High Frequency Trading in the US Treasury Market

– Evidence around Macroeconomic News Announcements

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Abstract

This paper investigates the role and effect of high frequency (HF) trading in the US Treasury market around major macroeconomic news announcements. Using tick-by-tick data on transactions and limit orders, we identify HF trades and orders based on the speed of execution that is deemed to be beyond manual capacity. Our results show that there are substantially more HF trades and orders following news announcements. Both HF trades and orders tend to increase subsequent market volatility. Nevertheless, HF trading has a mixed effect on market liquidity. While HF trading tends to widen bid-ask spreads, it helps to improve the overall depth of the limit order book. Finally, we show that HF orders are less informative than manual orders, especially during the post-announcement period. There is no evidence that HF trading helps promoting the price discovery process of US Treasury market.

JEL Classification: F3, G12, G14, G15.
Keywords: High Frequency Trading; Market Liquidity; Price Discovery; US Treasury Market.

I. Introduction

Automated trading or high frequency (HF) trading, carried out by computer programs, has become prevalent in financial markets during the past decade.[2] As reported in financial press, trading records are routinely broken in recent years and millions of data messages are regularly sent *per second* to various trading venues[3]. This anecdotal evidence is coupled with the hard fact that trading latency in several markets has decreased by two orders of magnitude over the past ten years (Moallemi and Saglam, 2011) and trading, as well as quoting activity, regularly takes place within a fraction of a second (see, *inter alia*, Clark, 2011; Hasbrouck, 2012; Scholtus and Van Djik, 2012 and the references therein). Although HF trading is one of the most significant market structure developments in recent years (SEC, 2010), the role and effect of these activities on market liquidity, volatility and price efficiency are still relatively unexplored finance literature.

A stream of recent studies has begun to investigate the impact of HF trading in equity markets (see, *inter alia*, Hendershott *et al.*, 2010; Hasbrouck and Saar, 2011; Brogaard, 2011a; 2011b; 2012; Hendershott and Riordan, 2011; Egginton *et al.*, 2012; Bohmer *et al.*, 2012 and the references therein). These studies focus mainly on two issues, namely, i) the impact of HF activities on market liquidity and volatility and ii) the role of HF activities on price discovery. The first group of studies records that, on average, HF activities improve market liquidity (Hendershott *et al.*, 2011; Brogaard, 2011; 2012a; Hasbrouck and Saar, 2011; Chaboud *et al.*, 2009). However, Boehmer *et al.* (2012) also suggest that HF activities reduce liquidity in small stocks and when market making is difficult. With regards to the issue of HF activities and price discovery, Chaboud

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[2] From a semantic viewpoint, HF trading can be seen as a subset of larger group of market activities carried out by computers labelled Algorithmic Trading, or AT (Chlistalla, 2011). Since this article focuses on the trading activities that are carried out by machines at a very high speed, we will refer to and study only these activities, labelling them throughout the article as HF trades and orders.

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

et al. (2011) find evidence that, in foreign exchange markets, transactions carried out by computers are less informative than the ones generated by human traders. On the contrary, Hendershott and Riordan (2010) find that computer quoting activity improves significantly the price discovery process by contributing more to innovations to efficient prices in NASDAQ. Similarly, Brogaard (2010) finds that HF activity has greater price impact and leads price discovery.

We note that while there is active research on HF trading in the equity market, very little research has been carried out on HF activities in other security markets.[4] This paper fills the gap of the existing literature by investigating HF activity around macroeconomic news announcement in the US Treasury market.[5] Given the increasingly larger role of HF trading and quoting in this important market during the past decade, we explore three main issues: First, given the relevance of macroeconomic variables in driving the price of Treasury securities (see, *inter alia*, Fleming and Remolona 1997; 1999; Balduzzi *et al.*, 2001; Andersen *et al.*, 2003; 2008 and Hoerdahl *et al.*, 2012; Menkveld et al., 2012 and the references therein), [6] we investigate how HF activity takes

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[4] The only exception is Chaboud *et al.* (2009) who investigate the role of algorithmic trading in the foreign exchange market.

[5] The US Treasury market is one of the world's largest financial markets with a daily trading volume that nearly five times that of the US equity market. The introduction of Electronic Communication Networks (ECNs) in the early 2000s has encouraged the establishment and development of HF trading and quoting activities in the US Treasury secondary markets (Aite Group, 2008). This evidence is supported by ICAP, one of the major brokers in this market, who quantifies that in 2009 more than 50 percent of their bids and offers are "black-box-oriented" and 45 percent of the overall trading in US Treasuries over their ECN, BrokerTec, is due to computer-based trading (Kite, 2010).

[6] There has been a vast literature examine the effect of macroeconomic news announcements in the US Treasury markets. Fleming and Remolona (1997) and Andersen *et al.* (2003; 2007) find that the largest price changes are mostly associated with macroeconomic news announcements in the Treasury spot and futures markets. Balduzzi *et al.* (2001), Fleming and Remolona (1999), Green (2004) and Hoerdahl *et al.* (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 *et al.* (2012) record

place around macroeconomic news announcements. One unique feature of HF activity is its quick reaction to information arrival. Computers, with their speed and capacity to handle a large amount of information, are in a privileged position to execute multiple actions in response to information shocks. Since many major macroeconomic news announcements are pre-scheduled, the Treasury market offers a unique setting to examine how HF activities respond to the arrival of new information. Second, we examine whether around these events HF activity improves or reduces liquidity and return volatility in the US Treasury market. While studies on equity market have shown that HF activities in general improves liquidity, the Treasury market has its unique market microstructure as an interdealer market and is perceived as much more liquid than equity market. It is unclear whether HF activities in the Treasury market overall improve or deplete market liquidity, magnifies or reduces return volatility. More importantly, whether HF activities in the Treasury market help or hinder price discovery around information arrival.[7] This is the third issue this paper examines. We investigate the informativeness of HF trades and orders relative to manual orders. More specifically, we aim at assessing whether HF activity facilitates or hinders the Treasury securities' price discovery process before and after the disclosure of fundamental public information. From a theoretical point of view some studies emphasize that HF trading improves the traders' ability to respond to new information and thus improves informational efficiency in the market (Biais *et al.*, 2010a). However, HF activity induces adverse selection in terms of the traders' speed of reaction to market events (Biais *et al.,* 2010b; Javanovic and

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similar findings for 30-year Treasury bond futures. Pasquariello and Vega (2007) find that private information manifests on announcement days with larger belief dispersion.

