High-frequency Trading around Macroeconomic News Announcements: Evidence from the US Treasury Market

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Abstract

This paper examines high-frequency (HF) trading in the US Treasury market around major macroeconomic news announcements. Using a comprehensive tick-by-tick data set, we identify HF trades and limit orders based on the speed of submission that is deemed beyond manual capacity. Our results show that HF trading increases market volatility during pre- and post-announcement periods. Amid information uncertainty, HF trading has an adverse effect on market liquidity and does not enhance the price efficiency of US Treasury securities. On the other hand, following information arrival, HF trading narrows bid-ask spreads and has a positive effect on price efficiency.

JEL classification: G10, G12, G14.

Keywords: High frequency trading; News announcement; US Treasury market; Market liquidity; Market volatility; Price efficiency.

1 Introduction

Automated trading and high-frequency (HF) trading, carried out by computer programs, has become prevalent in financial markets during the past decade[1]. As reported in the financial media, trading records have been routinely broken in recent years and millions of data messages per second are regularly sent to various trading venues.[2] This anecdotal evidence is coupled with the hard fact that trading latency in financial markets has decreased by about two orders of magnitude over the past decade (Moallemi and Saglam, 2011). As shown in the existing literature (e.g., Clark, 2011; Hasbrouck, 2012), trading and quoting activities regularly take place within a fraction of a second. Despite the prevalence of HF activities, there are serious concerns about the effect of HF trading on the overall quality of financial markets. In fact, the effect of HF trades and orders on market liquidity, volatility, and price efficiency has been one of the most contentious issues in recent literature (see, Jones, 2013 and the references therein).

The main advantage of HF trading is that computers, with their capacity to handle large amounts of information, are well positioned to quickly execute multiple actions in response to information. Thus, one ideal setting to assess the effect of HF trading on the overall quality of financial markets is a marketplace where fundamental news announcements are pre-scheduled. Under such a setting, pre- and post-announcement periods represent very different informational environments. Pre-announcement periods are charac-

[1]As noted by Hendershott and Riordan (2009), Brogaard (2010), and Chlistalla (2011), among others, HF trading is a subset of market activities carried out by computers known as algorithmic trading. This study focuses on trading activities that are carried out by machines at a very high speed and we refer to these activities as HF trading throughout the paper.

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

terized by information uncertainty, whereas post-announcement periods are characterized by uncertainty resolution.

In this study, we focus on HF trading activities in the US Treasury market around major macroeconomic news announcements. The US Treasury secondary market is one of the largest financial markets, with daily trading volume nearly five times that of the US equity market. It has a unique market microstructure since it is characterized by multiple dealers who operate over-the-counter (Fleming and Mizrach, 2009) and trading takes place virtually around the clock. In addition this market has experienced a dramatic increase in HF trading during the past decade.[3] More importantly, macroeconomic news announcements, the main drivers of Treasury security prices, are pre-scheduled and routinely monitored by market participants.[4]. In light of these important features, we explore in detail HF trading during pre-announcement periods and how it responds to information arrival during post-announcement periods.

The data used in our study are obtained from BrokerTec, a major trading platform for on-the-run secondary US Treasury securities. It contains tick-by-tick observations of transactions and limit order submissions, alternations, and cancelations for the two-, five-, and ten-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

[3] Some recent studies estimate that more than 50% of orders originate from algorithms (Safarik, 2005; Mizrach and Neely, 2006).

[4] A vast literature examines the effect of macroeconomic news announcements in the US Treasury markets. Fleming and Remolona (1997) and Andersen, Bollerslev, Diebold, and Vega (2003, 2007) find that the largest price changes are mostly associated with macroeconomic news announcements in the Treasury spot and futures markets. Fleming and Remolona (1999), Balduzzi, Elton, and Green (2001), Green (2004), and Hoerdahl, Remolona, and Valente (2013) point out that the price discovery process of bond prices mainly occurs around major macroeconomic news announcements and the same announcements are responsible for changes in risk premiums across different maturities.

trades and limit orders based on the speed of order placement or subsequent alterations of the orders. The procedure is similar in spirit to the method proposed by Hasbrouck and Saar (2011) in identifying low-latency orders. Specifically, using information on the time of order submission in reaction to changes in market conditions and its subsequent alteration, such as cancelation or execution, we classify HF trades and orders as those that are placed at a speed deemed beyond manual capacity.

We examine two major issues. First, we explore whether HF trades and orders around these important news announcements improve or reduce market liquidity and whether they increase or decrease bond return volatility. Second, we investigate the informativeness of HF trades and orders relative to their non-HF counterparts, as well as their role in enhancing or hindering price efficiency upon public information arrival. Our key finding is that the effect of HF trading on overall market quality largely hinges on the informational environment. Since information uncertainty resolves after news arrival, HF trading has a generally positive effect on market liquidity and bond price efficiency. In contrast, prior to news announcements, amid information uncertainty, HF trading significantly reduces market liquidity, increases market volatility, and has no effect in enhancing bond price efficiency.

More specifically, with regard to the impact of HF activities on liquidity, during pre-announcement periods, HF trading has a significantly negative effect on market liquidity. In fact, HF trades significantly widens bid–ask spread and reduces depth at the best quote. Not only do HF limit orders narrow the bid–ask spread but also they significantly reduce depth at the best quote. During post-announcement periods, the effect of HF activities appears to be beneficial to the market. Both HF trades and orders significantly narrow the bid–ask spread, but they also both significantly reduce depth at the best quote. In particular, HF limit orders appear to compete for best position in the limit order book. As a result, they lead to a shift of existing orders to less aggressive positions. Similar to the findings of Hendershott, Jones, and Menkveld (2011), the effect of HF trading on market liquidity is beneficial to relatively small trades.

We also find compelling evidence that HF trades and orders impact positively on subsequent bond return volatility. In particular, HF orders significantly increase subsequent volatility during the pre-announcement period.

Our results show that the informativeness of HF activities and their impact on price efficiency also hinge on the informational environment. In fact, we find that HF trades are more informative than non-HF trades and improve price efficiency only during post-announcement periods. During pre-announcement periods, HF activities exhibit no significant effect on price efficiency.

Our study joins a stream of recent contributions that investigate the impact of HF trading on various financial markets (see, e.g., Hendershott, Jones, and Menkveld, 2011; Hasbrouck and Saar, 2010; Brogaard, Hendershott, and Riordan, 2013; Boehmer, Fong, and Wu, 2012; and Scholtus and van Dijk, 2012, Scholtus, van Dijk and Frinis, 2012 for equity markets; Chaboud, Chiquoine, Hjalmarsson, and Vega, 2013, for foreign exchange markets). Our empirical analysis extends the current literature by focusing on different informational environments, as emphasized by the recent theoretical literature on HF trading. In fact, with regard to information uncertainty during pre-announcement periods, Martinez and Rosu (2013) model ambiguity-averse HF traders and show that they generate more volatility. Similarly, Jovanovic and Menkveld (2011) show that HF traders trade more upon information arrival. However, the speed advantage of HF traders potentially generates adverse selection (Biais, Foucault, and Moinas, 2011) and increases the price impact of trade (Foucault, Hombert, and Rosu, 2012). Jarrow and Protter (2012) also show that HF traders, acting on common signals, give rise to greater volatility. Our study provides new evidence to shed further light on these issues as we document that the impact of HF activities on market liquidity and volatility as well as the informativeness of HF trades and orders are different in various informational environments.[5] [6] [7]

The reminder of the paper is structured as follows: Section 2 introduces the data set employed in the empirical analysis and describes in detail the frameowork used to identify HF trades and orders. Section 3 discusses the empirical results and Section 4 concludes.

[5]Most of the empirical literature characterizes the impact of HF activities on market liquidity and price efficiency in normal times. The evidence show that the impact of HF activities differs among different dimensions of liquidity. In general, HF activities are associated with lower spreads (e.g., Hendershott, Jones, and Menkveld, 2011, and Menkveld, 2013, who use NYSE data and chi-X data, respectively). Hasbrouck and Saar (2010) find that HF trading is associated with deeper overall depth, while Hendershott, Jones, and Menkveld (2011) find that quoted depth declines with autoquotes. The findings on volatility are also mixed. Hasbrouck and Saar (2010) find a negative relation between low latency trading using Nasdaq data and volatility, while Boehmer, Fong, and Wu (2012) find that algorithmic trading increases volatility across 39 exchanges.

