overall program was largely known by to the market by March 2009, the specific securities they would buy and the bids they would accept at each auction were not. The participation levels and prices paid, just like any auction, reveal information to the markets. Lou et al. (2013) suggest that the bid-to-cover ratio is likely to be an informative signal. We find that a closely related variable, the accepted-to-submitted ratio explains up to 13% of market returns in the period following the auction.

5 Empirical Results

We analyze HFT quote and trade activities during US Treasury POMO auctions. We find that (1) HFT firms pull back as market makers during periods of information release; (2) HFT firms use information to trade aggressively in the direction of the news; (3) HFT firms provide less passive liquidity on the opposite side of the news; (4) market impact rises during US Treasury POMO auctions; (5) HFT profits rise during POMO events. The empirical evidence provides support to our theoretical model.

5.1 HFT Firms Pull Back from the Inside Quote

Our model implies that, around the release of news, market makers should become more cautious. Admati and Pfleiderer (1988) have emphasized that the risk of trading against valuable private information is higher, and market makers should widen spreads and reduce their depth.

To examine this empirically, we estimate how frequently HFT firms participate in the inside quote on the Nasdaq market. Our order book overlaps with the US Treasury POMO auctions on 5 trading days.

We calculate the percentage of ticks in which the HFT firms is at the inside bid or offer. Interpreting this raw percentage requires some care. First, we have to account for the trend in the data that we noted in Fig. 1. We find that a quadratic trend fits the data well.

The data are also seasonal intra-daily. The vast majority of POMO auctions occur between 10:30 and 11:00 AM. This is a relatively quiet time during the day in which HFT participation tends to fall off. Therefore, we include a time dummy for the period from 10:30 to 11:00 AM in the model.

We also need to control for the typical microstructure factors that influence order aggressiveness. These include realized volatility, which we measure as a ten-tick moving average, trade volume, and the order imbalance of buyer less seller initiated trades. These variables are all lagged one period.

We estimate the model in the probit form with robust standard errors on a pooled cross-section of the 120 stocks, using maximum likelihood. We report the result for the bid and offer side, respectively. Table 5 shows that the participation rate of HFT firms in the inside quote falls significantly during Treasury purchases, whether it is a positive or negative news. The result is consistent with our model.

HFT firms are almost 8% less likely to quote on the inside bid and 5% less frequently on the inside offer during US Treasury POMO auctions.

Table 5 HFT inside quote frequency during US treasury POMO

Variable	Bid	Offer
Trend	0.0022	0.0017
	(62.38)	(50.34)
$\text{Trend}^2/1000$	-0.0012	-0.0008
	(-16.00)	(-10.93)
Returns_{t-1}	0.0206	-0.0368
	(1.92)	(-3.55)
Realized vol_{t-1}	-0.0146	-0.0121
	(87.94)	(-77.25)
$\text{Volume}_{t-1}/1000$	0.0745	0.0401
	(221.70)	(158.12)
Order $\text{imbalance}_{t-1}/1000$	1.6756	-1.1129
	(13.36)	(-10.29)
S10:30–11:00	-0.0266	-0.0335
	(-4.62)	(-5.92)
Positive UST news	-0.0763	-0.0450
	(-4.00)	(-2.43)
Negative UST news	-0.0772	-0.0458
	(-6.87)	(-4.16)
Constant	-0.4383	-0.3251
	(-107.41)	(-82.64)
$\overline{R}^2$	0.1450	0.1155

t-statistics in parentheses

The table reports estimates of a model for the inside quote participation of the 26 HFT trading firms. We control for the growth in HFT activity using a linear and quadratic trend. We also include standard regressors for market making aggressiveness, past returns, volatility, volume, and order imbalance. We also include a time dummy for the quiet period from 10:30 to 11:00. Finally, we measure the effect of US Treasury POMO auctions using two dummy variables, one for positive news and the other for negative

5.2 HFT Firms Trade More Aggressively in the Direction of News

Given the fact that the HFT firms tend to withdraw liquidity from the inside quotes during POMO auctions, the other question to ask is whether they demand more liquidity from other non-HFT market participants. The trade data set tells us whether traders are HFT or non-HFT firms at both sides of a trade. We treat the HFT firms as a group and focus particularly on HN and NH trades, where the first letter refers to the liquidity seeker and the second to the liquidity provider. We study the trading behavior of the HFT firms when they expect a positive and a negative news, respectively.