[7] It is important to emphasize that the public information channel for bond yields determination explored in this paper is only one of the possible reasons why bond yields change and trading occurs on a day-to-day basis. The other mechanism, which we do not explore but we leave as an avenue for future research, is the aggregation of heterogeneous private information (see, *inter alia*, Brandt and Kavajecz, 2004; Pasquariello and Vega, 2007 and the references therein).

Menkveld, 2011) that is likely to persist in equilibrium since computers process information faster than slow or manual traders (Biais *et al.*, 2010b).[8] The speed component of adverse selection is necessary to explain certain empirical regularities from the world of high frequency trading (Foucault *et al.*, 2012).

We carry out the empirical investigation by using a comprehensive dataset from BrokerTec, a major venue for trading on-the-run US Treasury notes and bonds, which contains tick-by-tick transactions and order book information for the 2-, 5- and 10-year notes over the period of January 2004 – June 2007. Since computer and human trading and quoting activities are generally not identified in commercially available datasets, we introduce a new procedure to identify HF trades and orders. Using information on the submission timing of an order and its subsequent alteration, such as cancellation or execution, we identify high frequency (HF) activities based on the reaction time of order placement to changes in market conditions. We classify those orders that are placed to the market at a speed deemed beyond manual capacity as HF activities. Our results are as follows: First, both HF trades and orders increase substantially following macroeconomic news announcements. In particular, the HF intensity is substantially more pronounced during the 15-minute interval following the news releases. This suggests that HF trades and orders react to the arrival of public information. Second, although there is clear evidence that HF activity increases subsequent bond return volatility during both the pre- and post-announcement periods, our findings also suggest that higher-than-normal HF activities have a mixed effect on market liquidity. Specifically, HF activities generally lead to higher bid-ask spreads, but in the meantime tend to improve overall depth of the order book. Furthermore, the effect of HF trades and orders

[8] However, computer processing requires investments in trading technology. The impact of such investments generates negative externalities on slow traders only if the effect of the technology on the trading efficiency is low and it depends on the pre-investment level of market efficiency (Hoffman, 2012).

on market liquidity is more pronounced during the 15-minute pre-announcement period. Third, the results from the Kaniel and Liu (2006) test provide strong evidence that manual trades and orders tend to be more informative than HF trades and orders. The null hypothesis that HF trades and orders are equally informative as their manual counterparts is rejected more forcefully during the 15-minute post-announcement interval. For all three maturities, manual orders and trades are found to be significantly more informative than HF orders and trades. In addition, the examination of the effect of HF trades and orders on subsequent absolute mid-quotes serial correlation suggests that there is no consistent evidence that HF activity helps facilitate the price discovery process of US Treasury securities.

The reminder of the article is as follows: Section 2 introduces the dataset employed in the empirical analysis and describes in detail the procedure used to compute the variables associated with HF intensity. Section 3 discusses the empirical results and a final section concludes.

II. Data construction and summary statistics

II.1 Key Variables on Announcement Dates

The data on US Treasury securities used in this article is obtained from BrokerTec, an interdealer ECN in the secondary wholesale US Treasury securities market. Prior to 1999, the majority of interdealer trading of US Treasuries occurred through interdealer brokers. After 1999, two major ECNs emerged: eSpeed and BrokerTec and since then, the trading of on-the-run Treasuries has fully migrated to the electronic platforms (Mizrach and Neely, 2009; Fleming and Mizrach, 2009).[9] In our empirical investigation we use data on 2-, 5- and 10- year Treasury notes from the

[9] According to Barclay *et al.* (2006), the electronic market shares for the 2-, 5- and 10-year bond are, respectively, 75.2%, 83.5% and 84.5% during the period of January 2001 to November 2002. By the end of 2004, the majority of secondary interdealer trading occurred through ECNs with over 95% of the trading of active issues. BrokerTec is

BrokerTec limit order book over the period January 5th, 2004 to June 29th, 2007. The data set contains the tick-by-tick observations of transactions, order submissions, and order cancellations. It includes the time stamp of transactions and quotes, the quantity entered and/or deleted, the side of the market and, in the case of a transaction, an aggressor indicator.

The data on macroeconomic news announcements and the survey of market participants are obtained from Bloomberg.[10] In our empirical investigation we use a set of 31 key macroeconomic news announcements occurring either at 8:30 a.m. ET, in the majority of the cases, or later during the trading day. The full list of macroeconomic variables as well as the timing of the news announcements is reported in Table 1. In line with much empirical literature on announcement news and asset prices (see, *inter alia,* Andersen *et al.* 2003; 2007; Pasquariello and Vega, 2007 and the references therein), we construct standardized news surprises to measure public information shocks as follows:

$$SUR_{k,t} = \frac{A_{k,t} - E_{k,t}}{\sigma_k},$$

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 $A_{k,t} - E_{k,t}$. Table 1 reports some descriptive statistics computed over the sample period for the full set of macroeconomic announcements. It is instructive to point out that over the sample period investigated, there is a non-negligible number of instances when shocks to macroeconomic announcement exceed one or even two standard deviations of the time series of surprises. Overall these extreme shocks occur in 27 percent (one-standard deviation) and 5 percent (two-standard deviation) of the cases, respectively.

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more active in the trading of 2-, 3-, 5- and 10-year Treasuries, while eSpeed has more active trading for the 30-year maturity.

[10] Balduzzi *et al.* (2001) show that professional forecasts based on surveys are neither biased nor stale.

The summary statistics of the trading activities around news announcements are reported in Table 2. Panel A reports the results during the 15 minutes preceding the announcement and Panel B reports the results during the 15 minutes following the announcement. The results show that during the pre-announcement period, the 2-year note is the most liquid security followed by the 5-year note and then the 10-year note. In fact, the 2-year note records the largest trading volume, the deepest depth of the order book (at both the best quotes and overall) and the smallest spread. The other two on-the-run benchmarks are not very different from each other in that they exhibit comparable levels of trading volumes, depths and spreads. The patterns highlighted in Panel A are also confirmed in Panel B, where the variables of interest are recorded during the 15-minute interval following the news announcements. In general, the post-announcement period is characterize by lower spread, deeper depth, higher trading volume and higher volatility, consistent with findings in Fleming and Remolona (1997, 1999)

The variables reported in Table 2 are used in the subsequent empirical analysis. We take into account for potential time-series effects that might have occurred over the sample period by constructing abnormal values beyond their average levels recorded during the past 30 minutes across 5 past no-event dates. For example, we define abnormal spread, $SPRD^{*}$, as

$$SPRD^{*}_{t,1M(i)} = SPRD_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5}\left[\frac{1}{30}\sum_{j=1}^{30} SPRD^{NON}_{t-k,1M(i-j)}\right], \qquad (1)$$

where $SPRD_{t,1M(i)}$ denotes the average bid-ask spread in tick within *i*-th minute interval on announcement day *t* and $SPRD^{NON}_{t-k,1M(i-j)}$ denotes the average bid-ask spread in the past *t-k* no-event day during (*i-j*)*th* intervals, where *j* = 1,…30 minute intervals and *k* = 1,…,5 days.

