High Frequency Trading around Macroeconomic News Announcements

— Evidence from the US Treasury market

George J. Jiang   Ingrid Lo   Giorgio Valente[1]

This draft: October 2013

[1]George J. Jiang is from the Department of Finance and Management Science, College of Business, Washington State University, Pullman, Washington 99164. Email: george.jiang@wsu.edu. Ingrid Lo is from Bank of Canada, Ottawa, Canada and Department of Economics, Chinese University of Hong Kong, Shatin N.T., Hong Kong. Email: mail@ingridlo.net. Giorgio Valente is from the Essex Business School, University of Essex, Wivenhoe Park, Colchester, CO4 3SQ, Essex, United Kingdom. E-mail: gvalente@essex.ac.uk.
The authors wish to thank Ryan Riordan, Andriy Shkilko, Sarah Zhang, the participants at the 8th Central Bank Workshop on the Microstructure of Financial Markets, Ottawa; 2012 International Conference on Finance at National Taiwan University, Taipei and the seminar participants at the Hong Kong Polytechnic University. The study was fully supported by a grant from the Research Grants Council of Hong Kong Special Administrative Region, China (Project No. 4478712). This work was partly written while Giorgio Valente was visiting the Bank for International Settlements and City University of Hong Kong. The views expressed here are solely our own and do not necessarily reflect those of the Bank for International Settlements.

High Frequency Trading around Macroeconomic News Announcements — Evidence from the US Treasury market

Abstract

This paper investigates high frequency (HF) trading in the US Treasury market around major macroeconomic news announcements. Using a comprehensive tick-by-tick dataset, we identify HF trades and limit orders based on the speed of submission that is deemed beyond manual capacity. Our results show that while HF trading tends to narrow the spread after news announcements, it widens the spread and reduces the depth of limit order book during pre-announcement period amid information uncertainty. In addition, we show that HF trading tends to increase bond return volatility. Overall, HF trades are more informative than non-HF trades, but HF limit orders are less informative than non-HF limit orders. Finally, we provide evidence that HF trades enhance price efficiency during post-announcement period as information uncertainty resolves.

JEL classification: G10, G12, G14.

Keywords: High Frequency Trading; News Announcement; US Treasury Market; Market Liquidity; Market Volatility; Price Efficiency.

1 Introduction

Automated trading or high frequency (HF henceforth) trading, carried out by computer programs, has become prevalent in financial markets during the past decade[1]. As reported in financial media, trading records are routinely broken in recent years and millions of data messages are regularly sent per second to various trading venues [2]. This anecdotal evidence is coupled with the hard fact that trading latency in several 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; Hasbrouck, 2012; Scholtus and Van Djik, 2012; and Scholtus, Van Dijk and Frijns, 2012), trading and quoting activities regularly take place within a fraction of a second. At face value, there are several advantages from HF trading: it enables investors to react more quickly to new information and, as a result, improves market efficiency by quickly incorporating information into asset prices; it reduces monitoring cost; and it allows for fast processing of complex information and the submission of multiple orders at virtually the same time. Nonetheless, there are also 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.

The main advantage of HF trading is that computers, with their capacity to handle a large amount of information, are well positioned to execute multiple actions at a fast speed in response to information shocks. 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. Pre- and post-announcement periods represent very different informational environments. Pre-announcement periods are characterized by information uncertainty, whereas post-announcement periods are characterized by uncertainty resolution.

[1]As noted in Hendershott and Riordan (2009), Brogaard (2010), 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 article 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 article.

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

In this study, we focus on HF trading activities in the US Treasury market around major macroeconomic news announcements. We explore in detail the characteristics of HF trading during pre-announcement period and how it responds to information shocks during post-announcement period. The US Treasury market is open virtually around the clock with active trading activities during both pre- and post-announcement periods. More importantly, macroeconomic news announcements, the main drivers of Treasury security prices, are pre-scheduled and routinely monitored by market participants[3].

The data used in our study is obtained from BrokerTec, a major trading platform for on-the-run secondary US Treasury securities. The data contains tick-by-tick observations of transactions and limit order submissions, alternations, and cancellations for the 2-, 5- and 10-year notes. The sample period is from January 2004 to June 2007. 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. The procedure is similar in spirit 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 cancellation or execution, we classify HF trades and orders as those that are placed to the market at a speed deemed beyond manual capacity.

We explore the following three major issues. First, we investigate the patterns of HF trades and orders before and after macroeconomic news announcement. Second, we examine whether around these important events HF trades and orders improve or reduce market liquidity as well as whether they increase or decrease bond return volatility. Finally, we investigate the informativeness of

[3]There has been a vast literature examining 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. Balduzzi, Elton and Green (2001), Fleming and Remolona (1999), Green (2004) and Hoerdahl, Remolona and Valente (2012) 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 premia 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.

HF trades and orders, relative to their non-HF counterparts, as well as their role in enhancing or hindering price efficiency upon information arrival.

Our findings are summarized as follows. First, both HF trades and orders increase substantially following macroeconomic news announcements, consistent with theoretical implications of Foucault, Hombert and Rosu (2013) and Jonvanovic and Menkveld (2012). Both HF trades and limit orders also increase with the magnitude of announcement surprises. In addition, overall HF limit orders are placed at more aggressive positions in the order book relative to manual limit orders.

Second, our results indicate that the impact of HF activities on market liquidity depends on information environment. During pre-announcement period amid information uncertainty, HF trading overall has a significantly negative effect on market liquidity. HF trades significantly widens bid-ask spread and reduces depth at the best quote. HF limit orders not only does not narrow bid-ask spread but actually significantly reduces depth at the best quote. These findings are overall in line with the implications of recent theoretical models (Biais, Foucault and Moinas (2010); Martinez and Rosu, 2013). During post-announcement period as informational uncertainty is being resolved, the effect of HF activities appears to be beneficial to the market. Both HF trades and orders significantly narrow bid-ask spread but they also both significantly reduce depth at the best quote. These results are generally consistent those in Hendershott, Jones and Menkveld (2011) based on the US equity market. That is, the effect of HF trading on market liquidity appears to be beneficial to relatively small trades as the positive effect in smaller bid-ask spread offsets the negative effect in less depth at the best quotes.

Third, we find compelling evidence that HF trades and orders impact positively on subsequent bond return volatility. The effect of HF trades on bond return volatility is generally stronger than HF orders. Furthermore, the impact of HF trades on volatility is about three times larger than that of the non-HF trades. This evidence is in line with the implications of the theoretical models by Cartea and Panalva (2011) that high frequency trading increases price volatility.

Finally, the informativeness of HF activities and their impact of price efficiency also hinges on information environment. Our results show that HF trades is informative and improves price efficiency only during post-announcement periods when information uncertainty is resolved. In fact, during pre-announcement period amid information uncertainty, HF activities does not exhibit any significant effect on price efficiency. These findings are nicely tied up to those in the existing literature in helping our understanding of HF trading (see, for example, Brogaard, Hendershott and Riordan (2012); Hoffman (2012); Chaboud, Chiquoine, Hjalmarsson and Vega (2013)). In the spirit of Focault (2012), the effect of HF trading on price efficiency depends on the type of strategies used by HF traders rather than on the mere presence of those traders in the market.

The key of our findings is that the effect of HF trading on overall market quality largely hinges on the information environment. As information uncertainty resolves after news arrival, HF trading has 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. Our study joins a stream of recent contributions that have investigated the impact of HF trading in other important security markets (see, among others, Hendershott, Jones and Menkveld (2011); Hasbrouck and Saar (2011); Brogaard (2011a; 2011b; 2012); Hendershott and Riordan (2011);Egginton, van Ness and van Ness (2012); Boehmer, Fong and Wu (2012) for equity markets;Chaboud, Chiquoine, Hjalmarsson and Vega (2013) for foreign exchange markets). We extend the literature on two important respects: First, to the best of our knowledge, we are among the first study to investigate the behavior of HF trading in the US Treasury market. Second and most importantly, our empirical analysis is carried under a setting that explicitly takes into account of difference in information environment around public information arrival. With regards to this latter aspect, our work is closely related to recent theoretical studies that model the activity of HF traders. These studies emphasize that HF trading improves the traders' ability to respond to new information and thus improves informational efficiency in the market (Biais, Hombert and Weil (2010)). However, the activity of HF traders induces adverse selection in terms of the traders' speed of reaction to market events (Biais, Foucault and Moinas (2010); Javanovic and Menkveld, 2011) that is likely to persist in equilibrium since computers process information faster than manual traders (Biais, Foucault and

Moinas (2010)). The speed component of adverse selection is therefore necessary to explain certain empirical regularities from the world of high frequency trading (Foucault, Hombert and Rosu (2013)). 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 US equity market. However the Treasury market is characterized by different institutional and trading structures from the equity market. In addition, macroeconomic news play a more prominent role in the Treasury market as they are responsible for most of the sharpest changes in bon prices (Fleming and Remolona, 1999).

The reminder of the article is structured as follows: Section 2 introduces the dataset 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 is compiled to ensure that all important news items are included in our analysis. The full list contains 31 macroeconomic news items with 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, Bollerslev, Diebold and Vega (2003; 2007), and Pasquariello and Vega (2007), we compute the standardized announcement surprise for each news item as follows:

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

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. Table 1 also reports in the last two columns that around 27 percent of standardized news surprise are larger than one-standard deviation and around 5 percent are larger than 2 standard deviation. The variation in announcement surprises allows us to examine how HF trading responds to public information shock.