Table 6 Unconditional HFT net buy counts

	Positive UST news		Negative UST news		Non-POMO	
	HN	NH	HN	NH	HN	NH
Avg.	16.08	−9.11	−11.51	7.63	2.34	−1.71
SD	46.46	36.70	36.76	33.66	35.57	33.91
H_0: $\overline{c}_{\mathrm{POMO}} = \overline{c}_{\mathrm{Non}}$						
t-stat	1.94	−1.48	−2.10	1.68		

This table reports the average number of HFT net buys at a 1-min frequency from 10:30 to 11:00. HFT net buy is defined as the difference between the number of HFT buyer and seller initiated trades. We calculate it on days with positive and negative news from US Treasury auctions and on non-POMO days, and in aggressive HN and passive NH trades respectively

We report, in Table 6, the average difference of the number of HFT buyer and seller initiated trades between 10:30 and 11:00 AM and the rest of the day, at a 1-min frequency.

We divide US Treasury purchases into positive and negative news events based on the 1-h equity return after the start of the auction. The event is treated as positive news if the average return across the 120 stocks is greater than zero, and a negative one otherwise. Among 57 Treasury purchases, there are 32 positive and 25 negative news events.

We compute the average difference on non-POMO days and on days with positive and negative news from US Treasury auctions. We then test the differences in these net buy counts during event and non-event periods. We find a statistically significant reduction in buyer initiated trades on negative news days, with a reduction of 345 net buy trades during the POMO period. There is an increase of 482 net buy trades on positive news days, although this result is only significant at the 10% level.

POMO announcements days are volatile periods for the market, and this should lead to a less aggressive trading posture for HFT firms. To confirm and perhaps strengthen the results in Table 6, we need to then control for microstructure factors. We add lagged returns, realized volatility, volume and order imbalances as before, as well as a seasonal time dummy. We also include two dummy variables for positive and negative news.

The dependent variable is the 1-min net differential between buyer and seller initiated trades. We then estimate a least squares model in Table 7 for HFT net trade counts in aggressive HN and passive NH trades, respectively.

We estimate a significantly positive effect of US Treasury POMO events on HFT net trades, indicating the more aggressive stance of the HFT firms during the auctions. Once we control for microstructure factors, HFT firms increase their net buying by 600 trades on good news days and decrease their net buying by 891 trades when there is bad news. This result is similar to Brogaard et al. (2014) who find that, marketwide, HFT firms trade in the direction of the news flow.

Table 7 HFT net buy counts during US treasury POMO

Variable	HN	NH
Returns_{t-1}	−80.3836	−54.0185
	(−30.40)	(−18.46)
Realized vol_{t-1}	−0.0332	−0.0526
	(−2.90)	(−3.04)
$\text{Volume}_{t-1}/1000$	−0.0020	0.0021
	(−2.21)	(1.86)
Order $\text{imbalance}_{t-1}/1000$	0.0553	−0.0674
	(33.03)	(−32.03)
S10:30–11:00	0.0471	−0.0317
	(3.61)	(−2.04)
Positive UST news	0.1667	−0.1328
	(5.40)	(−3.65)
Negative UST news	−0.2476	0.1360
	(−7.59)	(3.50)
Constant	−0.0235	0.0075
	(−4.64)	(1.31)
$\overline{R}^2$	0.0024	0.0031

t-statistics in parentheses

The table reports estimates of models for HFT net trade counts in aggressive HN and passive NH trades, respectively. We include standard regressors for trading aggressiveness, past returns, volatility, volume, and order imbalance. We also include a time dummy for the quiet period from 10:30 to 11:00. Finally, we measure the effects of positive and negative US Treasury auctions using two dummy variables, respectively

5.3 *HFT Firms Reduce Their Passive Liquidity Supply*

We then do the same comparison in Table 6 for NH trades in which HFT firms are the passive liquidity suppliers. We find that non-HFT firms reduce their net buys by 273 trades on positive news days and increase their net buys by 229 trades on bad news days. This indicates that HFT firms have become more reluctant to supply passive liquidity to noise traders trading in the direction of the news. Neither of these results is significant at the 10% level though.

Introducing microstructure variable controls helps to isolate the effects predicted by our model. When we regress NH net buyers counts, the effect of the POMO auctions becomes much more strongly significant. Non-HFT firms decrease their net buying by 478 trades on good news days and increase their net buying by 490 trades with bad news.

We have now confirmed three of the primary predictions of the model. HFT firms become less active participants in the inside market on either the bid or offer. HFT firms increase their net buying activity on good news days and decrease on bad news days. Finally, we show that non-HFT firms are not able to trade as aggressively as HFT firms in the direction of the news because the HFT firms reduce their passive liquidity supply.

6 Additional Effects of HFT Activity

In this section, we study market impact and profits during the POMO auctions. Our model anticipates that the release of private information during the POMO events should raise market impact. Wider spreads and more informed trading should also lead to higher trading profits.

6.1 Market Impact of Trades by HFT Firms Becomes Higher

Another measure of liquidity is the market impact of trades. This is a dynamic indicator which incorporates the bid-ask spread, market depth, the persistence in order flow, and the resiliency of the order book.

Let $r_{i,t}$ be the change in the midpoint of the bid-ask spread, $(p^b_{i,t} + p^a_{i,t})/2 - (p^b_{i,t-1}+p^a_{i,t-1})/2$. $x_{i,t} \in \{-1, +1\}$ is an indicator variable which measures the trade direction. It is assigned as $+1(-1)$ if the transaction is a buy(sell). Let $V_{i,t}$ denote the size of the trade. We follow Hasbrouck (1991) using a vector autoregressive (VAR) model of their dynamic interaction. We also use Hasbrouck's identifying assumption that the current trade can effect the current quote, but not vice versa,

$$r_{i,t} = a_{r,0} + \textstyle\sum_{j=1}^{10} a_{r,j} r_{i,t-j} + \sum_{j=0}^{10} b_{r,j} x_{i,t-j} V_{i,t-j} + \varepsilon_{r,t}, \tag{16}$$

$$x_{i,t} V_{i,t} = a_{x,0} + \textstyle\sum_{j=1}^{10} a_{x,j} r_{i,t-j} + \sum_{j=1}^{10} b_{x,j} x_{i,t-j} V_{i,t-j} + \varepsilon_{x,t}. \tag{17}$$

We use 10 lags in the VAR. The estimates are not sensitive to this choice.

Market impact is a dynamic process

$$\partial r_{i,t+j} / \partial x_t V_t \tag{18}$$

which we will now compute during POMO and non-POMO intervals. We sum the aggregate effect

$$\overline{\Lambda} = \frac{1}{120} \textstyle\sum_{i=1}^{120} \sum_{j=1}^{50} \partial r_{i,t+j} / \partial x_{i,t} V_{i,t} \tag{19}$$

arbitrarily after 50 trades, filtering out negative impacts.

Table 8 HFT market impact

	10:30–11:00		11:00–11:30		13:45–14:15	
	POMO	Non-POMO	POMO	Non-POMO	FOMC	Non-FOMC
Avg. (10^{-5})	3.4138	3.1761	3.0856	3.0129	2.8937	2.8927
SD (10^{-5})	0.3007	0.3037	0.4289	0.2251	0.2317	0.3630
H_0: $\overline{\Lambda}_{\text{POMO}} = \overline{\Lambda}_{\text{Non}}$						
t-stat	2.54		1.10		0.71	

This table reports the average market impact calculated by (19). We use the eight FOMC announcements in 2009: January 29, March 18, April 29, June 24, August 12, September 23, November 4, and December 16. For the FOMC results we use the 60 Nasdaq stocks in the sample with quotes from the ITCH feed

The number of POMO days we can include is limited by the availability of our Nasdaq inside quote data. We have only 5 US Treasury POMO days to contrast with 14 non-POMO days. To do reasonable comparisons, we expand the sample to 14 POMO days using Nasdaq ITCH data.

Our HFT data set classifies trades into four categories. The trade has an aggressor and a passive supplier. Either can be a HFT or not. We report the comparison of average market impact by HFT trades, $x_t \in \{x_t^{HH}, x_t^{HN}, x_t^{NH}\}$, across the 120 stocks in Table 8.

We find, as our quote analysis indicated, that market impact from HFT is significantly higher during the US Treasury POMO auctions than the corresponding period on non-POMO days. A 1000 share order moves the market on average \$0.0318, but on POMO days this rises to \$0.0341. The rise in market impact of trades could make the trading costs of non-HFT firms even higher. These nonlinear market impacts are consistent with the empirical findings in Jawadi and Prat (2012).

6.2 *HFT Firms Make More Profits During POMO*

Menkveld (2013) makes a useful division of trading profits for a HFT firm. On passive trades, designated NH in our sample, they can expect to earn the bid-ask spread. On aggressive trades, designated HN, they must pay the spread, hoping to realize a positioning profit.

Under some assumptions, we can estimate the profitability of the HFT firms as a group using our trade data. We assume that HFT firms try to end the day flat and assess their profits by valuing any position at the day's average price. By construction, we consider only HN and NH trades.

The HFT daily profits for stock i are estimated as

$$\pi_i^{\text{HFT}} = \sum_{t=1}^{T} \left[D_{i,t}^S p_{i,t} q_{i,t} - D_{i,t}^B p_{i,t} q_{i,t}\right] + \frac{\sum_{t=1}^{T} p_{i,t} q_{i,t}}{\sum_{t=1}^{T} q_{i,t}} \sum_{t=1}^{T} \left[D_{i,t}^B q_{i,t} - D_{i,t}^S q_{i,t}\right], \tag{20}$$

Table 9 HFT daily profits per stock

	UST POMO	Non-POMO
Mean	\$1895.37	\$1300.35
SD	2736.70	3642.63
H_0: $\overline{\pi}^{\text{HFT}}_{\text{POMO}} = \overline{\pi}^{\text{HFT}}_{\text{Non}}$		
t-stat	1.65	

This table reports estimated HFT daily profits per stock by (20) during US Treasury POMO and non-POMO days

Table 10 HFT daily profits per share

	Total		HN		NH	
	UST	Non-POMO	UST	Non-POMO	UST	Non-POMO
Mean	\$0.0178	\$0.0129	\$0.0099	\$0.0032	\$0.0341	\$0.0298
SD	0.0085	0.0105	0.0132	0.0158	0.0149	0.0177
Min	−\$0.0036	−\$0.0254	−\$0.0235	−\$0.0594	\$0.0064	−\$0.0084
Max	\$0.0385	\$0.0422	\$0.0550	\$0.0484	\$0.0897	\$0.1002
% Days>0	96.49%	88.13%	87.72%	60.63%	100.00%	96.88%
H_0: $\overline{\pi}^{\text{HFT}}_{ps,\text{POMO}} = \overline{\pi}^{\text{HFT}}_{ps,\text{Non}}$						
t-stat	3.86		3.42		2.11	

This table reports estimated HFT daily profits per share by (21) during US Treasury POMO and non-POMO days. HFT profits are also calculated in aggressive HN and passive NH trades, respectively

where D^B and D^S are buy and sell indicators, respectively, $p_{i,t}$ is the price of stock i at time t, and $q_{i,t}$ is the quantity. It closes out open positions at the end of the day using daily average trade prices. The method of calculating profits is similar to Brogaard et al. (2014) and Baron et al. (2017).

Profits per stock for POMO US Treasury days are compared to profits on non-POMO days in Table 9.

On non-POMO days, we estimate profits of \$1300.35 per stock for the entire sample of trading days between December 2008 and February 2010. This compares to Brogaard et al.'s (2014) estimate of \$2284.89 for the entire trading sample back to January 2008. We find that HFT firms increase their average daily profits by 46% on US Treasury POMO days. The increase in profit of \$595.02 per stock is marginally significant at 10% level.

To approximate returns from HFT activity, we also estimate in Table 10 the profits per share $\pi^{\text{HFT}}_{i,ps}$ from their aggressive and passive trades,

$$\pi^{\text{HFT}}_{i,ps} = \frac{\pi^{\text{HFT}}_{i}}{\sum_{t=1}^{T} q_{i,t}/2}. \tag{21}$$

Given an average share price of around \$30, the returns are quite modest. The trades, however, are very short term and rarely lose money. On US Treasury POMO days, profits per share are positive 96.49% of the time. On the 2 days where the HFT firms lose money, they lose only $2/10$ and $3.6/10$ of one cent per share, respectively, compared with the largest gain of nearly \$0.04 per share on April 30, 2009.

