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by

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Abstract

This paper investigates high-frequency (HF) market and limit orders in the U.S. Treasury market around major macroeconomic news announcements. BrokerTec introduced i-Cross at the end of 2007 and we use this exogenous event as an instrument to analyze the impact of HF activities on liquidity and price efficiency. Our results show that HF activities have a negative effect on liquidity around economic announcements: they widen spreads during the pre-announcement period and lower depth on the order book during the post-announcement period. The negative impact on liquidity mainly derives from HF trades. Nonetheless, HF trades improve price efficiency during both the pre-announcement and post-announcement periods.

JEL classification: G10, G12, G14
Bank classification: Financial markets

Résumé

Dans cette étude, les auteurs observent les ordres de marché à haute fréquence et les ordres à cours limité sur le marché des titres du Trésor américain aux environs d'annonces macroéconomiques importantes. Les auteurs utilisent un événement exogène, soit le lancement d'i-Cross par BrokerTec à la fin de 2007, pour analyser l'incidence des activités de négociation à haute fréquence sur la liquidité et l'efficience des prix. D'après les résultats de leur étude, les activités de négociation à haute fréquence ont des répercussions négatives sur la liquidité aux environs des annonces macroéconomiques. En effet, elles causent un élargissement des écarts durant la période qui précède ces annonces et une réduction de la profondeur du carnet d'ordres durant la période qui suit les annonces. L'incidence défavorable sur la liquidité découle principalement des transactions à haute fréquence. Néanmoins, ces transactions entraînent une amélioration de l'efficience des prix durant les périodes qui précèdent et qui suivent les annonces.

Classification JEL : G10, G12, G14
Classification de la Banque : Marchés financiers

1 Introduction

High-frequency (HF henceforth) trading[1] carried out by computer programs has become prevalent in financial markets during the past decade. As reported in financial media, trading records have routinely been broken in recent years, and millions of data messages are regularly sent every second to various trading venues.[2] This anecdotal evidence is coupled with the hard fact that trading in latency markets has decreased by about two orders of magnitude over the past decade (Moallemi and Saglam (2011). As documented in the existing literature (e.g., Clark, 2011 and Hasbrouck (2012), trading and quoting activities regularly take place within a fraction of a second. The main advantage of HF trading is that computers, with their capacity to process a large amount of information, are well positioned to execute multiple actions rapidly in response to information arrival. However, the impact of HF activities on market quality around information arrival remains an open question. In theoretical models such as Biais, Foucault and Moinas (2011), Foucault, Hombert and Rosu (2013), and Martinez and Rosu (2013), HF traders use market orders to utilize their information-processing capacity and speed advantage. Their faster orders, which are based on more updated information, pick off orders that react more slowly to information arrival. This generates adverse selection and has a negative impact on market liquidity. On the other hand, Jovanovic and Menveld (2011) and Hoffman (2014) argue that HF traders who act as liquidity suppliers are able to update quotes quickly after news arrival and thus reduce adverse selection risk.

The U.S. Treasury market provides a unique opportunity to analyze the relationship between HF trading, news arrival and market quality. As one of the largest financial markets, with daily trading volume that is nearly five times that of the U.S. equity market, the Treasury market has a unique market microstructure as both an interdealer market and a limit order market with no

[1]As noted in Hendershott and Riordan (2013) and Chlistalla (2011) among others, HF trading or HFT is a subset of market activities carried out by computers known as Algorithmic Trading or AT. This paper focuses on trading activities that are carried out by machines at a very high speed, and thus we refer to these activities as HF trading throughout the paper.

[2]See “Speed and market complexity hamper regulation” *Financial Times*, October 7, 2011.

intervention from market makers. It is open virtually around the clock, with active trading activities taking place around pre-scheduled macroeconomic news releases. More importantly, pre-scheduled announcements in the U.S. Treasury market offer an ideal setting to assess the impact of HF trading. Pre-scheduled macroeconomic news announcements, which are the main drivers of Treasury security prices, are arguably among the most significant market events.[3] Pre- and post-announcement periods represent very different informational environments. The pre-announcement period is characterized by a relatively quiet market with pending information arrival, whereas the post-announcement period is characterized by the arrival of more precise economic signals about macroeconomic fundamentals and the resolution of public information shocks. In light of these important features, we analyze the characteristics of HF trading around pre-scheduled news announcements, i.e., how it affects market liquidity and price efficiency, as well as how the role of HF trading changes with the magnitude of public information shocks.

The data used in our study are obtained from BrokerTec, a major trading platform for on-the-run secondary U.S. Treasury securities. The data contain tick-by-tick observations of transactions and limit order submissions, alternations, and cancelations for 2-, 5- and 10-year notes. Since there is no readily available identifier in the data to distinguish automatic trading activities from manual activities, we propose a procedure to identify HF trades and limit orders based on the speed of order placement or subsequent alterations of the orders. Specifically, using information on the time of order submission in reponse to changes in market conditions, and any subsequent alterations, such as cancelation or execution, we classify HF trades and orders as those that are placed at a speed deemed beyond manual capacity. After identifying HF activities, we examine the causal effect of HF activities on market quality. We recognize that HF activities and variables capturing market

[3]A vast literature has examined the effect of macroeconomic news announcements in U.S. Treasury markets. Fleming and Remolona (1997) and Andersen et al. (2003, 2007) find that the largest price changes are mostly associated with macroeconomic news announcements in the Treasury spot and futures markets. Balduzzi, Elton and Green (2001), Fleming and Remolona (1999), Green (2004) and Hoerdahl, Remolona and Valente (2012) point out that the price discovery process for bond prices mainly occurs around major macroeconomic news announcements, and the same announcements are responsible for changes in risk premiums across different maturities. Menkveld, Sarkar and van der Wel (2012) record similar findings for 30-year Treasury bond futures. Pasquariello and Vega (2007) find that private information manifests on announcement days with larger belief dispersion.

quality could be endogenously determined. To establish causality, we use the introduction of i-Cross,[4] a co-location event, on BrokerTec as an instrument. The co-location service reduces the response time between HF activities and BrokerTec. It thus enables HF activities to react faster to information arrival and changes in market conditions, but does not have any other direct impact on market quality. We use this co-location event to identify the causal effects of HF activities on market quality.

We find that both HF market orders and limit orders increase following announcements and that the magnitude of their increase relative to the pre-announcement period is larger than the overall sample. The ratio of post-announcement HF volume relative to pre-announcement volume is significantly larger than that of the overall sample. This is consistent with predictions from the theoretical literature, such as Foucault, Hombert and Rosu (2013), Hoffman (2014), Jovanovic and Menkveld (2011), and Martinez and Rosu (2013), that the HF participation rate increases with news arrival.

We then examine how HF activities affect market liquidity around public information arrival. Theoretical models offer different predictions on how HF affects market liquidity upon public information arrival. In models that feature HF traders as market makers, such as Jovanovic and Menveld (2011) and Hoffman (2014), HF traders are able to update their quotes quickly upon news arrival. This reduces adverse selection risk. Alternatively, if HF traders use only market orders, these traders use either their speed advantage (as in Foucault, Hombert and Rosu (2013)) or better information-processing capacity, (or both as in Biais, Foucault and Moinas (2011) and Martinez and Rosu (2013)) to act as informed traders. This increases adverse selection risk and worsens market liquidity.

We find that an abnormal increase in HF activities leads to a significant increase in spreads preceding macroeconomic news announcements. The positive impact on spreads mainly comes

[4]According to ICAP, "i-Cross is a premium connectivity service from ICAP that provides API customers with a low-latency, high-speed connection...., i-Cross facilitates the housing of customers' hardware at a common data facility with ICAP. i-Cross provides a co-location solution for U.S. Treasury trading via BrokerTec in North America (Secaucus, NJ)." See www.icap.com/ /media/Files/I/Icap-Corp/pdfs/i-Cross-sheet.pdf.

from HF trades. Following the announcements, our results are consistent with Biais, Foucault and Moinas (2011), Foucault, Hombert and Rosu (2013) and Martinez and Rosu (2013), in that HF activities have a negative impact on liquidity upon public information arrival. Overall HF activities significantly reduces depth both at the best quotes and behind the best quotes. Disentangling the impact of HF trades and HF limit orders, we find that the negative impact on depth at the best quotes comes from HF trades, while that on behind best quotes comes from HF orders. Overall, our findings indicate that HF trades act as informed traders. They are associated with widening of spreads with pending public information arrival and with limit orders being placed at a less aggressive level to avoid being picked off following public information arrival.

