Information Shocks, Liquidity Shocks, Jumps, and Price Discovery

— Evidence from the U.S. Treasury Market

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Abstract

We examine large price changes, known as *jumps*, in the U.S. Treasury market. Using recently developed statistical tools, we identify price jumps in the 2-, 3-, 5-, 10-year notes and 30-year bond during the period of 2005-2006. Our results show that jumps mostly occur during pre-scheduled macroeconomic announcements. Nevertheless, announcement surprises have limited power in explaining bond price jumps. Our analysis shows that pre-announcement liquidity shocks have significant predictive power for price jumps in the U.S. Treasury market even after controlling for the effect of information shocks. Compared to announcements with no jumps, jumps at announcements are often preceded by a more significant increase of volatility, more dramatic widening of the bid-ask spread, and a more significant drop in market depth. Finally, we present evidence that jumps serve as a dramatic form of price discovery, and that post-jump order flow has less impact on bond prices.

I. Introduction

Recent studies provide strong empirical evidence that interest rates contain "surprise elements" or jumps.[1] It is well-known that compared to continuous price changes, jumps have distinctly different implications for risk management, portfolio allocation, as well as valuation of derivative securities. Thus, it is important to understand the magnitude of jump risk in the U.S. Treasury market, what drives jumps in bond prices, and how the market behaves prior to and post significantly large price changes. In this paper, we identify jumps in the U.S. Treasury bond prices using recently developed statistical tools. The data used in our study is obtained from the BrokerTec electronic trading platform and contains around-the-clock trades and quotes for the on-the-run 2-year, 3-year, 5-year, and 10-year notes and 30-year bond.[2] Based on 5-minute data over the period of 2005-2006, we identify 60 out of 477 trading days where the 2-year note experiences jumps in prices. On 8 of these 60 days, the 2-year note has multiple jumps in prices. The largest jumps in price are 0.24% on the upside and -0.17% on the downside (compared to an average 5-minute return standard deviation of 0.006%). Price jumps on longer maturity bonds are of larger magnitude. For example, the largest positive and negative jumps in price for the 10-year note are 0.70% and -0.64%, while those for the 30-year bond are 2.13 % and -3.55% respectively.

A natural question then is what causes these large jumps in bond prices? With identified intraday price jumps of U.S. Treasury securities, we first examine to what extent jumps are attributed to macroeconomic news announcements and then further examine whether jumps are also attributed to other market variables, such as market depth and liquidity shocks, etc. In this aspect, our study is different from existing literature that examines the effect of macroeconomic news announcements on bond prices. For instance, Fleming and Remolona (1999) examine a two-stage adjustment process for prices,

[1]There is now a growing body of literature that explicitly incorporates jumps in modeling the term structure dynamics of interest rate. For example, Das (2002) extends the Vasicek (1977) model to a jump-diffusion model and shows that incorporating jumps captures many empirical features of the Fed Funds rate that can not be explained by the continuous diffusion models. Johannes (2004) finds significant evidence for the presence of jumps in the 3-month Treasury bill rate. Piazzesi (2001, 2005) models the Fed's target rate as a jump process.

[2]During our sample period, the BrokerTec electronic trading platform accounts for about 60% of trading activity for these securities.

trading volume, and bid-ask spreads in the U.S. Treasury market in response to the arrival of public news announcement. Balduzzi, Elton and Green (2001) use intraday data to investigate the effects of scheduled macroeconomic announcements on bond prices, trading volume, and bid-ask spreads. Green (2004) further studies the impact of trading on government bond prices surrounding the release of macroeconomic news and finds a significant increase in the informational role of trading following economic announcement. Pasquariello and Vega (2007) analyze the role of private and public information in the U.S. Treasury bond price discovery process by studying the response of bond yields to order flow and real-time U.S. macroeconomic news. Huang, Cai, and Wang (2002) examine the trading behavior of primary dealers in the 5-year Treasury note interdealer broker market, and show that trading frequency is affected by both private and public information. Extending the above studies, Menkveld, Sarkar and van der Wel (2008) examine the effect of macroeconomic announcements on the 30-year U.S. Treasury bond futures market activities. Brandt, Kavajecz, and Underwood (2007) examine the price discovery in the futures market and its interaction with cash market. The approach of our study is similar to that of Fleming and Remolona (1997) with a focus on large changes in bond prices.[3]

Overall, we find that a large number of jumps occur during pre-scheduled macroeconomic news announcements. For example, nearly 90% of jumps in the 2-year note prices occur within a 10-minute window of pre-scheduled news announcement time. One advantage of our approach is that, by identifying jumps first we are able to search for potentially related news/events. In our analysis, we identify an extensive list of pre-scheduled macroeconomic news/events as potential causes of bond price jumps. The list includes major news announcements widely considered in existing literature as well as some news announcements that have been considered less important and thus largely omitted in previous studies. For instance, among the list of macroeconomic news announcements, we identify the following news associated with the largest number of jumps: Initial Jobless Claims, Consumer Price Index, Change in Nonfarm Payroll, Retail Sales, Producer Price Index, Consumer Confidence, and ISM index. Our results also show that jumps coincide with several news announcements, e.g., the NY Empire State Index (a regional economic indicator published by the Federal Reserve Bank of New York), that, to our

[3]Fleming and Remolona (1997) examine the twenty-five largest price changes in the on-the-run 5-year U.S. Treasury note from August 1993 to August 1994 and find that they are all associated with news announcements.

knowledge, have not been included in existing studies.

While we provide evidence that a majority of jumps occur during pre-scheduled news announcements, further analysis shows that information shocks, as measured by news announcement surprises,[4] have limited power in explaining jumps in bond prices. We find that pre-announcement liquidity shocks also play an important role in bond price jumps. One advantage of the BrokerTec data is that it contains not only information on transaction and market quotes but also information of the entire limit order book. This allows us to examine market activity and liquidity conditions around jumps. In our analysis, we use several measures constructed from the BrokerTec data to capture different aspects of market liquidity. They include the bid-ask spread, trading volume, and various measures of market depth calculated from the order book. Similar to Fleming and Remolona (1999), we document styled pre-announcement effects in the U.S. Treasury market. In particular, there is in general widening of the bid-ask spread and a sharp drop in both depth at the best quotes and overall market depth in anticipation of news announcement. More importantly, we find that there is a significantly higher return volatility and a significantly larger liquidity shock during the pre-announcement period on days with bond price jumps than those without.

To examine the explanatory power of information shocks versus liquidity shocks for jumps in bond prices, we perform double sorts on information shocks and liquidity shocks. The results show that firstly, pre-announcement liquidity shocks, in particular shocks to the bid-ask spread and shocks to overall market depth, are positively correlated with jumps in bond prices. Secondly, consistent with existing studies by, e.g., Fleming and Remolona (1999), Balduzzi, Elton and Green (2001), Green (2004), we document a significantly positive relation between announcement surprises and subsequent absolute 5-minute bond returns. Third and most interestingly, when there are significant liquidity shocks prior to news announcements, there is no longer a simple monotonic relation between announcement surprises and jumps. Specifically, when there is a significant increase of the bid-ask spread or a significant drop in market depth, jumps occur regardless of the magnitude of announcement surprises. These findings

[4]Following existing literature, we measure announcement surprises using the difference between the one-week ahead survey and the actual announcements. The survey data offers a measure of market expectations for certain macroeconomic news, and thus measures of both expected and unexpected components in the announcement.

suggest that pre-announcement liquidity shocks play an important role in bond price jumps in the U.S. Treasury market.

Since liquidity shocks can be due to pure imbalance of market orders or order withdrawal as a result of information uncertainty, we specify and estimate a Probit model to further examine the interaction between liquidity shocks and announcement surprises. The estimation results further confirm that liquidity shocks have significant predictive power for jump frequency. Interestingly, even after we explicitly control for the effect of announcement surprises, liquidity shocks remain significant in predicting jumps. In other words, the predictive power of liquidity shocks for upcoming jumps is not subsumed by information contained in announcement surprises. The findings suggest that liquidity shocks contribute to jumps beyond the effect of unexpected information shocks.

Finally, we examine the post-jump price discovery process of the U.S. Treasury market. The analysis is closely related to recent studies that examine the information content of order flow around announcements. Green (2004) finds that order flow has a higher information content on announcement days in the 5-year Treasury note relative to non-announcement days. Menkveld, Sarkar and van der Wel (2008) provide similar findings for the 30-year Treasury bond futures. Brandt and Kavajecz (2004) find that order flow imbalances account for up to 26% of the day-to-day variation in yields on days without major macroeconomic announcements and the effect of order flow on yields is strongest when liquidity is low. These studies focus on comparing the informational role of order flow on announcement days versus non-announcement days. We extend these studies and examine the effect of jumps on the price discovery process. Our results show that order flow imbalance has significantly less impact on bond prices after jumps at the announcement compared to the case where there is no jump at the announcement. Moreover, as post-jump time horizon extends, from 15-minute to 60-minute, the price impact of order flow tends to increase. We note that the lessened informational role for order flow during the 15-minute interval after a jump is accompanied by a surge of trading volume. Therefore, the lesser informational role of order flow is not due to a lack of trading or stagnant price discovery. Taken together, the results suggest that jumps serve as a dramatic form of price discovery and post-jump order flow tends to have less informational role.

The rest of the paper proceeds as follows. