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Abstract

This paper investigates high-frequency (HF) trading in the U.S. Treasury market around macroe-conomic news announcements. After identifying HF market and limit orders based on the speed of their placement alteration and cancellation deemed beyond manual ability, we use the introduction of the co-location facility (i-Cross) by BrokerTec as an exogenous instrument to assess the impact of HF trading on market liquidity and price efficiency. We find that HF trading increases after news announcements and improves price efficiency. However, it has a negative impact on liquidity, as it widens spreads before announcements and lowers depth of the order book after announcements.

Keywords: High-frequency Trading; Macroeconomic News Announcements; U.S. Treasury Market; Market Liquidity; Price Efficiency.

JEL Classification: G10, G12, G14.

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1 Introduction

High-frequency (HF henceforth) trading carried out by computers has become prevalent in financial markets during the past decade.[1] As reported in financial media, trading records have routinely been broken in recent years, and millions of data messages are regularly sent every second to various trading venues.[2] As a result of this market innovation, trading and quoting activities now regularly take place within a fraction of a second (e.g., Clark, 2011; Angel, Harris and Spatt, 2011; Hasbrouck, 2012; Hasbrouck and Saar, 2013).

One of the main advantages of trading at a very high speed is that computers, with the capacity to rapidly process a large amount of information, are well positioned to execute multiple actions in response to information arrival. Recent theoretical studies have explored the interplay between speed and information processing with mixed results. Some show that HF traders, who act as liquidity suppliers, are able to update quotes quickly after news arrival and thus reduce adverse selection risk (Jovanovic and Menkveld, 2011; and Hoffman, 2014). Others argue that HF traders are likely to place market orders to take advantage of their information-processing capacity and speed. These faster orders, which are based on updated information, pick off manual orders that react slowly to information arrival and, as a result, increase adverse selection and have a negative impact on market liquidity (Biais, Foucault and Moinas, 2015; Foucault, Hombert and Rosu, 2013; and Martinez and Rosu, 2013). Menkveld and Zoican (2015), extend these early results and show that increased trading speed allows HF traders who provide liquidity to update their quotes more quickly on incoming news, but it also allows more frequent trading with HF speculators ('bandits') that can hit the quotes of rivals faster on news. The net effect depends on the relative strengths of the two channels: market liquidity can decrease with trading speed around news events if HF liquidity

[1] In the spirit of SEC (2010), we broadly define, and use throughout this study, HF trading as the range of automated proprietary trading characterized by the following distinctive attributes: 1) the use of extraordinarily high-speed and sophisticated computer programs to generate, route and execute orders 2) the use of co-location services and individual data feeds offered by exchanges and others to minimize network and other time of latencies 3) very short time-frames for establishing and liquidating positions 4) the submission of numerous orders that are cancelled shortly after submission. See Chordia, Goyal, Lehmann and Saar (2013) and the studies included in the same special issue of the *Journal of Financial Markets*, O'Hara (2015).

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

suppliers' losses are large because of more frequent transactions with quicker HF speculators. As a result, HF liquidity suppliers will increase spreads to recover the increased adverse-selection cost. A corollary of this result is that HF traders, especially speculators, will engage in an arms race to outpace their rivals when processing information and hit quotes at a progressively higher speed.[3]

Despite the mounting theoretical literature and the ongoing policy debate on the role of computers in financial markets, there has been little empirical research on the impact of trading speed on liquidity and price efficiency especially around news announcements. We aim at filling this gap by investigating the effect of HF trading in the U.S. Treasury market before and after the release of macroeconomic news.

As one of the largest financial markets in the world, with daily trading volume nearly five times that of the U.S. equity market, the U.S. Treasury market has a unique market microstructure, operating as both an interdealer market and a limit order market with no intervention of market makers. It is open virtually around the clock, with active trading taking place over the year but especially around pre-scheduled macroeconomic news announcements. These announcements are the main drivers of Treasury security prices and they are arguably the most significant events in this market[4], unlike equity market where macroeconomic news announcements do not generate the largest price movements (Cutler, Poterba and Summers, 1989 and the references therein). Because of these important features, we argue that investigating pre-scheduled macroeconomic announcements in the U.S. Treasury market provides us with a unique setting to understand the relationship between HF trading, information arrival and market quality. Furthermore, the recent event occurred on October

[3]Budish, Cramton and Shim (2015) explore this specific issue and show that, because of the predominant market design characterized by a continuous limit-order book, HF trading naturally leads to mechanical deviations from the Law-of-One-Price even in the presence of symmetrically-observed public information.

[4]A vast literature has examined the effect of macroeconomic news announcements on the U.S. 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 (2018) point out that the price discovery process for bond prices mainly occurs around major macroeconomic news announcements. 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.

15th, 2014, where the U.S. Treasury secondary market experienced unusually high levels of volatility and a very rapid round-trip in prices minutes after a macroeconomic news release, remind us that the increasing presence of HF trading in the U.S. Treasury market may exert important effects on various dimensions of market quality (including liquidity and price efficiency) and the arrival of new information is also a key aspect that is likely to affect the intensity of HF trading and its impact on prices. Hence, the interplay between information and trading speed in the U.S. Treasury market is an important theme to explore to better understand "the evolution of [this] market and the implications for market structure and liquidity" (Joint Staff Report, 2015 p. 45).[5]

Recent studies have investigated the impact of HF trading on market quality without taking specifically into account the role of news (see, among others, Hendershott, Jones, and Menkveld, 2011; Hasbrouck and Saar, 2013; Boehmer, Fong and Wu, 2012; for the equity market, Chaboud, Chiquoine, Hjalmarsson and Vega, 2014; for foreign exchange markets).[6] One common finding of these studies is that HF trading generally improves both market liquidity and price efficiency.

Our study reassesses these early results and extends the existing literature along the following dimensions: First, we propose an empirical procedure aiming at identifying from publicly available data HF market and limit orders (HFMO and HFLO henceforth) based on their speed of submission/cancellation/amendment deemed to be beyond manual ability.[7] Second, we explore the patterns of HFMO and HFLO around news announcements and assess their impacts on market liquidity and price efficiency before and after these significant information events. Third, we take into account that HF trading, market liquidity and price efficiency could be endogenously determined. Hence, to meaningfully assess causality in this context, we use the introduction of a co-location service facility (i-Cross) by one of the major electronic brokers in the U.S. Treasury secondary

[5] See also Treasury Market Practice Group (2015) on automated trading in the U.S. Treasury market.

[6] Notable exceptions are represented by Brogaard, Hendershott and Riordan (2014) and Scholtus, van Dijk and Frijns (2014) who examine the impact of HF trading and trading speed on price discovery and market quality around macroeconomic news announcements in the US equity market, respectively.

[7] This identification procedure is in the spirit of the ones proposed by Scholtus and van Dijk (2012), Hasbrouck and Saar (2013) and Scholtus, van Dijk and Frijns (2014) who use the speed of order submissions/cancellations after changes in market conditions to identify empirical proxies for HF trading activities.

market (ICAP BrokerTec), as an exogenous instrument in the empirical analysis.[8] [9]. Our framework allows us to understand the role played by HFLO and explore both periods before and after news announcements (pre- and post-announcement periods, henceforth) differently from most of the existing contributions that focus only on trade patterns recorded after news announcements.

We find a host of interesting results: First, we find that although HFLO tend to flee the market before news announcements, both HFMO and HFLO increase substantially following news releases. The increment experienced by HF trading activity during post-announcement periods is significantly higher than the increment recorded for the overall trading activity during the same times. This is consistent with the predictions of theoretical models suggesting that the participation rate of HF traders increases with the arrival of news (Foucault, Hombert and Rosu, 2013; Hoffmann, 2014; Jovanovic and Menkveld, 2011; and Martinez and Rosu, 2013).

Second, we find that during pre-announcement periods, higher HF trading leads to larger bid-ask spreads (mostly due to the impact of HFMO) and larger depth behind the best quotes, while the depth at the best quote is virtually unaffected. However, during post-announcement periods, bid-ask spreads are mostly unaffected by higher HF trading while depth at and behind the best quotes decrease significantly. These findings suggest a picture that differs from the earlier view that increased HF trading narrows spreads, regardless of the information environment (Jovanovic and Menkveld, 2011; Hendershott, Jones and Menkveld, 2011; and Menkveld, 2013). Our results corroborate the theoretical findings for which HF trading has an overall negative impact on liquidity due to faster reaction to public information arrival (Biais, Foucault and Moinas, 2015; Foucault, Hombert and Rosu, 2013; and Martinez and Rosu, 2013). Furthermore, the impact of HF trading on depth can be rationalized in the spirit of Hendershott and Riordan (2013) who suggest that algorithmic traders react quickly to information arrival and use liquidity-demanding trades to execute

[8] i-Cross was introduced on the BrokerTec platform by ICAP at the end of 2007. According to ICAP, http://www.icap.com/what-makes-us-different/in-and-on-the-news/ /media/Files/I/Icap-Corp/pdfs/i-cross-sheet.pdf, "i-Cross is a premium connectivity service from ICAP that provides API customers with a low-latency, high-speed connection...., i-Cross facilitates the housing of customers' hardware at a common data facility with ICAP. i-Cross provides a co-location solution for U.S. Treasury trading via BrokerTec in North America (Secaucus, NJ)."