Similarly, abnormal depth measures and volatility are computed as

$$DPTH^{BST*}_{t,1M(i)} = DPTH^{BST}_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5}\left[\frac{1}{30}\sum_{j=1}^{30} DPTH^{BST,NON}_{t-k,1M(i-j)}\right], \tag{2}$$

$$DPTH^{ALL*}_{t,1M(i)} = DPTH^{ALL}_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5}\left[\frac{1}{30}\sum_{j=1}^{30} DPTH^{ALL,NON}_{t-k,1M(i-j)}\right], \tag{3}$$

$$VLTY^{*}_{t,1M(i)} = |\Delta mid|_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5}\left[\frac{1}{30}\sum_{j=1}^{30}|\Delta mid|^{NON}_{t-k,1M(i-j)}\right], \tag{4}$$

where $DPTH^{BST*}_{t,1M(i)}$, $DPTH^{ALL*}_{t,1M(i)}$ and $VLTY^{*}_{t,1M(i)}$ denote abnormal depth recorded at the best quote, the overall depth and the abnormal volatility, respectively; and $DPTH^{BST}_{t,1M(i)}$, $DPTH^{ALL}_{t,1M(i)}$ and $|\Delta mid|_{t,1M(i)}$ are the average of the visible depth at the best quote, the overall depth and absolute change in mid-quote recorded within *i*-th minute interval on announcement day *t*.

The behavior of these key variables on announcement and non-announcement days are plotted in Figure 1. Bid-ask spreads are higher on announcement dates *vis-à-vis* non announcement dates. On announcement days, spreads increase just before the announcement time and the value of the spreads reverts to pre-announcement values almost instantaneously.

The depth of the order book (both at the best quote and overall), decrease substantially on announcement dates. Similarly to bid-ask spreads, the depth of the order book decreases just before the announcement time and revert to pre-announcement values within the next 5 minutes. However, differently from the pattern exhibited by bid-ask spreads, the decline in the depth of the order book is more pronounced for the 2-year note than the 5- and 10-years notes. In fact, around announcement times the average depth of the limit order book for the 2-year note decreases between 50 percent (overall) and 80 percent (best quote). The finding of a lower liquidity preceding macroeconomic announcement is consistent with the evidence reported in the extant literature and it is rationalized on the ground that traders withdraw liquidity to avoid the uncertainty associated with the upcoming announcements (see Fleming and Remolona, 1999; Jiang *et al.*, 2012 and the references therein).

With regards to trading volume, as in much empirical literature on bond trading and macroeconomic news announcements (see, *inter alia*, Fleming and Remolona, 1997; 1999), on announcement dates trading volume is higher and the difference peaks at announcement times for all benchmarks. However, the difference is larger for the 2-year note than for the other two bond maturities. Bond return volatility mimic a similar pattern exhibited by trading volume in that it is higher on announcement dates and the difference with non-announcement dates peak exactly at announcement times.

II.2 Identification of HF Trades and Orders

Our dataset does not contain information about whether a trade or order is placed through computer program or manually. However, the dataset records reference numbers that provide information on the submission timing of an order and its subsequent alteration, cancellation or execution. Using this useful piece of information, we identify high frequency (HF) activity by looking at the reaction time of order and transactions to changes in market conditions. We select those trades/orders that are placed to the market at a speed deemed beyond human reaction.

More specifically, we label trades as originating from computers if a market buy (sell) order is placed to hit the best ask (bid) quote within a second of the changes of the best quotes (High Frequency Market Order, HFMO henceforth). We label orders as originating from computers if 1) a limit order at the best quote is modified within one second of changes in best quotes on the same side of the market (High Frequency Limit Order 1, HFLO1 henceforth) 2) a limit order at the best quote is modified within one second of changes in best quote on the opposite side of the market (HFLO2 henceforth), 3) a limit buy (sell) order placed at the second best quote is modified within one second of the changes of the buy (sell) best quotes (HFLO3 henceforth) or 4) a limit order is cancelled or modified within one second of its placement regardless of market condition changes

(HFLO4 henceforth).

It is important to emphasize that the procedure described above is specifically designed to infer HF activities on the basis of the speed at which trades are executed and orders are submitted to or withdrawn from the market. However, some important caveats are in order. First, manual orders can be mistakenly identified as HF orders if manual orders are placed earlier but arrive exactly one second before market conditions change. As a consequence, some manual trades and orders may be misidentified as HF trades and orders. Second, 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. In fact, due to the existence of discrete tick sizes, market microstructure noise may be aggravated as the sampling frequency increases. In order to mitigate the problem arising from using ultra-high-frequency data, we aggregate our information at the 1-minute frequency, in line with existing empirical studies (see, *inter alia*, Fleming and Remolona, 1999; Balduzzi *et al.*, 2001 and the references therein).

After constructing orders and trades that are likely to be generated by computers, we define a measure of abnormal HF activities around macroeconomic news announcements. Consistent with the methodology proposed in the previous Section II.1 for other key variables of interest, the abnormal values of HF trades and orders are computed as the value of actual HF trades and orders in excess of the average HF trades and orders recorded during the previous 30 minutes interval over the past 5 days with no major news announcements or economic events. More formally:

$$HF_{t,1M(i)}^{TRADE*} = HF_{t,1M(i)}^{TRADE} - \frac{1}{5}\sum_{k=1}^{5}\left[\frac{1}{30}\sum_{j=1}^{30} HF_{t-k,1M(i-j)}^{TRADE,NON}\right], \quad (5)$$

$$HF_{t,1M(i)}^{ORDER*} = HF_{t,1M(i)}^{ORDER} - \frac{1}{5}\sum_{k=1}^{5}\left[\frac{1}{30}\sum_{j=1}^{30} HF_{t-k,1M(i-j)}^{ORDER,NON}\right], \quad (6)$$

where $HF_{t,1M(i)}^{Z}$ is the number of HF, *Z*=trades, orders within the *i*-th minute interval on announcement day *t*, $HF^{Z,NON}_{t-k,1M(i-j)}$ denotes the HF trades and orders identified in the past *t-k* no-event day during (*i-j*)*th* intervals, where *j*=1,…30 and *k*=1,…,5. The term $\frac{1}{5}\sum_{k=1}^{5}[\frac{1}{30}\sum_{j=1}^{30} HF^{Z,NON}_{t-k,1M(i-j)}]$ denotes the average of past HF trades and orders recorded over the past five no-event days during the 30-minute interval prior to the *i*-th minute interval.