Data on US Treasury securities used in our study is obtained from BrokerTec, an interdealer Electronic Communication Network (ECN) platform of the US Treasury secondary market, owned by the largest interdealer brokerage (IDB) firm ICAP PLC. Prior to 1999, the majority of interdealer trading of US Treasuries occurred through interdealer brokers. Since then two major ECNs emerged: eSpeed and BrokerTec. Trading of on-the-run US Treasury securities has mostly, if not completely, migrated to electronic platforms (Mizrach and Neely, 2006; Fleming and Mizrach, 2009). According to Barclay, Hendershott and Kotz (2006), the electronic market accounts 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 Treasuries, while eSpeed has more active trading for the 30-year maturity. The BrokerTec data used in our study contains tick-by-tick observations of transactions as well as submissions and cancellations of limit orders for on-the-run 2-, 5- and 10-year US Treasury notes. It includes the time stamp of transactions and limit orders, the quantity entered and/or cancelled, 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 focus on HF trading activities around news announcements. We define the 15-minute interval prior to the announcement as pre-announcement period and the 15-minute interval following the announcement as post-announcement period. For all three 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 ($ million) at the end of each minute interval during both pre-announcement period and post-announcement period. We also compute the average trading volume (in $ million) and the average return volatility during pre-announcement period and post-announcement period. Trading volume is computed as the total dollar value of all trades, and return volatility is computed as the absolute value of 15-minute log return based on the mid-point of bid and ask.

Table 2 reports summary statistics of market activities around news announcements. During pre-announcement period, the 2-year note is, on average, the most liquid security followed by the 5-year and the 10-year notes. The 2-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 2-year note exhibits the lowest return volatility, whereas the 10-year note exhibits the highest return volatility. The higher volatility of the 10-year note is partly due to the fact that its tick size is twice that of 2- and 5-year notes. As expected, compared to pre-announcement period, all three notes of different maturities have lower spread, deeper depth, higher trading volume and higher return volatility during the post-announcement period. These results are consistent with findings in existing studies on the effect of macroeconomic news announcements in the US Treasury market (see, e.g., Fleming and Remolona 1997; 1999, Fleming and Piazzesi (2006), Mizrach and Neely (2008)).

Figure 1 plots the intraday patterns of market activities around news announcements. For the purpose of comparison, market activities at the same calendar time on non-announcement days are also plotted. The plots are for the 2-year note. The intraday patterns for other maturities are similar and thus not reported for brevity. 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. For announcement days, bid-ask spread starts to increase and peaks right before announcement. Trading volume spikes at the 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 is clear evidence that dealers withdraw their orders to avoid being picked off right before anticipated information arrival. This finding is consistent with evidence documented in, e.g., Fleming and Remolona, 1999, Jiang, Lo and Verdelhan (2011) etc. As public information arrives, spread reverts to pre-announcement level quickly. Trading volume gradually declines but stays at elevated level during the entire 15-minute post-announcement period. Return volatility exhibits similar patterns. Both depth at the best quotes and overall depth increase gradually after new announcement and are back almost to the normal level at the end of post-announcement window.

2.2 HF Trades and Orders: Identification and Summary Statistics

While automated trading occurs on the BrokerTec platform, the data from BrokerTec does not contain information about whether a trade or order is placed manually or through computers.[4] However, the data includes reference numbers that provide information on the timing of submission of an order and its subsequent execution, alteration, or cancellation. Using this piece of information, we identify HF trades and orders based on the reaction time to changes in market conditions. We classify those trades and orders as HF trades and orders if they are placed at a speed deemed to be beyond manual capacity. The procedure is similar in spirit proposed by Hasbrouck and Saar (2011) in identifying low latency orders. 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 change of the best quote on either side of the market (highest bid or lowest ask).

and 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 placement regardless of market condition changes;

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

[4]For an excellent review of the transition to ECN in the secondary US Treasury market, please refer to Mizrach and Neely (2005).

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

The above procedure is specifically designed to infer HF trades and orders on the basis of the speed at which they are executed or submitted to/withdrawn from the market. We exclude 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 order due to locked market.[5] In essence, the classification is mainly based up the reaction speed of the trades or orders to changes in market condition. As documented in existing studies (see, Scholtus and van Dijk (2012)), speed is the most important advantage of HF trading. [6]. Thus, our procedure captures the salient feature of HF trading. Following our classification, those trades and orders that are not classified as HF trades or orders are referred to as non-HF trades and orders. It is important to note that the above procedure is not perfect in identifying HF trades and orders per se. 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. Nevertheless, above 90% of HF orders identified comes from HFLO1 (Table 3) which are orders cancelled or modified less than one second of their placement regardless of market condition changes. These orders are unlikely come placed manually by dealers.

Table 3 reports summary statistics of HF trades and orders and non-HF trades and orders for all three notes during both pre-announcement period and post-announcement period. The results in

[5]On the BrokerTec platform, the percentages of 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 order due to locked market are 1.5%, 1% and 0.8%, respectively, for the 2-, 5- and 10-year notes.

[6]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"

Panel A show that HF trades identified in our study are only a fraction of non-HF trades in dollar volume. For the 2-year note, the average volume of HF trades and non-HF trades over the 15-minute pre-announcement period are, respectively, \$203 million and \$802 million. As expected, trading activity picks up substantially following news announcements. For the 2-year note, the average volume of HF trades and non-HF trades over the 15-minute post-announcement period are, respectively, \$525 million and \$2,000 million. These patterns are also observed for other maturities. The results in Panel B show that HF orders identified in our study are also only a fraction of non-HF orders in dollar volume. For the 2-year note, the average volume of HF orders (ALL HFLO) and non-HF trades over the 15-minute pre-announcement period are, respectively, \$6,239 million and \$17,217 million. Similarly, depth of limit order book also increases substantially following macroeconomic news announcements as a result of more order placements. For the 2-year note, the average volume of HF orders and non-HF orders over the 15-minute post-announcement period are, respectively, \$19,567 million and \$53,593 million. Again, similar patterns for HF versus non-HF orders are observed for other two maturities. Result sin Panel B also show that among the three different categories of HF orders identified in our study, limit orders that are cancelled or modified within one second of their placement, namely, HFLO1, account for the majority of HF orders. This further illustrates the advantage of HF trading in quickly cancelling or modifying orders when deemed necessary.

Figure 2 plots intraday patterns of HF trades and orders around macroeconomic news announcements for all three notes, again with comparisons versus HF trades and orders on non-announcement days. The plots show similar patterns of HF trading activities as overall trading volume as plotted in Figure 1. That is, on non-announcement days there are no obvious changes in HF trading activities. For announcement days, however, both the volume of trades and the volume of orders increase substantially following announcements. The volumes of HF trades and orders, while gradually declining, stay at elevated levels even toward the end of the 15-minute post-announcement interval. These findings are consistent with Jovanovic and Menkveld (2012) and Foucault, Hombert and Rosu (2013) who show that there are more HF trading activities when hard information arrives at the market.

As shown in exiting studies, HF trading activities have increased substantially and steadily over the past decades. As such, there is a time trend in most of the trading activity variables. For example, over our sample period the proportion of HF orders and trades has 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. Similar to Bamber (1987) and Ajinkya and Jain (1989), the abnormal volume of HF trades and orders are 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 5 no-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 no-announcement days, where $k = 1, \ldots, 5$. The matching to the same 1-minute interval over the past no-announcement days also helps to adjust for potential intraday seasonality in HF trading activities.

Similarly, abnormal non-HF trades and orders are defined as

$$NHFTR^{*}_{t,1M(i)} = NHFTR_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5} NHFTR^{NA}_{t-k,1M(i)} \tag{4}$$

$$NHFTLO^{*}_{t,1M(i)} = NHFLO_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5} NHFTR^{NA}_{t-K,1M(i)} \tag{5}$$

where $NHFTR_{t,1M(i)}$ and $NHFLO_{t,1M(i)}$ denote the dollar volume of non-HF trades and orders within the i^{th} 1-minute interval on any announcement day t, $NHFTR^{NA}_{t-k,1M(i)}$ and $NHFTR^{NA}_{t-K,1M(i)}$

denote the volume of non-HF trades and orders identified within i^{th} 1-minute interval and computed over the past k no-announcement days, where $k = 1, \ldots, 5$.

Panel C of Table 3 reports summary statistics of abnormal HF trades and orders and non-HF trades and orders for all three Treasury notes during both pre-announcement period and post-announcement period. We observe similar patterns for the differences between abnormal volume of HF trades and non-HF trades and between pre-announcement period and post-announcement period as those in Panel A. Interestingly, the abnormal volumes of HF and non-HF orders are often negative during pre-announcement period. This is consistent with the plots in Figure 2 where HF orders during pre-announcement period are often below normal levels, reflecting the effect of information uncertainty.

Next, we are interested in the average size and aggressiveness of HF trades and orders relative to non-HF trades and orders. 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 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 size of HF trades is in general smaller than that of non-HF trades. The pattern is consistent across different maturities and during both pre-announcement period and post-announcement. Nevertheless, the average size of HF orders is in general larger than that of non-HF orders. In particular, among all three categories of HF limit orders identified in our study, HFLO2, i.e., those orders at the best quote that are modified within one second of change of the best quote on either side of the market, are of the largest size.

The results in Panel B of Table 4 show that combining the three most aggressive positions (better than the best quote, at the best quote, and 1-tick behind the best quote), HF orders are overall more aggressive than non-HF orders. For all three maturities and during both pre-announcement period and post-announcement period, the percentage of three most aggressive positions combined for HF orders is consistently higher that for non-HF orders. In particular, there is a higher percentage of HF orders 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.

One of the focuses in our study is the announcement effect on HF trading. In the following, we investigate whether and how HF trading activities are affected by unexpected information shocks. For each news item, we divide all announcement days into three equal groups or terciles according to absolute announcement surprises $|SUR_{k,t}|$, and then compute the mean of HF trading volume and HF order volume in each tercile as well as the differences between top and bottom terciles. To avoid the effect of confounding events, we exclude days with multiple news announcements released at the same time. Table 5 reports the averages of mean HF trading volume and HF order volume in each tercile across all news items in Panel A. The statistical inference on the differences between top and bottom terciles are based on t-statistics calculated from standard errors across all news items. The results show that for all three maturities, the volume of HF trades and orders are positively related to the magnitude of announcement surprises. The differences between the volume of HF trades in the upper tercile and lower tercile of announcement surprises is statistically significantly positive at conventional level for all three maturities of notes. The differences in abnormal HF trades and orders are also significantly different. Nevertheless, we recognize that for days with larger announcement surprises, it is very likely that overall market activities also increase with heavier trading. To address this issue, we also calculate the percentage of HF trades and orders out of the total trades and orders during post-announcement period each day. The results in Panel A of Table 5 show that although there are significantly higher HF trades and orders on days with larger announcement surprises, the same can not be said for the percentages of HF trades and orders. While the percentage of HF orders is positively related to the magnitude of announcement surprises for all three notes, the relation is insignificant for the 10-year note. On the other hand, the percentage of HF trades has a negative relation with the magnitude of announcement surprises for the 2-year and 5-year notes, but a positive relation for the 10-year note. The negative relation for the 10-year note is significant at the 10% level. That is, for 2-year note, HF trades, while increasing with announcement surprises, increases less proportionally than the overall market trades.

A further interesting question is whether HF trading has predictive power of upcoming announcement surprises. That is, is HF trading prior to news announcement somehow related to subsequent news announcement surprise? To answer this question, we also compute the average volume of HF trades and HF orders in each tercile formed in Panel A. To improve the power of our analysis, we focus on HF trading activities over the 5-minute interval right before news announcement time. The results are reported in Panel B of Table 5. Overall, for both HF trades and orders and across different maturities, there is no clear patterns in the differences between high and low terciles of announcement surprises. This is evidence that neither HF trades nor HF orders have predictive power of upcoming announcement surprises.

3 Empirical Analysis

In our study, we are interested in the following issues pertinent to high frequency trading in the US Treasury market around macroeconomic news announcements: i) the effect of HF trades and orders on subsequent market liquidity, ii) the effect of HF trades and orders on subsequent market volatility, iii) the informativeness of HF trades and orders relative to non-HF trades and orders, as well as iv) the effect of HF trades and orders on price efficiency of US Treasury notes.

3.1 The Impact of HF Trading on Market Liquidity and Volatility

In this section, we examine the impact of HF trading activities on subsequent market liquidity and volatility. Theoretical literature has mixed implications about the impact of HF activities on market liquidity. Some studies argue that HF trading allows faster reaction to information and thus reduces monitoring cost and encourages liquidity provision. For example, Biais, Hombert and Weil (2010) point out that traders using algorithms could take advantage of the price reversal following negative liquidity shocks. Javanovic and Menveld (2011) suggest that HF trading participates more at times when hard information is relatively important. On the other hand, other studies point out that the ability by HF traders to react faster than slow traders may induce adverse selection. Biais, Foucault and Moinas (2011) suggest that small institutions which cannot afford the fixed cost in investment of HF trading would exit the market when HF trading becomes prevalent. Foucault, Hombert and Rosu (2012) suggest that the price impact of trade is larger when HF liquidity demanders are able to react to news faster. Empirical studies also document mixed evidence on the impact of HF trading activities on market liquidity. For example, as shown in Hendershot and Riordan (2013) and Brograad (2010), HF orders more likely come to the market and act as liquidity supplier when spread is wide. On the other hand, Hendershot, Jones and Menkveld (2011) and Hasbrouck and Saar (2011) show that higher intensity of HF activities is associated with narrower spread and higher overall depth. Hendershot, Jones and Menkveld (2011) find mixed evidence that as a result of HF trading, quoted depth drops but bid-ask spread narrows.

To understand the potential impact of HF trades and orders on market liquidity and volatility, 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 is available in our dataset, we are cautious about using ultra-high-frequency data because of the concerns of market microstructure effects. To mitigate the market microstructure effects, we perform our empirical analysis based on data aggregated over 1-minute interval, in line with existing empirical studies (see, e.g., Fleming and Remolona (1999); Balduzzi, Elton and Green (2001) etc). In our empirical analysis, we use bid-ask spread, depth at the best quotes, and depth behind the best quotes as three proxies of liquidity. Specifically, for each 1-minute interval, we compute the average bid-ask spread, average depth at the best quotes, and average depth behind the best quotes at the end of each 1-minute interval. We recognize that the US Treasury market has evolved over time with steady improvement in market liquidity, as measured in all three proxies. As such, in our analysis we construct measures of abnormal market liquidity around macroeconomic news announcements to adjust for potential time trend. The approach is similar to the construction of abnormal HF trades and orders in Section 2.2. Similar liquidity variables are also used in Fleming and Piazzesi (2006), Fleming and Mizrach (2009) and Mizrach and Neely (2008). That is, we define abnormal bid-ask spread, abnormal depth at the best quotes, and abnormal depth behind the best quotes as:

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

$$DPTH^{BHD*}_{t,1M(i)} \;=\; DPTH^{BHD}_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5} DPTH^{BHD,NA}_{t-k,1M(i)}, \tag{6}$$

where $SPRD_{t,1M(i)}$, $DPTH^{BST}_{t,1M(i)}$, and $DPTH^{BHD}_{t,1M(i)}$ denote, respectively, average bid-ask spread, the average depth at the best quotes, and average depth behind the best quotes at the end of the i^{th} 1-minute interval on announcement day t, $SPRD^{NA}_{t-k,1,M(i)}$, $DPTH^{BST,NA}_{t-k,1M(i)}$, and $DPTH^{BHD,NA}_{t-k,1M(i)}$ denote, respectively, average bid-ask spread at the end of the i^{th} 1-minute interval over the past k no-announcement days, where $k = 1, \ldots, 5$. Again, the matching to the same 1-minute interval over the past no-announcement days also helps to adjust for potential intraday seasonality in HF trading activities.

Return volatility is measured by the absolute value of log returns based on the mid-quotes in each 1-minute interval. The use of mid-quotes is to mitigate the effect of market microstructure noises, such as the 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 return volatility of the i^{th} 1-minute interval on announcement day t, and $VLTY^{NA}_{t-k,1M(i)}$ denotes return volatility of the i^{th} 1-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:

$$LIQ^{*}_{t,1M(t+1)} = a + \sum_{j=0}^{3} LIQ^{*}_{t,1M(t-j)} + U^{LIQ^*}_{t,1M(t+1)}, \tag{7}$$

$$VLTY^{*}_{t,1M(t+1)} = a + \sum_{j=0}^{3} VLTY^{*}_{t,1M(t-j)} + U^{VLTY^*}_{t,1M(t+1)}, \tag{8}$$

where $LIQ^{*}_{t,1M(t+1)}$ denotes one of the three measures of market liquidity as defined in Section 2.1 (i.e. $SPRD^{*}_{t,1M(i)}$, $DPTH^{BST*}_{t,1M(i)}$, $DPTH^{ALL*}_{t,1M(i)}$) and $VLTY^{*}_{t,1M(i)}$ denotes the measure of bond returns volatility as defined in Section 2.1. The lag of the above auto-regressions is determined based on Akaike information criterion. The estimation results remain qualitatively similar using 5 lags in the autregressive equation. 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

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

$$\begin{aligned} U^{LIQ^*}_{t,1M(i+1)} &= (\alpha_{2yr} D_{2yr} + \alpha_{5yr} D_{5yr} + \alpha_{10yr} D_{10yr}) \\ &\quad + \gamma TR^*_{t,1M(i)} + \varphi LO^*_{t,1M(i)} + \delta \left| SUR_{k,t} \right| + \epsilon_{t,1M(i+1)} \end{aligned} \tag{9}$$

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

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

To further disentangle the effects of high frequency trades and orders versus non-high frequency trades and orders on subsequent market liquidity and volatility, we estimate the following models with high frequency trades and orders and non-high frequency trades and orders as explanatory variables:

$$\begin{aligned} U^{LIQ^*}_{t,1M(i+1)} &= (\alpha_{2yr} D_{2yr} + \alpha_{5yr} D_{5yr} + \alpha_{10yr} D_{10yr}) \\ &\quad + \gamma_0 HFTR^*_{t,1M(i)} + \varphi_1 HFLO^*_{t,1M(i)} + \gamma_1 NHFTR^*_{t,1M(i)} + \varphi_0 NHFLO^*_{t,1M(i)} \\ &\quad + \delta \left| SUR_{k,t} \right| + \epsilon_{t,1M(i+1)} \end{aligned} \tag{11}$$

$$\begin{aligned} U^{VLTY^*}_{t,1M(i+1)} &= (\alpha_{2yr} D_{2yr} + \alpha_{5yr} D_{5yr} + \alpha_{10yr} D_{10yr}) \\ &\quad + \gamma_0 HFTR^*_{t,1M(i)} + \varphi_0 HFLO^*_{t,1M(i)} + \gamma_1 NHFTR^*_{t,1M(i)} + \varphi_1 NHFLO^*_{t,1M(i)} \\ &\quad + \delta \left| SUR_{k,t} \right| + \epsilon_{t,1M(i+1)} \end{aligned} \tag{12}$$

where 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 (NHF trades and limit orders) at $i - th$ 1-minute interval of day t, and D_{2yr} D_{5yr} D_{10yr} are maturity dummies. Again, we pool the observations for all three maturities in our estimation in order to improve the power of statistical inference.