[9] The use of instruments when assessing causality is in line with the approaches followed by Hendershott, Jones and Menkveld (2011), Boehmer, Fong and Wu (2012) and the references therein.

limit orders upon news release. This leads to a reduction of depth at the best quotes as more limit orders are placed less aggressively during post-announcement periods to avoid being picked off.

Third, our analysis shows that, during both pre- and post-announcement periods, HF trading improves price efficiency, measured by the absolute serial correlation of returns (Boehmer and Kelley, 2009; Boehmer, Fong and Wu, 2012). The positive impact on price efficiency mainly comes from HFMO, especially during post-announcement periods. Our results lend support to the predictions of theoretical studies, such as Martinez and Rosu (2013), that HFMO quickly incorporate information into prices upon information arrival and they are also consistent with the empirical evidence documented by Chaboud, Chiquoine, Hjalmarsson and Vega (2014) and Brogaard, Hendershott and Riordan (2014) who show that HF trading improves price efficiency and the improvement mainly comes from HFMO. However, in addition to this empirical evidence, we provide further evidence suggesting that HFLO have also a positive and significant impact on price efficiency, especially after news announcements.

Our study is closely related to Brogaard, Hendershott and Riordan (2014), Scholtus, van Dijk and Frijns (2014) and Chordia, Green and Kottimukkalur (2015) who explore the effect of HF trading on price discovery, liquidity, volatility and profitability in the US equity and futures market around macroeconomic news announcements. Another related paper is Brogaard, Hagstromer, Norden and Ryordan (2015) who investigate the optional co-location upgrade available at NASDAQ OMX Stockholm to assess the impact of changes in trading speed to market liquidity. Our analysis differs from these studies in several important respects. First, our study investigates HF trading in the U.S. Treasury market that is considerably different in size and structure from both the US and Swedish equity markets. In fact, apart from the obvious institutional differences (Fleming and Remolona, 1999), information that is relevant to Treasury prices originates nearly exclusively from macroeconomic fundamentals, unlike the equity market where information "comes from many sources and in many forms" (Brogaard, Hendershott and Riordan (2014, p. 27). Hence, assessing the impact of HF trading around macroeconomic news announcements in the U.S. Treasury market allows us to identify, in a more accurate way, periods of information uncertainty from periods where such uncertainty is resolved. Furthermore, in comparison with the earlier studies, we explore a larger panel of macroeconomic variables, spanning a total of 31 major US news announcements.[10] Second, in the spirit of Brogaard, Hagstromer, Norden and Ryordan (2015) we also use the introduction of a co-location facility to assess the causality link between speed and market liquidity (and price efficiency). However, differently from this and the earlier studies, we use the introduction of the co-location facility as an exogenous instrument in the empirical investigation and we extend the analysis to the full sample period not limiting ourselves to a smaller window around the co-location event. Third, our proposed identification procedure allows us to distinguish the effect of HFMO from the one exerted by HFLO on the same variables of interest. This richer characterization, allows us to uncover important patterns that are not recorded in studies that use aggregate measures of HF trading activity.

The remainder of the paper is structured as follows. Section 2 introduces the data set used in our analysis and describes in detail the empirical procedure for identifying HFMO and HFLO. Section 3 presents the main empirical results. Section 4 discusses a set of robustness checks and extensions, and a final section concludes.

2 Data

2.1 Summary Statistics

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

[10]Brogaard, Hendershott and Riordan (2014), Scholtus, van Dijk and Frijns (2014) and Chordia, Green and Kottimukkalur (2015) investigate 8, 20 and 27 macroeconomic announcements, respectively.

standardized announcement surprises for each news item as follows:

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

where $A_{k,t}$ is the actual value of announcement $k = 1, 2, ..., K$ on day $t = 1, 2, ..., T$, $E_{k,t}$ is the median forecast of the announcement k prevailing on the announcement day, and σ_k is the time-series standard deviation of $(A_{k,t} - E_{k,t})$. The standardized announcement surprise is used in our study as a measure of unexpected information shock.[11]

The data on U.S. Treasury securities used in our study are obtained from BrokerTec, an interdealer Electronic Communication Network (ECN) platform of the U.S. Treasury secondary market, owned by the largest interdealer brokerage firm, ICAP PLC. [12] The BrokerTec data used in our study contain tick-by-tick observations of transactions as well as limit order submissions and subsequent alterations and cancellations for on-the-run 2-, 5- and 10-year U.S. Treasury notes. It includes the time stamp of transactions and limit order submissions as well as their subsequent alterations, the quantity entered and/or cancelled, the side of the market involved and, in the case of a transaction, an aggressor indicator indicating whether the transaction is buyer- or seller-initiated. The sample period is from January 3, 2006 to December 29, 2011.

In our empirical analysis, we define pre- and post-announcement periods as the 15-minute interval prior to and following the announcement, respectively. For all three maturities, we first compute the average relative bid-ask spread and the average depth of the limit order book, both at the best quotes and behind the best quotes ($ million) at the end of each 1-minute interval. These variables are then averaged each day within the pre-announcement and post-announcement

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

[12]Prior to 1999, the majority of interdealer trading of U.S. Treasuries occurred through interdealer brokers. Since then, two major ECNs have emerged: eSpeed and BrokerTec. Trading of on-the-run U.S. Treasury securities has mostly, if not completely, migrated to electronic platforms. According to Barclay, Hendershott and Kotz (2006), the electronic market accounted for 75.2%, 83.5% and 84.5% of the trading of the 2-, 5- and 10-year notes, respectively, during the period from January 2001 to November 2002. By the end of 2004, over 95% of interdealer trading of active issues occurred on electronic platforms. BrokerTec is more active in the trading of 2-, 3-, 5- and 10-year notes, while eSpeed is more active in the trading of 30-year bonds. For an comprehensive description of the transition to ECNs in the secondary U.S. Treasury market, see Mizrach and Neely (2006).

periods. The summary statistics of the variables around announcements are reported in Table 2.

Figure 1 plots the patterns of the liquidity variables around news announcements for the 2-year note, as the patterns for other maturities are similar, and thus are not reported for the sake of brevity. For the purpose of comparison, we also report the value recorded, for the same variables, on days without announcements. The relative spread on announcement days peaks right before the announcement and both depth at the best quotes and depth behind the best quotes drop substantially before announcement time. The reduction is more pronounced for depth at the best quotes. This indicates that dealers withdraw their orders to avoid being picked off right before public information arrival. This finding is consistent with the evidence from an earlier sample period documented in Fleming and Remolona (1999) and Jiang, Lo and Verdelhan (2011). After news announcements, the relative spread reverts quickly to the pre-announcement level. Both depth at the best quotes and behind the best quotes increase gradually after news releases and return to levels comparable with the ones of non-announcement days.

2.2 The Empirical Identification of HFMO and HFLO

The BrokerTec data include reference numbers that provide information on the timing of an order submission and its subsequent execution, alteration or cancellation. We use this information and identify HF market and limit orders on the basis of the speed of submission, cancellation and amendment deemed beyond manual ability. Specifically, we identify HFMO as market orders (buy or sell) that are placed within a second of a change in the best quote on either side of the market (highest bid or lowest ask). We identify HFLO as follows:

- Limit orders (buy or sell) that are cancelled or modified within one second of their placements, regardless of changes in the best quote on either side of the market (HFLO1);

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

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

The criteria mentioned above are specifically designed to use speed as differentiating factor to separate HF from non-HF orders.[13] Furthermore, the empirical procedure is also similar in spirit to the one proposed by Hasbrouck and Saar (2013) to identify low latency orders. Nonetheless, we recognize our identification procedure is far from perfect. In fact, non-HF orders can be mistakenly identified as HF orders if non-HF orders are placed earlier but arrive within one second of any change in market conditions. Similarly, some HF orders may also be classified as non-HF orders if they are recorded beyond one second of any change in market conditions. Although limitations and potential misclassifications are intrinsic in any empirical identification procedure, we also note that most of the HFLO we identify are orders cancelled or modified within one second of their placement, regardless of changes in the best quote on either side of the market. Because of this low latency, these orders are highly unlikely to be placed manually and therefore allow us to capture the speed aspect of HF trading that we are especially interested in in this empirical investigation.[14] One may also argue that this identification could be purely mechanical as, around macroeconomic announcements, more trading activity would make orders to cluster together around the same time, including manual orders. Although we cannot rule out that this possibility a priori, we have preliminarily tested whether the percentage share of empirically-identified HF orders is higher on announcement days than on non-announcement days. The results of this exercise, discussed in detail in Section 4.1, show clearly that our procedure generates a comparable proportion of HF orders on both announcement and non-announcement days.

Figure 2 shows the ratio of total monthly volume of HFMO and HFLO to the total volume of all market and limit orders submitted over the same period. This ratio increases substantially over

[13]In our empirical analysis, we exclude those orders deleted by the central system, orders deleted by the proxy, stop orders, and passive orders that are automatically converted by the system to aggressive orders due to a locked market. On the BrokerTec platform, the percentages of these types of orders account for 1.5%, 1% and 0.8% of the total number of orders for the 2-, 5- and 10-year notes, respectively.

[14]If a full-second threshold is considered too large to characterize recent HF trading activity, our results are confirmed even with a smaller time-threshold of 200ms, which is clearly beyond the ability of manual traders. See Section 4.3 for further details.

the sample period from 24% in the first quarter of 2006 to 40% in the last quarter of 2011. This denotes a substantial increment in HF trading in the U.S. Treasury market during the sample period. Table 3 reports summary statistics of HFMO and HFLO and overall market and limit orders for all three notes during both pre-announcement periods and post-announcement periods. The results in Panel A show that the identified HFLO are around one-third of all limit orders for each of the three maturities. Both HFLO and all limit orders more than double after news announcements. However, the increment of HFLO is larger than the one exhibited by all limit orders. The daily average ratio of post-announcement HFLO volume relative to their pre-announcement level is significantly larger than that of all limit order volume. Panel B shows that the HFMO identified are around one-quarter of the overall trading volume for all three maturities. Similar to the case of HFLO, HFMO increase after announcements and the daily average ratio of HFMO volume during post-announcement periods relative to the pre-announcement level is significantly larger than that of the overall volume of all market orders.

Figure 3 shows the minute-by-minute volume of HFMO and HFLO for the 2-year note before and after announcements news on announcement and non-announcement days. The patterns for the 5- and 10-year notes are similar and thus not reported for brevity. The volume of both HFMO and HFLO spikes up following macroeconomic news releases and drops subsequently. Nonetheless, the volume of HFMO and HFLO on announcement days remains higher than on non-announcement days at the end of the post-announcement periods. Together, these findings suggest that HF trading responds to the arrival of public information and confirm the predictions of the theoretical literature. We assess these initial findings by computing abnormal volumes of HFMO and HFLO on announcement days in the spirit of Bamber (1987) and Ajinkya and Jain (1989). More specifically, we construct the abnormal volume of HFMO and HFLO as the dollar volume of HFMO and HFLO in excess of the average dollar volume recorded over the past five non-announcement days:

$$HFMO^{*}_{t,1M(j)} = HFMO_{t,1M(j)} - \frac{1}{5}\sum_{n=1}^{5} HFMO^{NA}_{t-n,1M(j)}, \quad (2)$$

$$HFLO^{*}_{t,1M(j)} = HFLO_{t,1M(j)} - \frac{1}{5}\sum_{n=1}^{5} HFLO^{NA}_{t-n,1M(j)}, \quad (3)$$

where $HFMO_{t,1M(j)}$ and $HFLO_{t,1M(j)}$ denote the dollar volume of HFMO and HFLO recorded within the j^{th} 1-minute interval of the announcement day t, respectively with $j = -15, ..., 15$. Similarly, $HFMO^{NA}_{t-n,1M(j)}$ and $HFLO^{NA}_{t-n,1M(j)}$ denote the dollar volume of HFMO and HFLO recorded during the same 1-minute interval over the past n non-announcement days, where $n = 1, \ldots, 5$. The results of this exercise are reported in Panel C of Table 3. $HFMO^{*}$ and $HFLO^{*}$ are negative in most cases during pre-announcement periods and positive during post-announcement periods. This indicates that HFMO and HFLO flee the market before announcements, compared with non-announcement days, and they are submitted more frequently after the arrival of new information.

3 Empirical Analysis

3.1 HF Trading and Endogeneity

The main goal of our analysis is to investigate the effect of HF trading on liquidity and price efficiency around macroeconomic news announcements. More specifically, we build upon Hendershott, Jones and Menkveld (2011) and formally test the relationship between our proposed measures of HF trading and variables capturing market liquidity and price efficiency during the pre- and post-announcement periods as follows:[15]

$$X^{*}_{i,t,1M(j)} = \delta_{0i} + \delta_{1i,t,1M(j)} + \delta_{2i} HF^{*}_{i,t,1M(j)} + \delta^{'}_{3i} C_{t,1M(j)} + \eta_{i,t,1M(j)}, \quad (4)$$

[15]Consistent with the notation introduced in Equations (2) and (3), we denote throughout the paper with an asterisk all variables that are constructed as the difference between their value recorded on the j-th minute during the announcement day t and their average value computed during the same minute interval over the past five non-announcement days.

where $X^*_{i,t,1M(j)}$ denotes a measure of liquidity or price efficiency computed for the Treasury note i, $HF^*_{i,t,1M(j)}$ denotes a measure of HF trading computed for the for the Treasury note i, δ_{0i} captures bond-specific fixed effects, $\delta_{1i,t,1M(j)}$ is a minute-of-the-interval dummy variable capturing any residual seasonal patterns around announcement times, and $C_{t,1M(j)}$ is a set of variables controlling for market conditions. In this paper, the control variables comprise the absolute change in mid-quote, a proxy for volatility, and the term spread, defined as the difference between the yields of the 2-year note and the 10-year note (Fama and French, 1993; Campbell and Ammer, 1993; and Li, Wang, Wu and He, 2009).

As emphasized in recent studies, HF trading and market liquidity are endogenously determined (Hendershott, Jones and Menkveld, 2011; and Boehmer, Fong and Wu, 2012). Contemporaneous changes in HF trading and market liquidity could be due to either HF trading reacting to changes in market liquidity or to HF trading causing changes to market liquidity. Similarly, the relationship between HF trading and price efficiency may be subject to the same endogeneity problem.

In order to meaningfully assess the causal relationship between the variables of interest, we follow Boehmer, Fong and Wu (2012) and use the introduction of a co-location facility on the BrokerTec platform by ICAP (labelled i-Cross) at the end of 2007 as an exogenous instrument in our empirical investigation. i-Cross hosts customers' equipment and network connectivity within two of Equinix's Internet Business Exchange centers in the New York region[16], which enables a low latency data exchange between HF trading firms and the BrokerTec platform. In the official press release, it is explicitly indicated that the benefits of i-Cross include "High-speed, low-latency connection" and "faster time to market $\cdots$ for a range of fixed income products" (ICAP, November 7th, 2007). The introduction of i-Cross is likely to provide HF trading firms with even faster access to the BrokerTec platform and the ability to react faster to changes in market conditions or the

[16]According to the co-location service brochure of Equinix (Equinix, 2014, "Are your digital assets mission-critical?"(available at http://www.equinix.com/resources/infopapers/equinix-colocation-brochure/), International Business Exchange™ (IBX) data centers are built to have "direct access to the data distribution system to allow quickly deployable interconnections" and their infrastructure "minimizes interference problems and permits rapid provisioning of bandwidth from a large choice of participating providers." (Equinix, 2014, page 2)

arrival of new information. We explore the impact of the introduction of i-Cross as follows:

$$M^*_{i,t,1M(j)} = \alpha_{0i} + \alpha_{1i,t,1M(j)} + \alpha_{2i}time + \alpha_{3i}D^{crisis}_t + \alpha_{4i}Q_t + \varepsilon_{i,t,1M(j)}, \tag{5}$$

where $M^*_{i,t,1M(j)}$ denotes the relevant dependent variable, for example, total HF trading, HFLO, HFMO, volatility or the term spread; Q_t is a dummy variable capturing the introduction of i-Cross that equals 1 after January 1, 2008 and zero otherwise. As in Equation (4), α_{0i} denotes maturity-specific fixed effect; and $\alpha_{1i,t,1M(j)}$ is a dummy variable capturing residual seasonal patterns around announcements, $time$ denotes a logarithmic time-trend[17] and D^{crisis}_t is a dummy variable that captures the effects of the 2007-2009 financial crisis.[18] Table 4 reports the estimate of α_{4i} for each of the regressions. The results show a clear impact of the introduction of i-Cross on HF trading as both HFMO and HFLO increase after the inception of the co-location facility, even after taking into account a secular time trend and the recent financial crisis. The result holds true for all notes and the effect is larger in magnitude for the 5- and 10-year notes. On the other hand, there is no consistent relationship between the introduction of i-Cross and volatility and term spread.

Following the results reported in Table 4, we then adopt an instrumental variable approach, beginning with the estimation of the following first-stage regression:

$$HF^*_{i,t,1M(j)} = \beta_{0i} + \beta_{1i,t,1M(j)} + \beta_{2i}time + \beta_{3i}D^{crisis}_t + \beta_{4i}Q_t + \beta^{'}_{i5}C_{t,1M(j)} + u_{i,t,1M(j)}, \tag{6}$$

where $HF^*_{i,t,1M(j)}$ is the dependent variable capturing HF trading, $C_{t,1M(j)}$ denotes the set of control variables including volatility, term spread and the standardized announcement surprise during post-announcement periods and the remaining variables are defined as in Equation (5).

The fitted values of $HF^*_{i,t,1M(j)}$ from Equation (6) are used in the second stage for the estimation of the following equation:

$$X^*_{i,t,1M(j)} = d_{0i} + d_{1i,t,1M(j)} + d_{2i}\widehat{HF}^*_{i,t,1M(j)} + d^{'}_{3i}C_{t,1M(j)} + e_{i,t,1M(j)}, \tag{7}$$

where $\widehat{HF}^*_{i,t,1M(j)}$ is the fitted value from Equation (6) and $X^*_{i,t,1M(j)}$ denotes the relevant measure of liquidity, i.e., relative bid-ask spread, depth at the best quotes and depth behind the best quotes,

[17]We include a time trend to capture the secular pattern exhibited by HF trading over the sample period, as documented in Figure 2.