A summary of identified high frequency trades and orders is reported in Table 3. Panel A reports the average number of HF trades (HFMO) over a 15-minute interval over the full sample period and across different macroeconomic news announcements. For all maturity tenors, average HF trades range between 28 (77) and 71 (185) before (after) news announcements. The HF intensity seems more pronounced during the 15 minutes after the announcement with a value that more than 2 times larger than that recorded prior to news announcements.

Panel B shows the average number HF orders originating from the filter discussed earlier in this Section. The values are disaggregated by the type of filter (HFLO1 to HFLO4) and then aggregated (all HF orders). Across different types of potentially HF orders, limit orders that are cancelled or modified within one second of their placement regardless of market condition changes (HFLO4) exhibit the largest number. However, regardless of the filter applied and across different maturity tenors, the figures reported in Panel B confirm that HF quoting activity is larger after macroeconomic news announcements than before announcements. If we take into account potential time trends and seasonality in computing the figures in Panels A and B and compute abnormal HF orders and trades as in Equations (5) and (6), the difference between pre- and post-announcement periods, reported in Panel C, is even more striking. In fact, the change in the number of HF trades and orders between pre- and post-announcement periods is further magnified recording, on average across benchmarks, multipliers of the order of 9 and 53 for HF trades and orders, respectively.

These findings are visually corroborated by the patterns showed in Figure 2. In fact, across all maturities, HF orders and trades are substantially larger at and after the announcement time than the period preceding the announcements. The shift is larger for the 5- and 10-year notes which record increments of more than 500 percent for HF orders and trades at the announcement time in comparison to pre-announcement periods. The 2-year note, although smaller in magnitude, records increments of 300-400 percent at the announcement time. In all cases the levels of HF orders and trades do not revert completely to their pre-announcement levels within 15 minutes although they show a clear convergence path.

III. Empirical Analysis

In this section, we address the following issues around public information arrival: i) the effect of HF trades and orders on (subsequent) market liquidity and volatility, and ii) the informativeness of HF trades and orders as well as the effect of HF trades and orders on market efficiency.

III.1. HF Activity and Liquidity/Volatility

The first issue we examine using the measures discussed in Section II relates to the potential impact of HF activities on (subsequent) market liquidity and volatility. We do this by investigating how abnormal HF trades and orders correlate with similarly abnormal measures of market liquidity and volatility around macroeconomic announcement times. Formally, we estimate the following regressions:

$$LIQ^{*}_{t,1M(i+1)} = \alpha + \varphi_0 \mathrm{HF}^{\mathrm{ORDER}*}_{t,1M(i)} + \gamma_0 \mathrm{HF}^{\mathrm{TRADE}*}_{t,1M(i)} + \varphi_1 \mathrm{NHF}^{\mathrm{ORDER}*}_{t,1M(i)} + \gamma_1 \mathrm{NHF}^{\mathrm{TRADE}*}_{t,1M(i)} + \beta LIQ^{*}_{t,1M(i)} + \varepsilon_{t,1m(i)} \quad (7)$$

$$VLTY^*_{t,1M(i+1)} = \alpha + \varphi_0 \mathrm{HF}^{\mathrm{ORDER}*}_{t,1M(i)} + \gamma_0 \mathrm{HF}^{\mathrm{TRADE}*}_{t,1M(i)} + \varphi_1 \mathrm{NHF}^{\mathrm{ORDER}*}_{t,1M(i)} + \gamma_1 \mathrm{NHF}^{\mathrm{TRADE}*}_{t,1M(i)} + \beta VLTY^*_{t,1M(i)} + \varepsilon_{t,1m(i)} \tag{8}$$

where $NHF^{Z*}_{t,1M(i)} = NHF^{Z}_{t,1M(i)} - \frac{1}{5}\sum_{k=1}^{5}[\frac{1}{30}\sum_{j=1}^{30} NHF^{Z,NON}_{t-k,1M(i-j)}]$ denotes the abnormal non-HF Z =trades,orders computed in the i-th minute interval on day t, $LIQ^*_{t,1M(i+1)}$ denotes a measure of abnormal market liquidity (i.e. $SPRD^*_{t,1M(i)}$, $DPTH^{BST*}_{t,1M(i)}$, $DPTH^{ALL*}_{t,1M(i)}$), $VLTY^*_{t,1M(i)}$ denotes the measure of abnormal bond returns volatility and the other variables are defined as in Section II.

The parameter estimates of Equations (7) and (8) are reported in Table 4. Panels A-C report the results for the cases where $LIQ^*_{t,1M(i+1)}$ is proxied by the abnormal spread in tick, the abnormal depth of the order book at the best quote and the abnormal overall depth of the order book, respectively. Panel D reports the case where the dependent variable is the abnormal volatility. Equations (7) and (8) are estimated by assuming that either the impact of abnormal HF activity on the dependent variables is equal to the one exhibited by the abnormal non-HF activity, i.e. $\varphi_0 = \varphi_1$ and $\gamma_0 = \gamma_1$ (specification 1) or that the impact of HF and non-HF activity is different, i.e. $\varphi_0 \neq \varphi_1$ and $\gamma_0 \neq \gamma_1$ (specification 2).

The main results can be summarized as follows. First, across various liquidity measures, all trades (or market orders) tend to reduce subsequent liquidity in terms of higher bid-ask spreads or smaller depth of the order book at the best quote. Differently all limit orders tend to improve liquidity in terms of smaller bid-ask spread. The result is less clear cut when we considered depth at the best quote. All limit orders improve depth at the best quote at pre-announcement period but it is related to drop in depth at the best quote at the post-announcement period. On the other hand, all limit orders improves overall depth in both pre- and post-announcement periods. This result indicates that more limit orders are placed behind the best depth during the post-announcement period

Second, when orders and trades are separated in the two HF and non-HF groups, some new light is shed on the previous results. The finding of trades reducing liquidity in terms of abnormal spread and depth at the best quote seems to be driven by HF trades. By the same token, the finding of orders improving liquidity in terms of spread seems to be driven by non-HF orders. HF orders, in fact, are also related to wider subsequent spread. Furthermore, the significance of the HF orders and trades is higher during the pre-announcement period rather than the post-announcement period in both spread and depth at the best quote equations. The results suggest that the impact of HF activity on subsequent spread and depth at the best quote is higher during periods characterized by larger uncertainty.