[6]The literature generally finds that HF activities improve price efficiency. Chaboud, Chiquoine, Hjalmarsson, and Vega (2013) find that HF activities reduce triangular arbitrage opportunities. Brogaard, Hendershott, and Riordan (2013) find that HF trades are informative.

[7]A paper closely related to ours is Scholtus, van Dijk and Frinis (2012) that explores the role of HF trading around macroeconomic announcements in the US equity market. However, this contribution differs from ours in several important respects. First, Scholtus, van Dijk and Frinis (2012) focus on the US equity market, which is characterized by a different institutional and trading structure than the US Treasury secondary market. Second, they investigate the role of speed on event-based trading profitability while we document the role of HF trading on various aspect of market quality in different informational environments.

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. We select 31 pre-scheduled announcements to ensure that all important news items are included in our analysis. 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, Bollerslev, Diebold, and Vega (2003, 2007), and Pasquariello and Vega (2007), we compute the standardized announcement surprise for each news item as follows:

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

where $A_{k,t}$ is the actual value of announcement k on day t, $E_{k,t}$ is the median forecast of announcement k on day t, and σ_k is the time-series standard deviation of $A_{k,t} - E_{k,t}, t = 1, 2, \cdots, T$. Our study uses the standardized announcement surprise as a measure of unexpected public information shock.[8]

The data on US Treasury securities used in our study were obtained from BrokerTec, an interdealer electronic communication network (ECN) platform of the US Treasury secondary market, owned by the largest interdealer brokerage firm, ICAP PLC. Prior to 1999, the majority of the interdealer trading of US Treasuries occurred through interdealer brokers. Since then, two major ECNs emerged: eSpeed and BrokerTec. The trading of on-the-run US Treasury securities has mostly, if not completely, migrated to electronic platforms.[9]

[8]As shown by Balduzzi, Elton, and Green (2001), professional forecasts based on surveys are neither biased nor stale.

[9]For an excellent review of the transition to ECN in the secondary US Treasury market, see Mizrach and

According to Barclay, Hendershott, and Kotz (2006), the electronic market accounts for 75.2%, 83.5%, and 84.5% of the trading of two-, five-, and ten-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 were taking place on electronic platforms. BrokerTec is more active in the trading of two-, three-, five-, and ten-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 for on-the-run two-, five-, and ten-year US Treasury notes. They include the time stamps of transactions and limit order submissions, as well as subsequent alterations, the quantity entered and/or canceled, the side of the market, 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 2, 2004 to June 30, 2007.

In our empirical analysis, 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 bond maturities, we compute the average quoted bid–ask spread (in ticks) and the average depth of the limit order book, both at the best quotes and behind the best quotes (in millions of US dollars) at the end of each one-minute interval during both pre- and post-announcement periods. We also compute the average trading volume (in millions of US dollars) and the average return volatility as the total dollar value of all trades and the sum of the absolute value of the one-minute log return based on the mid-point of the bid and ask price, respectively.

Table 2 reports summary statistics of market activities around news announcements.

Neely (2005).

During pre-announcement periods, the two-year note is, on average, the most liquid security, followed by the five- and ten-year notes. The two-year note has the smallest bid–ask spread, the largest depth of the order book (both at and behind the best quotes), and the highest trading volume. The two-year note exhibits the lowest return volatility, whereas the ten-year note exhibits the highest return volatility. The higher volatility of the ten-year note is partly due to the fact that its tick size is twice that of the two- and five-year notes. As expected, compared to pre-announcement periods, all three notes have lower spreads, more depth, larger trading volumes, and higher return volatility during post-announcement periods. These results are consistent with findings on news announcement effects in the US Treasury market in other studies (e.g., Fleming and Remolona 1997, 1999; Fleming and Piazzesi, 2006; Mizrach and Neely, 2008).

Figure 1 plots the patterns of market activities around news announcements for the two-year note. The patterns for other maturities are similar and are thus not reported, for brevity. For purposes of comparison, market activities at the same calendar time on non-announcement days are also plotted. Overall, trading volume and return volatility are higher on announcement days than on non-announcement days. However, both depth at the best quotes and overall depth are lower on announcement days than on non-announcement days. On announcement days, the bid–ask spread starts to increase and peaks right before the announcement time. Trading volume spikes at announcement time. Both depth at the best quotes and overall depth start to drop substantially before announcement time. The drop is more pronounced for depth at the best quotes. This evidence suggests that dealers withdraw their orders to avoid being picked off right before the anticipated information arrival. This finding is consistent with evidence documented in, for example, Fleming and Remolona (1999) and Jiang, Lo, and Verdelhan (2011). As public information is disclosed, the spread quickly reverts to pre-announcement levels. Trading volume gradually declines but remains high during the following 15 minutes. Return volatility exhibits similar patterns. Both depth at the best quotes and overall depth increase gradually after the new announcement and are back almost to pre-announcement levels at the end of the post-announcement window.

2.2 HF trades and orders: Identification and summary statistics

The BrokerTec data include reference numbers that provide information on the timing of order submissions and their subsequent execution, alteration, or cancelation. Using this piece of information, we identify HF trades and orders based on reaction times to changes in market conditions. We classify trades and orders as HF trades and orders if they are placed at a speed deemed beyond manual capacity. The procedure is similar in spirit to that proposed by Hasbrouck and Saar (2011) in identifying low-latency orders. Specifically, the following criterion is used to identify HF trades (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 limit orders (HFLO) in three different categories:

- Limit orders (buy or sell) that are canceled or modified within one second of their placement, regardless of market condition changes (HFLO1).

- Limit orders (buy or sell) at the best quote that are modified within one second of a change in the best quote on either side of the market (highest bid or lowest ask) (HFLO2).

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

We exclude those orders deleted by the central system, orders deleted by proxy, stop orders, and passive orders that are automatically converted by the system to aggressive orders due to a locked market.[10] The above procedure is specifically designed to infer HF trades and orders on the basis of the speed at which they are submitted, executed, or altered. Nevertheless, we recognize that non-HF orders can be mistakenly identified as HF orders if the former 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 labeled incorrectly as HF trades and orders and vice versa. We note that more than 90% of HF orders identified are from the first group (HFLO1), which are orders canceled or modified within less than one second of their placement, regardless of market condition changes. These orders are unlikely to have been placed manually by dealers. As noted in other studies (Scholtus and van Dijk, 2012), speed is the most important advantage of HF trading.[11]

[10]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 two-, five-, and ten-year notes, respectively.

[11]As a robustness check, we also use a three-second cutoff to classify non-HF trades and orders and the results are qualitatively similar to the ones discussed in the main text.

Table 3 reports summary statistics of HF and non-HF trades and orders for all three maturities during both pre- and post-announcement periods. The results in Panel A show that the HF trades are a fraction of non-HF trades in dollar volume. For the two-year note, the average volumes of HF trades and non-HF trades over pre-announcement periods are, respectively, \$203 million and \$802 million. As expected, trading activity picks up substantially following news announcements. For the two-year note, the average volumes of HF trades and non-HF trades over post-announcement periods are, respectively, \$0.5 billion and \$2 billion. These patterns are also observed for other maturities.

The results in Panel B of Table 3 show that for the two-year note, the average volumes of HF and non-HF limit orders over pre-announcement periods are, respectively, \$6 billion and \$17 billion. The average volumes of HF orders and non-HF orders over post-announcement periods are, respectively, \$19 billion and \$53 billion. Again, similar patterns are recorded for the other two maturities. The results also show that, among the three different categories of HF orders identified in our study, limit orders that are canceled or modified within one second of their placement, HFLO1, account for the majority. This finding further illustrates the advantage of HF trading in quickly canceling or modifying orders when deemed necessary.

A potential time trend therefore exists in most of the trading activity variables since HF trading activities have increased substantially and steadily over the past decades. For example, over our sample period the proportion of HF orders and trades increased from 12% in the first quarter of 2004 to 27% in the second quarter of 2007. In our analysis, we construct measures of abnormal HF trading activities around macroeconomic news announcements. As Bamber (1987) and Ajinkya and Jain (1989), we compute the abnormal volume of HF trades and orders 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 one-minute interval over the past five no-announcement days:

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

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

where $HFTR_{t,1M(i)}$ and $HFLO_{t,1M(i)}$ denote the dollar volume of HF trades and orders within the $i-$th one-minute interval on announcement day t, respectively, and $HFTR^{NA}_{t-k,1M(i)}$ and $HFLO^{NA}_{t-k,1M(i)}$ denote the dollar volume of HF trades and orders during the same one-minute interval over the past k no-announcement days, respectively, with $k = 1, \ldots, 5$. Matching to the same one-minute interval over the past no-announcement days also helps adjusting for potential intraday seasonality in HF trading activities. Abnormal non-HF trades ($NHFTR^{*}_{t,1M(i)}$) and orders ($NHFLO^{*}_{t,1M(i)}$) are similarly defined.

Panel C of Table 3 reports summary statistics of abnormal HF and non-HF trades and orders for all three maturities during both pre- and post-announcement periods. We observe similar patterns for the differences between the abnormal volumes of HF and non-HF trades and between pre- and post-announcement periods exhibit similar pattern of those recorded in Panel A. Interestingly, the abnormal volumes of HF and non-HF orders are often negative during pre-announcement periods.

Table 4 reports the average sizes of HF trades and orders in comparison to those of non-HF trades and orders in Panel A and the positions of HF orders in the limit order book in comparison to those of non-HF orders in Panel B. The results in Panel A show that the average sizes of HF trades are generally smaller than those of non-HF trades. The pattern is consistent across different maturities and during both pre- and post-announcement periods. Nevertheless, the average sizes of HF orders are generally larger than those of non-HF orders. In particular, among all three categories of HF limit orders identified in our study, HFLO2 are the largest.

The results in Panel B of Table 4 show that when the three most aggressive positions (better than the best quote, at the best quote, and one tick behind the best quote) are combined, HF orders are, overall, more aggressive than non-HF orders. For all three maturities and during both the pre- and post-announcement periods, the percentage of the three most aggressive positions combined for HF orders is consistently higher than for non-HF orders. In particular, a higher percentage of HF orders is placed ahead of the best quote than non-HF orders. Somehow, the percentage of HF orders placed at the best quote is slightly lower than that of non-HF orders.

3 Empirical analysis

In this section we explore the following issues: i) the effect of HF trades and orders on subsequent market liquidity and volatility, ii) the informativeness of HF trades and orders relative to non-HF trades and orders, as well as iii) the effect of HF trades and orders on the price efficiency of US Treasury securities.

3.1 Impact of HF trading on market liquidity and volatility

The first issue we examine relates to the impact of HF trading activities on subsequent market liquidity and volatility. In particular, we examine how HF trades and orders are related to subsequent unexpected changes in market liquidity and volatility. We note that while tick-by-tick data are available in our data set, we are cautious about using those data because of the concerns of potential market microstructure effects. To mitigate these effects, we perform our empirical analysis based on data aggregated over one-minute intervals, in line with other empirical studies (e.g., Fleming and Remolona, 1999; Balduzzi, Elton, and Green, 2001). We use bid–ask spread, depth at the best quotes, and depth behind the best quotes as three proxies for liquidity. We recognize that the US Treasury market has evolved over time, with a steady improvement in market liquidity, as measured by all three proxies. We therefore construct measures of abnormal market liquidity around macroeconomic news announcements to adjust for potential time trends as follows:

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

where $SPRD_{t,1M(i)}$, $DPTH^{BST}_{t,1M(i)}$, and $DPTH^{BHD}_{t,1M(i)}$ denote, respectively, the average bid–ask spread, average depth at the best quotes, and average depth behind the best quotes at the end of the $i-$th one-minute interval on announcement day t and $SPRD^{NA}_{t-k,1,M(i)}$, $DPTH^{BST,NA}_{t-k,1M(i)}$, and $DPTH^{BHD,NA}_{t-k,1M(i)}$ denote, respectively, the average bid–ask spread at the end of the $i-$th one-minute interval over the past k no-announcement days, where $k = 1, \ldots, 5$. The approach is similar to the construction of abnormal HF trades and orders in Section 2.2. Similar liquidity variables are also used by Fleming and Piazzesi (2006), Mizrach and Neely (2008), and Fleming and Mizrach (2009).

Return volatility is measured by the absolute value of log returns based on the mid-quotes in each one-minute interval, where mid-quotes are used to mitigate the effect of bid–ask bounces. Similarly, abnormal return volatility is computed as

$$VLTY^{*}_{t,1M(i)} = VLTY_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5} VLTY^{NA}_{t-k,1M(i)},$$

where $VLTY_{t,1M(i)}$ denotes the return volatility of the $i-$th one-minute interval on announcement day t and $VLTY^{NA}_{t-k,1M(i)}$ denotes the return volatility of the $i-$th one-minute interval over the past k no-announcement days, where $k = 1, \ldots, 5$.

In addition, we recognize that both market liquidity and volatility tend to be highly persistent over time. As such, for each bond maturity we estimate the following autoregressive models:

$$LIQ^{*}_{t,1M(t+1)} = a + \sum_{j=0}^{3} LIQ^{*}_{t,1M(t-j)} + U^{LIQ^{*}}_{t,1M(t+1)}, \tag{2}$$

$$VLTY^{*}_{t,1M(t+1)} = a + \sum_{j=0}^{3} VLTY^{*}_{t,1M(t-j)} + U^{VLTY^{*}}_{t,1M(t+1)}, \tag{3}$$

where $LIQ^{*}_{t,1M(t+1)}$ denotes one of the three measures of market liquidity defined above (i.e., $SPRD^{*}_{t,1M(i)}$, $DPTH^{BST*}_{t,1M(i)}$, and $DPTH^{ALL*}_{t,1M(i)}$) and $VLTY^{*}_{t,1M(i)}$ denotes the measure of bond return volatility as defined above.[12] In the above regressions, the residuals $U^{LIQ^{*}}_{t,1M(t+1)}$ and $U^{VLTY^{*}}_{t,1M(t+1)}$ denote unexpected changes in market liquidity and volatility, respectively.

[12]The lag of the above autoregressions is determined based on the Akaike Information Criterion (AIC). We confirm that the estimation results remain qualitatively similar by using five lags in the autoregressive equation.

To understand how trades and limit orders impact subsequent market liquidity and volatility, we first estimate the following models:

$$\begin{aligned} U^{LIQ^*}_{t,1M(i+1)} &= (\alpha_{2yr}D_{2yr} + \alpha_{5yr}D_{5yr} + \alpha_{10yr}D_{10yr}) \\ &\quad + \gamma TR^*_{t,1M(i)} + \varphi LO^*_{t,1M(i)} + \delta\left|SUR_{k,t}\right| + \epsilon_{t,1M(i+1)}, \end{aligned} \tag{4}$$

$$\begin{aligned} U^{VLTY^*}_{t,1M(i+1)} &= (\alpha_{2yr}D_{2yr} + \alpha_{5yr}D_{5yr} + \alpha_{10yr}D_{10yr}) \\ &\quad + \gamma TR^*_{t,1M(i)} + \varphi LO^*_{t,1M(i)} + \delta\left|SUR_{k,t}\right| + \epsilon_{t,1M(i+1)}, \end{aligned} \tag{5}$$

where $TR^*_{t,1M(i)}$ and $LO^*_{t,1M(i)}$ denote abnormal overall trades and limit orders at $i-$th one-minute interval of day t, respectively, and D_{2yr}, D_{5yr}, and D_{10yr} are maturity dummies for the two-, five-, and ten-year bonds, respectively. We pool the observations for all three maturities in our estimation to improve the power of statistical inference.

In order to further disentangle the effects of HF trades and orders from those of non-HF trades and orders on subsequent market liquidity and volatility, we then estimate the following models:

$$\begin{aligned} U^{LIQ^*}_{t,1M(i+1)} &= (\alpha_{2yr}D_{2yr} + \alpha_{5yr}D_{5yr} + \alpha_{10yr}D_{10yr}) \\ &\quad + \gamma_0 HFTR^*_{t,1M(i)} + \varphi_1 HFLO^*_{t,1M(i)} + \gamma_1 NHFTR^*_{t,1M(i)} + \varphi_0 NHFLO^*_{t,1M(i)} \\ &\quad + \delta\left|SUR_{k,t}\right| + \epsilon_{t,1M(i+1)}, \end{aligned} \tag{6}$$

$$\begin{aligned} U^{VLTY^*}_{t,1M(i+1)} &= (\alpha_{2yr}D_{2yr} + \alpha_{5yr}D_{5yr} + \alpha_{10yr}D_{10yr}) \\ &\quad + \gamma_0 HFTR^*_{t,1M(i)} + \varphi_0 HFLO^*_{t,1M(i)} + \gamma_1 NHFTR^*_{t,1M(i)} + \varphi_1 NHFLO^*_{t,1M(i)} \\ &\quad + \delta\left|SUR_{k,t}\right| + \epsilon_{t,1M(i+1)}, \end{aligned} \tag{7}$$

where $HFTR^*_{t,1M(i)}(NHFTR^*_{t,1M(i)})$ and $HFLO^*_{t,1M(i)}(NHFLO^*_{t,1M(i)})$ denote abnormal HF trades and limit orders (non-HF trades and limit orders) at the $i-$th one-minute interval of day t and D_{2yr}, D_{5yr}, and D_{10yr} are maturity dummies.

The above models are estimated separately during pre- and post-announcement periods. By definition, during the pre-announcement period, the announcement surprise is set at zero, that is $|SUR_{k,t}| = 0$.

Table 5 reports the estimation results of Eq. (6) under Models 1 and 2 for three proxies for liquidity shocks. We first discuss the impact of overall trades and orders and then the respective effects of HF versus non-HF trades and orders. Under normal market conditions, trades, as they consume liquidity, are expected to have a negative effect on market liquidity, whereas limit orders, as they provide liquidity, are expected to have a positive effect on market liquidity. Hence, we expect trades to widen the bid–ask spread and reduce the depth of the order book, whereas limit orders potentially narrow the bid–ask spread and increase the depth of the order book.

The results under Model 1 in Table 5 show that the empirical results of the effect of overall trades and orders on market liquidity are generally consistent with expectations. Specifically, overall trades are positively correlated with subsequent bid–ask spreads and negatively correlated with both subsequent depth at the best quote and depth behind the best quote. Also consistent with expectations, overall limit orders are negatively correlated with subsequent bid–ask spreads and positively correlated with both subsequent depth at the best quote and depth behind the best quote. The only inconsistent signs are the ones on the effect of trades on depth behind the best quote during the pre-announcement period and the effect of limit orders on depth at the best quote during the post-announcement period. Nevertheless, in both cases the coefficient estimates are statistically insignificant.

After disentangling the effects of HF trades and orders from those of non-HF trades and orders, we observe different patterns. In fact, the results under Model 2 in Table 5 show that the effects of non-HF trades and orders are largely consistent with expectations and these relations hold in both pre- and post-announcement periods. The only deviation is the effect of non-HF limit orders on subsequent bid–ask spreads, where the coefficient is positive but only significant at the 10% critical level.

However, market liquidity exhibits a rather complex relation with HF trades and orders. First, while HF trades have a significantly positive relation with subsequent bid–ask spreads during pre-announcement periods, the relation is significantly negative during post-announcement periods. The coefficient of HF trades in the bid–ask spread regression is significantly positive at the 1% level during pre-announcement periods, but negative at the 5% level during post-announcement periods. Second, while HF trades, as expected, have a negative effect on depth at the best quote, HF limit orders also have a negative effect on depth at the best quote. Although the effect of magnitude is smaller compared to that of HF trades, the coefficient is significantly negative at the 1% level during both pre- and post-announcement periods. Third, HF trades have a positive effect on depth behind the best quote and the effect is significant at the 5% level during pre-announcement periods. However, HF orders have no significant effect on depth behind the best quote during either pre- or post-announcement periods.

These mixed findings highlight the evident role played by the informational environment. During pre-announcement periods, dealers withhold their orders due to information uncertainty. Therefore, limit order books are thin and trades are more likely to have a larger impact in widening the bid–ask spread. In addition, HF trades may be perceived as informed, which will increase the level of adverse selection of other participants, further widening the bid–ask spread. In turn, adverse selection causes other market participants to be more conservative when placing their orders, which leads to the withdrawal of aggressive limit orders at the best quotes. These findings are in line with the implications of recent theoretical models in which HF trading generates adverse selection because of the enhanced speed of machine information processing (Biais, Foucault, and Moinas, 2010, and references therein).

During post-announcement periods, with the release of macroeconomic news and information uncertainty being resolved, more HF trades facilitate the convergence of bond valuation among market participants. As a result, the bid–ask spread narrows. The improvement of best quotes implies that existing orders at the best quote are shifted to the lower tier behind the best quote and become less aggressive. This pattern is consistent with general findings in the literature, that electronic trading has induced an overall reduction in transaction costs and, in particular, a reduction in bid–ask spreads (Hasbrouck and Saar, 2011; Hendershott, Jones, and Menkveld, 2011; Jovanovic and Menkveld, 2011). For example, using data from the NYSE, Hendershott, Jones, and Menkveld (2011) show that algorithmic trading narrows spread in large cap stocks but in the meantime simultaneously reduces quoted depth. Taken together, our results suggest that, as measured by bid–ask spread, HF trades consume market liquidity in the presence of information uncertainty but improve market liquidity when information uncertainty is being resolved after the arrival of public information.

Table 6 reports the estimation results of Eq. (7) under Models 1 and 2 for volatility regressions. Under normal market conditions, trades are expected to increase asset return volatility, whereas limit orders are expected to impart a negative effect on it. This is because trades are more likely to widen the bid–ask spread and changes in asset prices, whereas limit orders help reduce price fluctuations through lower bid–ask spreads and greater limit order book depth. The results under Model 1 in Table 6 show that, during post-announcement periods, the sign of the estimated coefficients are consistent with our expectations. In fact, trades generally have a positive effect on return volatility, whereas orders generally have a negative effect on return volatility. However, during pre-announcement periods, both trades and orders have a significantly positive effect on return volatility.

The results under Model 2 in Table 6 show that the effects of non-HF trading on volatility are also generally consistent with our expectations. Specifically, non-HF trades have a significantly positive effect on volatility during both pre- and post-announcement periods. Non-HF orders have an insignificant effect on volatility during pre-announcement periods, but a significantly negative effect on volatility during post-announcement periods.

On the other hand, the parameters associated with HF trading exhibit signs that are positive, except that the coefficient on HF orders that is insignificant during post-announcement periods. This result clearly suggests that HF trading generally has a positive effect on the return volatility of US Treasury notes. This finding also mirrors those reported in other studies focusing on other financial markets (see, e.g., Zhang, 2010; Boehmer, Fong, and Wu, 2012, and references therein). In particular, we note that the positive relation between overall orders and subsequent return volatility during pre-announcement periods is largely driven by HF limit orders. During pre-announcement periods, while non-HF orders have no significant effect on volatility, HF orders exert a positive effect on return volatility that is statistically significant at the 1% level. This finding is consistent with the results reported in Table 5, where during pre-announcement periods, HF orders have a positive, although insignificant, effect on the bid–ask spread and a significantly negative effect on depth at the best quote.

To summarize, our results show that HF trading has a distinctive effect on both market liquidity and market volatility compared to non-HF trading. More importantly, the effects of HF trading on market liquidity and market volatility vary under different informational environments. Our results show that during pre-announcement periods, HF trading has an overall significant and negative effect on market liquidity, as HF trades widens the bid–ask spread and reduce depth at the best quote. Contrary to our expectations, HF orders not only do not significantly narrow the bid–ask spread but also significantly reduce depth at the best quote. During post-announcement periods, the effect of HF trading on market liquidity is mixed. While both HF trades and orders significantly narrow the bid–ask spread, they also have a significant effect in reducing depth at the best quote. These results are generally consistent with those recorded by Hendershott, Jones, and Menkveld (2011), where the effect of HF trading on market liquidity appears to be beneficial to relatively small trades. In fact, the positive effect of the smaller bid–ask spread offsets the negative effect of shallow depth at the best quotes.

Finally, our results show that HF trading generally tends to increase return volatility, especially during pre-announcement periods. Altogether, these findings suggest that HF activities have an adverse impact on market liquidity when the market is uncertain about information. This naturally leads to the question of the role of HF trading on price efficiency. Although HF trading potentially facilitates the incorporation of information into prices on information arrival, its impact on price efficiency is unclear uncertainty about information is not resolved.

3.2 Informativeness of HF trading and the impact on price efficiency

This sub-section examine the informativeness of HF trades and orders and their impact on the price efficiency. The literature proposes several approaches to studying the informativeness of orders and price efficiency. In our empirical investigation, we compare the informativeness of HF trades and orders against their non-HF counterparts. To compare the informativeness of HF versus non-HF trades and orders, we employ the test proposed by Kaniel and Liu (2006). Intuitively, this test assesses the informativeness of trades (orders) by comparing the actual percentages of trades (orders) placed in the "right" side of the market or predicts the "correct" direction of the market. Specifically, the right side, or correct direction, of the market is defined as a case where a buy (sell) order is followed by a higher (lower) mid-quote in the future. If HF trades (orders) have a significantly higher percentage on the right side of the market than non-HF trades (orders) do, then HF trades (orders) are more informative than non-HF trades (orders) are. Otherwise, non-HF trades (orders) are more informative than HF trades (orders).

Formally, let P_{NHF} denote the probability that a trade (order) is a non-HF trade, n the total number of times the trades (orders) are in the correct direction, and n_{NHF} the number of times non-HF orders are in the correct direction of the market. Under the null hypothesis that HF trades (orders) and non-HF trades (orders) are equally informative, Kaniel and Liu (2006) show that, out of these n quotes, the probability that n_{NHF} non-HF trades (orders) are in the correct direction of the market is given by

$$\phi = 1 - N\left[\frac{n_{NHF} - nP_{NHF}}{\sqrt{n \cdot P_{NHF}\left(1 - P_{NHF}\right)}}\right]. \tag{8}$$

If the probability ϕ is lower (higher) than 5% (95%), we reject the null hypothesis of the equal informativeness of HF trades and non-HF trades suggesting that HF trades and orders (or non-HF trades and orders) being more informative. We also divide the whole sample of trades (orders) into three equal groups, or terciles, according to size (small, medium, and large) and perform the Kaniel–Liu (2006) test for each subsample.

Table 7 reports the results of the Kaniel and Liu (2006) test for all three maturities and different-sized groups of trades (orders). The evidence suggests that non-HF limit orders are more informative than their HF counterparts. The findings are particularly striking during post-announcement periods, where in all cases non-HF orders are found to be more informative than HF orders. These findings are consistent with Brogaard, Hendershott, and Riordan (2013), who find that HF orders tend to be subject to adverse selection. The results for trades are less conclusive during pre-announcement periods. However, HF trades are found to be more informative than non-HF trades for all three maturities during post-announcement periods. The results are in line with the predictions of the theoretical literature (Biais, Foucault, and Moinas, 2011; Foucault, Hombert, and Rosu, 2013). These results are also similar to the empirical findings of Brogaard, Hendershott, and Riordan (2013) and Hirschey (2013).[13]

We also perform the Kaniel–Liu (2006) test to compare the informativeness of HF buy trades (orders) versus HF sell trades (orders). The results of this additional exercise are

[13] Robustness checks using a three-second cutoff for non-HF trades further suggests that HF trades are more informative than their non-HF counterparts for all maturities.

reported in Table 8. The findings provide a picture clearly suggesting that, over the sample period investigated, HF sell (trades) orders are significantly more informative than HF buy (trades) orders. This result holds true for all maturities, with a slight weaker evidence for the ten-year note, and across all size groups.

Finally, we examine the effect of HF trading activities on price efficiency following the methodology proposed by Boehmer and Kelley (2010) and Boehmer, Fong, and Wu (2012). In particular, we examine the potential effect of HF trading activities on subsequent price inefficiency, as measured by the serial correlation of bond returns. The intuition is that if prices follow a random walk, serial correlations of bond returns should be equal to zero at all horizons. Deviations from zero on either the positive or negative side imply return predictability or price inefficiency.

Our analysis is based on serial correlations of returns over five-minute intervals. Specifically, over each five-minute interval, we first compute tick-by-tick returns based on the mid-point of the quoted bid and ask of each transaction and then compute the first-order autocorrelation of the time-series of those returns. As in Section 3.1 we first examine the effect of overall trades and orders on the price efficiency of US Treasury securities. That is, we first estimate the following equation:

$$\begin{aligned}\log\left|AC_{t,5M(i+1)}\right| \;=\;& (\alpha_{2yr}D_{2yr}+\alpha_{5yr}D_{5yr}+\alpha_{10yr}D_{10yr})+\gamma_0 TR^*_{t,5M(i)}+\varphi_0 LO^*_{t,5M(i)}\\ &+\beta_1 DPTH^{BST^*}_{t,5M(i)}+\beta_2 DPTH^{BHD^*}_{t,5M(i)}+\beta_3 SPRD^*_{t,5M(i)}\\ &+\delta\left|SUR_{k,t}\right|+\varepsilon_{t,5M(i+1)},\end{aligned} \tag{9}$$

where $\log|\mathrm{AC}_{t,5M(i+1)}|$ denotes the log absolute autocorrelation of tick-by-tick returns computed from the mid-point of the quoted bid and ask for each transaction over the $i+1-$th five-minute interval on announcement day t; $TR^*_{t,5M(i)}$ and $LO^*_{t,5M(i)}$ denote, respectively, abnormal overall trades and orders over the $i-$th five-minute interval on announcement day t; and D_{2yr}, D_{5yr}, and D_{10yr} are maturity dummies. In the regression, we also include unexpected liquidity shocks and announcement surprises as control variables.

To disentangle the respective effects of HF trading from those of non-HF trading on price efficiency, we then estimate the following equation with both HF and non-HF trades and orders as explanatory variables:

$$\begin{aligned}\log\left|AC_{t,5M(i+1)}\right| &= (\alpha_{2yr}D_{2yr}+\alpha_{5yr}D_{5yr}+\alpha_{10yr}D_{10yr}) \\ &\quad +\gamma_0 HFTR^*_{t,5M(i)}+\varphi_0 HFLO^*_{t,5M(i)}+\gamma_1 NHFTR^*_{t,5M(i)}+\varphi_1 NHFLO^*_{t,5M(i)} \\ &\quad +\beta_1 DPTH^{BST^*}_{t,5M(i)}+\beta_2 DPTH^{BHD^*}_{t,5M(i)}+\beta_3 SPRD^*_{t,5M(i)} \\ &\quad +\delta\left|SUR_{k,t}\right|+\varepsilon_{t,5M(i+1)}, \end{aligned} \tag{10}$$

where $HFTR^*_{t,5M(i)}$ and $HFLO^*_{t,5M(i)}$ denote, respectively, abnormal HF trades and orders over the $i-$th five-minute interval on the announcement day and $NHFTR^*_{t,5M(i)}$ and $NHFLO^*_{t,5M(i)}$ denote, respectively, abnormal non-HF trades and orders over the $i-$th five-minute interval on the announcement day t.

The results reported in Table 9 show that overall trades and orders are generally both statistically insignificant. The only exception is represented by trades are statistically significant at conventional levels during post-announcement periods. This suggests that following news announcements, overall trades reduce the serial correlation of the quote mid-point, hence improving price efficiency. Disentangling the effects of HF from non-HF activities, the results show that the improvement in price efficiency during the post-announcement period is mainly driven by HF trades that significantly reduce the serial correlation of mid-quote returns. These findings are consistent with the results reported in Table 7, that HF trades are more informative than non-HF trades during post-announcement periods.

Overall, our findings suggest that the informativeness of HF trades depends on the informational environment. In fact, HF trades are informative and improve price efficiency only during periods when information uncertainty is resolved. In periods of information uncertainty, HF activities exhibit no significant effects on price efficiency. In addition, the informativeness of HF orders is generally lower than that exhibited by their non-HF counterparts.[14] Our results extend and refine the findings recorded in the recent empirical literature (see, e.g., Brogaard, Hendershott, and Riordan, 2012, and Chaboud, Chiquoine, Hjalmarsson, and Vega, 2013, and references therein), which show that HF activities improve overall price efficiency. In fact we provide clear evidence that the impact of HF activities on price efficiency depends on the informational environment. HF trading improves price efficiency only after the resolution of information uncertainty.

4 Conclusion

This study investigates the activity of HF trading in the US 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 US Treasury market, we identify HF trades and orders based on their speed of placement, alteration,

[14]The control variables, $DPTH^{BST^*}_{t,5M(i)}, DPTH^{BHD^*}_{t,5M(i)}, and SPRD^*_{t,5M(i)}$, used in Eq. (10) are not all significant at conventional levels. The bid–ask spreads are only statistically significant during the post-announcement period, while the depth of the order book at the best quote positively affects the serial correlation of mid-quote returns during both the pre- and post-announcement periods. The size of the announcement shocks is found to be significant over both specification and the signs of the parameter estimates suggest that the larger the announcement shocks the stronger and more positive the impact is on price efficiency.

or cancelation that is deemed beyond manual capacity. We examine i) how HF trades and orders take place around macroeconomic news announcements, ii) whether HF trades and orders increase or deplete market liquidity and volatility, and iii) the informativeness of HF trades and orders and the role of HF activities in improving or reducing the price efficiency of the US Treasury market.

Our results show that both HF trades and orders increase substantially after macroeconomic news announcements. The overall position of HF limit orders is more aggressive than that of non-HF limit orders. Specifically, the percentages of HF limit orders that are positioned better than the best quote and one tick behind the best quote are significantly larger than those of non-HF limit orders. In addition, our results show that, although there is clear evidence that HF trades and orders generate higher (subsequent) bond return volatility, their effect on market liquidity depends on the informational environment. Higher-than-normal HF activity generally has a negative impact on liquidity before announcements, but it is associated with lower bid–ask spreads, especially during post-announcement periods, when information uncertainty is resolved. Moreover, our results show that during post-announcement periods, HF (trades) limit orders are (more) less informative than their non-HF counterparts. Finally, our results show that only HF trades have a significant effect in enhancing price efficiency during the post-announcement period.

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Table 1
List of Macroeconomic News Announcements

This table reports the list of macroeconomic news announcements included in our analysis. The term N denotes the total number of announcements during our sample period, from January 2, 2004 to June 30, 2007. The day denotes the weekday or day of the month for the announcement of each news item; time denotes the time (Eastern Standard Time) of the announcement; σ denotes the standard deviation of announcement surprises; $\mathbf{N}_{|SUR|>k\sigma}$ denotes the number of announcements with absolute surprise that is k times greater than its standard deviation; and N.A. means not applicable.

Announcements	**N**	**Day**	**Time**	$\mathbf{N}_{\|SUR\|>\sigma}$	$\mathbf{N}_{\|SUR\|>2\sigma}$
Building Permits	42	18th workday of the month (around 24th/25th)	8:30	14	1
Business Inventories	42	Around the 15th of the month	8:30/10:00	11	1
Capacity Utilization	42	Around 15th/16th of the month	9:15	12	2
Construction Spending	43	Around 1st/2nd of the month	10:00	16	1
Consumer Confidence	42	Around 25th of the month	10:00	12	3
CPI	42	Around 16th of the month	8:30	13	4
Durable Orders	42	Around the 26th of the month	8:30	2	2
Existing Home Sales	42	Around the 25th of the month	10:00	17	2
Factory Orders	42	Around the first business day of the month	10:00	11	3
Fed's Beige Book	28	Two weeks prior to each Federal Open Market Committee Meeting	14:00	N.A.	N.A.
FOMC Meeting	8	Eight regularly scheduled meetings per year	14:15	0	0
FOMC Minutes	19	Approximately three weeks after the FOMC meeting	8:30	N.A.	N.A.
GDP-Adv.	14	Around 27th of the Jan, April, July, Oct	8:30	5	1
GDP-Final	14	Around 28th of March, June, Sep, Dec	8:30	1	1
GDP-Prel.	14	Around 29th of Feb, May, Aug, Nov	8:30	2	1
Housing Starts	42	2 or 3 weeks after the reporting month	8:30	10	3
Industrial Production	42	Around the 15th of the month	9:15	14	2
Initial Claims	182	Each Thursday	8:30	47	10
ISM Index	42	1st business day of the month	10:00	12	2
ISM Services	42	3rd business day of the month	10:00	18	1
Leading Indicators	42	Around the first few business days of the mont	10:00	12	3
New Home Sales	42	17th workday of the month (around 25th/26th)	10:00	12	3
Nonfarm Payrolls	42	First Friday of the month	8:30	14	2
NY Empire State Index	42	15th/16th of the month	8:30	16	2
Personal Spending	42	Around the first or last business day of the month	8:30	9	2
PPI	42	3rd week of each month	8:30	12	5
Retail Sales	42	Around the 12th of the month	8:30	8	4
Trade Balance	42	Around the 20th of the month	8:30	12	2
Treasury Budget	42	About the third week of the month for the prior month	14:00	12	2
Unemployment Rate	42	First Friday of the month	8:30	6	2
Personal Income	42	Around the 1st business day of the month	8:30	25	7

Table 2
Summary Statistics of Market Activities around News Announcements

This table reports summary statistics of market activities around news announcements. Each announcement day, we obtain observations of the quoted bid–ask spread (in ticks), the depth of the order book at the best bid and ask quotes (millions of dollars), the depth of the order book behind the best quote (millions of dollars) at the end of each one-minute interval, and the trading volume (millions of dollars) during each one-minute interval. We then compute the average of these variables during the 15-minute pre- and post-announcement periods, respectively. The realized volatility of bond returns is computed as $(\sum_{i=0}^{15}(\ln p_i - \ln p_{i-1})^2)^{1/2} \times 100$ during both the 15-minute pre- and post-announcement periods, where p_i is the mid-quote at the end of i-th one-minute interval. The table reports the summary statistics of these variables across all announcement days. The sample period is from January 2, 2004 to June 30, 2007.

	Pre-announcement Period					Post-announcement Period				
	Mean	**Median**	**Std.**	**Max**	**Min**	**Mean**	**Median**	**Std.**	**Max**	**Min**
Panel A: 2-year Note										
Bid-ask spread (tick)	1.183	1.067	0.265	2.733	0.933	1.099	1.067	0.165	2.533	0.933
Depth at best quote ($ mil)	444.0	398.9	303.2	1339.2	47.9	535.5	496.4	364.0	1543.1	48.6
Depth behind best quote ($ mil)	3288.0	2711.3	2842.3	11166.5	49.7	3923.1	3565.6	3109.3	11781.5	89.3
Trading volume ($ mil)	889.7	755.0	552.3	3391.0	92.0	2236.7	1752.0	1674.6	8190.0	159.0
Volatility	0.0159	0.0141	0.0092	0.0802	0.0000	0.0315	0.0248	0.0225	0.1699	0.0068
Panel B: 5-year Note										
Bid-ask spread (tick)	1.477	1.267	0.569	5.000	0.933	1.273	1.200	0.323	3.933	0.933
Depth at best quote ($ mil)	89.5	83.5	44.9	260.1	21.9	101.5	99.0	51.8	229.3	25.1
Depth behind best quote ($ mil)	864.3	649.9	728.0	3526.0	38.8	1077.3	853.9	898.4	3844.3	64.9
Trading volume ($ mil)	767.9	728.0	367.5	2124.0	118.0	1687.7	1439.0	988.3	4933.0	247.0
Volatility	0.0343	0.0289	0.0209	0.1771	0.0117	0.0759	0.0584	0.0563	0.3964	0.0137
Panel C: 10-year Note										
Bis-ask spread (tick)	1.344	1.200	0.404	3.667	0.933	1.171	1.133	0.192	2.467	0.867
Depth at best quote ($ mil)	88.1	85.2	40.8	205.9	18.9	102.8	102.0	46.8	224.1	23.7
Depth behind best quote ($ mil)	1077.4	844.1	810.5	3610.1	53.3	1392.4	1171.2	1012.9	3873.9	53.1
Trading volume ($ mil)	662.3	585.0	363.8	2031.0	110.0	1555.3	1293.0	952.9	4542.0	176.0
Volatility	0.0571	0.0497	0.0288	0.2517	0.0219	0.1208	0.0964	0.0852	0.6603	0.0271

Table 3

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

This table reports the average volumes of HF and non-HF trades (Panel A), HF and non-HF limit orders (Panel B), as well as abnormal volumes of HF and non-HF trades and limit orders (Panel C) over the 15-minute pre- and post-announcement periods. The term HFTR denotes HF trades that are identified as market buy (sell) orders placed within a second of changes in the best quotes on either side of the market. The term HFLO1 denotes limit orders canceled or modified within one second of being placed, 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; and 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 Eqs. (5) and (6) in the main text. There terms NHFTR and NHFLO denote, respectively, non-HF trades and limit orders. The abnormal values of NHFTR and NHFLO are computed as in Eqs. (7) and (8) in the main text.