[18]We identified the period associated with the financial crisis following the NBER business cycle contraction dates.

used in early studies in similar contexts (see, Fleming and Piazzesi, 2006; Mizrach and Neely, 2008; and Fleming and Mizrach, 2009).[19] During post-announcement periods, we also include the absolute value of the standardized announcement surprises to explore whether the effect of HF trading on market liquidity depends upon the size of the news surprise:

$$X^*_{i,t,1M(j)} = d_{0i} + d_{1i,t,1M(j)} + d_{2i}\widehat{HF}^*_{i,t,1M(j)} + \rho_i^X \widehat{HF}^*_{i,t,1M(j)} \times |SUR_t| + d'_{3i}C_{t,1M(j)} + e_{i,t,1M(j)}, \tag{8}$$

where $|SUR_t|$ is a vector containing the absolute value of standardized announcement surprises, as defined in Equation (1), for all macroeconomic variables.

We assess the impact of HF trading on price efficiency in a similar fashion. More specifically we use the absolute value of the serial correlation coefficient of Treasury returns as a proxy for price inefficiency (Boehmer and Kelley, 2009; Boehmer, Fong and Wu, 2012).[20] [21] If Treasury prices follow a random walk, the serial correlations of their returns should be equal to zero at all horizons. Deviations from zero suggest evidence of price inefficiency. We estimate:

$$|AC_{i,t,5M(j)}| = \gamma_{0i} + \gamma_{1i,t,5M(j)} + \gamma_{2i}\widehat{HF}^*_{i,t,5M(j)} + \gamma'_{3i}C_{t,5M(j)} + \psi_{i,t,5M(j)}, \tag{9}$$

where $|AC_{i,t,5M(j)}|$ is the absolute value of the first-order serial correlation coefficient of the Treasury note i's log returns computed using the prevailing mid-quote at each transaction over a five-minute interval. The remaining variables are as in Equation (7) but computed over five-minute intervals.[22] As in Equation (8), during post-announcement periods, the absolute value of announce-

[19]The control variables $C_{t,1M(j)}$ in the estimation also include lags of the the dependent liquidity variables added to account for the high serial correlation of the liquidity variables (see, among others, Acharya and Pedersen, 2005 and the references therein).

[20]The use of returns based on the mid-point of the quoted bid and ask helps to mitigate the effect of market microstructure noise, particularly bid-ask bounce.

[21]We recognize that the serial correlation of returns is not the only proxy to capture price efficiency. For example, one could also look at measures that capture how much fundamental information gets revealed during trading in the spirit of Kyle (1985, p. 1330). In this study for the sake of simplicity and a direct link with existing studies, we use the measure discussed above, but we leave the investigation of alternative measures of price efficiency as agenda for future research.

[22]We use five minutes to compute returns as transactions are unevenly distributed if sampled at the one-minute frequency, especially the ones immediately preceding and following news announcements. We increase the window of observations to improve the accuracy of our estimates.

ment surprises and their interaction with HF variables are included in the regressions as follows:

$$|AC_{i,t,5M(j)}| = \gamma_{0i} + \gamma_{1i,t,5M(j)} + \gamma_{2i}\widehat{HF}^{*}_{i,t,5M(j)} + \rho_i^{AC}\widehat{HF}^{*}_{i,t,5M(j)} \times |SUR_t| + \gamma'_{3i}C_{t,5M(j)} + \psi_{i,t,5M(j)}. \quad (10)$$

3.2 The Impact of HF Trading on Market Liquidity

Table 5 reports the results of the analysis of HF trading and market liquidity based on the framework detailed in Section 3.1. We examine both the impact of the total HF trading in Model 1, and the individual impact of HFMO and HFLO separately in Model 2.

Overall, we find that HF trading tends to worsen liquidity both before and after announcements. In particular, during pre-announcement periods, a higher HF trading significantly widens bid-ask spreads by 0.0001 basis points (Model 1, Panel A). One standard deviation change in total HF trading leads to a 11% increase in the bid-ask spread for the 2-year note.[23] Similar calculations show that a one-standard-deviation change in HF trading leads to 6.3% and 2.5% increases in the relative spreads for the 5- and 10-year notes, respectively.[24] The impact on bid-ask spreads comes mainly from HFMO. Positive variations in HFMO (HFLO) lead to an increment (reduction) of bid-ask spreads. Higher HF trading also leads to more depth at less aggressive levels during pre-announcement periods. Higher HF trading significantly increases depth behind the best quote (Model 1, Panel C) but has no significant impact on depth at the best quotes (Model 1, Panel B). A one-standard-deviation increase in HF trading is associated with an increment of 1.5%, 3.9% and 2.9% of the depth behind the best quotes for the 2-, 5- and 10-year notes. In addition, the positive impact of HF trading on depth behind the best quotes comes from HFLO. High HFLO are associated with larger depth behind best quotes (Model 2, Panel C), while high HFMO significantly reduce depth behind the best quotes.

[23] Given an overall HF trading standard deviation of 927.61 for the 2-year note, a one-standard-deviation change in overall HF value is associated with a $927.61 \times 0.0001 = 0.09$ basis points, which represents $0.09 \times 100/0.85 = 11\%$ increase in the relative spread for the 2-year note.

[24] This result suggest that there is a term structure of liquidity effects that is consistent with the market narrative indicating that the 2-year Treasury benchmark is the most traded maturity followed by the other two maturities explored in this study. Furthermore, this hump-shaped pattern is similar to the one recorded for bond yields around a smaller sample of announcement in Hoerdahl et al. (2018).

During post-announcement periods, HF trading has no significant impact on bid-ask spreads but has a significantly negative impact on depth. Higher HF trading significantly reduces both depth at the best quotes (Model 1a of Panel B) and depth behind the best quotes (Model 1a, Panel C). HFMO have a significantly negative impact on depth at the best quotes (Model 2a, Panel B) but a significantly positive impact on depth behind best quotes (Model 2a, Panel C).

These findings suggest a picture that differs from the earlier view that increased HF trading narrows spreads, regardless of the information environment (Jovanovic and Menkveld, 2011; Hendershott, Jones and Menkveld, 2011; and Menkveld, 2013). Our results corroborate the recent theoretical findings suggesting that HF trading has an overall negative impact on liquidity due to faster reaction to public information arrival (Biais, Foucault and Moinas, 2015; Foucault, Hombert and Rosu, 2013; and Martinez and Rosu, 2013). Furthermore, the impact of HF trading on depth can be rationalized in the spirit of Hendershott and Riordan (2013) who suggest that algorithmic traders react quickly to information arrival and use liquidity-demanding trades to execute limit orders upon news release. This leads to a reduction of depth at the best quotes as more limit orders are placed less aggressively during post-announcement periods to avoid being picked off.

We finally explore whether the impact of HF trading is affected by the size of announcement surprises. The coefficient estimates of the interaction term between $|SUR_t|$ and the various HF variables show that the effect of HF trading on bid-ask spread and depth at the best quotes does not depend on the size of surprises. However, a larger $|SUR_t|$ intensifies the impact of HF trading on depth behind the best quotes. In fact, the parameter of the interaction term with $|SUR_t|$ has the same sign exhibited by the ones estimated on the various HF variables. This suggests that larger announcement surprises magnify the impact of HF trading on depth behind the best quotes.

3.3 The Impact of HF Trading on Price Efficiency

Table 6 reports the results of the estimations related to the effect of HF trading on price efficiency. We find that HF trading improves price efficiency during both the pre- and post-announcement periods. The sign of the coefficient on the HF trading is significantly negative (Model 1, Model 1a and Model 1b), implying that HF trading significantly reduces the serial correlation of Treasury returns after and before announcements. We also find that the improvements in price efficiency come from HFMO during both the pre- and post-announcement periods.[25] The coefficients associated with HFMO are significantly negative (Model 2, Model 2a and Model 2b), while those associated with HFLO are either insignificant (Model 2) or significantly positive (Model 2a and Model 2b). Thus, while HFMO have a negative impact on market liquidity, they help to quickly incorporate information into prices. However, the size of announcement surprises tends to counteract the impact of HF trading and, more specifically, the effect of HFMO on price efficiency. The coefficients on the interaction terms with $|SUR_t|$ are significantly positive at the 1% level for the overall HF and HFMO. This suggests that larger announcement surprises hinder the process whereby HF trading incorporates information into prices.

Taken together, these results lend support to the predictions of theoretical studies, such as Martinez and Rosu (2013), that HFMO quickly incorporate information into prices upon information arrival and they are also consistent with Chaboud, Chiquoine, Hjalmarsson and Vega (2014) and Brogaard, Hendershott and Riordan (2014) who show that HF trading improves price efficiency and the improvement mainly comes from HFMO. However, in addition to this empirical evidence, we show that HFLO, counteracting the effect of HFMO, reduce price efficiency, especially after news announcements.

4 Robustness and Extensions

This section checks the robustness of the baseline results reported in Section 3.2. Specifically, we first assess the robustness of our identification procedure to order clustering on announcement days. We then examine whether our main results are robust to the consideration of a subset of important macroeconomic news announcements, a shorter cutoff time in classifying HFMO and HFLO and the explicit consideration of the expandable limit orders or workup trading protocol adopted in the

[25]We investigate further the results of improved price efficiency due to HFMO during pre-announcement periods in the subsequent Section 4.5.