Despite the fact that HF activities are related to wider subsequent spread and lower depth at the best quote, they improve liquidity in terms of overall depth. HF trades and orders are related to subsequent increase in overall depth during both the pre- and post-announcement period (with the exception of the two-year note in the pre-announcement period). The coefficient of HF trades is significantly positive at 1% interval for all three maturities. The results of HF trades reducing depth at best quote and improving overall depth suggests that HF trades attract provision of liquidity behind the best quote on the order book.

Third, all orders and trades affect positively subsequent bond return volatility and the effect of trades is much larger than the one exhibited by orders. When orders and trades are classified as originating from HF and non-HF, the results suggest that *both* HF trades and orders have a very strong and positive effect on subsequent volatility while non-HF trades and orders exhibit some marginal effect. Interestingly, non-HF orders seem to exhibit a dampening effect on volatility which is particularly significant during post-announcement period.

Forth, all dependent variables exhibit a moderate to high serial correlation as the coefficients of lagged variables in their respective regressions are positive and highly significant. It is thus important to include them as control variables in their respective regressions.

III.2. HF Activity and its Effect on Price Efficiency

The second issue we examine relates to the price discovery process of the Treasury securities. The relationship between price discovery and trading activity has been largely explored in the literature and several approaches have been proposed. In our empirical investigation we examine this important issue from two angles: first, we compare HF orders and trades against ‘slow’ (or manual) orders and trades to assess which group is more informative. We do this by using the test proposed by Kaniel and Liu (2006). More specifically, we divide the whole population of orders and trades into two samples. The first sample consists of the HF orders (trades) while the second sample consists of orders (trades) which are submitted to the market with a delay of 3 seconds or more following market changes. We exclude orders that are submitted more than 1 second but less than 3 seconds following market changes. Intuitively, the Kaniel and Liu (2006) test assesses the informativeness of orders (trades) from the two samples by comparing the actual percentages of orders (trades) on the ‘right’ side of the market or predicting the ‘correct’ direction of the market.[11] 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_{man} $(1 - P_{man})$ as the probability that a submitted order (trade) is a manual or HF order (trade), respectively; *n* 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 either a manual or a HF order (trade) and n_{man} the number

[11] In this context, ‘Correct’ direction means that a buy (sell) order is followed by higher (lower) mid-quote in the future.

of midpoint changes in the correct direction that follow manual orders. Under the null hypothesis, Kaniel and Liu (2006) show that out of these n quotes, n_{man} or more is followed by manual order is given by

$$\phi = 1 - N\left[\frac{n_{man} - nP_{man}}{\sqrt{n \cdot P_{man}(1 - P_{man})}}\right] \tag{9}$$

If the probability ϕ is lower (higher) than 5% (95%), we reject the null hypothesis of equal informativeness of HF orders (trades) and manual orders (trades) in favor of the alternative that manual (HF) orders (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 results of the Kaniel and Liu's (2006) testing procedure are reported in Table 5. Panel A reports the probabilities ϕ computed for both orders and trades for all bond maturities during the pre-announcement period. Panel B reports the probabilities ϕ computed for both orders and trades for all bond maturities during the post-announcement period. We also divide both trades and orders into three size groups.

The results of the Kaniel and Liu (2006) test applied to limit orders strongly suggest that manual orders overall tend to be more informative. Although the results already depict a clear picture for the pre-announcement period across bond maturities and order sizes, the results of the test are particularly striking during the post-announcement period where in all cases manual orders are found to be more informative than HF orders. The results of the test applied to trades (market orders) are less conclusive. However, during the post-announcement period, the test seems to suggest some informativeness of HF trades but only in a small handful of cases, mostly concentrated with the 2-year note. Overall the results reported in Table 5 are very similar in spirit to the ones recently proposed in Chaboud *et al.* (2009). In fact, they record that the share of variance in returns that can be attributed to HF trading is surprisingly small when compared to the share of variance attributed to human trading activity.

We assess and complement the findings from the Kaniel and Liu (2006) test by examining the effect of HF trading on subsequent mid-quotes serial correlation, as suggested in Boehmer and Kelley (2010) and Boehmer *et al.* (2012). The intuition is that, if prices follow a random walk, quote mid-points autocorrelation should be equal to zero at all horizons. Deviations from zero imply predictability. To put this framework to the data, we compute the quote mid-point return serial correlation within each 5-minute intervals using 1-minute interval data after any macroeconomic news announcement in our sample. In the spirit of Boehmer *et al.* (2012), we estimate the following equation:

$$\left|AC_{t,5m(i)}\right| = \alpha + \varphi_0 HF^{ORDER*}_{t,5m(i-1)} + \gamma_0 HF^{TRADE*}_{t,5m(i-1)} + \varphi_1 NHF^{ORDER*}_{t,5m(i-1)} + \gamma_1 NHF^{TRADE*}_{t,5m(i-1)} + \beta_1 VLTY^{*}_{t,5m(i-1)} + \beta_2 DPTH^{BST*}_{t,5m(i-1)} + \beta_3 DPTH^{ALL*}_{t,5m(i-1)} + \beta_4 SPRD^{*}_{t,5m(i-1)} + \gamma\left|SUR_t\right| + \varepsilon_{t,5m(i)}, \qquad (12)$$

where $\left|AC_{t,5m(i)}\right|$ denotes the absolute value of the mid-quote serial correlation coefficient and the other variables are constructed as in Section II. As for Equations (7) and (8) we estimate the parameters of Equation (12) by assuming two specifications: one where the impact of abnormal HF activity on the dependent variables is equal to the one exhibited by the abnormal non-HF activity, i.e. $\varphi_0 = \varphi_1$ and $\gamma_0 = \gamma_1$ (specification 1) and another where the impact of HF and non-HF activity on the dependent variable is different, i.e. $\varphi_0 \neq \varphi_1$ and $\gamma_0 \neq \gamma_1$ (specification 2).

The results of the estimation for all specifications are reported in Table 6. When we consider all trades and orders, only trades are statistically significant at conventional level but only for the 5- and 10-year notes and only for the pre-announcement period. None of the orders and trades are statistically significant during the post-announcement period. When orders and trades are classified as HF or non-HF, the estimates suggest that non-HF trades positively affect the serial correlation of mid-quote returns across all bond maturities. Similarly, HF orders positively affect the serial correlation of mid-quote returns. However, the impact of HF orders is much smaller than the one exhibited by non-HF trades. The significance of those variables is only recorded during the pre-announcement period. Nevertheless, the sign of the coefficients associated with abnormal non-HF trades and HF orders is positive suggesting that a larger non-HF trading and HF quoting activity is associated with smaller informational efficiency.