The above models are estimated separately during the pre-announcement period and the post-announcement period. During the pre-announcement period, the announcement surprise is set as zero, i.e., $|SUR_{k,t}| = 0$. As noted in the introduction, one of the unique features in our empirical analysis is the contrast of informational environments during the periods preceding and following macroeconomic news announcements. This setting allows us to investigate the effect of HF trading during the pre-announcement period when information uncertainty is high and during the post-announcement period when information uncertainty is being resolved following the release of macroeconomic news.

Table 6 reports the estimation results of Equation (11) (under "Model 1") and Equation (13) (under "Model 2") for three different proxies of liquidity shocks. We first discuss the impact of overall trades and orders and then the respective effects of HF trades and orders versus non-HF trades and orders. Under normal market conditions, trades or market orders, as liquidity consumption, are expected to have a negative effect on market liquidity whereas limit orders, as liquidity provision, are expected to have a positive effect on market liquidity. That is, we expect that trades tend to widen bid-ask spread and reduce depth of the order book, whereas limit orders may potentially narrow bid-ask spread and tend to increase depth of the order book. The results under "Model 1" in Table 6 show that the empirical results on the effect of overall trades and orders on market liquidity are generally consistent with expectation. Specifically, overall trades are positively correlated with subsequent bid-ask spread, and negatively correlated with both subsequent depth at the best quote and depth behind the best quote. The only inconsistent sign is the effect of trades on depth behind the best quote during pre-announcement period. Nevertheless, the coefficient estimate is statistically insignificant. Also consistent with expectation, overall limit orders are negatively correlated with subsequent bid-ask spread, and positively correlated with both subsequent depth at the best quote and depth behind the best quote. The only inconsistent sign is the effect of limit orders on depth at the best quote during post-announcement period. Again, the coefficient estimate is statistically insignificant.

Disentangling the effects of HF trades and orders versus those of non-HF trades and orders, we observe different patterns for HF trading versus non-HF trading. The results under "Model 2" in Table 6 show that the effects of non-HF trades and orders are largely consistent with expectations. For instance, non-HF trades have a significantly negative relation with both depth at the best quote and the depth behind the depth quote, whereas non-HF orders have a significantly positive relation with both depth at the best quote and the depth behind the depth quote. These relations hold in both pre-announcement period and post-announcement period. The only deviation is the effect of non-HF limit orders on subsequent bid-ask spread where the coefficient is positive. However, it is significant only at the 10% critical level. In contrast to non-HF trades and orders, HF trades and orders have a rather complex relation with subsequent market liquidity. First of all, while HF trades have a significantly positive relation with subsequent bid-ask spread during the pre-announcement period, the relation is significantly negative during the post-announcement period. The coefficient of HF trades in the bid-ask spread regression is significantly positive at 1% critical level during pre-announcement period but is negative at 5% critical level during post-announcement period. Secondly, while, as expected, HF trades have a negative effect on depth at the best quote, our results show that 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 negative coefficient is significant at 1% critical level during both pre-announcement period and post-announcement period. Thirdly, HF trades have a positive effect on depth behind the best quote and the effect is significant at the 5% level during pre-announcement period. In the meantime, HF orders have no significant effect on depth behind the best quote during both pre-announcement period and post-announcement period.

The mixed effects of HF trades on bid-ask spread highlight the difference in informational environment between pre-announcement period and post-announcement period. During the pre-announcement period, dealers withhold their orders due to information uncertainty. As such, limit order books are thin and trades more likely have a larger impact in widening bid-ask spread. In addition, high frequency trades may be perceived as informed which will increase the level of adverse selection of other participants, leading to widening of bid-ask spread. The finding is in line with the implications of recent theoretical models that HF trading generates adverse selection because of the machines enhanced speed of information processing (Biais, Foucault and Moinas (2010) and the references therein). It also corroborates with finding in Kirilenko, Kyle, Samadi, and Tuzun (2011) show that high frequency trades consume liquidity during time of information uncertainty. On the other hand, during the post-announcement period, with the release of macroeconomic news and information uncertainty being resolved, HF limit orders may compete for the best position in the order bookn. One of the advantages of HF activites is the speed of placing orders in reaction to information arrival. As a result, the competition among HF orders may lead to immediate reduction in bid-ask spread. This finding is consistent with literature such as Hendershott, Jones and Menkveld (2011), Jovanovic and Menkveld (2011) and Hasbrouck and Saar (2011) that HF trading is associated with improvement in spread. 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 resolves with arrival of public information.

The finding that HF limit orders have a negative impact on depth at the best quote reveals certain unique characteristics of HF trading. We note that the finding of a negative effect of HF trades on depth at the best quote is not unique to the US Treasury market. In fact, using data from the US equity market, Hendershott, Jones and Menkveld (2011) show that algorithmic trading narrows spread in large cap stocks but in the meantime reduces quoted depth. The results during pre-announcement period are consistent with information uncertainty story. When HF orders are perceived as informed due to machine enhanced speed of information processing (Biais, Foucault and Moinas (2010) and the references therein), it generates adverse selection, causing other market participants to be more conservative when placing their orders. This generates a shift of more aggressive limit orders at the best quote towards less aggressive positions behind the best quote. During the post-announcement period, as a result of more HF orders, we see a similar drop in more aggressive limit orders at the best quote. Nevertheless, during post-announcement period, this shift is coupled with a significantly negative effect of HF orders on bid-ask spread as reported in Panel A of Table 6. This suggest that as information uncertainty is being resolved, HF orders tend to be aggressive in competing for best positions in the limit order book. As a result, HF orders help to reduce bid-ask spread. 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 existing literature that electronic trading has induced an overall reduction of transaction costs and, in particular, reduction of bid-ask spread.

Table 7 reports the estimation results of Equation (12) (under "Model 1") and Equation (14) (under "Model 2") for volatility regressions. Under normal market conditions, trades or market orders are expected to increase asset return volatility, while limit orders are expected to have a negative effect on asset return volatility. This is because trades more likely lead to price changes as well as widening of bid-ask spread, whereas limit orders helps to reduce price fluctuations through lower bid-ask spread and more depth of the limit order book. The results under "Model 1" in Table 7 show that during post-announcement period, consistent with expectation trades in general have a positive effect on market volatility, whereas orders in general have a negative effect on market volatility. However, during pre-announcement period, both trades and orders have a significantly positive effect on market volatility.

Turning to the respective effects of HF trades and orders versus non-HF trades and orders on market volatility, again we observe different patterns for HF trading versus non-HF trading. The results under "Model 2" in Table 7 show that the effects of non-HF trading on market volatility are generally consistent with expectation. Specifically, non-HF trades have a significantly positive effect on market volatility during both pre-announcement period and post-announcement period. Non-HF orders have a insignificant effect on market volatility during pre-announcement period, but a significantly negative effect on market volatility during post-announcement period. On the other hand, for HF trading, the signs of all four coefficient estimates are positive, except that the coefficient of HF orders is insignificant during post-announcement period. This suggests that HF trading generally has a positive effect on bond return volatility in the US Treasury. This finding mirrors those reported in existing studies focusing on other financial markets (see, e.g., Zhang (2010); Boehmer, Fong and Wu (2012) and the references therein). In particular, we note that the positive relation between overall orders and subsequent market volatility during pre-announcement period is largely driven by HF orders. During pre-announcement period, while non-HF orders have no significant effect on market volatility, HF orders have a significantly positive effect on market volatility at 1% critical level. This finding is consistent with earlier results on the effect of HF orders on market liquidity. As reported in Table 6, during pre-announcement period, HF orders have a positive, although insignificant, effect on bid-ask spread, and a significantly negative effect on depth at the best quote. As discussed earlier, these effects tend to contribution to increased variations in bond prices.

To summarize, our results show that non-HF trading has a distinctive effect on both market liquidity and market volatility compared to non-HF trading. Moreover, the effects of HF trading on market liquidity and market volatility vary under different market conditions in terms of information uncertainty. Our results show that during pre-announcement period with high information uncertainty, HF trading overall has a significantly negative effect on market liquidity. Consistent with expectation, HF trades widens bid-ask spread and reduces depth at the best quote. Contrary to expectation, HF orders not only does not significantly narrow bid-ask spread but also significantly reduces depth at the best quote. During post-announcement period as informational uncertainty is being resolved, the effect of HF trading on market liquidity is mixed. While both HF trades and orders significantly narrows, bid-ask spread, they also both have a significant effect in reducing depth at the best quote. These results are generally consistent those in Hendershott, Jones and Menkveld (2011) based on US equity market. That is, the effect of HF trading on market liquidity appears to be beneficial to relatively small trades as the positive effect in smaller bid-ask spread offsets the negative effect in less depth at the best quotes. Finally, our results how that HF trading in general tends to elevate market volatility, especially during per-announcement period. Altogether these findings suggest that HF activities have adverse impact on market liquidity when the market is uncertain to information. This naturally leads to the question of the role of HF trading on market efficiency. Although HF trading potentially facilitates incorporation of information into price on information arrives, its impact on price efficiency is undetermined when market is uncertain about information. These are the issues we are going to explore in the next section.