U.S. Treasury market. We show that our main results are robust to all of these issues. Finally we also present some additional results aiming at assessing whether HF order imbalances computed during pre-announcement periods exhibit any predictive power in predicting Treasury bond returns over post-announcement periods.

4.1 Empirical Identification and Announcement Days

The identification procedure proposed in Section 2.2 may potentially overestimate the number of HF orders as, around macroeconomic announcements, more trading activity would make orders to cluster together around the same time, including manual orders. We try to assess the robustness of our methodology against this possibility by computing the average percentage share of HFMO and HFLO, out of all market and limit orders, on announcement and non-announcement days. More specifically, we compute ratio between the number of HFMO (HFLO) and the total number of market (limit) orders submitted during pre-announcement periods on days with and without announcements. The same calculation is carried out during post-announcement periods.

If our identification procedure systematically provides the wrong classification of manual orders during announcement days, we should be able to see that the percentage share of HFMO and HFLO is higher on announcement days than on non-announcement days. The results of this check, reported in Table 7, document that the percentage of market and limit orders classified as HFMO and HFLO is virtually the same on both announcement and non-announcement days. The results hold true for all bond maturities and during pre- and post-announcement periods.

4.2 Important Announcements

In this section we assess whether the impact of HF trading on market liquidity and price efficiency documented in the previous section is different if only important macroeconomic news announcements are used in the empirical analysis. The list of important announcements is selected based on the Bloomberg relevance index and all of which are shown to have important impact on the U.S. Treasury market in the existing literature (e.g., Green, 2004; and Pasquariello and Vega, 2007).

The list includes the seven most important announcements, namely CPI, Change in Nonfarm Payroll, Initial Jobless Claims, Consumer Confidence Index, GDP Advance, ISM Non-manufacturing and Retail Sales.

The results of this exercise, reported in Tables 8 and 9, confirm those reported and discussed in Section 3.2. In fact, the sign and significance of the coefficients are largely similar to those reported in Tables 5 and 6. During pre-announcement periods, HF trading still significantly widens spreads, has no impact on depth at best quotes, deepens depth behind best quotes and improves price efficiency. However, the impact of HF trading seems to be more pronounced around announcements of important news. In particular, the coefficient capturing the impact of abnormal HF trading on relative spreads is almost triple the magnitude of the one based on all news announcements. During post-announcement periods, the results for the impact of HF trading on liquidity variables are also similar to those based on all news announcements.

4.3 Alternative HF Trading Classification

Another potential concern relates to the time-threshold (1 full second) used to identify HFMO and HFLO. In fact, Kosinski (2013) reports that "human reaction times are in the order of 200 milliseconds." As a robustness check, we use 200 milliseconds as an alternative time-threshold in our identification procedure. The results, reported in Table 10, show that using 200 milliseconds does not affect the patterns of HF trading around news announcements. Although the volume of HFMO and HFLO drops naturally, as a result of using a smaller time threshold, the results are qualitatively similar to those reported in Table 3. The volume of HFMO and HFLO under the alternative classification scheme also increases during post-announcement periods. In addition, the increase of the volume of HFMO (HFLO) during post-announcement periods relative to the volume during pre-announcement periods is significantly higher than the relative increase of all market (limit) orders. This finding holds true for all three maturities. The abnormal volume of both HFMO and HFLO under the alternative classification scheme also have consistent patterns with those reported in Table 3.

4.4 The Workup Process and Price Efficiency

A unique feature of the secondary U.S. Treasury market is the workup process. As detailed in Boni and Leach (2004), the U.S. Treasury market adopts a trading protocol which allows for Expandadable Limit Orders, or workups, where traders who submit limit orders have the right to expand the quantity associated with their limit orders at the *same* prevailing price. As a result, during workup phases bond prices are essentially frozen while trades still take place. Since our identification of HFMO depends on changes in best quotes, a potential concern is that our measure of HF trading may potentially be biased toward finding results supportive of increased price efficiency.

To address this important concern, we repeat the analysis on the impact of HF trading on price efficiency in Section 3 by explicitly excluding transactions involved in the workup process. Specifically, the serial correlation of bond returns is recalculated after excluding trades that occur within each workup. This filter removes instances at which prices are unchanged due to the workup process but trading still takes place. The results of this robustness exercise are reported in Table 11 and show that our baseline findings are qualitatively similar when workups are explicitly taken into account. In fact, during pre-announcement periods, the coefficient on HF trading remains significantly negative, indicating that it does improve price efficiency. Both HFMO and HFLO are found to improve price efficiency, although the coefficient of HFMO is not statistically significant at conventional level. During post-announcement periods, the results are similar to those in Table 6, both qualitatively and quantitatively.

4.5 The Predictive Ability of HF Order Imbalances

The results reported in Section 3 suggest that HF trading improves price efficiency also before news announcements and most of the improvement comes from HFMO, as HFLO do not play a substantial role during that time interval. It is worthwhile investigating this aspect further to understand whether the improvement in price efficiency may be due to information leakage before announcement. We put this conjecture to a test by estimating whether HF order imbalances computed during pre-announcement periods exhibit any predictive power for Treasury bond returns computed over post-announcement periods. In addition, the consideration of order imbalances allows us to check whether directional trading is affected differently by buy and sell orders. More specifically we estimate the following equation:

$$r_{i,t,1M(0\to y)} = a_{0i} + a_{1i}HFIMB_{i,t,1M(-15\to 0)} + \sum_{q=1}^{K_I} a_{(1+q)i}SUR_{q,t} + \chi_{i,t,1M(0\to y)} \tag{11}$$

where $r_{i,t,1M(0\to y)}$ denote Treasury note i's returns computed at the 1-minute frequency over the interval y = 1, 5 minutes of post-announcement periods; $HFIMB_{i,t,1M(-15\to 0)}$ is the difference between the volume of HF ask orders and volume of HF bid orders recorded during the 15-minute preceding the announcement, and $SUR_{q,t}$ is the news surprise of the $q = 1, ..., K_I$ important announcements, as defined in Section 4.2.

For the sake of completeness, we compute the parameters of interest in Equation (11) by using an order imbalance measure for all HF orders (models 1-2) and separating the effects originating from either HFMO or HFLO order imbalances (models 3-4). The results of this exercise are reported in Table 12. In all cases, the coefficients on HF order imbalances are not statistically significant at conventional levels, regardless of the model specification.[26] This evidence suggests that there is no obvious information leakage, as order imbalances that occur over the period preceding announcements do not predict Treasury returns computed over post-announcement periods.

5 Conclusion

This paper investigates HF trading in the U.S. Treasury market around macroeconomic news announcements. Using a comprehensive dataset provided by BrokerTec, one of the leading interdealer electronic trading platforms in the secondary U.S. Treasury market, we identify HFMO and HFLO based on the speed of their placement, alteration or cancellation that is deemed beyond manual ability. We examine how HFMO and HFLO occur around macroeconomic news announcements, whether they increase or deplete market liquidity, and assess their impact on the price efficiency of the U.S. Treasury securities.

[26]There results are qualitatively and quantitatively similar if HF order imbalances are scaled by total HF volume.

Our results show that although HFLO tend to flee the market before news announcements, both HFMO and HFLO increase substantially following news releases. During pre-announcement periods, higher HF trading leads to larger bid-ask spreads (mostly due to the impact of HFMO) and larger depth behind the best quotes, while the depth at the best quote is virtually unaffected. However, during post-announcement periods, bid-ask spreads are mostly unaffected by higher HF trading while depth at and behind the best quotes decrease significantly. We also document that during both pre- and post-announcement periods, HF trading improves price efficiency. The positive impact on price efficiency mainly comes from HFMO, although there is no clear evidence of information leakage during pre-announcement periods.

Our results are robust to a variety of potential issues including, but not limited to, the consideration of a subset of important macroeconomic news announcements, a shorter cutoff time in classifying HFMO and HFLO and the explicit consideration of the expandable limit orders or workup trading protocol adopted in the U.S. Treasury market.

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Table 1. List of Macroeconomic News Announcements

This table reports the list of macroeconomic news announcements included in our analysis. *N* denotes the total number of announcements during our sample period from January 3, 2006 to December 29, 2011. *Time* denotes the time (eastern) of the announcement. *Day* denotes the weekday or day of the month of the announcement. σ denotes the standard deviation of announcement surprises. $\mathrm{N}_{|SUR|>k\sigma}$ denotes the number of announcements with absolute surprise k times greater than its standard deviation.