IV. Conclusion

This article explores the role of HF activity and its effects on liquidity, volatility and the price discovery process of US Treasury securities around macroeconomic news announcements. Using a comprehensive dataset provided by BrokerTec, we propose and construct measures of HF activity by looking at orders and transactions that have been recorded at a speed that is deemed beyond human capability. Using these new measures we assess 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 role of HF activities in the price discovery process for US Treasury securities.

Our results are as follows: First, both HF trades and orders increase substantially immediately following macroeconomic news announcements. In particular, the HF intensity is substantially more pronounced during the 15 minutes following the news releases. Second, there is clear evidence that HF activity increases subsequent bond return volatility and to a certain extent it has a mixed effect on market liquidity. While higher-than-normal HF activity generates subsequent higher bid-ask spreads, it is also related to a larger subsequent overall depth of the order book. The effect of HF trades and quotes on liquidity is higher during the 15 minutes preceding the news announcements. Finally, our results also show that manual trades and orders tend to be more informative than the HF counterparts and HF trades and orders do not seem to help facilitate the price discovery process of Treasury securities.

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Table 1

Macroeconomic News Announcements

This table reports the list of macroeconomic news announcements included in our analysis. N denotes the total number of announcements during the period from January 5, 2004 to June 29, 2007; Day denote the weekday or day of the month of announcement; σ denotes the standard deviation of announcement surprises; $N_{|SUR|}$ denotes the number of announcements with surprise greater than one or two standard deviations.

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

Table 2

Summary Statistics of Trading Activities

This table reports summary statistics of trading volume ($ million), spread in ticks, depth at the best bid and ask ($ millions), depth of the entire order book ($ millions) and volatility (absolute mid-quote change multiplied by 1,000) during the 15 minutes preceding the announcement (Pre-announcement period) and the 15 minutes following the announcement (Post-announcement period). All variables are calculated as the average over one-minute interval. The sample period is from January 5, 2004 to June 29, 2007.

	Mean	**Median**	**Std**	**Max**	**Min**
Panel A: Pre-Announcement Period					
2-year note					
Spread (tick)	1.12	1.00	0.36	4.00	1.00
Trading volume ($ mln)	55.87	21.00	81.33	485.00	0.00
Depth at best quotes ($ mln)	438.50	337.00	361.35	1653.00	13.00
Overall depth ($ mln)	3730.78	2896.00	3288.28	12940.00	86.00
Volatility	2.10	0.00	3.25	15.63	0.00
5-year note					
Spread (tick)	1.32	1.00	0.76	9.00	0.00
Trading volume ($ mln)	49.96	37.00	47.61	248.00	0.00
Depth at best quotes ($ mln)	88.04	72.00	65.84	346.00	5.00
Overall depth ($ mln)	952.40	712.00	837.33	4087.00	43.00
Volatility	5.50	3.91	5.86	35.16	0.00
10-year note					
Spread (tick)	1.24	1.00	0.57	7.00	0.00
Trading volume ($ mln)	43.00	31.00	41.81	215.00	0.00
Depth at best quotes ($ mln)	86.97	75.00	59.27	291.00	5.00
Overall depth ($ mln)	1165.29	930.00	903.76	3991.00	37.00
Volatility	9.47	7.81	10.01	62.50	0.00

	Mean	Median	Std	Max	Min
Panel B: Post-Announcement Period					
2-year note					
Spread (tick)	1.09	1.00	0.30	3.00	0.00
Trading volume ($ mln)	144.16	87.00	166.80	882.00	0.00
Depth at best quotes ($ mln)	522.83	458.00	392.36	1755.00	18.00
Overall depth ($ mln)	4461.95	4045.00	3517.02	13266.00	113.00
Volatility	4.61	3.91	5.88	39.06	0.00
5-year note					
Spread (tick)	1.25	1.00	0.51	4.00	0.00
Trading volume ($ mln)	110.64	86.00	92.15	466.00	0.00
Depth at best quotes ($ mln)	99.85	85.00	70.13	358.00	6.00
Overall depth ($ mln)	1179.27	943.00	960.66	4164.00	69.00
Volatility	12.07	7.81	13.67	105.47	0.00
10-year note					
Spread (tick)	1.16	1.00	0.42	3.00	0.00
Trading volume ($ mln)	101.86	80.00	85.01	442.00	0.00
Depth at best quotes ($ mln)	101.55	90.00	64.98	338.00	6.00
Overall depth ($ mln)	1496.01	1275.00	1070.79	4172.00	54.00
Volatility	19.78	15.63	21.11	156.25	0.00

Table 3

HF Trades and Orders

This table reports the average number of HF trades (Panel A), HF orders (Panel B), as well as abnormal HF orders and traders (Panel C) over the 15 intervals preceding (pre-announcement) and following (post-announcement) the news releases. HF trades (HFMO) are identified as a market buy (sell) order hitting the best ask (bid) quote within a second of the changes of the best quotes. HFLO1 denotes limit orders at the best quote modified within one second that the best quote on the same side of the market is changed. HFLO2 denotes limit orders at the best quote modified within one second that the best quote on the opposite side of the market is changed. HFLO3 denotes limit buy (sell) orders at the second best quote modified within one second that the best buy (sell) quote is changed. HFLO4 denotes limit orders cancelled or modified within one second of its placement regardless of market condition changes. Abnormal trades and orders are defined as in Equations (5) and (6) 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: HF Trades						
HFMO	28.34	71.48	77.38	184.68	75.63	182.12
Panel B: HF Orders						
HFLO1	10.19	13.13	19.55	32.26	17.81	26.58
HFLO2	13.55	30.28	33.15	70.22	31.45	64.45
HFLO3	9.96	25.00	29.40	68.30	25.58	56.36
HFLO4	527.87	1549.14	1289.46	3558.26	1556.34	4417.23
All orders	561.57	1617.54	1371.56	3729.04	1631.19	4564.62
Panel C: Abnormal HF Trades and Orders						
Abnormal Trades	5.09	43.41	10.40	102.55	10.29	103.75
Abnormal Orders	51.95	931.34	44.43	2057.07	48.85	2611.88

Table 4
The Impact of HF Trades and Orders on Subsequent Market Liquidity

This table reports the parameter estimates of Equations (7) and (8) of the main text. ***, **, and * denotes significance at 1%, 5%, and 10% levels, respectively. For each equation Specification (1) assumes that $\varphi_0 = \varphi_1$ and $\gamma_0 = \gamma_1$ while specification (2) let $\varphi_0 \neq \varphi_1$ and $\gamma_0 \neq \gamma_1$.