3.2 Informativeness of HF Trading and the Impact on Price Efficiency

In this section, we examine the informativeness of HF trades and orders and their impact on price efficiency of US Treasury securities. Theoretical literature in general suggests that HF trades act as informed traders. Foucault, Hombert and Rosu(2013) suggest that HF trades forecast price changes. Biais, Foucault and Moinas(2011) show that HF trades adversely select slow traders. These results are similar to empirical findings in Brogaard, Hendershott and Riordan (2011) and Hirschey (2013) in US equity market. Brogaard, Hendershott and Riordan (2011) find that HF trades are more informative while Hirschey (2013) finds that HF trades predicts non-HF trades. Looking at price efficiency, the theoretical predictions are mixed. Bias, Hombert and Weill (2010) and Martinez and Rosu (2011) find that HF traders facilitate diffusion of information and thus improve price efficiency. On the other hand, Zhang (2010) find that HF trading may increase stock price volatility and impede the market's ability to incorporate firm fundamentals into asset prices. Similarly, Hoffman (2013) find that in the presence of HF trading, slow traders may submit less aggressive limit order to avoid being picked off and thus leads to an efficiency loss.

Several approaches have been proposed in the literature in 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. More specifically, we divide the whole sample of trades and orders into HF trades and orders as well as non-HF trades and orders. We also perform robustness checks based on non-HF trades and orders identified using a 3-second cutoff point. That is, trades and orders that are submitted more than 1 second but less than 3 seconds following changes of market condition are categorized as neither HF trades and orders nor non-HF trades and orders.

To compare the informativeness of HF trades and orders versus non-HF trades and orders, we employ the test proposed by Kaniel and Liu (2006). Intuitively, the Kaniel and Liu (2006) test assesses the informativeness of trades and orders from the two samples by comparing the actual percentages of trades (or orders) placed in the 'right' side of the market or predicting the 'correct' direction of the market. Specifically, 'right' side or 'correct' direction of the market means that a buy (sell) order is followed by higher (lower) mid-quote in the future. If one sample has significantly larger number of quotes on the 'right' side of the market than expected, then the sample is relatively more informed than the other sample.

Formally, define P_{NHF} $(1 - P_{NHF})$ as the probability that a submitted trade is a non-HF trade (HF trade); n is the total number of times the quote midpoint is in the correct direction (that is above the one at submission for a buy order and below the one at submission for a sell order) following a submission of all trades (either a non-HF or a HF trade); and n_{NHF} the number of midpoint changes in the correct direction that follow non-HF orders. Under the null hypothesis, Kaniel and Liu (2006) show that out of these n quotes, n_{NHF} or more is followed by non-HF trade is given by

$$\phi = 1 - N\left[\frac{n_{NHF} - nP_{NHF}}{\sqrt{n \cdot P_{NHF}\left(1 - P_{NHF}\right)}}\right], \tag{13}$$

If the probability ϕ is lower (higher) than 5% (95%), we reject the null hypothesis of equal informativeness of HF trades and non-HF trades in favor of the alternative that non-HF (HF) trades are more informative. In implementing the test, we also divide the orders according to their size: small size (in the bottom tercile), medium size (in the middle tercile) and large size (in the top tercile). The test of equal informativeness of HF orders and non-HF orders is defined in a similar fashion.

Table 8 reports the results of the Kaniel and Liu (2006) test for all three notes and different groups of order sizes. The evidence in Table 8 strongly suggests that non-HF limit orders are more informative than their HF counterparts. Although the results are already clear for pre-announcement periods, across bond maturities and order sizes, 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 finding are consistent with Brogaard, Hendershott and Riordan

(2011)that HF orders tend to be subject to adverse selection. The results of the test applied to trades are less conclusive during the pre-announcement period. However, HF trades are found to be more informative than non-HF trades for all three notes during the post-announcement period when information uncertainty is being resolved. The results are in line with predictions of the theoretical literature (Foucault, Hombert and Rosu(2013) and Biais, Foucault and Moinas(2011)). These results are also similar to empirical findings in Brogaard, Hendershott and Riordan (2011) and Hirschey (2013). Robustness checks using a 3-second cutoff for non-HF trades further suggests that HF trades are more informative than their non-HF counterparts for all maturities.

We also perform the Kaniel and Liu (2006) test to compare the informativeness of HF buy trades (orders) versus HF sell trades (orders). The results of this additional exercise are reported in Table 9. The findings provide a clear picture suggesting that, over the sample period investigated in this paper, HF sell (trades) orders are statistically significantly more informative than HF buy (trades) orders. This result holds true for virtually all bond maturities (with slight weaker evidence for the 10-year note) and across all order sizes.

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). That is, we examine the potential effect of HF trading activities on subsequent price inefficiency, as measured by 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 either on the positive side or negative side imply return predictability or price inefficiency.

Our analysis is based on serial correlations of returns over 5-minute interval. Specially, over each 5-minute interval, we first compute tick-by-tick returns based on mid-point of quoted bid and ask at each transaction, and then compute first order autocorrelation of tick-by-tick returns. The use of returns based on mid-point of quoted bid and ask is to mitigate the effect of market microstructure noise, such as bid-ask bounces. Similar to the analysis on the effect of HF trading on market liquidity and volatility, we first examine the effect of overall trades and orders on price efficiency of US Treasury securities. That is, we first estimate the following equation:

$$\begin{aligned}\log|AC_{t,5M(i+1)}| &= (\alpha_{2yr}D_{2yr} + \alpha_{5yr}D_{5yr} + \alpha_{10yr}D_{10yr}) + \gamma_0 TR^*_{t,5M(i)} + \varphi_0 LO^*_{t,5M(i)} \\ &\quad +\beta_1 DPTH^{BST^*}_{t,5M(i)} + \beta_2 DPTH^{BHD^*}_{t,5M(i)} + \beta_3 SPRD^*_{t,5M(i)} \\ &\quad +\delta|SUR_{k,t}| + \varepsilon_{t,5M(i+1)}, \qquad (14)\end{aligned}$$

where $\log|\mathrm{AC}_{t,5M(i+1)}|$ denotes the log absolute autocorrelation of tick-by-tick returns computed from the mid-point of quoted bid and ask at each transaction over the $i+1^{th}$ 5-minute interval on announcement day t, $TR^*_{t,5M(i)}$ and $LO^*_{t,5M(i)}$ denote, respectively, the abnormal overall trades and orders over the i^{th} 5-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. We pool the observations for all three maturities in our estimation in order to improve the power of statistical inference.

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

$$\begin{aligned}\log|AC_{t,5M(i+1)}| &= (\alpha_{2yr}D_{2yr} + \alpha_{5yr}D_{5yr} + \alpha_{10yr}D_{10yr}) \\ &\quad +\gamma_0 HFTR^*_{t,5M(i)} + \varphi_0 HFLO^*_{t,5M(i)} + \gamma_1 NHFTR^*_{t,5M(i)} + \varphi_1 NHFLO^*_{t,5M(i)} \\ &\quad +\beta_1 DPTH^{BST^*}_{t,5M(i)} + \beta_2 DPTH^{BHD^*}_{t,5M(i)} + \beta_3 SPRD^*_{t,5M(i)} \\ &\quad +\delta|SUR_{k,t}| + \varepsilon_{t,5M(i+1)}, \qquad (15)\end{aligned}$$

where $\log|\mathrm{AC}_{t,5M(i+1)}|$ denotes the log absolute autocorrelation of quotes mid-price calculated from tick-by-tick returns based on mid-quote at each transaction over the next five-minute interval and the other variables are as discussed in Section 2. Again, we pool the observations for all three maturities in our estimation in order to improve the power of statistical inference. Similar to Section 3.1, we perform robustness checks using a 3-section cutoff to identify non-HF trades and orders.

The results of the estimation for the two specifications are reported in Table 10. Looking at the impact of overall trades and orders, we find that both trades and orders are statistically insignificant. Only overall trades are statistically significant at conventional level during the post-announcement period. That is, following news announcements overall trades reduce the serial correlation of the quote mid-point, hence improving price efficiency. Disentangling the effect of HF and non-HF activities, the results show that the improvement in price efficiency during the post-announcement period comes from HF trades. HF trades significantly reduce the serial correlation of mid-quote returns. These findings provide additional support to the results of the Kaniel and Liu (2006) test, reported in Table 8, that HF trades are more informative than non-HF trades during the post-announcement period. Overall our findings suggest that the informativeness of HF trades depend on the information environment. HF trades is informative and improves price efficiency only during periods when information uncertainty is resolved. In fact, in periods of high information uncertainty e.g. during the pre-announcement period, HF activities do not exhibit any significant effect on price efficiency. In addition, the informativeness of HF orders is generally lower than the one exhibited by the non-HF counterparts. Thus our results extend the findings in the recent empirical literature (see, for example, Brogaard, Hendershott and Riordan (2012); Chaboud, Chiquoine, Hjalmarsson and Vega (2013) and the references therein) which find that HF activities improves overall price efficiency. We show that the impact of HF activities on price efficiency depend on information environment: they improve price efficiency after resolution of information uncertainty. Our findings are in line with Foucault (2012), which find that the effect of HFT on prices depends on the type of strategies used by HF traders rather than on the mere presence of those traders in the market.