Macroeconomic News	N	Time	Day	$\mathrm{N}_{\lvert SUR \rvert>\sigma}$	$\mathrm{N}_{\lvert SUR \rvert>2\sigma}$
Building Permits	72	8:30	Around 24th/25th of the month	25	2
Business Inventories	72	10:00	Around the 15th of the month	17	3
Capacity Utilization	72	9:15	Two weeks after month end	17	4
Change in Nonfarm Payrolls	72	8:30	First Friday of the month	26	2
Construction Spending	72	10:00	Two weeks after month end	21	7
Consumer Confidence Index	72	10:00	Last Tuesday of the month	22	3
CPI	72	8:30	Around the 13th of the month	20	3
Durable Goods Orders	68	8:30	Around the 26th of the month	17	4
Existing Home Sales	72	10:00	Around the 25th of the month	21	3
Factory Orders	72	10:00	Around the first business day of the month	22	4
Fed's Beige Book	48	14:00	Two weeks prior to each Federal Open Market Committee Meeting	0	0
FOMC Minutes	44	14:00	Thursday following the next FOMC meeting	0	0
FOMC Rate Decision	24	12:30/14:15	According to schedule	0	0
GDP Advance	24	8:30	3rd/4th week of the month for prior quarter	7	2
GDP Final	24	8:30	3rd/4th week of second month following the quarter	8	2
GDP Preliminary	24	8:30	3rd/4th week of first month following the quarter	6	1
Housing Starts	72	8:30	Two or three weeks after the reporting month	19	3
Industrial Production	72	9:15	Around the 15th of the month	17	3
Initial Jobless Claims	313	8:30	Thursday weekly	83	21
ISM Manufacturing Index	72	10:00	First business day of the month	28	2
ISM Services Index	72	10:00	Third business day of the month	20	3
Leading Indicators	72	10:00	Around the first few business days of the month	17	6
New Home Sales	72	10:00	Around the last business day of the month	18	6
NY Empire State Index	72	8:30/15:00	Around the 15th/16th of the month	23	3
Personal Income	72	8:30	Around the first business day of the month	8	4
Personal Spending	72	8:30	Around the first business day of the month	28	6
PPI	72	8:30	Around the 11th of the month	19	4
Retail Sales	72	8:30	Around the 12th of the month	15	5
Trade Balance	72	8:30	Around the 20th of the month	26	3
Treasury Budget	70	14:00	About the third week of the month for the prior month	9	2
Unemployment Rate	72	8:30	First Friday of the month	28	5

Table 2. Summary Statistics of Liquidity Variables

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

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

Table 3. HFMO and HFLO around News Announcements

This table reports the average volume of HFLO (Panel A), HFMO (Panel B), as well as abnormal volume of HFLO and HFMO (Panel C) over the 15-minute pre-announcement and 15-minute post-announcement periods. HFLO1, HFLO2, HFLO3 and HFMO are defined as in Section 3.1. Abnormal HFMO and HFLO are defined as in Equations (2) and (3) of the main text. $\frac{HF^{post}}{HF^{pre}}$ denotes the ratio of the HF trading volume during the post-announcement periods versus that during the pre-announcement periods each day while $\frac{All^{post}}{All^{pre}}$ denotes the ratio of total trading volume during post-announcement periods versus that of pre-announcement periods each day. The table reports average differences between these two ratios for both limit and market orders. HFLO*, HFMO*, All LO* and All MO* are abnormal HFLO, HFMO and abnormal total limit and market orders as defined in Section 3.1, respectively. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

	2-year			5-year			10-year		
	Pre-ann	Post-ann	$\frac{HF^{post}}{HF^{pre}} - \frac{All^{post}}{All^{pre}}$	Pre-ann	Post-ann	$\frac{HF^{post}}{HF^{pre}} - \frac{All^{post}}{All^{pre}}$	Pre-ann	Post-ann	$\frac{HF^{post}}{HF^{pre}} - \frac{All^{post}}{All^{pre}}$
Panel A: Limit orders									
HFLO1	10425.35	25386.16		11979.39	27403.47		9063.69	22187.06	
HFLO2	127.69	231.96		105.34	171.61		85.86	130.47	
HFLO3	121.32	262.13		114.05	189.32		93.35	152.48	
All HFLO	10674.36	25880.24		12198.78	27764.40		9242.91	22470.02	
All limit orders	32283.24	78858.25	0.22***	32317.99	68229.92	0.48***	24753.13	54818.98	0.53***
Panel B: Market orders									
HFMO	241.93	501.64		276.64	557.07		232.28	470.39	
All market orders	1173.19	2533.40	0.63***	1067.61	2062.87	0.34***	905.75	1806.57	0.27***
Panel C: Abnormal limit and market orders									
HFLO*	-993.73	13196.99		-1624.28	13009.23		-1452.99	10947.94	
All LO*	-4761.57	38124.95		-5643.52	27376.75		-4390.49	23263.71	
HFMO*	12.34	253.03		-5.34	259.81		-5.06	219.47	
All MO*	6.26	1236.50		-60.11	860.69		-53.92	770.14	

Table 4. The Impact of i-Cross on HF Trading

This table reports the impact of i-Cross on total HF trading, HFLO, HFMO, volatility, and term spread. Total HF trading is defined as the sum of HFLO volume and HFMO volume. Volatility is defined as the absolute price change and the term spread is defined as the difference between the yields of the 2-year note and the 10-year note. The Table reports the estimates of the following regression:

$$M^*_{i,t,1M(j)} = \alpha_{0i} + \alpha_{1i,t,1M(j)} + \alpha_{2i} time + \alpha_{3i} D_t^{crisis} + \alpha_{4i} Q_t + \varepsilon_{i,t,1M(j)},$$

where $M^*_{i,t,1M(j)}$ equals abnormal total HF trading (HF*), abnormal HFLO (HFLO*), abnormal HFMO (HFMO*), volatility or term spread; Q_t is a dummy variable capturing the introduction of i-Cross that equals one after January 1, 2008 and zero otherwise. α_{0i} denotes maturity-specific fixed effect, $\alpha_{1i,t,1M(j)}$ is a dummy variable capturing residual seasonal patterns around announcements, $time$ denotes a logarithmic time-trend and D_t^{crisis} is a dummy variable that captures the effects of the 2007-2009 financial crisis. The table reports the estimate of α_{4i} for each of the regressions. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	HF*	HFLO*	HFMO*	Volatility	Term Spread
All Maturities	99.992***	99.235***	0.757***	0.001	0.000
2-year Note	19.472***	19.267***	0.205**	-0.000***	0.000
5-year Note	164.946***	163.907***	1.039***	0.002	0.000
10-year Note	114.768***	113.736***	1.031***	0.000	0.000

Table 5. HF trading and Market Liquidity

This table reports the results of the second-stage regression of the instrumental variable estimation:

$$X^*_{i,t,1M(j)} = d_{0i} + d_{1i,t,1M(j)} + d_{2i}(1 + \rho_i^X \times |SUR_t|)\widehat{HF}^*_{i,t,1M(j)} + d_{3i}^{'} C_{t,1M(j)} + e_{i,t,1M(j)},$$

where $X^*_{i,t,1M(j)}$ denotes a measure of liquidity, i.e. abnormal relative bid-ask spread, abnormal depth at best quotes, and abnormal depth behind best quotes; $\widehat{HF}^*_{i,t,1M(j)}$ is the fitted value of HF trading from Equation (6) of the main text; and $C_{t,1M(j)}$ denotes a set of control variables including term spread, volatility and absolute news surprises as described in Section 3.1. $\widehat{HF}^*_{i,t,1M(j)}$ equals to either abnormal total HF trading (HF*) or abnormal HFLO (HFLO*) and abnormal HFMO (HFMO*). ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, based on heteroscedasticity and autocorrelation consistent standard errors. Adj.R^2 denotes the adjusted R^2.

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
Panel A: Relative Bid-ask spread						
HF*	0.0001***		0.0000	0.0000		
HF* ×|SUR|				0.0000		
HFLO*		-0.0005***			-0.0001**	-0.0001*
HFLO* ×|SUR|						0.0000
HFMO*		0.0453***			0.0056*	0.0056*
HFMO* ×|SUR|						0.0002
|SUR|			0.0044	0.0197	0.0037	0.0195
Term Spread	0.0608	0.1470	0.0846*	0.0842*	0.0986**	0.0987**
Volatility	0.1890***	0.2084***	-0.0324	-0.0249	-0.0300	-0.0210
Adj R^2	0.2126	0.2140	0.0179	0.0179	0.0179	0.0180
Panel B: Depth at Best Quote						
HF*	-0.0060		-0.0280***	-0.0278***		
HF* ×|SUR|				-0.0008		
HFLO*		0.0798***			0.0086	0.0029
HFLO* ×|SUR|						0.0186
HFMO*		-6.9139***			-2.8345***	-2.4837***
HFMO* ×|SUR|						-1.2774
|SUR|			-7.0600***	-6.3037*	-6.6525***	-7.4713**
Term Spread	-14.4375	-27.6874	17.831	18.7638	10.772	10.2004
Volatility	13.4434	10.4846	0.4878	0.9566	-0.7308	-7.4101
Adj R^2	0.6911	0.6914	0.4239	0.4234	0.4241	0.4236

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
Panel C: Depth Behind Best Quote						
HF*	0.0508***		-0.2643***	-0.2220***		
HF* $\times$|SUR|				-0.1283***		
HFLO*		0.1759***			-0.5931***	-0.4012***
HFLO* $\times$|SUR|						-0.6433***
HFMO*		-10.0098***			24.9347***	15.7925***
HFMO* $\times$|SUR|						33.9150***
|SUR|			-69.3605***	48.9373***	-73.0892***	84.4490***
Term Spread	19.0206	-0.2942	76.9869***	67.8991**	140.4337***	172.0594***
Volatility	41.7165	37.4284	-22.4290	36.3596	-11.5952	236.5172***
Adj R^2	0.9516	0.9516	0.8488	0.8496	0.8493	0.8508

Table 6. HF Trading and Price Efficiency

This table reports the results of the second-stage regression of the instrumental variable estimation:

$$|AC_{i,t,5M(j)}| = \gamma_{0i} + \gamma_{1i,t,5M(j)} + \gamma_{2i}(1 + \rho_i^{AC} \times |SUR_t|)\widehat{HF}^*_{i,t,5M(j)} + \gamma'_{3i}C_{t,5M(j)} + \psi_{i,t,5M(j)},$$

where $|AC_{i,t,5M(j)}|$ denotes the absolute value of the first-order serial correlation coefficient of the Treasury note i's log returns computed using the prevailing mid-quote at each transaction over a five-minute interval and the other variables are as in Table 5 computed over the same five-minute interval. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, based on heteroscedasticity and autocorrelation consistent standard errors. Adj.R^2 denotes the adjusted R^2. See also notes to Table 5.