	Pre-announcement Period						**Post-announcement Period**					
	2-year		**5-year**		**10-year**		**2-year**		**5-year**		**10-year**	
Panel A: Spread in tick												
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.5593***	0.5454***	1.3805***	1.2876***	2.0407***	1.9539***	0.1405***	0.1473***	0.4088***	0.4637***	0.2695***	0.2902***
SPRD*	0.1788***	0.1743***	0.2499***	0.2374***	0.1986***	0.1926***	0.2428***	0.2403***	0.2610***	0.2561***	0.1638***	0.1616***
ORDER*	-0.0022***		-0.0037***		-0.0029***		-0.0003*		-0.0004**		-0.0006**	
TRADE*	0.0579***		0.0630***		0.0285		0.0069		0.0008		0.0154**	
NHF^{ORDER*}		-0.0061***		-0.0135***		-0.0102***		-0.0006*		-0.0019***		-0.0012**
NHF^{TRADE*}		0.0525***		0.0007		-0.0213		-0.0024		-0.0035		-0.0109
HF^{ORDER*}		0.0055***		0.0117***		0.0088***		0.0001		0.0019***		0.0002
HF^{TRADE*}		0.0723***		0.1878***		0.1336***		0.0242**		0.0072		0.0470***
|SUR|							1.4857***	1.4541***	3.0241***	2.7772***	3.3179***	3.1298***
R^2	0.0271	0.029	0.042	0.0496	0.0284	0.0311	0.079	0.0795	0.0907	0.0928	0.0359	0.0368

Panel B: Depth at best quote												
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	-63.77***	-63.05***	-11.57***	-11.27***	-11.56***	-11.27***	0.7068	1.3012	-1.1677	-1.1456	-1.7375**	-1.7314**
$DPTH^{BST}$*	0.5714***	0.5656***	0.3900***	0.3870***	0.4323***	0.4250***	0.2535***	0.2527***	0.1566***	0.1562***	0.2426***	0.2415***
ORDER*	0.1172***		0.0140***		0.0239***		-0.1017***		-0.0083***		0.0015	
TRADE*	-4.3717***		-0.3561***		-0.6222***		-1.8981***		-0.2167***		-0.2528***	
NHF^{ORDER*}		0.4591***		0.0499***		0.0537***		-0.1027**		-0.0075*		0.0022
NHF^{TRADE*}		-3.8102***		-0.2882*		-0.3171**		0.1791		-0.0016		-0.092
HF^{ORDER*}		-0.5593***		-0.0426***		-0.0238***		-0.0972		-0.0073		0.0012
HF^{TRADE*}		-5.6650***		-0.6329***		-1.1712***		-4.8691***		-0.4790***		-0.4480***
|SUR|							-169.87***	-167.66***	-23.64***	-22.86***	-28.51***	-27.81***
R^2	0.3154	0.318	0.1497	0.1517	0.1641	0.1669	0.087	0.0876	0.0418	0.0423	0.0748	0.0754
Panel C: Overall depth												
Intercept	-152.74***	-152.54***	-43.73***	-44.37***	-46.35***	-47.10***	-3.2545	-4.1376	-0.8811	1.5167	-2.9634*	0.9967
$DPTH^{ALL}$*	0.9531***	0.9513***	0.9634***	0.9658***	0.9700***	0.9732***	0.8648***	0.8656***	0.9105***	0.9150***	0.9271***	0.9367***
ORDER*	0.4247***		0.0789***		0.0564***		0.2283***		0.0503***		0.0445***	
TRADE*	0.3677		0.6212*		0.9813***		1.3745		0.132		0.7065***	
NHF^{ORDER*}		0.9319***		0.0342		-0.0286		0.2399***		-0.0213**		-0.0404***
NHF^{TRADE*}		-11.8166***		-1.7780***		-1.2330**		-1.4169		-0.5398**		-0.0448
HF^{ORDER*}		-0.7917		0.1261***		0.1741***		0.1924*		0.1556***		0.1553***
HF^{TRADE*}		21.3234***		4.2589***		4.7355***		5.6104***		1.0553***		1.9367***
|SUR|							-873.58***	-874.86***	-227.19***	-240.36***	-271.92***	-285.34***
R^2	0.8163	0.8168	0.8474	0.8478	0.8672	0.8677	0.7961	0.7961	0.8689	0.8702	0.9031	0.9046

Panel D: Volatility

	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.3206***	0.3157***	0.6775***	0.6214***	0.9534***	0.8851***	0.8801***	0.9263***	2.1229***	2.2805***	3.8601***	4.0583***
VLTY*	0.1584***	0.1508***	0.1826***	0.1761***	0.1388***	0.1337***	0.2930***	0.2853***	0.3227***	0.3114***	0.2834***	0.2741***
ORDER*	0.0025***		0.0016***		0.0015***		0.0005*		0.0002		-0.001	
TRADE*	0.0915***		0.0793***		0.1611***		0.0465***		0.0624***		0.1386***	
NHF^{ORDER*}		0.0013		-0.0027***		-0.0017		-0.0012**		-0.0036***		-0.0050***
NHF^{TRADE*}		0.0679***		0.0255		0.0655**		0.0224		0.0438**		0.0836***
HF^{ORDER*}		0.0045***		0.0080***		0.0059***		0.0037***		0.0059***		0.0043**
HF^{TRADE*}		0.1510***		0.1842***		0.3285***		0.0915***		0.0988***		0.2238***
|SUR|							11.0030***	10.8967***	27.4197***	26.9838***	41.6166***	41.0709***
R^2	0.0751	0.0769	0.0614	0.0662	0.0482	0.0514	0.2889	0.2904	0.3281	0.3298	0.2851	0.2866

Table 5

Informativeness of HF Trades and Orders Relative to Other Trades and Orders

The table reports results of Kaniel and Liu (2006) test for the informativeness of HF trades and orders relative to other trades and orders. A probability above 95% indicates relative informativeness of HF order (trade), whereas a probability below 5% indicates relative informativeness of other orders (trades). We also report the results based on trades and orders in different size categories. “Small” indicates orders (trades) in the bottom tercile, “Medium” indicates orders (trades) in the middle tercile, and “Large” indicates orders (trades) in the top tercile.