The control variables, $DPTH^{BST*}_{t,5M(i)}, DPTH^{BHD*}_{t,5M(i)}, SPRD^{*}_{t,5M(i)}$, used in Equation (14) are not all significant at conventional level. In fact, bid-ask spreads are only statistically significant during the post-announcement period while the depth of the order book at the best quote affect positively the serial correlation of the mid-quote returns during both pre- and post-announcement periods. The size of the announcement shocks is found to be significant over both specification and the sign of the parameter estimate suggest that larger announcement shocks improve the price efficiency.

4 Conclusion

This article investigates the activity of HF trading in the US Treasury market around macroeconomic news announcements. Using a comprehensive dataset 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 the speed of their placement, alteration or cancellation 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 non-HF limit orders. Specifically, the percentages of HF limit orders that are positioned better than the best quote and 1 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 a higher (subsequent) bond return volatility, their effect on market liquidity depends on information environment. Higher-than-normal HF activities in general have negative impact on liquidity before announcements, but they are associated with lower bid-ask spreads, especially during post-announcement periods as information uncertainty is resolved. Moreover, our results show that during post-announcement period when information uncertainty is resolved, HF limit orders are less informative than their HF counterpart but HF trades are more informativeness than non-HF trades. Finally, our results show that only HF trades has a significant effect in enhancing price efficiency during post-announcement period.

Reference

Ajinkya, B. B. and P. C. Jain, (1989), "The behavior of daily stock market trading volume," Journal of Accounting and Economics, 11, 331359.

Andersen, T., T. Bollerslev, F. Diebold and C. Vega, (2003) "Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange," American Economic Review 93, 38-62.

Andersen, T., T. Bollerslev, F.X. Diebold, and C. Vega (2007). "Real-Time Price Discovery in Global Stock, Bond and Foreign Exchange Markets," Journal of International Economics 73, 251-277.

Aite Group Report (2008), "U.S. Electronic Fixed Income Trading Platforms: The World Ain't Standing Still", Boston.

Balduzzi, P., E. Elton, and C. Green (2001), "Economic News and Bond Prices: Evidence From the U.S. Treasury Market," Journal of Financial and Quantitative Analysis 36, 523-543.

Bamber, L. S. (1987), "Unexpected earnings, firm size, and trading volume around quarterly earnings announcements," The Accounting Review, 62, 510 522.

Barclay, M., T. Hendershott, and K. Kotz (2006), "Automation versus Intermediation: Evidence from Treasuries Going Off the Run." Journal of Finance 61, 2395–2414.

Biais, B. and P. Wooley (2011), "High Frequency Trading", University of Toulouse and LSE, mimeo.

Biais, B., J. Hombert and P. Weill (2010), "Trading and Liquidity with Limited Cognition", NBER Working Paper No 16628.

Biais, B., T. Foucault and S. Moinas (2010), "Equilibrium Algorithmic Trading", HEC Paris, Working paper.

Boehmer, E., and E. Kelley, (2009), "Institutional Investors and the Informational Efficiency of Prices." Review of Financial Studies 22, 3563-3594.

Boehmer, E., Fong, K. and J. Wu (2012), "International Evidence on Algorithmic Trading", EDHEC Business School, Working paper.

Boni, L. and C. Leach (2002), "Supply Contraction and Trading Protocol: An Examination of Recent Changes in the U.S. Treasury Market," Journal of Money Credit and Banking 34, 740-762.

Boni, L. and C. Leach (2004), “Expandable limit order markets”, Journal of Financial Markets 7, 145-189.

Brandt, M. and K. Kavajecz (2004), “Price Discovery in the US Treasury Market: The Impact of Order Flow and Liquidity on the Yield Curve”, Journal of Finance 59, 2623-2654.

Brogaard, J. (2011), “High Frequency Trading and Market Quality”, Northwestern University, Working paper.

Brogaard, J. (2012a), “The Activity of High Frequency Traders”, Northwestern University, Working paper.

Brogaard, J. (2012b), “High Frequency Trading and Volatility”, Northwestern University, Working paper.

Brogaard, J., T. Hendershott and R. Riordan (2012), ”High Frequency Trading and Price Discovery”, Working paper, University of California at Berkeley

Chaboud, A., B. Chiquoine, E. Hjalmarsson and C. Vega (2013), “Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market”, Federal Reserve Board, Working paper.

Chlistalla, M. (2011), “High Frequency Trading. Better than Its Reputation?”, Working Paper, Deutsche Bank Research.

Clark, E. (2011), ‘The Algorithmic Hare and the Legal Tortoise: High Frequency Trading and the Challenge for Regulators”, Griffith University Working paper.

Cutler, D., J. Poterba, and L. Summers (1987), ‘What Moves Stock Prices”, NBER Working Paper N. 2538.

Dichev, I., K. Huang and Zhou, D. (2011), “The Dark Side of Trading”, Emory University, Working paper.

Egginton, J., B. van Ness and R. van Ness (2012), “Quote Stuffing”, University of Mississippi Working paper.

Fleming, M., and E. Remolona (1997), “What Moves the Bond Market?”, Federal Reserve Bank of New York Economic Policy Review 3, 31–50.

Fleming, M., and E. Remolona (1999), “Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information.” Journal of Finance 54, 1901-15.

Fleming, M. , and B. Mizrach (2009), “The Microstructure of a U.S. Treasury ECN: The BrokerTec Platform”, Federal Reserve Bank of New York, Working paper.

Foucault, T., J. Hombert and I. Rosu (2013), “News Trading and Speed”, HEC Paris Working paper.

Green, T. (2004), “Economic News and the Impact of Trading on Bond Prices”, Journal of Finance 59, 1201-1233.

Hasbrouck, J. (2012), “High-Frequency Quoting: Measurement, Detection and Interpretation”, New York University, Working paper.

Hasbrouck, J. and G. Saar (2011), “Low Latency Trading”, New York University, Working paper.

Hendershott, T., C. Jones and A. Menkveld (2011), “Does Algorithmic Trading Improves Liquidity?”, Journal of Finance 66, 1-33.

Hendershott, T. and R. Riordan (2013), “Algorithmic Trading and the Market for Liquidity,”, Journal of Financial and Quantitative Analysis, *forthcoming*.

Hirschey, N. (2013), “Do High-Frequency Traders Anticipate Buying and Selling Pressure?”, London Business School, Working paper.

Hoerdahl, P., E. Remolona and G. Valente (2012), “Risk Premia, Macroeconomic Fundamentals and the Yield Curve at 8:30AM”, BIS, Working paper.

Hoffman, P. (2012), “A Dynamic Limit-Order Market with Fast and Slow Traders”, European Central Bank Working paper.

Jiang, G. , I. Lo, and A. Verdelhan (2011): Information Shocks, Liquidity Shocks, Jumps, and Price Discovery: Evidence from the U. S. Treasury Market, Journal of Financial and Quantitative Analysis, 46, 527-551.

Jovanovic, B. and A. Menkveld (2011), “Middlemen in Limit-Order Markets”, New York University, Working paper.

Kaniel, R., and H. Liu (2006), “So what orders do informed traders use?” Journal of Business 79, 1867-1913.

Kite, S. (2010), “Algos Take Hold in Fixed-Income Markets”, Securities Technology Monitor, February.

Menkveld, A., A. Sarkar and M. van der Wel, (2012), “Customer Order Flow, Intermediaries, and Discovery of the Equilibrium Risk-free Rate”, Journal of Financial Quantitative Analysis forthcoming.

Martinez, V., and I. Rosu (2012), ”High Frequency Traders, News and Volatility”, Working Paper, HEC Paris.

Mizrach, B., and C. Neely (2008), “Information Shares in the U.S. Treasury Market,” Journal of Banking and Finance 32, 1221–33.

Mizrach, B. and C. Neely (2006), “The Microstructure of the U.S. Treasury.” In Encyclopedia of Complexity and Systems Science, R. A. Meyers (ed.), New York, NY: Springer-Verlag.

Moallemi, C. and M. Saglam (2011), “The Cost of Latency”, Working Paper, Columbia University.

Pasquariello, P. and C. Vega (2007), “Informed and Strategic Order Flow in the Bond Markets”, Review of Financial Studies 20, 1975-2019.

Safarik, D.(2005) Fixed Income Meets the Black Box. Wall Street and Technology, October.

SEC (2010). “Concept Release on Equity Market Structure.” Release No. 34-61358; File No. S7-02-10.

Scholtus, M. and D. van Dijk (2012), “High-frequency Technical Trading: The Importance of Speed,” Tinbergen Institute Discussion Paper No. 12-018/4.

Scholtus, M., D. van Dijk and B. Frijns (2012), “Speed, Algorithmic Trading, and Market Quality around Macroeconomic News Announcements,” Tinbergen Institute Discussion Paper No. 2012-121/III.

Zhang, F. (2010), “High-Frequency Trading, Stock Volatility, and Price Discovery”,Working Paper, Yale School of Management.