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
HF*	-0.0023***		-0.0007***	-0.0007***		
HF* $\times$|SUR|				0.0001***		
HFLO*		-0.0001			0.0042***	0.0042***
HFLO* $\times$|SUR|						0.0001***
HFMO*		-0.2059**			-0.3603***	-0.3603***
HFMO* $\times$|SUR|						0.0001***
|SUR|			0.0001***	0.0001***	0.0001***	0.0001***
Term Spread	0.1599	0.0025	0.7911	0.7911	0.3720	0.3720
Volatility	-1.8346	-2.4702	0.2558	0.2558	-0.9162	-0.9162
Adj R^2	0.0077	0.0082	0.0173	0.0171	0.0243	0.0239

Table 7. HFMO and HFLO Classification on Announcement and non-Announcement Days

This table reports the average percentage share of HFLO and HFMO computed on announcement and non-announcement days. Percentage shares are computed as ratio between the number of HFMO (HFLO) and the total number of market (limit) orders submitted during either pre- or post-announcement periods on days with and without announcements.

	Non-announcement Days		Announcement Days	
	% HFLO	% HFMO	% HFLO	% HFMO
Panel A: Pre-announcement Periods				
2-year	33.74	16.96	34.00	16.53
5-year	37.10	24.90	37.97	24.54
10-year	37.36	24.65	37.86	24.43
Panel B: Post-announcement Periods				
2-year	33.90	17.00	34.15	19.18
5-year	36.52	24.95	41.88	28.31
10-year	36.87	24.66	41.83	27.68

Table 8. HF Trading and Market Liquidity: Important Announcements

This table reports the results of the second-stage regressions as in Table 5 based on the list of important announcements. The selected announcements include CPI, Change in Nonfarm Payroll, Initial Jobless Claims, Consumer Confidence Index, GDP Advance, ISM Services Index and Retail Sales. The same control variables are included. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, based on heteroscedasticity and autocorrelation consistent standard errors. Adj.R^2 denotes the adjusted R^2.

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
Panel A: Relative Bid-ask spread						
HF*	0.0004***		0.0000	0.0000		
HF* $\times$|SUR|				0.0000		
HFLO*		-0.0006***			-0.0002*	-0.0001
HFLO* $\times$|SUR|						-0.0001
HFMO*		0.0828***			0.0130**	0.0127**
HFMO* $\times$|SUR|						0.0020
|SUR|			0.0236	0.0473*	0.0226	0.0512*
Term Spread	-0.1185	0.0150	0.1310**	0.1315**	0.1637**	0.1682**
Volatility	0.1248	0.1632**	-0.0307	-0.0220	-0.0241	-0.0025
Adj R^2	0.3197	0.3231	0.0278	0.0280	0.0282	0.0283
Panel B: Depth at Best Quote						
HF*	-0.0058		-0.0161***	-0.0161***		
HF* $\times$|SUR|				0.0028		
HFLO*		0.0963***			0.0230	0.0076
HFLO* $\times$|SUR|						0.0385**
HFMO*		-8.2864***			-2.9341**	-1.9829
HFMO* $\times$|SUR|						-2.2622*
|SUR|			-6.4732	-9.7118	-6.2041	-12.9205**
Term Spread	-9.6443	-23.2574	15.4251	15.5339	8.0660	5.2605
Volatility	10.3735	6.5239	1.4785	0.2585	-0.0057	-14.5033
Adj R^2	0.6406	0.6413	0.4282	0.4280	0.4284	0.4283

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
			Panel C: Depth Behind Best Quote			
HF*	0.0730***		-0.2706***	-0.2410***		
HF* $\times$|SUR|				-0.0808***		
HFLO*		0.1823***			-0.5275***	-0.4161***
HFLO* $\times$|SUR|						-0.3412***
HFMO*		-8.7784**			18.7914***	14.1615***
HFMO* $\times$|SUR|						16.3983***
|SUR|			-99.2221***	-9.5451	-101.2935***	14.1728
Term Spread	-11.2682	-25.8429	104.0971***	102.8563***	152.0679***	177.7741***
Volatility	28.8579	24.7660	-10.7951	22.5738	-1.1850	130.1921***
Adj R^2	0.9445	0.9445	0.8522	0.8529	0.8525	0.8536

Table 9. HF Trading and Price Efficiency: Important Announcements

This table reports the results of the second-stage regression as in Table 6 based on the list of important announcements. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, based on heteroscedasticity and autocorrelation consistent standard errors. Adj.R^2 denotes the adjusted R^2. See notes to Table 8.

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
HF*	-0.0030***		0.0003	0.0003		
HF* $\times$|SUR|				0.0001***		
HFLO*		-0.0012			0.0029***	0.0029***
HFLO* $\times$|SUR|						0.0001***
HFMO*		-0.1593			-0.1800**	-0.1800**
HFMO* $\times$|SUR|						0.0001***
|SUR|			0.0001***	0.0001***	0.0001***	0.0001***
Term Spread	1.8681	1.7317	-0.1093	-0.1093	-0.3058	-0.3058
Volatility	-1.6589	-2.2004	-0.4126	-0.4126	-1.0697	-1.0697
Adj R^2	0.0095	0.0096	0.0124	0.0119	0.0146	0.0137

Table 10. HFMO and HFLO: Alternative Classification

This table reports the average volume of HFLO (Panel A), HFMO (Panel B), as well as abnormal volume HFLO and HFMO (Panel C) using 200 milliseconds time-threshold to classify HF activities. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively. See notes to Table 3.

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

Table 11. The Workup Process and Price Efficiency

This table reports the results of the second stage regression of the instrumental variable estimation as in Table 6 where transactions occurring within the workup process are excluded as discussed in Section 4.4 of the main text. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, based on heteroscedasticity and autocorrelation consistent standard errors. Adj R^2 denotes the adjusted R^2. See notes to Table 6.

	Pre-announcement		Post-announcement			
	Model 1	Model 2	Model 1a	Model 1b	Model 2a	Model 2b
HF*	-0.0021***		-0.0010***	-0.0010***		
HF* $\times$|SUR|				0.0001***		
HFLO*		-0.0021*			0.0042***	0.0042***
HFLO* $\times$|SUR|						0.0001***
HFMO*		-0.0020			-0.3862***	-0.3862***
HFMO* $\times$|SUR|						0.0001***
|SUR|			0.0001***	0.0001***	0.0001***	0.0001***
Term Spread	0.4636	0.4637	0.4329	0.4329	-0.0168	-0.0168
Volatility	-0.0097	-0.0097	-0.0084	-0.0084	-0.0210	-0.0210
Adj R^2	0.0056	0.0055	0.0176	0.0175	0.0268	0.0265

Table 12. The Predictive Ability of HF Order Imbalances

This table reports the results of the the regression

$$r_{i,t,1M(0\to y)} = a_{0i} + a_{1i}HFIMB_{i,t,1M(-15\to 0)} + \sum_{q=1}^{K_I} a_{(1+q)i}SUR_{q,t} + \chi_{i,t,1M(0\to y)}$$

where $r_{i,t,1M(0\to y)}$ denote Treasury note i's returns computed at the 1-minute frequency over the the interval $y = 1,\ 5$ minutes of post-announcement periods; $HFIMB_{i,t,1M(-15\to 0)}$ is the difference between the volume of HF ask orders and volume of HF bid orders recorded during the 15-minute preceding the announcement, and $SUR_{q,t}$ is the news surprise of the $q = 1, ..., K_I$ important announcements, as defined in Section 4.2. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, based on heteroscedasticity and autocorrelation consistent standard errors. Adj. R^2 denotes the adjusted R^2.