In HN trades, HFT firms also rarely lose money on Treasury POMO days. They make profits 87.72% of the time. Crossing the spread on non-POMO days is much more risky. Profits are positive on only 60.63% of non-POMO trading days. The average profit per share when crossing the spread is typically small, only \$0.0032 per share, but this rises by a statistically significant 300% during POMO auctions. The wider spreads on POMO days, while helping their passive profits, should reduce.

In NH trades where HFT firms are passive liquidity providers, profits per share are always positive on US Treasury POMO days. Compared to their performance on non-POMO days, HFT firms increase the average profits per share by 38% on US Treasury POMO days, and the effect is statistically significant.

On POMO days, HFT firms became more aggressive. While this should raise the profits on their passive activity, it should actually reduce their profits on aggressive trades unless their positioning profits are higher. This is evidence that HFT firms receive valuable private information during the POMO auctions because their profits per share rise despite the wider spreads.

Extrapolating the daily profit estimates to the broader market requires an estimate of the percentage of high frequency trading in the market captured by our sample. We present an estimate here in based on the 12.3% of total market capitalization represented by the firms in our sample. We sum daily profits across the 120 stocks, the 57 US Treasury POMO days, and we assume similar activity in the sample we do not observe. We estimate profits of over \$105 million during US Treasury POMO auctions.

7 Robustness Checks

7.1 *Time Window*

We analyze the HFT firm behavior in the half-hour after US Treasury POMO as a robustness check. In terms of inside quote frequency by the HFT firms, we use a similar model described in Sect. 5.1 but replace the variable US Treasury Purchase with a dummy variable indicating the half-hour after purchases. The results for the HFT inside bid and offer participations are reported in Table 11. The effect is not statistically significant for either bids or offers during the half-hour after US Treasury POMO auctions.

Table 11 HFT inside quote frequency after US treasury POMO

Variable	Bid	Offer
Trend	0.0013	0.0011
	(32.88)	(28.59)
$\text{Trend}^2/1000$	−0.0007	−0.0006
	(−8.26)	(−7.06)
Returns_{t-1}	0.0348	−0.0561
	(2.95)	(−4.83)
Realized vol_{t-1}	−0.0088	−0.0078
	(48.18)	(−44.28)
$\text{Volume}_{t-1}/1000$	0.0394	0.0323
	(116.47)	(109.12)
Order $\text{imbalance}_{t-1}/1000$	1.3817	−1.1281
	(10.45)	(−8.93)
Inside quote_{t-1}	1.6012	1.6150
	(465.57)	(473.96)
S11:00–11:30	0.0006	−0.0035
	(0.08)	(−0.52)
After UST purchases	−0.0235	0.0076
	(−1.67)	(0.54)
Constant	−1.0536	−1.0210
	(−220.77)	(−217.52)
$\overline{R}^2$	0.4211	0.4118

t-statistics in parentheses
The table reports estimates of a model for the inside quote participation of the 26 HFT firms in the half-hour after US Treasury purchases. We use a similar model presented in Table 5 but replace UST news variables with a dummy variable indicating the half-hour after purchases

The market impact of HFT trades in the half-hour after US Treasury POMO is not significantly different from the same period of non-POMO days either. The result is shown in the second set of columns in Table 8.

7.2 FOMC Days

We also contrast our results with the behavior of HFT firms on the eight Federal Open Market Committee (FOMC) dates in our sample listed in the third set of columns in Table 8.

We compare the market impact of HFT trades during the period from 13:45 to 14:15, the half-hour before the Fed announces its policy intentions. We felt this period was analogous to our half-hour before the release of POMO Treasury purchases. We used trades from the HFT database and quotes from the Nasdaq ITCH feed. This limits our analysis to the 60 Nasdaq stocks in the sample. For the 60 stocks, the market impact on FOMC and non-FOMC days is little changed. From this, we conclude that the POMO auctions were more important events for the market.

8 Conclusion

HFT firms perform a dual role as market makers. During the POMO auctions though, our model predicts that they may shift their focus from being liquidity providers to trading aggressively. We find that HFT firms reduce their presence at the inside quote and less frequently provide liquidity to non-HFT firms. Studying HFT activity in event windows like POMO may give us a better indication of how HFT firms will perform in stressful market conditions.

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