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 2, 2004 to June 30, 2007. Day denotes the weekday or day of the month for the announcement of each news item. Time denotes the time (eastern standard) of 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. N.A. indicates 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. On each announcement day, we obtain observations of quoted bid-ask spread (in ticks), depth of the order book at the best bid and ask quote ($ million), depth of the order book behind the best quote ($ million) at the end of each 1-minute interval, and trading volume ($ million) during each 1-minute interval. We then compute the average of these variables during the 15-minute pre- and 15-minute post-announcement periods, respectively. 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 15-minute post-announcement periods, where p_i is the mid-quote at the end of i^{th} 1-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 volume of HF and non-HF trades (Panel A), HF and non-HF limit orders (Panel B), as well as abnormal volume of HF and non-HF trades and limit orders (Panel C) over the 15-minute pre- and 15-minute post-announcement periods. HFTR denotes HF trades that are identified as market buy (sell) orders placed within a second of changes of the best quotes on either side of the market. HFLO1 denotes limit orders cancelled or modified within one second of its placement regardless of market condition changes. HFLO2 denotes limit orders at the best quote modified within one second of change of 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 changes of the best buy (sell) quote. Abnormal HF trades and orders are defined as in Equations (5) and (6) of the main text. NHFTR and NHFLO denote, respectively, non-HF trades and limit orders. The abnormal values of NHFTR and NHFLO are computed as in Equations (7) and (8) of 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 size of HF and non-HF trades and limit orders (Panel A) and the distribution of HF and non-HF limit orders placed in different positions of the limit order book (Panel B) over the 15-minute pre- and 15-minute post-announcement periods. For variable definitions, please refer to 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
Announcement Surprises and HF Trades and Limit Orders

For each news item, we sort all announcement days into terciles (H, M, and L) according to absolute announcement surprise ($|SUR_{k,t}|$). We then calculate the mean volume of HF trades and limit orders, as well as abnormal volume of HF trades and orders in each tercile. "% of All Trades" denotes the percentage of HF trading volume out of total trading volume and "% of All Orders" is the percentage of the volume of HF limit orders out of the total volume of all limit orders. This table reports the average of all variables in each tercile as well as the difference between the top and bottom terciles (H-L) across all news items during the 15-minute post-announcement period (Panel A) and the 5-minute pre-announcement period (Panel B), respectively. The t-statistics (unreported) for differences between the top and bottom terciles (H-L) are calculated based on standard errors across all news items. Days with multiple announcements are excluded. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. For variable definitions, please refer to Table 3.

	Trades		Limit Orders					Abnormal	
	HFTR ($ mil)	% of All Trades	HFLO1 ($ mil)	HFLO2 ($ mil)	HFLO3 ($ mil)	ALL HFLO ($ mil)	% of All Orders	HFTR	HFLO
Panel A: 15-minute Post-announcement Period									
2-year Note									
H	495.96	19.10%	20110.41	702.36	290.80	21103.57	27.36%	288.44	11875.02
M	438.49	19.84%	15954.95	691.94	287.70	16934.59	25.14%	238.73	8812.57
L	423.28	21.41%	12280.20	555.23	217.73	13053.17	23.55%	217.78	6304.47
H-L	72.68**	-2.31*	7830.21***	147.13***	73.07**	8050.40***	3.81**	70.66**	5570.55***
5-year Note									
H	474.28	26.37%	15228.73	633.27	191.26	16053.26	32.05%	243.98	9058.44
M	458.35	27.39%	14240.34	459.96	181.04	14881.34	31.41%	222.88	7678.33
L	409.04	26.85%	11923.34	473.62	146.79	12543.75	30.89%	179.03	6269.72
H-L	65.25**	-0.48	3305.39**	159.65*	44.47***	3509.51**	1.16*	64.96**	2788.72**
10-year Note									
H	420.39	25.35%	13464.06	404.36	144.05	14012.47	31.60%	228.34	8396.04
M	393.71	25.44%	13891.56	379.26	148.58	14419.40	32.73%	197.02	7871.75
L	355.10	25.17%	11124.91	400.60	122.08	11647.59	31.38%	157.77	6111.96
H-L	65.29**	0.18	2339.15*	3.76	21.97**	2364.87*	0.22	70.57**	2284.08**

	Trades		Limit Orders					Abnormal	
	HFTR ($ mil)	% of All Trades	HFLO1 ($ mil)	HFLO2 ($ mil)	HFLO3 ($ mil)	ALL HFLO ($ mil)	% of All Orders	HFTR	HFLO
Panel B: 5-minute Pre-Announcement Period									
2-year Note									
H	60.28	20.04%	1921.13	470.26	37.92	2429.31	32.99%	8.21	385.40
M	67.40	21.78%	1849.93	106.68	39.25	1995.86	28.64%	17.61	221.59
L	55.78	21.60%	1419.61	547.01	32.30	1998.92	32.64%	6.58	71.81
H-L	4.49	-1.56	501.52*	-76.75	5.62	430.39	0.35	1.63	313.59
5-year Note									
H	66.57	27.55%	1438.26	110.65	25.51	1574.42	31.58%	9.24	-49.39
M	68.47	28.52%	1667.46	104.11	23.73	1795.30	34.77%	10.44	-113.93
L	61.24	27.03%	1166.97	104.22	22.86	1294.05	30.97%	2.62	-284.45
H-L	5.33	0.52	271.29*	6.43	2.65	280.37*	0.61	6.61	235.06*
10-year Note									
H	54.58	25.58%	1295.64	100.53	20.67	1416.84	30.94%	5.93	5.24
M	55.70	25.42%	1573.33	88.13	21.04	1682.50	34.12%	4.05	158.41
L	51.87	25.83%	1151.79	101.50	18.08	1271.38	30.81%	-0.25	-124.39
H-L	2.71	-0.26	143.85	-0.97	2.59	145.46	0.13	6.17	129.63

Table 6
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: $\varepsilon^{LIQ*}_{t,1M(i+1)} = (\alpha_{2yr}D_{2yr} + \alpha_{5yr}D_{5yr} + \alpha_{10yr}D_{10yr}) + \varphi_0 HFLO^*_{t,1M(i)} + \gamma_0 HFTR^*_{t,1M(i)} + \varphi_1 NHFLO^*_{t,1M(i)} + \gamma_1 NHFTR^*_{t,1M(i)} + \delta\,|SUR_{k,t}| + \epsilon_{t,1M(i+1)}$, 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, please refer to 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 7
The Impact of HF Trades and Limit Orders on Subsequent Market Volatility

This table reports the results of the bond return volatility regression against HF trades and limit orders: $\varepsilon^{VLTY^*}_{t,1M(i+1)} = (\alpha_{2yr}D_{2yr}+\alpha_{5yr}D_{5yr}+\alpha_{10yr}D_{10yr})+\varphi_0 HFLO^*_{t,1M(i)}+\gamma_0 HFTR^*_{t,1M(i)}+\varphi_1 NHFLO^*_{t,1M(i)} + \gamma_1 NHFTR^*_{t,1M(i)} + \delta\,|SUR_{k,t}| + \epsilon_{t,1M(i+1)}$, where $\varepsilon^{VLTY^*}_{t,1M(i+1)}$ denotes the abnormal return volatility computed as in Equation (4) in the main text. The regressions is performed during the 15-minute pre- and 15-minute post-announcement periods, respectively. 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, abnormal return volatility is regressed against abnormal volume of total trades and limit orders, whereas in Model 2, abnormal return volatility is regressed against abnormal volume of HF and non-HF trades and limit orders. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. $Adj.R^2$ denotes the adjusted R^2. For variable definitions, please refer to 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 8
Informativeness of HF versus Non-HF Trades and Limit Orders

The table reports the results of the Kaniel and Liu (2006) test for the informativeness of HF trades and limit orders compared to non-HF trades and limit orders. A p-value close to 1 indicates informativeness of HF trades (limit orders) relative to non-HF trades (limit orders), whereas a p-value close to 0 indicates informativeness of non-HF trades (limit orders) relative to HF trades (limit orders). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, for the informativeness of HF trades (limit orders), whereas $^{+++}$,$^{++}$, and $^{+}$ denote significance at 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 9
Informativeness of HF Buy versus HF Sell Trades and Limit Orders

The table reports the results of the Kaniel and Liu (2006) test for the informativeness of HF buy versus HF sell trades and limit orders. A p-value close to 1 indicates informativeness of HF buy trades (limit orders) relative to HF sell trades (limit orders), whereas a p-value close to 0 indicates relative informativeness of HF sell trades (limit orders) relative to HF buy trades (limit orders). ***, **, 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^{+++}

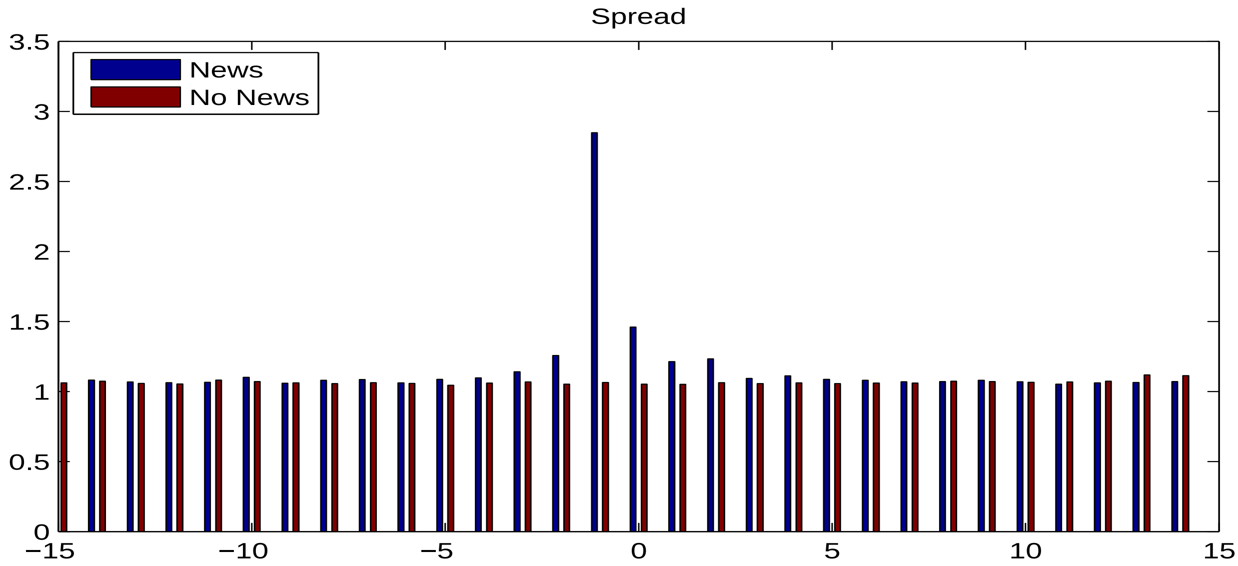
Table 10
The Impact of HF Trades and Limit Orders on Bond Price Efficiency