	y = One Minute				y = Five Minute			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: HF Order Imbalances								
HF Imbalance	0.0000	0.0001			0.0000	0.0003		
HFLO Imbalance			0.0000	0.0001			0.0000	0.0003
HFMO Imbalance			-0.0113	-0.0049			-0.0228	-0.0100
CPI		-0.0124		-0.0078		0.0008		0.0102
Change in Nonfarm Payrolls		-4.3778***		-4.3674***		-8.7167***		-8.6955***
Consumer Confidence Index		-0.0346		-0.0167		-0.0603		-0.0237
Durable Goods Orders		-0.0719		-0.0757		-0.1221		-0.1299
GDP Advance		-0.1235		-0.1262		-0.2096		-0.2153
ISM Non-Manufacturing		-0.0179		-0.0074		-0.0157		0.0056
Retail Sales		-0.0690		-0.0643		-0.1205		-0.1108
Adj R2	-0.0007	0.0061	-0.0012	0.0055	0.0005	0.0182	0.0001	0.0177
Panel B: HF Order Imbalances Scaled by HF Volume								
HF Imbalance	-0.1580	0.1800			-0.2936	0.3801		
HFLO Imbalance			-0.1064	0.1517			-0.1895	0.3252
HFMO Imbalance			-0.4392	-0.1225			-0.8844	-0.2555
CPI		-0.0132		-0.0099		-0.0008		0.0063
Change in Nonfarm Payrolls		-4.3675***		-4.3608***		-8.6963***		-8.6824***
Consumer Confidence Index		-0.0335		-0.0246		-0.0581		-0.0396
Durable Goods Orders		-0.0748		-0.0761		-0.1278		-0.1305
GDP Advance		-0.1136		-0.1217		-0.1897		-0.2064
ISM Non-Manufacturing		-0.0129		-0.0096		-0.0056		0.0011
Retail Sales		-0.0729		-0.0700		-0.1279		-0.1218
Adj R2	-0.0007	0.0060	-0.0012	0.0054	0.0005	0.0181	0.0000	0.0175

Figure 1. Liquidity around News Announcements

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

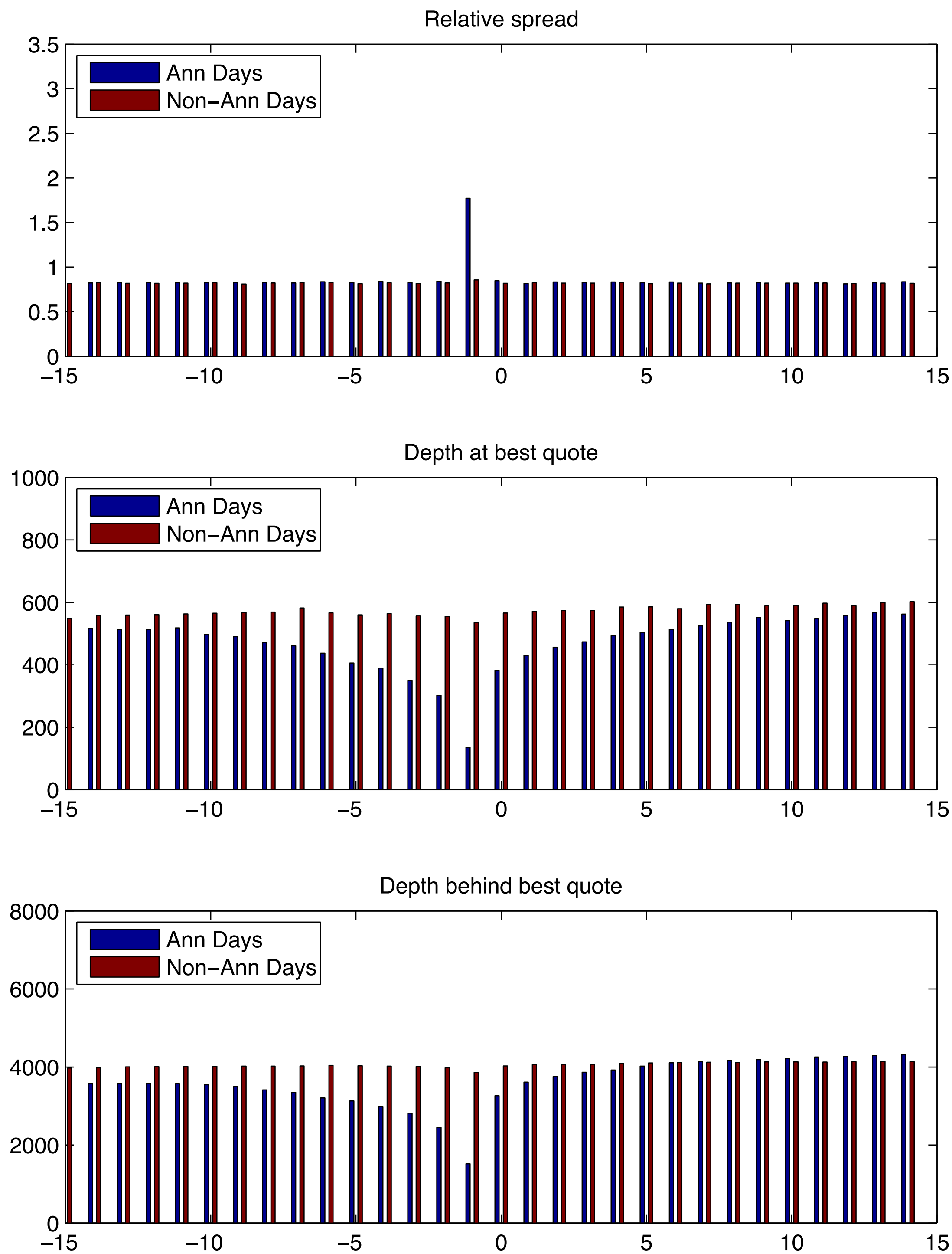

Figure 2. HF Trading Over Time

This figure shows the ratio of total HF order volume, defined as the sum of HFLO and HFMO volumes, relative to the total volume of both limit orders and market orders each month for the 2-, 5- and 10-year notes during the sample period from January 3, 2006 to December 29, 2011.

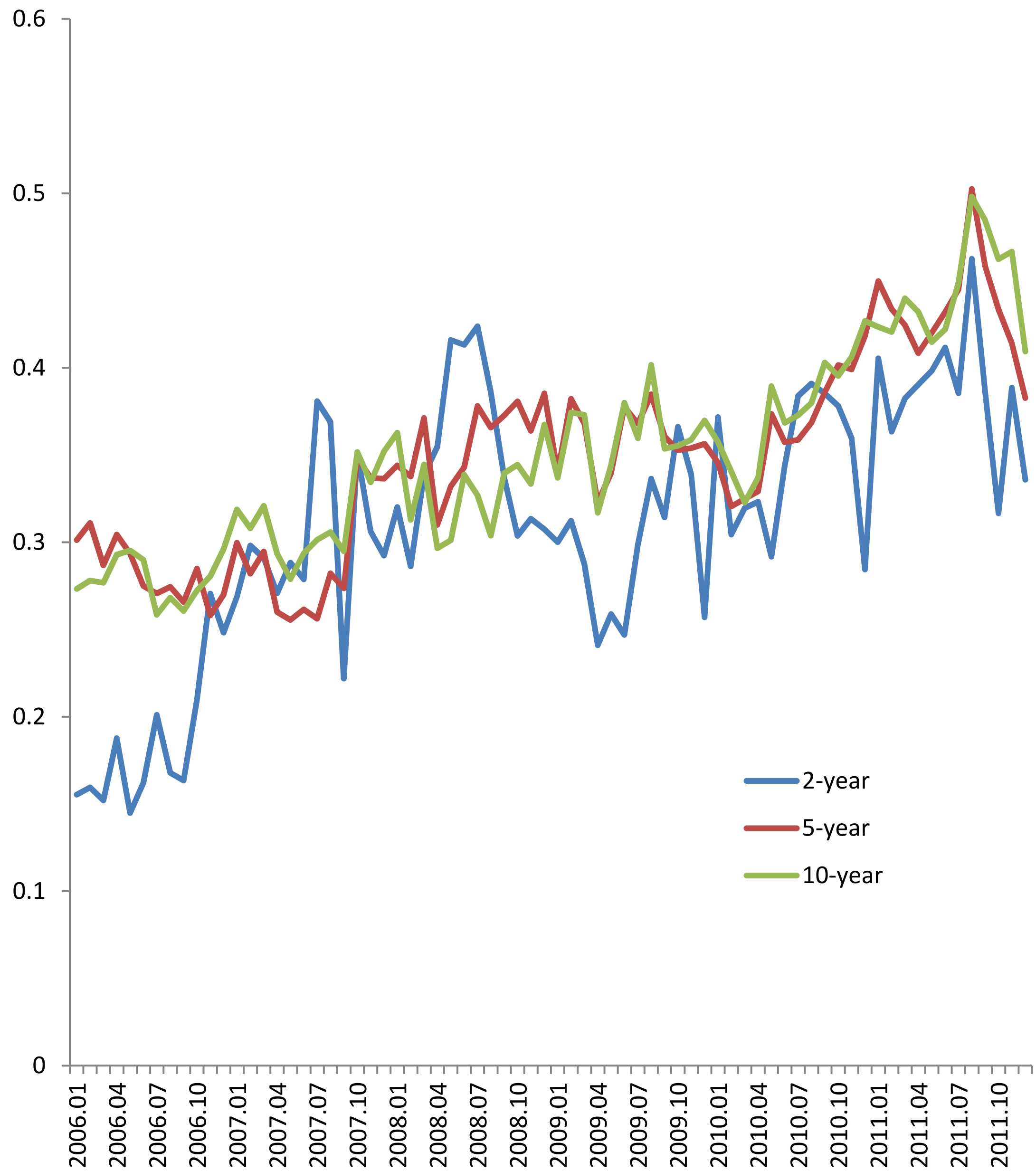

Figure 3. HF Trading around News Announcements

This figure shows the volume of HFMO and HFLO for the 2-year note during the 15-minute pre-announcement and post-announcement periods. For comparison, the corresponding volume of HFMO and HFLO recorded at the same time on non-announcement days are also reported.