	2-year Note		**5-year Note**		**10-year Note**	
	Pre-ann.	**Post-ann.**	**Pre-ann.**	**Post-ann.**	**Pre-ann.**	**Post-ann.**
Panel A: Trades ($ mil)						
HFTR	203.82	525.08	216.15	497.06	178.88	435.86
NHFTR	802.68	2000.83	608.65	1323.75	549.37	1270.82
Panel B: Limit Orders ($ mil)						
HFLO1	5634.58	18564.26	4734.90	15161.73	4173.25	14100.48
HFLO2	478.10	719.81	334.20	565.58	328.25	488.98
HFLO3	126.95	283.31	89.53	188.02	68.90	143.97
All HFLO	6239.63	19567.38	5158.63	15915.33	4570.39	14733.44
NHFLO	17217.48	53593.11	12508.75	33161.89	11180.92	30324.57
Panel C: Abnormal Trades and Limit Orders ($ mil)						
Abnormal HFTR	20.24	315.19	18.51	265.92	8.78	244.22
Abnormal NHFTR	79.27	1147.97	6.23	649.04	0.68	653.06
Abnormal HFLO	352.89	11346.38	-485.66	9173.43	-385.08	8903.52
Abnormal NHFLO	-2477.53	30845.03	-2241.66	16751.59	-1998.31	15762.63

Table 4

HF and Non-HF Trades and Limit Orders: Size and Positions

This table reports the average sizes of HF and non-HF trades and limit orders (Panel A) and the distributions of HF and non-HF limit orders placed in different positions of the limit order book (Panel B) over the 15-minute pre- and post-announcement periods. For variable definitions, see Table 3.

	2-year Note		**5-year Note**		**10-year Note**	
	Pre-ann.	**Post-ann.**	**Pre-ann.**	**Post-ann.**	**Pre-ann.**	**Post-ann.**
Panel A: Average Size ($ mil)						
Trades						
HFTR	12.77	12.06	4.88	4.27	4.04	3.73
NHFTR	16.77	17.03	5.85	5.31	5.15	4.82
Limit Orders						
HFLO1	13.18	13.89	4.35	4.66	3.15	3.44
HFLO2	35.34	31.20	13.06	13.12	13.50	12.31
HFLO3	17.95	15.70	4.71	4.20	4.14	3.90
All HFLO	13.92	14.20	4.55	4.77	3.35	3.53
NHFLO	12.19	12.73	4.44	4.37	3.45	3.46
Panel B: Position of Limit Orders (%)						
HF Limit Orders						
Better than best quote	3.68%	2.87%	4.15%	3.96%	3.04%	2.58%
At best quote	40.35%	38.77%	30.60%	31.80%	28.80%	28.95%
1-tick behind best quote	23.94%	24.17%	39.04%	33.42%	44.14%	38.94%
More than 1-tick behind best quote	32.03%	34.19%	26.21%	30.82%	24.02%	29.53%
Non-HF Limit Orders						
Better than best quote	1.36%	1.05%	1.95%	1.64%	1.50%	1.22%
At best quote	43.20%	40.76%	33.90%	33.54%	31.98%	31.42%
1-tick behind best quote	22.35%	20.99%	28.69%	24.52%	35.28%	30.03%
More than 1-tick behind best quote	33.09%	37.19%	35.45%	40.30%	31.24%	37.34%

Table 5
The Impact of HF Trades and Limit Orders on Subsequent Market Liquidity

This table reports the results of liquidity shock regressions against HF trades and limit orders: $U^{LIQ*}_{t,1M(i+1)} = (\alpha_{2yr}D_{2yr} + \alpha_{5yr}D_{5yr} + \alpha_{10yr}D_{10yr}) + \varphi_0 HFLO^*_{t,1M(i)} + \gamma_0 HFTR^*_{t,1M(i)} + \varphi_1 NHFLO^*_{t,1M(i)} + \gamma_1 NHFTR^*_{t,1M(i)} + \delta\,|SUR_{k,t}| + \epsilon_{t,1M(i+1)}$, where $\varepsilon^{LIQ}_{t,1M(i+1)}$ denotes the liquidity shock computed as in Equations (1)-(3) in the main text. The regressions are performed during the 15-minute pre- and 15-minute post-announcement periods, respectively. Panel A reports the results based on quoted bid-ask spread, Panel B reports the results based on the depth of the order book at the best quote, and Panel C reports the results based on the depth of the order book behind the best quote. D_{2yr} D_{5yr} D_{10yr} are maturity dummies for the 2-year, 5-year or 10-year notes, respectively. $|SUR_{k,t}|$ denotes the absolute announcement surprise. In Model 1, liquidity shock is regressed against abnormal volume of total trades and limit orders, whereas in Model 2, liquidity shock is regressed against abnormal volume of HF and non-HF trades and limit orders. ***, **, and * denotes significance at 1%, 5%, and 10% levels, respectively. $Adj.R^2$ denote the adjusted R^2. For variable definitions, see Tables 2 and 3.

	Pre-announcement Period		**Post-announcement Period**	
	Model 1	Model 2	Model 1	Model 2
Panel A: Bid-Ask Spread				
D_{2yr}	-0.678***	-0.676***	0.148**	0.0710
D_{5yr}	0.1820	0.1710	0.136**	0.146**
D_{10yr}	0.688***	0.678***	-0.0090	0.0010
$TRADE^*$	0.246*		0.0440	
$ORDER^*$	-0.037***		-0.009***	
$HFTR^*$		1.049***		-0.265**
$HFLO^*$		0.0220		-0.032***
$NHFTR^*$		0.1780		0.089*
$NHFLO^*$		-0.079***		0.006*
$\|SUR_{k,t}\|$			0.469***	0.547***
$Adj.R^2$	0.0015	0.0019	0.0017	0.0027
Panel B: Depth at the Best Quote				
D_{2yr}	-19.841***	-19.882***	-3.804***	-4.953***
D_{5yr}	9.801***	9.777***	5.268***	5.329***
D_{10yr}	9.743***	9.807***	5.386***	5.450***
$TRADE^*$	-8.856***		-1.981**	
$ORDER^*$	0.533***		-0.0320	
$HFTR^*$		-7.938**		-5.746**
$HFLO^*$		-0.706***		-0.342***
$NHFTR^*$		-11.716***		-1.5960
$NHFLO^*$		1.390***		0.182***
$\|SUR_{k,t}\|$			-0.962***	-0.854***
$Adj.R^2$	0.0068	0.0083	0.0020	0.0024

	Pre-announcement Period		Post-announcement Period	
	Model 1	Model 2	Model 1	Model 2
Panel C: Depth behind the Best Quote				
D_{2yr}	-27.276***	-27.406***	-1.6960	-6.079*
D_{5yr}	7.092**	6.836**	-30.066***	-30.883***
D_{10yr}	7.799***	7.738***	-24.711***	-25.312***
$TRADE^*$	3.0920		-3.478*	
$ORDER^*$	1.389***		0.760***	
$HFTR^*$		17.947**		2.3800
$HFLO^*$		0.0900		-0.3490
$NHFTR^*$		-3.0450		-7.652***
$NHFLO^*$		2.254***		1.557***
$\|SUR_{k,t}\|$			12.931***	13.278***
$Adj.R^2$	0.0050	0.0054	0.0204	0.0215

Table 6
The Impact of HF Trades and Limit Orders on Subsequent Market Volatility

This table reports the results of the bond return volatility regression on HF trades and limit orders: $U^{VLTY*}_{t,1M(i+1)} = (\alpha_{2yr}D_{2yr} + \alpha_{5yr}D_{5yr} + \alpha_{10yr}D_{10yr}) + \varphi_0 HFLO^*_{t,1M(i)} + \gamma_0 HFTR^*_{t,1M(i)} + \varphi_1 NHFLO^*_{t,1M(i)} + \gamma_1 NHFTR^*_{t,1M(i)} + \delta\,|SUR_{k,t}| + \epsilon_{t,1M(i+1)}$, where $\varepsilon^{VLTY*}_{t,1M(i+1)}$ denotes the abnormal return volatility computed as in Eq. (4) in the main text. The regressions are performed during the 15-minute pre- and post-announcement periods, respectively. The terms D_{2yr}, D_{5yr}, and D_{10yr} are maturity dummies for the two-, five-, and ten-year notes, respectively. The term $|SUR_{k,t}|$ denotes absolute announcement surprise. In Model 1, abnormal return volatility is regressed against the abnormal volumes of total trades and limit orders, whereas in Model 2 abnormal return volatility is regressed against the abnormal volumes of HF and non-HF trades and limit orders. The superscripts ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The term $Adj.R^2$ denotes the adjusted R^2. For variable definitions, see Tables 2 and 3.