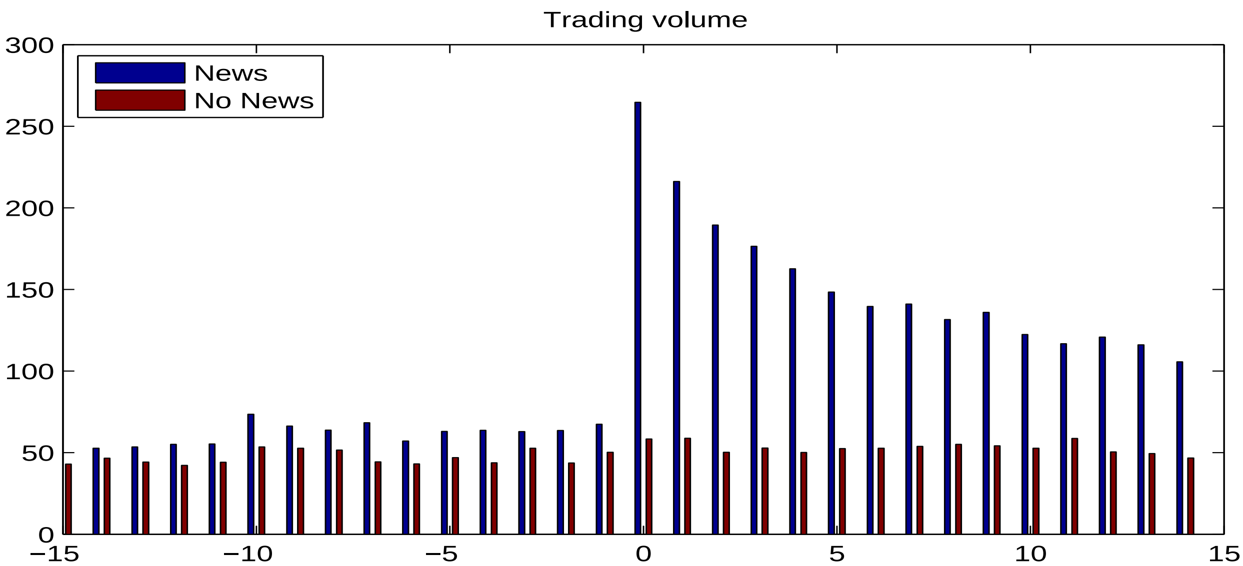
This table reports the results of the regression: $\log|AC_{t,5M(i+1)}| = (\alpha_{2yr}D_{2yr} + \alpha_{5yr}D_{5yr} + \alpha_{10yr}D_{10yr}) + \varphi_0 HFLO^*_{t,5M(i)} + \gamma_0 HFTR^*_{t,5M(i)} + \varphi_1 NHFLO^*_{t,5M(i)} + \gamma_1 NHFTR^*_{t,5M(i)} + \beta_1 DPTH^{BST^*}_{t,5M(i)} + \beta_2 DPTH^{BHD^*}_{t,5M(i)} + \beta_3 SPRD^*_{t,5M(i)} + \delta\,|SUR_{k,t}| + \epsilon_{t,5M(i+1)}$, where $\log|\text{AC}_{t,5M(i+1)}|)$ is the autocorrelation of tick-by-tick returns over each rolling 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 15-minute post-announcement periods, respectively. 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, $\log|\text{AC}_{t,5M(i+1)}|)$, a measure of price efficiency, is regressed against abnormal volume of total trades and limit orders, whereas in Model 2, $\log|\text{AC}_{t,5M(i+1)}|)$ is regressed against abnormal volume of HF and non-HF trades and limit orders. In all regressions, liquidity shocks are included as control variables. $SPRD^*_{t,5M(i)}, DPTH^{BST^*}_{t,5M(i)}$, and $DPTH^{BHD^*}_{t,5M(i)}$ denote, respectively, the abnormal bid-ask spread, the abnormal depth of the order book at best quote and the abnormal depth of the order book behind the best quote. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. $Adj.R^2$ denotes the adjusted R^2. For variable definitions, please refer to 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 1-minute interval during the 15-minute pre- and 15-minute post-announcement periods. Variables include bid-ask spread (in ticks), trading volume ($ mil), depth at best quote ($ mil), overall depth ($ mil), and return volatility is defined as the absolute value of the change of logarithmic mid-quote over each 1-minute interval ($\times 1,000$). For comparison, corresponding values of each variable at the same time on non-announcement days are also depicted.





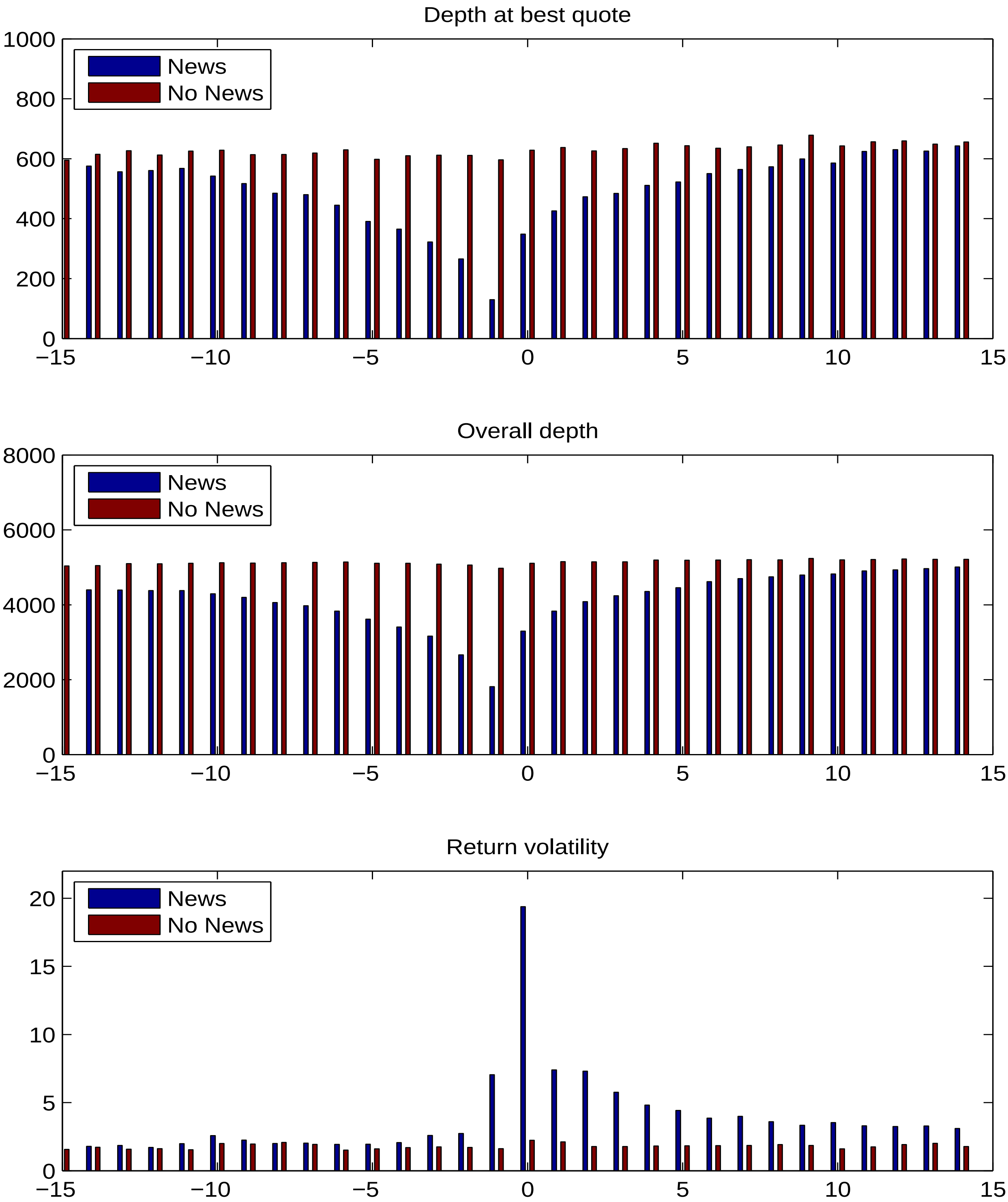

Depth at best quote
News
No News
Overall depth
News
No News
Return volatility
News
No News

FIGURE 2

Market Activities around News Announcements

This figure depicts the volume of HF trades and limit orders in each 1-minute interval during the 15-minute pre- and 15-minute post-announcement periods. For comparison, corresponding values of each variable at the same time on non-announcement days are also depicted.