	Trades (Market Orders)				**Orders (Limit Orders)**			
Panel A: Pre-Announcement Period								
	All	Small	Medium	Large	All	Small	Medium	Large
2yr	**0.9929**	**0.9840**	0.9242	0.7210	**0.0089**	**1.0000**	0.5764	**0.0000**
5yr	0.6726	0.5810	0.3850	0.8096	**0.0000**	**0.0083**	**0.0000**	0.1870
10y	0.0896	0.0281	0.4959	0.4478	**0.0131**	0.8725	**0.0010**	**0.0028**
Panel B: Post-announcement Period								
	All	Small	Medium	Large	All	Small	Medium	Large
2yr	**1.0000**	**0.9997**	**1.0000**	**0.9557**	**0.0000**	**0.0060**	**0.0029**	**0.0000**
5yr	0.9467	0.8409	0.9174	0.6228	**0.0000**	**0.0000**	**0.0000**	**0.0020**
10y	0.9458	0.8982	0.7888	0.7504	**0.0000**	**0.0119**	**0.0000**	**0.0000**

Table 6

Price Informativeness of HF Trades and Orders

This table reports the estimates of Equation (12) in the main text. The absolute autocorrelation ($|AC_{t,5m(i)}|$), a measure of price informativeness, is calculated from minute by minute mid-quote returns over the next five minute interval. For each equation Specification (1) assumes that $\varphi_0 = \varphi_1$ and $\gamma_0 = \gamma_1$ while specification (2) let $\varphi_0 \neq \varphi_1$ and $\gamma_0 \neq \gamma_1$. See also notes to Table 4.

	Pre-announcement Period						Post-announcement Period					
	2-year		5-year		10-year		2-year		5-year		10-year	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.6878***	0.6871***	0.7721***	0.7635***	0.6442***	0.6462***	0.3433***	0.3422***	0.3447***	0.3438***	0.4008***	0.4016***
ORDER*	0.0017		0.0001		-0.0003		-0.0001		-0.0002		-0.0002	
TRADE*	-0.0415		0.0610**		0.0826***		-0.0049		0.0009		0.0036	
NHF^{ORDER*}		-0.0004		-0.0066***		-0.0037**		0.0006		-0.0003		0.0001
NHF^{TRADE*}		0.1013**		0.0780*		0.1331***		-0.0056		-0.0037		0.0006
HF^{ORDER*}		0.0074*		0.0121***		0.0056**		-0.001		-0.0001		-0.0005
HF^{TRADE*}		-0.2661***		0.0594		0.024		-0.0059		0.0062		0.0076
VLTY*	-0.2532**	-0.2519**	-0.2270***	-0.2219***	-0.0617*	-0.0543	0.0074	0.0074	-0.0102	-0.0107	-0.005	-0.0048
$DPTH^{BST}$*	-0.0677***	-0.0696***	-0.1355*	-0.1358*	0.0043	0.0029	-0.0058	-0.006	-0.016	-0.0143	-0.0022	-0.0041
$DPTH^{ALL}$*	-0.0088***	-0.0078***	-0.0350***	-0.0328***	-0.0475***	-0.0449***	0.0012	0.0011	0.0035	0.0036	0.0051**	0.0051**
SPRD*	0.068	0.101	0.1251	0.1177	0.0711	0.0726	-0.0190**	-0.0181**	-0.0038	-0.0038	-0.0068**	-0.0069**
|SUR|							-0.0042	-0.0034	-0.0294**	-0.0297**	-0.0274*	-0.0269
R^2	0.0548	0.0656	0.034	0.0407	0.0656	0.0708	0.031	0.032	0.0385	0.039	0.0449	0.0453

Figure 1. Key Variables Around News Announcements

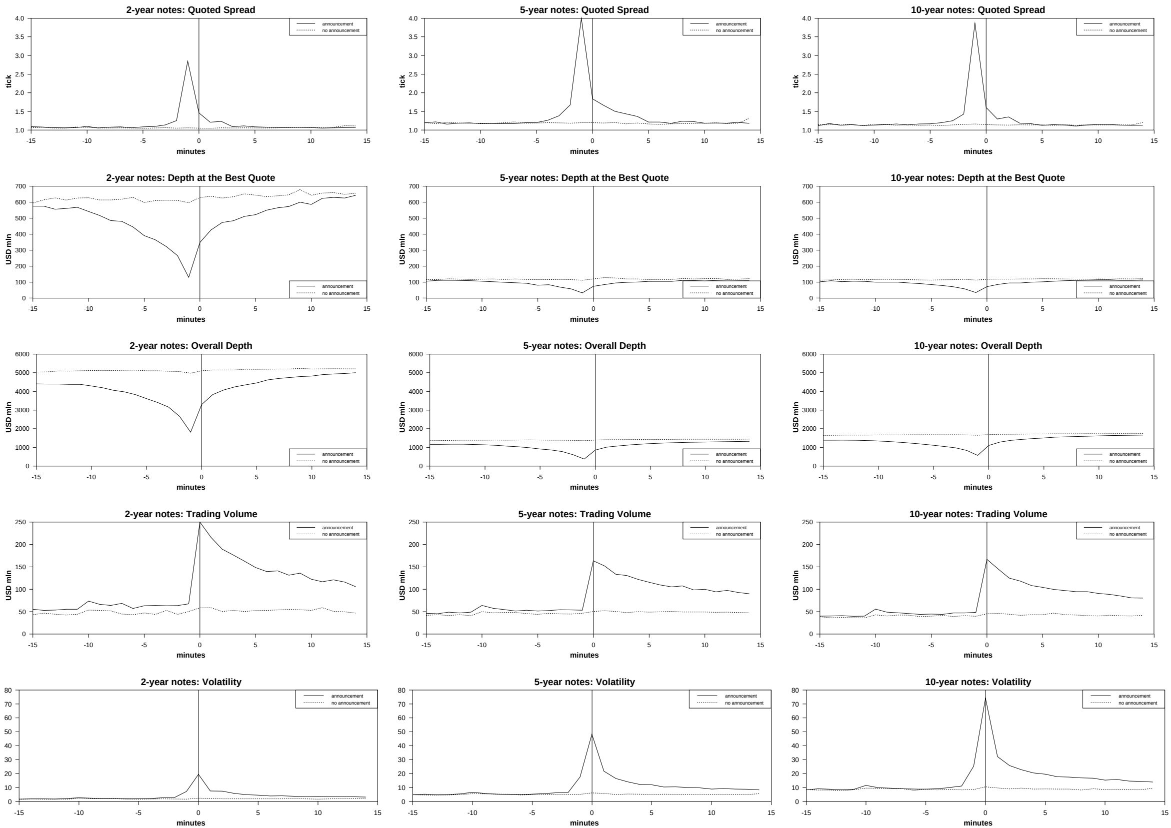

Figure 2. HF Activity around News Announcements

HF Trades and Orders, 1-minute averages