On the other hand, our findings indicate that overall HF activities improve price efficiency. An abnormal increase in HF activities significantly reduces the absolute autocorrelation of returns during both the pre- and post-announcement periods. The improvement in price efficiency mainly comes from HF trades, especially during the post-announcement period. This finding is consistent with Martinez and Rosu (2013) that HF trades incorporate information into prices quickly upon information arrival. On the other hand, HF orders have no significant effect on price efficiency before announcements and they have a negative impact on price efficiency after announcements.

The existing literature mainly focuses on the overall impact of HF trading on market quality in normal times (e.g., Hendershott, Jones and Menkveld (2011); Hasbrouck and Saar (2013); Brogaard, Hendershott and Riorda (2013); Boehmer, Fong and Wu (2012); Scholtus and van Dijk (2012) for equity markets; and Chaboud, Chiquoine, Hjalmarsson and Vega (2014) for foreign exchange markets). They find that the impact of HF activities improves liquidity and price efficiency in general. Hendershott, Jones and Menkveld (2011) using NYSE data, and Menkveld (2013) using Chi-X data, show that HF activities are associated with lower spreads. Hasbrouck and Saar (2013) find that HFT is associated with deeper overall depth, while Hendershott, Jones and Menkveld (2011) find that quoted depth declines with autoquote. Our study extends the existing literature by demonstrating that HF activities around significant information events negatively affect market liquidity. Looking at price efficiency, Chaboud et al. (2014) find that HF activities reduce triangular arbitrage opportunities. Brogaard, Hendershott and Riordan (2013) find that HF trades are informative. Our study confirms and extends their findings that HF trades improve price efficiency during both the pre-announcement period and the post-announcement periods. A related paper is the study by Scholtus and van Dijk (2012) that explores the role of speed in HF trading around major macroeconomic announcements in the U.S. equity market.

The remainder of this paper is structured as follows. Section 2 introduces the data set employed in the empirical analysis and describes in detail the procedure used to identify HF trades and orders. Section 3 discusses the empirical results, and the final section concludes.

2 Data

2.1 Market Activities around News Announcements

Data on pre-scheduled macroeconomic news announcements and the survey of market participants are obtained from Bloomberg. Following Pasquariello and Vega (2007), the list of announcements was compiled to ensure that all important news items are included in our analysis. The full list contains 31 pre-scheduled announcements. Table 1 reports the day and time of announcement for each news item. The majority of announcements occur at 8:30 a.m. ET and 10:00 a.m. ET. Following Balduzzi, Elton and Green (2001); Andersen et al. (2003, 2007); and Pasquariello and Vega (2007), we compute the standardized announcement surprise for each news item as follows:

$$\text{SUR}_{k,t} = \frac{A_{k,t} - E_{k,t}}{\sigma_k}, \quad k = 1, 2, \cdots, K, t = 1, 2, ...T \tag{1}$$

where $A_{k,t}$ is the actual value of announcement k on day t, $E_{k,t}$ is the median forecast of the announcement k on day t and σ_k is the time-series standard deviation of $A_{k,t} - E_{k,t}, t = 1, 2, \cdots, T$. The standardized announcement surprise is used in our study as a measure of unexpected public information shock. As shown in Balduzzi, Elton and Green (2001), professional forecasts based on surveys are neither biased nor stale.

The data on U.S. Treasury securities used in our study are obtained from BrokerTec, an inter-dealer Electronic Communication Network (ECN) platform of the U.S. Treasury secondary market, owned by the largest interdealer brokerage (IDB) firm, ICAP PLC. Prior to 1999, the majority of interdealer trading of U.S. Treasuries occurred through interdealer brokers. Since then, two major ECNs have emerged: eSpeed and BrokerTec. Trading of on-the-run U.S. Treasury securities has mostly, if not completely, migrated to electronic platforms.[5] According to Barclay, Hendershott and Kotz (2006), the electronic market accounted for 75.2%, 83.5% and 84.5% of the trading of the 2-, 5- and 10-year notes, respectively, during the period from January 2001 to November 2002. By the end of 2004, over 95% of interdealer trading of active issues occurred on electronic platforms. BrokerTec is more active in the trading of 2-, 3-, 5- and 10-year notes, while eSpeed is more active in the trading of 30-year bonds. The BrokerTec data used in our study contain tick-by-tick observations of transactions as well as limit order submissions and subsequent alterations and cancellations for on-the-run 2-, 5- and 10-year U.S. Treasury notes. It includes the time stamp of transactions and limit order submissions as well as their subsequent alterations, the quantity entered and/or cancelled, the side of the market involved and, in the case of a transaction, an aggressor indicator indicating whether the transaction is buyer- or seller-initiated. The sample period is from January 3, 2006 to December 29, 2011.

In our empirical analysis, we focus on HF trading activities around news announcements. We define the 15-minute interval prior to the announcement as the pre-announcement period and the 15-minute interval following the announcement as the post-announcement period. For all three maturities, we compute the average relative bid-ask spread and the average depth of the limit order book both at the best quotes and behind the best quotes ($ million) at the end of each 1-minute interval during both the pre-announcement period and the post-announcement periods. The summary statistics of the liquidity variables around announcements are shown in Table 2.

Figure 1 plots the patterns of market activities around news announcements. For the purpose of comparison, market activities at the same time on days without announcements are also plotted. The plots are for the 2-year note. The patterns for other maturities are similar and thus are not reported for the sake of brevity. Compared with non-announcement days, the bid-ask spread on

[5]For an excellent review of the transition to ECNs in the secondary U.S. Treasury market, please refer to Mizrach and Neely (2006).

announcement days starts to increase and peaks right before the announcement. Both depth at the best quotes and depth behind the best quotes start to drop substantially before announcement time. The drop is more pronounced for depth at the best quotes. This indicates that dealers withdraw their orders to avoid being picked off right before public information arrival. This finding is consistent with evidence using an earlier sample documented in Fleming and Remolona (1999) and Jiang, Lo and Verdelhan (2011). After public information arrives, bid-ask spread reverts quickly to the pre-announcement level. Both depth at the best quotes and depth behind the best quotes increase gradually after a news announcement and are back almost to the level of non-announcement days.

2.2 HF Trades and Orders: Identification and Summary Statistics

The BrokerTec data include reference numbers that provide information on the timing of an order submission and its subsequent execution, alteration or cancellation. Using this information, we identify HF activities based on the reaction time to changes in market conditions. We recognize that HF activities could be supplying liquidity to the market or demanding liquidity from the market. We classify those trades and orders as HF trades and orders if they are placed at a speed deemed beyond manual capacity. Specifically, the following criterion is used to identify HF trades (HFTR hereafter):

- HFTR – Market orders (buy or sell) that are placed within a second of a change in the best quote on either side of the market (highest bid or lowest ask).

The following criteria are used to identify HF orders (HFLO hereafter) in three different categories:

- HFLO1 – Limit orders (buy or sell) that are cancelled or modified within one second of their placements, regardless of changes in market conditions;
- HFLO2 – Limit orders (buy or sell) at the best quotes that are modified within one second of a change of the best quotes on either side of the market (highest bid or lowest ask);

- HFLO3 – Limit orders (buy or sell) at the second-best quote that are modified within one second of a change of the best quote on either side of the market (highest bid or lowest ask).

The above procedure is specifically designed to identify HF trades and orders on the basis of the speed at which they are submitted, executed or altered. In fact, the procedure for identifying HFLO1 is similar in spirit to the one proposed by Hasbrouck and Saar (2013) in identifying low latency orders. We exclude those orders deleted by the central system, orders deleted by the proxy, stop orders, and passive orders that are automatically converted by the system to aggressive orders due to a locked market.[6] Nevertheless, we recognize that non-HF orders can be mistakenly identified as HF orders if non-HF orders are placed earlier but arrive within one second of market condition changes. Similarly, some HF orders may be classified as non-HF orders if they arrive at the system beyond one second of market condition changes. As a result, some non-HF trades and orders may be labelled incorrectly as HF trades and orders, and vice versa. That is, the above procedure is not perfect for identifying HF trades and orders per se. We note that more than 90% of the HF orders identified come from HFLO1 (Table 3), which are orders cancelled or modified within less than one second of their placement, regardless of market condition changes. These orders are unlikely to be placed manually by dealers. As documented in existing studies (see Scholtus and van Dijk (2012)), speed is the most important advantage of HF trading.[7] Thus, our procedure captures the most salient feature of HF trading.

Figure 2 shows the ratio of overall HF activities, defined as the total monthly volume of HF trades and orders, to the total volume of trades and limit orders submitted over the sample period. The ratio of HF activities increases substantially over the sample period. As such, there is a potential time trend in most of the trading activity variables. In fact, over our sample period the ratio of

[6]On the BrokerTec platform, the percentages of these types of orders account for 1.5%, 1% and 0.8% of the total number of orders for the 2-, 5- and 10-year notes, respectively.

[7]This is supported by evidence that traders compete to locate their servers close to exchanges in order to reduce the latency in managing their orders. One example is Thomson Reuters Hosting Solutions - Prime Brokerage (http://thomsonreuters.com/financial/thomson-reuters-elektron/) "We host algorithmic trading applications at our data centers located in close proximity to the world's leading financial centers .... We manage algorithmic trading applications co-located in exchange data centers...Market data is delivered with ultra-low latency from the markets"

HF orders and trades has increased from 24% in the first quarter of 2006 to 40% in the last quarter of 2011. Therefore, we construct measures of abnormal HF trading activities around macroeconomic news announcements in our analysis to remove the potential time trend. Similar to Bamber (1987) and Ajinkya and Jain (1989), the abnormal volume of HF trades and orders is computed as the dollar volume of actual HF trades and orders in excess of the average dollar volume of HF trades and orders over the same 1-minute interval over the past five non-announcement days:

$$HFTR^{*}_{t,1M(i)} = HFTR_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5} HFTR^{NA}_{t-k,1M(i)}, \tag{2}$$

$$HFLO^{*}_{t,1M(i)} = HFLO_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5} HFLO^{NA}_{t-k,1M(i)}, \tag{3}$$

where $HFTR_{t,1M(i)}$ and $HFLO_{t,1M(i)}$ denote the dollar volume of HF trades and orders within the i^{th} 1-minute interval on announcement day t, $HFTR^{NA}_{t-k,1M(i)}$ and $HFLO^{NA}_{t-k,1M(i)}$ denote the dollar volume of HF trades and orders during the same 1-minute interval over the past k non-announcement days, where $k = 1, \ldots, 5$. The matching to the same 1-minute interval over the past non-announcement days also helps to adjust for potential intraday seasonality in HF trading activities.

Table 3 reports summary statistics of HF trades and orders and overall trades and orders for all three notes during both the pre-announcement period and the post-announcement period. The results in Panel A show that HF orders identified are around one-third of all orders for all three maturities. Both HF orders and all limit orders more than double following announcements. The magnitude of the increase in HF orders is larger than that of the overall market. The daily average ratio of post-announcement HFLO volume relative to their pre-announcement volume is significantly larger than that of all limit order volume. Panel B shows that the HF trades identified are around one-quarter of the overall trade volume for all three maturities. Similar to the case for HF orders, HF trades increase after announcements and the daily average ratio of HF trade volume during the post-announcement period relative to the pre-announcement period is significantly larger than that of the overall trade volume. Figure 2 shows the minute-by-minute volume of HFTR and HFLO for the 2-year note around announcements, contrasting with the same time on non-announcement days. The pattern for the 5- and 10-year notes is similar and thus not reported. The volume of both HFTR and HFLO spikes up following macroeconomic news releases and subsequently drops. Nonetheless, the volume of HFTR and HFLO on announcement days remains higher than on non-announcement days at the end of the post-announcement interval. Together, these findings suggest that HF activities actively respond to the arrival of public information and conform with the predictions of the theoretical literature that the HF participation rate increases with news arrival.

To study abnormal HF activities more closely, Panel C of Table 3 reports summary statistics of the abnormal volume of HF trades and orders and overall trades and orders for all three Treasury notes during both the pre- and post-announcement periods. The abnormal volume of HF trades and orders, as well as that of the overall sample, is negative in most cases. This indicates that HF orders and trades withdraw from the market before announcements, compared with the same time on non-announcement days. The abnormal volume of HF activities and that of the overall sample turns positive during the post-announcement interval. This indicates that both HF trades and orders, like their overall sample counterpart, are more active after information arrival compared with non-announcement days.

3 Empirical Analysis

3.1 Instruments for HF Activities

The main goal of the analysis is to investigate the effect of HF activities on liquidity and price efficiency around macroeconomic announcements. More specifically, we build upon Hendershott, Jones and Menkveld (2011) and formally test the relationship between our proposed measures of HF activities and market liquidity and price efficiency during the 15-minutes preceding the announcement times and the 15-minutes following the announcement times, respectively, as follows:

$$X_{it(j)} = \alpha_i + \gamma_{it(j)} + \beta HF_{it(j)} + \varphi' C_{it(j)} + \eta_{it(j)}, \tag{4}$$

where $X_{it(j)}$ denotes a measure of liquidity or price efficiency computed for the U.S. Treasury note i, in minute j during day t. $HF_{it(j)}$ denotes our measure of HF activities. α_i is a bond-specific fixed effect. $\gamma_{it(j)}$ is a minute-of-the-interval dummy variable. $C_{it(j)}$ is a set of variables controlling for market conditions. In this paper, we use the absolute change in mid-quote as a proxy for volatility and term spread as variables controlling for market conditions. To control for potential time trend and seasonalities, as evident in Figure 1 and Figure 2, the variables $X_{it(j)}$, $HF_{it(j)}$ and $C_{it(j)}$ are constructed as the difference between their value in minute j during the announcement day t and their average value computed during the same minute interval over the past five non-announcement days.

As emphasized in recent studies such as Hendershott, Jones and Menkveld (2011) and Boehmer, Fong and Wu (2012), HF activities and market liquidity are endogenously determined. A contemporaneous change in HF activities and market liquidity could be due to either HF activities reacting to changes in market liquidity or to HF activities causing changes in market liquidity. To examine the causal relationship between HF activities and market liquidity, we follow Boehmer, Fong and Wu (2012) and Brogaard, Hendershott and Riordan (2013) and use the introduction of a co-location facility on the BrokerTec platform by ICAP (labelled i-Cross) at the end of 2007 as an exogenous event. i-Cross hosts customers' equipment and network connectivity within two of Equinix's Internet Business Exchange centers [8]in the New York region, which enables a low latency data exchange between HF trading firms and the BrokerTec platform. In the official press release, it is explicitly indicated that the benefits of i-Cross include "High-speed, low-latency connection" and "faster time to market... for a range of fixed income products"(ICAP, November 7th, 2007). The introduction of i-Cross has provided HF trading firms with faster access to the BrokerTec platform and to react faster to changes in market conditions or the arrival of new information. Thus, i-Cross has had a significant impact on HF activities, but it is unlikely to be correlated with the idiosyn-

[8]According to the co-location service brochure of Equinix (available at http://www.equinix.com/platform-equinix/platform-advantages/ibx-data-centers/), International Business Exchange (IBX) data centers are built to have "direct access to the data distribution system to allow quickly deployable interconnections." and their infrastructure "minimizes interference problems and permits rapid provisioning of bandwidth from a large choice of participating providers."

cratic liquidity component, $\eta_{it(j)}$, in Equation (4). Table 4 shows the impact of the introduction of i-Cross on HF activities and variables controlling for market conditions. The introduction of i-Cross is associated with a significant increase in the abnormal volume of overall HF activities, HF orders (HFLO) and HF trades (HFTR). The result holds for all notes and for individual notes. The effect is larger for longer maturity 5- and 10-year notes. On the other hand, there is no consistent relationship between the introduction of i-Cross and variables controlling for market conditions.

In our empirical investigation, we adopt an instrumental variable approach, beginning with the estimation of the following first-stage regression:

$$HF_{it(j)} = \alpha_i + \gamma_{it(j)} + \beta Q_{it(j)} + \varphi^{'} C_{it(j)} + \varepsilon_{it(j)}, \tag{5}$$

where $HF_{it(j)}$ is the dependent variable capturing abnormal HF activities; $Q_{it(j)}$ is a dummy variable that equals 0 during the period between January 1, 2006 and November 7, 2007 and 1 after January 1, 2008; α_i is a bond-specific fixed effect; $\gamma_{it(j)}$ is a minute-of-the-interval dummy variable capturing potential seasonal patterns around announcement times,; and $C_{it(j)}$ includes volatility, term spread and absolute standardized surprise during the post-announcement period.

The estimates from Equation (5) are used in the second stage, which we estimate the following equation:

$$X_{it(j)} = \alpha_i + \gamma_{it(j)} + \beta \widehat{HF}_{it(j)} + \varphi^{'} C_{it(j)} + \eta_{it(j)}, \tag{6}$$

where $\widehat{HF}_{it(j)}$ is the predicted value from Equation (5), and $C_{it(j)}$ is a vector of control variables, including volatility, term spread and three lags of $X_{it(j)}$. The number of lags of dependent variables in the regression is based on the Akaike information criterion (AIC). We confirm that the estimation results remain qualitatively similar using five lags in Equation (6). In the post-announcement period, we also include an absolute standardized surprise and incorporate the interaction of HF variables with the absolute standardized surprise to analyze the role of public information shocks and whether the role of HF activities depends on them. $\gamma_{it(j)}$ is a minute-of-the-interval dummy variable capturing potential seasonal patterns of liquidity variables around announcement times, as shown in Figure 1. $X_{it(j)}$ is abnormal liquidity variables, i.e., bid-ask spread, depth at the best quotes and depth behind the best quotes. Abnormal liquidity variables are constructed similarly to those for HF trades and orders in Equation (2) and Equation (3). More specifically, we define abnormal bid-ask spread, abnormal depth at the best quotes and abnormal depth behind the best quotes as:

$$\begin{aligned} SPRD^{*}_{t,1M(i)} &= SPRD_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5} SPRD^{NA}_{t-k,1M(i)}, \\ DPTH^{BST*}_{t,1M(i)} &= DPTH^{BST}_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5} DPTH^{BST,NA}_{t-k,1M(i)}, \\ DPTH^{BHD*}_{t,1M(i)} &= DPTH^{BHD}_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5} DPTH^{BHD,NA}_{t-k,1M(i)}, \end{aligned} \tag{7}$$

In the second-stage regression for price efficiency, we use the log absolute autocorrelation of mid-quote, calculated from tick-by-tick returns based on mid-quote at each transaction over the five-minute interval as a proxy for price efficiency, as in Boehmer and Kelley (2010) and Boehmer, Fong and Wu (2012). More specifically, we estimate:

$$\log|AC_{t,5M(i+1)}| = \alpha_i + \gamma_{it,5M(i+1} + \beta\widehat{HF}_{it,5M(i+1)} + \varphi' C_{it,5M(i+1)} + \eta_{it,5M(i+1)}, \tag{8}$$

where $\log|AC_{t,5M(i+1)}|)$ is the log absolute autocorrelation of quotes mid-price calculated from tick-by-tick returns based on mid-quote at each transaction over five-minute intervals, $\widehat{HF}_{it(j)}$ is the predicted value from Equation (5) estimated over five-minute intervals. $C_{it(j)}$ is a vector of control variables, including term spread, volatility and, in the post-announcement interval, absolute news surprise and the interaction of HF variables with absolute standardized surprise.

3.2 The Impact of HF Activities on Market Liquidity and Price Efficiency

In this section, we examine the impact of HF trading activities on market liquidity and price efficiency. Table 5 reports the results on market liquidity. We look at the impact of overall HF activities in Model 1 and the impact of HF orders and HF trades separately in Model 2. HF activities tend to worsen liquidity both before and after announcements. During the pre-announcement period, HF activities on the whole significantly widen abnormal relative spreads ($\times$ 10,000) by 0.0002 basis points as shown in Model 1 in Panel A. Given an overall HF standard deviation of 927.61 for the 2-year note, a one-standard-deviation change in overall HF is associated with a 927.61*0.0002=0.18 basis points, which represents $0.18 \times 100/0.85 =$ a 22.1% increase in the relative spread for the 2-year note. Similar calculations show that a one-standard-deviation change in overall HF activities leads to 12% and 5% increases in the relative spreads for the 5- and 10-year notes, respectively. Disentangling the impact of HF orders and HF trades, the widening impact on abnormal relative spreads comes from abnormal HF trades. An abnormal increase in HFTR causes a significant drop in relative spreads. Abnormal HFLO, on the other hand, causes a significant narrowing of relative spreads.

HF activities also lead to deepening of depth at a less aggressive level during the pre-announcement period. We find that overall HF activities significantly increase depth behind the best quote (Model 1 in Panel C), while they have no significant impact on the best quotes (Model 1 in Panel B). A one-standard-deviation increase in overall HF activities is associated with 138.40, 95.97 and 72.37 million increases in depth behind the best quotes for the 2-, 5- and 10-year notes, respectively. This is equivalent to 4.4%, 11.5% and 8.5% increases in the behind best quotes for the 2-, 5- and 10-year notes. Further, the positive impact of HF activities on depth behind the best quotes comes from HF orders. An abnormal increase in HFLO is associated with a significantly positive impact on depth behind best quotes (Model 2 in Panel C), while an abnormal increase in HF trades significantly reduces depth behind the best quotes.

During the post-announcement period,we find that HF activities have a negative impact on depth, while they have no significant impact on bid-ask spreads. An increase in abnormal overall HF activities significantly reduces depth both at the best quotes (Model 1a in Panel B) and behind the best quotes (Model 1a in Panel C). A one-standard-deviation increase in overall HF activities is associated with drops of 58.53, 38.65, 30.91 million in depth at the best quotes, which is equivalent to drops of 11.50%, 47.86% and 41.52% in depth at the best quotes. Similarly, a one-standard-deviation increase in overall HF activities is associated with drops of 17.08%, 43.83% and 32.86%

in depth behind best quotes. Disentangling the impact of HF trades and orders, we find that the HFTR has a significantly negative impact on the depth at the best quotes (Model 2a of Panel B) while it has a significantly positive impact on depth behind best quotes (Model 2a of Panel C). These results suggest that HF trades potentially act as informed trades so that limit orders are placed at less aggressive levels to avoid being picked off. On the other hand, more HFLO significantly increases depth at the best quotes, while it reduces depth behind the best quotes.

We further study whether the impact of HF activities changes with the magnitude of public information shocks. The interaction of $|SUR_{k,t(j)}|$ with HF variables has no significant effect on bid-ask spread and depth at the best quotes. However, a larger $|SUR_{k,t(j)}|$ intensifies the impact of HF variables on depth behind the best quotes. The interaction term of HF variables with $|SUR_{k,t(j)}|$ is the same sign as those for HF variables. For example, a larger absolute announcement surprise enlarges the negative impact of abnormal overall HF activities on depth behind the best quotes with the coefficient of $HF \times |SUR|$ being negative and statistically significant at the 1 % level. The results suggest that overall HF activities causes a larger drop in behind best depth with a larger public information shock.

Table 6 reports the results on price efficiency. We find that overall HF activities improves price efficiency during both the pre- and post-announcement periods. The i-Cross instrument of overall HF activities is significantly negative (Model 1, Model 1a and Model 1b), implying that overall HF activities reduces the absolute autocorrelation of returns around announcements. Disentangling the impact of HF trades and orders, we find that the improvement in price efficiency comes from HF trades during both the pre- and post-announcement periods. The coefficients associated with HF trades are significantly negative in Model 2, Model 2a and Model 2b, while those associated with HF orders are either insignificant (Model 2) or significantly positive (Model 2a and Model 2b). Thus, while HF trades have a negative impact on market liquidity, they help to incorporate information into prices. However, the magnitude of public information shocks tends to counteract the impact of overall HF activities and HF trades on price efficiency. The coefficients of $HF \times |SUR|$ and $HFTR \times |SUR|$ are both significantly positive at the 1% level. The results suggest that a larger public information shock slows the process by which overall HF activities and HF trades incorporate information into prices.

4 Robustness and Extensions

This section checks the robustness and presents refinement of the results reported in the previous section. More specifically, we examine examine whether our main results depend on the importance of announcements. We also check whether using a shorter threshold than one second affects the pattern of HF trades and orders around announcements. Lastly, we analyze whether our results are robust to the unique workup process in the Treasury securities market

4.1 Impact of Important Announcements

We first analyze whether the impact of HF activities depends on the significance of announcements. The set of announcements included is based on the Bloomberg relevance index and is perceived to be important in the literature. We include seven announcements: CPI, Change in Nonfarm Payroll, Initial Unemployment Claims, Consumer Confidence Index, GDP Advance, ISM Non-manufacturing and Retail Sales.

Table 7 reports the results on liquidity variables using observations in the 15-minute interval around these announcements. We find that our results are robust to the significance of the announcement. The sign and significance of the coefficients are largely similar to the case of using all announcements. During the pre-announcement period for important announcements, overall HF activities significantly widens spreads, has no impact on depth at best quotes, deepens depth behind best quotes and improves price efficiency. The impact of HF activities seems to be larger for important announcements. In particular, the coefficient capturing the impact of abnormal overall HF activities on abnormal relative spread is almost three times that for the all-announcements case. During the post-announcement period, the results for liquidity variables are similar to the case for all announcements, except that overall HF activities actually widens spreads, as shown in Model 1b in Panel A. The positive impact on spreads comes from HF trades, in which the associated coefficient almost doubles that for the case using all announcements. Table 8 reports the impact of HF activities on price efficiency after important announcements. We find that abnormal overall HF activities does not have a statistically significant impact on absolute autocorrelation. HF trades continues to improve price efficiency during the post-announcement period, but its effect is cancelled out by that of HF orders.

4.2 Alternative timing classification

Kosinky (2013) reports that "human reaction times are in the order of 200 milliseconds." As a robustness check for our use of a 1-second threshold in classifying HF activities, we use 200 milliseconds as a threshold to see whether the pattern of HF activities remains robust around announcements. Table 9 reports the HF trades and limit orders under this alternative timing classification. We find that using 200 milliseconds as the threshold does not affect the pattern of HF activities around announcements. Although the volume of HF orders and trades drops automatically as a result of using a shorter threshold, the pattern of results remains similar to those in Table 3. The volume of all classes of HF orders and HF trades under the alternative classification scheme still increases during the post-announcement period. Furthermore, the average daily ratio of the volume of HF trades (orders) post-announcement to pre-announcement remains significantly higher than the overall sample. This finding holds for all three notes. Looking at abnormal volume, the results are similar to the case of using the one-second threshold. The abnormal volume of both HF trades and orders under the alternative classification scheme is mostly negative during the pre-announcement period, indicating a withdrawal of orders, and they are positive during the post-announcement period, indicating more active HF participation following macroeconomic news releases.

4.3 Price Efficiency and the Workup Process

A unique feature of the secondary Treasury market is the workup process. As detailed in Boni and Leach (2004), the workup process essentially gives traders who submit limit orders the right to expand their orders at the same price immediately after execution. Therefore, workups are periods in which prices are frozen but trades still take place. Since our identification of HFTR depends on changes in best quotes, a potential concern is that our measure of HF trading may potentially be biased toward finding that it improves price efficiency.

To address this concern, we exclude trades inside a workup in calculating the absolute log autocorrelation in the price-efficiency regression. This removes instances at which prices are frozen due to the workup process. The results shown in Table 10 indicate that our findings are robust to the workup process. During the pre-announcement period, the coefficient of overall abnormal HF activities remains significantly negative, which indicates that overall HF activities improves price efficiency. Both abnormal HFTR and HFLO significantly improve price efficiency, although the coefficient of HFTR is smaller in magnitude and less significant compared with the pre-announcement case in Table 6. During the post-announcement period, the results are similar to those in Table 6, both qualitatively and quantitatively. The overall abnormal HF activities significantly improves price efficiency. In addition, similar to the findings in Table 6, HF trades significantly improve price efficiency in both Model 2a and 2b, while HF orders reduce price efficiency.

5 Conclusion

This paper investigates the activity of HF trading in the U.S. Treasury market around macroeconomic news announcements. Using a comprehensive data set provided by BrokerTec, one of the leading interdealer electronic trading platforms in the secondary U.S. Treasury market, we identify HF trades and orders based on the speed of their placement, alteration or cancellation that is deemed beyond manual capacity. We examine how HF trades and orders take place around macroeconomic news announcements, whether HF trades and orders increase or deplete market liquidity, and the impact of HF activities in the price efficiency of the U.S. Treasury market.

Our results show that both HF trades and orders increase substantially following macroeconomic news announcements. The ratio of the volume of post-announcement HF trades (orders) relative to the volume of pre-announcement HF trades (orders) is significantly larger than that of the overall sample. HF trades and orders tend to have a negative impact on liquidity around public information arrival. During the pre-announcement period, HF activities significantly widen spreads. The positive impact on spreads comes from HF trades. During the post-announcement period, HF activities significantly reduce depth, both at the best quotes and behind the best quotes. The negative impact on depth at the best (behind the best) quotes comes from HF trades (HF orders). On the other hand, we find that overall HF activities tend to improve price efficiency, and the improvement comes from HF trades. An abnormal increase in HF trades significantly reduces the absolute autocorrelation of returns during both the pre- and post-announcement periods. The magnitude of the public information shocks, however, significantly offsets the improvement in price efficiency.

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Table 1
List of Macroeconomic News Announcements

This table reports the list of macroeconomic news announcements included in our analysis. *N* denotes the total number of announcements during our sample period from January 3, 2006 to December 29, 2011. *Time* denotes the time (eastern standard) of the announcement. *Day* denotes the weekday or day of the month for the announcement of each news item. σ denotes the standard deviation of announcement surprises. $\mathbf{N}_{|SUR|>2\sigma}$ denotes the number of announcements with an absolute surprise that is k times greater than its standard deviation. N.A. indicates not applicable.

Announcements	**N**	**Time**	**Day**	$\mathbf{N}_{\lvert SUR\rvert>\sigma}$	$\mathbf{N}_{\lvert SUR\rvert>2\sigma}$
Building Permits	72	8:30	18th workday of the month (around 24th/25th)	25	2
Business Inventories	72	10:00	Around the 15th of the month	17	3
Capacity Utilization	72	9:15	Around the 15th/16th of the month	17	4
Change in Nonfarm Payrolls	72	8:30	First Friday of the month	26	2
Construction Spending	72	10:00	Around the 1st/2nd of the month	21	7
Consumer Confidence Index	72	10:00	Around the 25th of the month	22	3
CPI	72	8:30	Around 16th of the month	20	3
Durable Goods Orders	68	8:30	Around the 26th of the month	17	4
Existing Home Sales	72	10:00	Around the 25th of the month	21	3
Factory Orders	72	10:00	Around the first business day of the month	22	4
Fed's Beige Book	48	14:00	Two weeks prior to each Federal Open Market Committee Meeting	N.A.	N.A.
FOMC Minutes	44	14:00	Approximately three weeks after the FOMC meeting	N.A.	N.A.
FOMC Rate Decision	24	12:30/14:15	Eight regularly scheduled meetings per year	0	0
GDP Advance	24	8:30	Around the 27th of Jan, April, July, Oct	7	2
GDP Final	24	8:30	Around the 28th of March, June, Sep, Dec	8	2
GDP Preliminary	24	8:30	Around the 29th of Feb, May, Aug, Nov	6	1
Housing Starts	72	8:30	2 or 3 weeks after the reporting month	19	3
Industrial Production	72	9:15	Around the 15th of the month	17	3
Initial Jobless Claims	313	8:30	Each Thursday	83	21
ISM Index	72	10:00	1st business day of the month	28	2
ISM Services	72	10:00	3rd business day of the month	20	3
Leading Index	72	10:00	Around the first few business days of the month	17	6
NY Empire State	72	8:30/15:00	15th/16th of the month	23	3
New Home Sales	72	10:00	17th workday of the month (around 25th/26th)	18	6
PPI	72	8:30	3rd week of each month	19	4
Personal Income	72	8:30	Around the 1st business day of the month	8	4
Personal Spending	72	8:30	Around the first or last business day of the month	28	6
Retail Sales	72	8:30	Around the 12th of the month	15	5
Trade Balance	72	8:30	Around the 20th of the month	26	3
Treasury Budget	70	14:00	About the third week of the month for the prior month	9	2
Unemployment Rate	72	8:30	First Friday of the month	28	5

Table 2

Summary Statistics of Liquidity Variables

The table reports the summary statistics of liquidity variables in the 15-minute interval preceding announcements (the pre-announcement period) and following announcements (the post-announcement period). Liquidity variables are averaged over 1-minute intervals. Liquidity variables include the relative bid-ask spread, average depth at best bid and ask ($ mil) and average depth behind the best bid and ask ($ mil) during the sample period from January 3, 2006 to December 29, 2011. We report the mean, median, standard deviation (STD) and the 10th and 90th percentile of the liquidity variables.

	Pre-announcement period					**Post-announcement period**				
	MEAN	MEDIAN	STD	10%	90%	MEAN	MEDIAN	STD	10%	90%
2-year note										
Relative Spread ($\times$ 10,000)	0.85	0.78	0.22	0.78	0.79	0.83	0.78	0.18	0.78	0.79
Depth at best bid and ask ($ mil)	427.18	335.00	350.01	65.00	936.00	504.72	432.00	361.93	103.00	1032.00
Depth behind best bid and ask ($ mil)	3144.70	2443.00	2518.48	605.00	7043.00	4041.07	3818.00	2560.39	1028.00	7817.00
5-year note										
Relative Spread ($\times$ 10,000)	1.01	0.78	0.47	0.77	1.57	0.94	0.78	0.33	0.77	1.56
Depth at best bid and ask ($ mil)	68.80	52.00	58.51	15.00	145.00	80.74	63.00	61.35	23.00	163.00
Depth behind best bid and ask ($ mil)	829.21	631.00	705.60	196.00	1668.00	1040.14	830.00	780.58	308.00	2035.00
10-year note										
Relative Spread ($\times$ 10,000)	1.93	1.57	0.88	1.53	3.13	1.82	1.57	0.60	1.52	3.10
Depth at best bid and ask ($ mil)	62.80	46.00	53.97	13.00	137.00	74.45	57.00	58.69	20.00	153.00
Depth behind best bid and ask ($ mil)	853.18	599.00	767.34	202.00	1999.00	1109.90	778.00	903.28	313.00	2644.00

Table 3
HF and Non-HF Trades and Limit Orders around News Announcements

This table reports the average volume of HF limit orders (Panel A), HF trades (Panel B), as well as abnormal volume in HF trades and limit orders (Panel C) over the 15-minute pre-announcement and 15-minute post-announcement periods. We also calculate the difference between the average daily ratio of the post-announcement period volume of HF orders (trades) relative to the pre-announcement volume and that of all (orders) trades. HFTR denotes HF trades that are identified as market buy (sell) orders placed within a second of a change in the best quotes on either side of the market. HFLO1 denotes limit orders cancelled or modified within one second of placement, regardless of market condition changes. HFLO2 denotes limit orders at the best quote modified within one second of a change in the best quote on either side of the market. HFLO3 denotes limit buy (sell) orders at the second-best quote modified within one second of a change in the best buy (sell) quote. Abnormal HF trades and orders are defined as in Equations (2) and (3) of the main text. A "***", "**", or "*" denotes significance at 1%, 5% or 10% levels, respectively

	2-year			5-year			10-year		
	Pre-ann.	**Post-ann.**	$\frac{HF^{post}}{HF^{pre}} - \frac{All^{post}}{All^{pre}}$	**Pre-ann.**	**Post-ann.**	$\frac{HF^{post}}{HF^{pre}} - \frac{All^{post}}{All^{pre}}$	**Pre-ann.**	**Post-ann.**	$\frac{HF^{post}}{HF^{pre}} - \frac{All^{post}}{All^{pre}}$
Panel A: Limit orders									
HFLO1	10425.35	25386.16		11979.39	27403.47		9063.69	22187.06	
HFLO2	127.69	231.96		105.34	171.61		85.86	130.47	
HFLO3	121.32	262.13		114.05	189.32		93.35	152.48	
All HFLO	10674.36	25880.24		12198.78	27764.40		9242.91	22470.02	
All limit orders	32283.24	78858.25	0.22***	32317.99	68229.92	0.48***	24753.13	54818.98	0.53***
Panel B: Market orders									
HFTR	241.93	501.64		276.64	557.07		232.28	470.39	
All market orders	1173.199	2533.406	0.63***	1067.613	2062.87	0.34***	905.753	1806.579	0.27***
Panel C: Abnormal limit and market orders									
abnormal HFLO	-993.73	13196.99		-1624.28	13009.23		-1452.99	10947.94	
abnormal limit orders	-4761.57	38124.95		-5643.52	27376.75		-4390.49	23263.71	
abnormal HFTR	12.34	253.03		-5.34	259.81		-5.06	219.47	
abnomral market orders	6.26	1236.50		-60.11	860.69		-53.92	770.14	

Table 4

Impact of i-Cross on Abnormal Overall HF, HFLO and HFTR

This table shows the impact of i-Cross on abnormal overall HF, HFLO, HFTR and other variables. Overall HF is defined as the sum of HFLO and HFTR volume. We regress each of the variables used in IV analysis on the i-Cross dummy, $Q_{it(j)}$,

$$M_{it(j)} = \alpha_i + \gamma_{it(j)} + \beta Q_{it(j)} + \varepsilon_{it(j)},$$

where $M_{it(j)}$ includes abnormal HFLO, abnormal HFTR, volatility and term spread; $Q_{it(j)}$ is a dummy variable that equals 0 during the period between January 1, 2006 and November 7, 2007 and 1 after January 1, 2008; α_i is a bond-specific fixed effect; and $\gamma_{it(j)}$ is a minute-of-the-interval dummy variable capturing seasonal patterns around announcements. A "***", "**" or "*" denotes significance at 1%, 5% or 10% levels, respectively

	Abnormal HF	**Abnormal HFLO**	**Abnormal HFTR**	**Volatility**	**Term Spread**
All	62.652***	62.402***	0.250***	0.000	0.000
2-year note	18.652***	18.605***	0.047*	-0.000***	0.001
5-year note	115.302***	114.897***	0.406***	0.001	0.002
10-year note	67.859***	67.677***	0.182*	0.000*	0.003

Table 5
HF Activities and Liquidity

This table reports the results of the second-stage regression in the IV analysis,

$$X_{it(j)} = \alpha_i + \gamma_{it(j)} + \beta\widehat{HF}_{it(j)} + \varphi' C_{it(j)} + \eta_{it(j)},$$

where $X_{it(j)}$ is liquidity variables, i.e.bid-ask spread, depth at best quotes and depth behind best quotes; $\widehat{HF}_{it(j)}$ is the predicted value from Equation (5); and $C_{it(j)}$ is a vector of control variables including term spread, volatility and absolute news surprise. Fixed effects, lag effects and time dummies are included but not shown for brevity. A "***", "**" or "*" denotes significance at the 1%, 5% or 10% levels, respectively, using heteroscedasticity and autocorrelation consistent errors. $Adj.R^2$ denotes the adjusted R^2.

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
Panel A: Bid-ask spread						
HF	0.0002***		-0.0000	-0.0000		
HF × |SUR|				-0.0000		
HFLO		-0.0004***			-0.0001*	-0.0001
HFLO × |SUR|						-0.0000
HFTR		0.0472***			0.0056*	0.0056*
HFTR × |SUR|						-0.0002
|SUR|			0.0048	0.0205	0.0043	0.0197
Term Spread	0.0488	0.1439	0.0870*	0.0859*	0.1009**	0.0996**
Volatility	0.1856**	0.1985***	-0.0322	-0.0247	-0.0301	-0.0235
AdjR^2	0.2000	0.2014	0.0177	0.0176	0.0177	0.0177
Panel B: Depth at Best Quote						
HF	0.0038		-0.0284***	-0.0289***		
HF × |SUR|				0.0006		
HFLO		0.1838***			0.0222**	0.0171
HFLO × |SUR|						0.0148
HFTR		-13.7429***			-3.7954***	-3.5211***
HFTR × |SUR|						-0.9365
|SUR|			-5.4899**	-6.0451*	-5.1294**	-6.8872*
Term Spread	-14.7841	-42.8808**	19.7701*	19.8298*	10.4344	9.4231
Volatility	12.2082	8.4561	0.7205	0.4627	-0.7057	-6.1761
AdjR^2	0.6463	0.6478	0.4152	0.4149	0.4154	0.4151

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
Panel C: Depth Behind Best Quote						
HF	0.1492***		-0.3350***	-0.2872***		
HF $\times$ $\lvert$SUR$\rvert$				-0.1172***		
HFLO		0.5669***			-0.8464***	-0.6710***
HFLO $\times$ $\lvert$SUR$\rvert$						-0.4809***
HFTR		-31.6159***			37.5941***	29.9662***
HFTR $\times$ $\lvert$SUR$\rvert$						23.8111***
$\lvert$SUR$\rvert$			-58.1093***	52.0439***	-61.7546***	80.0631***
Term Spread	4.0905	-60.9855	105.3344***	98.1415***	199.6547***	218.0802***
Volatility	35.5218	26.8384	-9.7682	43.4110	4.7190	191.1228***
AdjR^2	0.9364	0.9367	0.8473	0.8481	0.8485	0.8497

Panel D: P-Value of First-stage F test statistic		
	Pre-announcement	**Post-announcement**
HF	< 0.0001	< 0.0001
HFLO	< 0.0001	< 0.0001
HFTR	< 0.0001	< 0.0001

Table 6

HF Activities and Price Efficiency

This table reports the results of the second-stage regression in the IV analysis,

$$\log|AC_{t,5M(i+1)}| = \alpha_i + \gamma_{it,5M(i+1} + \beta\widehat{HF}_{it,5M(i+1)} + \varphi' C_{it,5M(i+1)} + \eta_{it,5M(i+1)},$$

where $\log|AC_{t,5M(i+1)}|$) is the log absolute autocorrelation of quotes mid-price calculated from tick-by-tick returns based on mid-quote at each transaction over the five-minute interval, $\widehat{HF}_{it(j)}$ is the predicted value from Equation (8) and $C_{it(j)}$ is a vector of control variables including term spread, volatility and absolute news surprise. Fixed effects, lag effects and time dummies are included but not shown for brevity. A "***", "**" or "*" denotes significance at the 1%, 5% or 10% levels, respectively, using heteroscedasticity and autocorrelation consistent errors. $Adj.R^2$ denotes the adjusted R^2.