	Pre-announcement Period		**Post-announcement Period**	
	Model 1	Model 2	Model 1	Model 2
D_{2yr}	-0.076***	-0.076***	-0.348***	-0.338***
D_{5yr}	-0.008	-0.009	-0.121***	-0.122***
D_{10yr}	0.051***	0.050***	0.102***	0.101***
$TRADE^*$	0.047***		0.032***	
$ORDER^*$	0.002***		-0.003***	
$HFTR^*$		0.112***		0.083**
$HFLO^*$		0.003***		0.000
$NHFTR^*$		0.035***		0.026*
$NHFLO^*$		0.001		-0.005***
$\|SUR_{k,t}\|$			2.274***	2.264***
$Adj.R^2$	0.0037	0.0039	0.1394	0.1396

Table 7

Informativeness of HF versus Non-HF Trades and Limit Orders

This table reports the results of the Kaniel– Liu (2006) test of the informativeness of HF trades and limit orders compared to that of non-HF trades and limit orders. A p-value close to one indicates the greater informativeness of HF trades (limit orders) relative to that of non-HF trades (limit orders), whereas a p-value close to zero indicates the greater informativeness of non-HF trades (limit orders) relative to that of HF trades (limit orders). The superscripts ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, for the informativeness of HF trades (limit orders), whereas $^{+++}$,$^{++}$, and $^{+}$ denote significance at the 1%, 5%, and 10% levels, respectively, for the informativeness of non-HF trades (limit orders). We also report the results based on trades and orders in different size categories. Small, medium, and large denote trades (limit orders) in the bottom, intermediate, and top size terciles of all trades (limit orders), respectively.

	Pre-announcement Period				Post-announcement Period			
	All	**Small**	**Medium**	**Large**	**All**	**Small**	**Medium**	**Large**
HF Trades vs. Non-HF Trades								
2-year Note	0.99***	0.98**	0.92*	0.72	1.00***	1.00***	1.00***	0.96**
5-year Note	0.67	0.58	0.38	0.81	0.95**	0.84	0.92*	0.62
10-year Note	0.09^{+}	0.03^{++}	0.50	0.45	0.95**	0.90*	0.79	0.75
HF Limit Orders vs. Non-HF Limit Orders								
2-year Note	0.01^{+++}	1.00***	0.58	0.00^{+++}	0.00^{+++}	0.01^{+++}	0.00^{+++}	0.00^{+++}
5-year Note	0.00^{+++}	0.01^{+++}	0.00^{+++}	0.19	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}
10-year Note	0.01^{+++}	0.87	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.01^{+++}	0.00^{+++}	0.00^{+++}

Table 8
Informativeness of HF Buy versus HF Sell Trades and Limit Orders

This table reports the results of the Kaniel– Liu (2006) test for the informativeness of HF buy versus HF sell trades and limit orders. A p-value close to one indicates the greater informativeness of HF buy trades (limit orders) relative to that of HF sell trades (limit orders), whereas a p-value close to zero indicates the greater informativeness of HF sell trades (limit orders) relative to that of HF buy trades (limit orders). The superscripts ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, for the informativeness of HF buy trades (limit orders), whereas $^{+++}$, $^{++}$, and $^{+}$ denote significance at the 1%, 5%, and 10% levels, respectively, for the informativeness of HF sell trades (limit orders). We also report the results based on trades and limit orders in different size categories. Small, medium, and large denote trades (limit orders) in the bottom, intermediate, and top size terciles of all trades (limit orders), respectively.

	Pre-announcement Period				Post-announcement Period			
	All	**Small**	**Medium**	**Large**	**All**	**Small**	**Medium**	**Large**
HF Buy Trades vs. HF Sell Trades								
2-year Note	0.00^{+++}	0.01^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}
5-year Note	0.00^{+++}	0.00^{+++}	0.03^{++}	0.12	0.00^{+++}	0.01^{+++}	0.01^{+++}	0.06^{+}
10-year Note	0.01^{+++}	0.02^{++}	0.64	0.08^{+}	0.80	0.84	0.49	0.92*
HF Buy Limit Orders vs. HF Sell Limit Orders								
2-year Note	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}
5-year Note	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}
10-year Note	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.00^{+++}	0.70	0.00^{+++}

Table 9
The Impact of HF Trades and Limit Orders on Bond Price Efficiency

This table reports the results of the regression $\log|AC_{t,5M(i+1)}| = (\alpha_{2yr}D_{2yr} + \alpha_{5yr}D_{5yr} + \alpha_{10yr}D_{10yr}) + \varphi_0 HFLO^*_{t,5M(i)} + \gamma_0 HFTR^*_{t,5M(i)} + \varphi_1 NHFLO^*_{t,5M(i)} + \gamma_1 NHFTR^*_{t,5M(i)} + \beta_1 DPTH^{BST^*}_{t,5M(i)} + \beta_2 DPTH^{BHD^*}_{t,5M(i)} + \beta_3 SPRD^*_{t,5M(i)} + \delta\,|SUR_{k,t}| + \epsilon_{t,5M(i+1)}$, where $\log|\mathrm{AC}_{t,5M(i+1)}|)$ is the autocorrelation of tick-by-tick returns over each five-minute interval. The tick-by-tick return is computed based on the mid-quote at each transaction. The regression is performed during the 15-minute pre- and post-announcement periods, respectively. The variables D_{2yr}, D_{5yr}, and D_{10yr} are maturity dummies for the two-, five-, and ten-year notes, respectively. The term $|SUR_{k,t}|$ denotes the absolute announcement surprise. In Model 1, $\log|\mathrm{AC}_{t,5M(i+1)}|$, a measure of price efficiency, is regressed against the abnormal volumes of total trades and limit orders, whereas in Model 2, $\log|\mathrm{AC}_{t,5M(i+1)}|$ is regressed against the abnormal volumes of HF and non-HF trades and limit orders. In all regressions, liquidity shocks are included as control variables. The terms $SPRD^*_{t,5M(i)}, DPTH^{BST^*}_{t,5M(i)}$, and $DPTH^{BHD^*}_{t,5M(i)}$ denote, respectively, the abnormal bid–ask spread, the abnormal depth of the order book at the best quote, and the abnormal depth of the order book behind the best quote. The superscripts ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. The term $Adj.R^2$ denotes the adjusted R^2. For variable definitions, see Tables 2 and 3.

	Pre-announcement Period		**Post-announcement Period**	
	Model 1	Model 2	Model 1	Model 2
D_{2yr}	-1.8246***	-1.8221***	-1.9812***	-1.9997***
D_{5yr}	-2.1572***	-2.1575***	-2.4749***	-2.4656***
D_{10yr}	-2.1476***	-2.1474***	-2.4619***	-2.4562***
$TRADE^*$	0.0057		-0.0242***	
$ORDER^*$	-0.1053		0.0093	
$HFTR^*$		0.0704		-0.0630**
$HFLO^*$		-0.0011		-0.0009
$NHFTR^*$		-0.0137		-0.0184
$NHFLO^*$		-0.001		0.0009
$SPRD^*$	-0.0075	-0.0087	0.0212***	0.0217***
$DPTH^{BST*}$	0.0109*	0.0112**	0.0132***	0.0132***
$DPTH^{BHD*}$	-0.0522	-0.0545	-0.0029	-0.0183
$\|SUR_{k,t}\|$			-0.0980**	-0.0953**
$Adj.R^2$	0.547	0.5471	0.7281	0.7284

FIGURE 1
Market Activities around News Announcements

This figure depicts market activities in each one-minute interval during the 15-minute pre- and post-announcement periods. Variables include the bid–ask spread (in ticks), trading volume (millions of US dollars), the depth at the best quote (millions of US dollars), and overall depth (millions of US dollars) and the return volatility is defined as the absolute value of the change of the logarithmic mid-quote over each one-minute interval ($\times 1,000$). For comparison, the corresponding values of each variable at the same time on non-announcement days are also depicted.