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
HF	-0.0050***		-0.0010***	-0.0010***		
HF × |SUR|				0.0001***		
HFLO		-0.0012			0.0043***	0.0043***
HFLO × |SUR|						0.0001***
HFTR		-0.3529***			-0.3745***	-0.3745***
HFTR × |SUR|						0.0001***
|SUR|			0.0001***	0.0001***	0.0001***	0.0001***
Term Spread	0.1253	-0.1389	0.7906	0.7906	0.3630	0.3630
Volatility	-1.1214	-2.2221	0.3563	0.3563	-0.8597	-0.8597
Adj.R^2	0.0129	0.0144	0.0193	0.0191	0.0255	0.0251

Table 7
HF Activities and Liquidity for Important Announcements

This table reports the results of the second-stage regression in the IV analysis for important announcements. They include CPI, Change in Nonfarm Payroll, Initial Unemployment Claims, Consumer Confidence Index, GDP Advance, ISM Non-manufacturing and Retail Sales. Control variables, e.g., term spread, volatility, absolute news surprise, fixed effects, lag effects and time dummies are included but not shown for brevity. A "***", "**" or "*" denotes significance at the 1%, 5% or 10% levels, respectively, using heteroscedasticity and autocorrelation consistent errors. $Adj.R^2$ denotes the adjusted R^2.

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
Panel A: Bid-ask Spread						
HF	0.0006***		0.0000	0.0001**		
HF × |SUR|				-0.0000		
HFLO		-0.0003**			-0.0001	-0.0001
HFLO × |SUR|						-0.0001
HFTR		0.0710***			0.0111*	0.0104*
HFTR × |SUR|						0.0025
|SUR|			0.0228	0.0479*	0.0225	0.0533*
AdjR^2	0.3216	0.3238	0.0280	0.0281	0.0282	0.0282
Panel B: Depth at Best Quote						
HF	0.0059		-0.0151**	-0.0163**		
HF × |SUR|				0.0028		
HFLO		0.2303***			0.0444**	0.0301
HFLO × |SUR|						0.0317*
HFTR		-17.3185***			-4.3169***	-3.5479**
HFTR × |SUR|						-1.8097
|SUR|			-6.3678	-9.6167	-6.1847	-12.8801**
AdjR^2	0.6406	0.6432	0.4282	0.4282	0.4285	0.4286

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
Panel C: Depth behind Best Quote						
HF	0.1789***		-0.3281***	-0.2949***		
HF $\times$ $\lvert$SUR$\rvert$				-0.0816***		
HFLO		0.6306***			-0.8408***	-0.7289***
HFLO $\times$ $\lvert$SUR$\rvert$						-0.3074***
HFTR		-34.3288***			36.5238***	32.3008***
HFTR $\times$ $\lvert$SUR$\rvert$						13.9365***
$\lvert$SUR$\rvert$			-95.5830***	-0.9324	-97.5239***	25.6217
AdjR^2	0.9447	0.9449	0.8530	0.8539	0.8542	0.8554

Panel D: P-Value of First-stage F test statistic

	Pre-announcement	Post-announcement
HF	< 0.0371	< 0.0001
HFLO	< 0.0286	< 0.0001
HFTR	< 0.0001	< 0.0001

Table 8

HF Activities and Price Efficiency for Important Announcements

This table reports the results of the second-stage regression in the IV analysis for important announcements,

$$\log|AC_{t,5M(i+1)}| = \alpha_i + \gamma_{it,5M(i+1} + \beta\widehat{HF}_{it,5M(i+1)} + \varphi' C_{it,5M(i+1)} + \eta_{it,5M(i+1)},$$

where $\log|AC_{t,5M(i+1)}|)$ is the log absolute autocorrelation of quotes mid-price calculated from tick-by-tick returns based on mid-quote at each transaction over the five-minute interval, $\widehat{HF}_{it(j)}$ is the predicted value from Equation (8) and $C_{it(j)}$ is a vector of control variables including term spread, volatility and absolute news surprise. Fixed effects, lag effects and time dummies are included but not shown for brevity. A "***", "**" or "*" denote significance at the 1%, 5% or 10% levels, respectively, using heteroscedasticity and autocorrelation consistent errors. $Adj.R^2$ denotes the adjusted R^2.

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
HF	-0.0042***		0.0002	0.0002		
HF × |SUR|				0.0001***		
HFLO		-0.0019			0.0030**	0.0030**
HFLO × |SUR|						0.0001***
HFTR		-0.1984			-0.1885**	-0.1885**
HFTR × |SUR|						0.0001***
|SUR|			0.0001***	0.0001***	0.0001***	0.0001***
AdjR^2	0.0114	0.0117	0.0118	0.0113	0.0138	0.0129

Table 9

HF and Non-HF Trades and Limit Orders: Alternative Timing Classifications

This table reports the average volume of HF orders (Panel A), HF trades (Panel B), as well as abnormal volume in HF trades and limit orders (Panel C) using 200 milliseconds as the cutoff in classifying HF activities over the 15-minute pre- and post-announcement periods. We also calculate the difference between the average daily ratio of the post-announcement period volume of HF orders (trades) relative to the pre-announcement volume and that of all (orders) trades. HFTR denotes HF trades that are identified as market buy (sell) orders placed within 200ms of changes in the best quotes on either side of the market. HFLO1 denotes limit orders cancelled or modified within 200ms of placement, regardless of market condition changes. HFLO2 denotes limit orders at the best quote modified within 200ms of change in the best quotes on either side of the market. HFLO3 denotes limit buy (sell) orders at the second-best quotes modified within 200ms of change in the best buy (sell) quotes. Abnormal HF trades and orders are defined as in Equations (2) and (3) of the main text. A "***", "**", or "*" denotes significance at 1%, 5% or 10% levels, respectively

	2-year			5-year			10-year		
	Pre-ann.	**Post-ann.**	$\frac{HF^{post}}{HF^{pre}} - \frac{All^{post}}{All^{pre}}$	**Pre-ann.**	**Post-ann.**	$\frac{HF^{post}}{HF^{pre}} - \frac{All^{post}}{All^{pre}}$	**Pre-ann.**	**Post-ann.**	$\frac{HF^{post}}{HF^{pre}} - \frac{All^{post}}{All^{pre}}$
Panel A: Limit orders									
HFLO1	6291.47	14622.76		6547.90	14692.69		4899.76	11885.38	
HFLO2	120.95	225.75		100.35	168.99		82.48	128.63	
HFLO3	117.04	253.80		111.01	187.13		90.60	150.50	
All HFLO	6529.46	15102.32	0.47***	6759.26	15048.81	0.51***	5072.84	12164.52	0.58***
Panel B: Market orders									
HFTR	211.34	414.68	0.68***	231.79	438.57	0.27***	195.40	374.15	0.24***
Panel C: Abnormal orders									
abnormal HFLO	-517.32	7537.72		-799.97	7070.98		-791.47	5853.34	
abnormal HFTR	3.30	212.93		-8.03	198.08		-7.43	171.41	

Table 10

Price Efficiency and Work-up Process

This table reports the results of the second-stage regression in the IV analysis:

$$\log|AC_{t,5M(i+1)}| = \alpha_i + \gamma_{it,5M(i+1} + \beta\widehat{HF}_{it,5M(i+1)} + \varphi' C_{it,5M(i+1)} + \eta_{it,5M(i+1)},$$

where $\log|AC_{t,5M(i+1)}|)$ is the log absolute autocorrelation of mid-quote calculated from tick-by-tick returns based on mid-quote at each transaction, where the transaction is not involved in a workup process, over the five-minute interval; $\widehat{HF}_{it(j)}$ is the predicted value from Equation (8); and $C_{it(j)}$ is a vector of control variables including term spread, volatility and absolute news surprise. Fixed effects, lag effects and time dummies are included but not shown for brevity. A "***", "**" or "*" denote significance at the 1%, 5% or 10% levels, respectively, using heteroscedasticity and autocorrelation consistent errors. $Adj.R^2$ denotes the adjusted R^2.

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
HF	-0.0049***		-0.0014***	-0.0014***		
HF × |SUR|				0.0001***		
HFLO		-0.0049***			0.0036***	0.0036***
HFLO × |SUR|						0.0001***
HFTR		-0.012*			-0.3568***	-0.3568***
HFTR × |SUR|						0.0001***
|SUR|			0.0001***	0.0001***	0.0001***	0.0001***
Term Spread	0.4167	0.4119	0.4278	0.4278	0.0203	0.0203
Volatility	-0.0022	-0.0024	-0.0073	-0.0073	-0.0189	-0.0189
AdjR^2	0.0111	0.0109	0.0215	0.0213	0.0279	0.0275

FIGURE 1

Market Activities around News Announcements

This figure depicts market activities for the 2-year note in each 1-minute interval during the 15-minute pre- and 15-minute post-announcement periods. Variables include relative spread (× 10,000), depth at best bid and ask ($ mil) and depth behind the best bid and ask ($ mil) during the sample period from January 3, 2006 to December 29, 2011. For comparison, corresponding values of each variable at the same time on non-announcement days are also depicted.

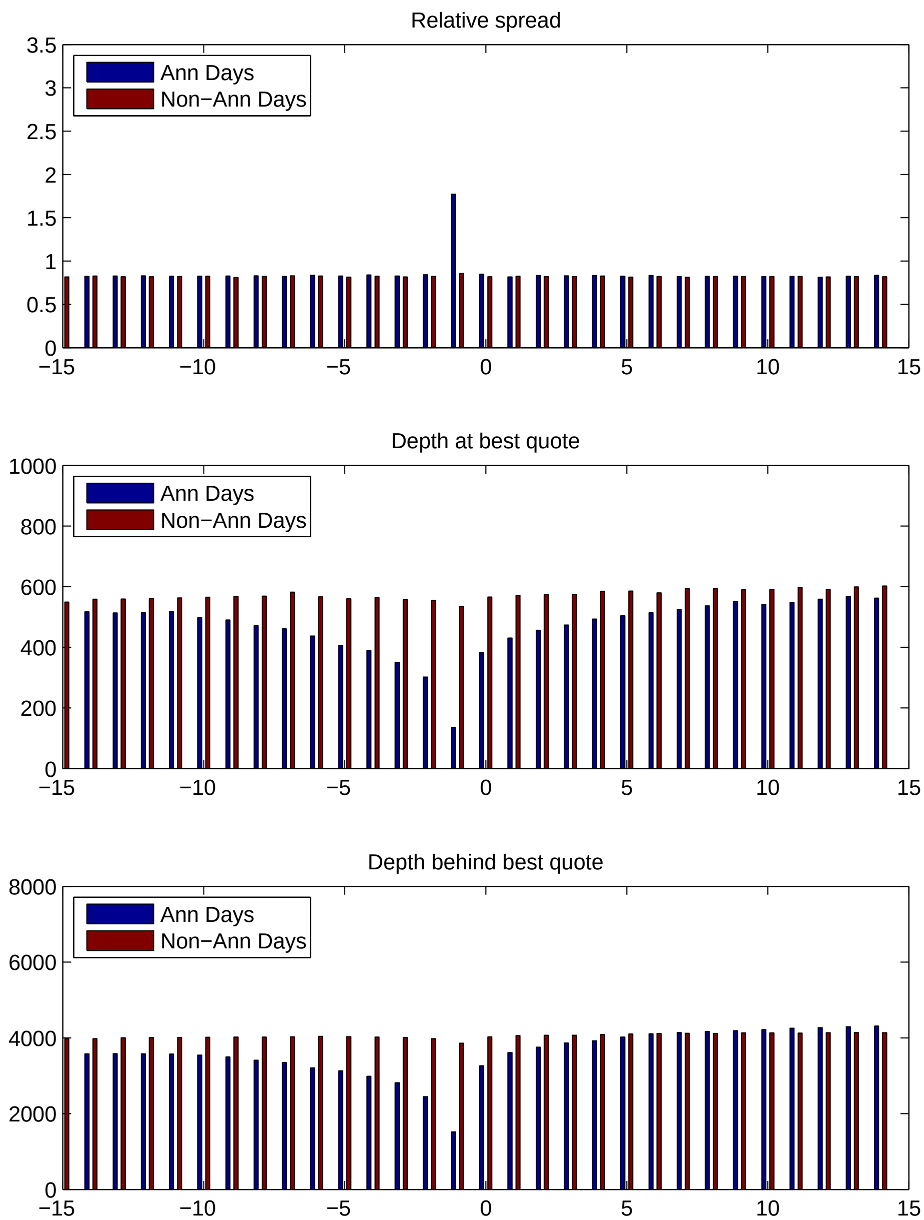

FIGURE 2

Proportion of Overall HF Activities

This figure plots the monthly ratio of overall HF volume, defined as the total monthly volume of HFLO and HFTR, scaled by the total monthly volume of limit orders and market orders, for the 2-, 5- and 10-year notes during the sample period from January 3, 2006 to December 29, 2011.

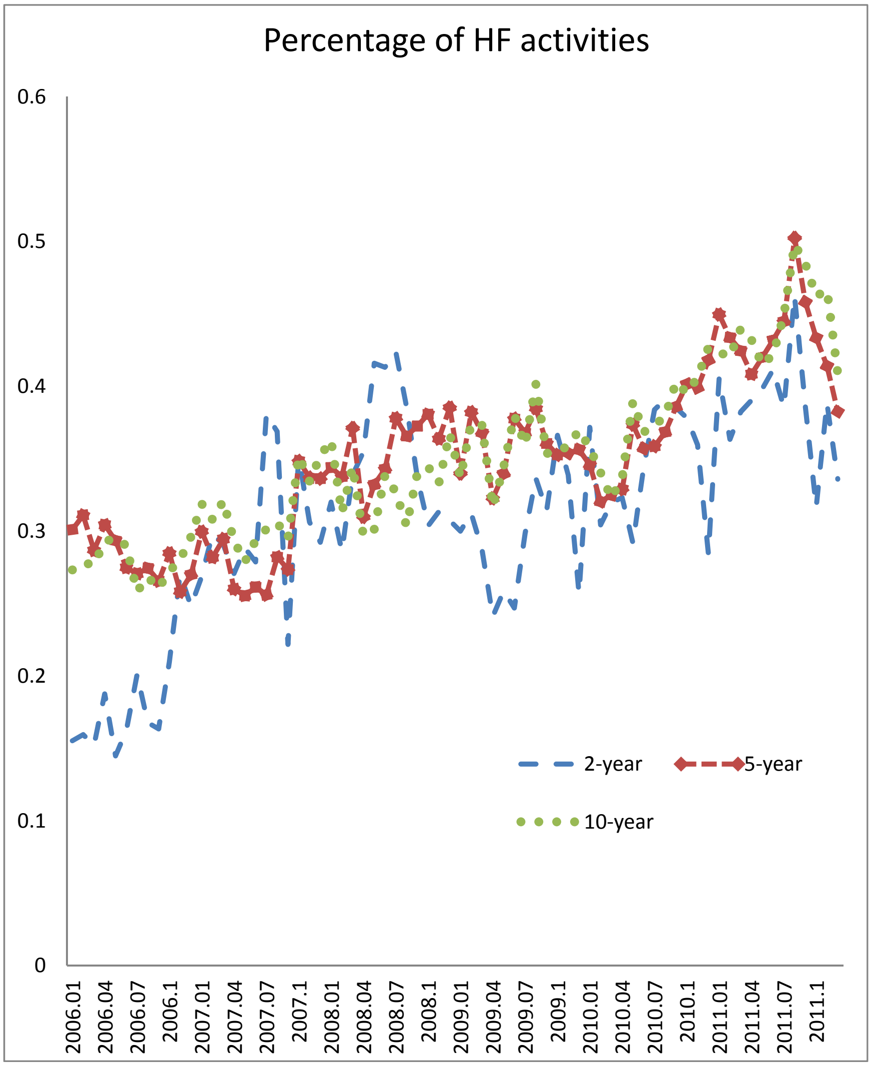

FIGURE 3

HF Activities Around Announcements

This figure depicts the volume HFTR and HFLO of the 2-year note during the 15-minute pre-announcement period and 15-minute post-announcement period. For comparison, corresponding values of HFTR and HFLO volume at the same minute interval on non-announcement days are also depicted.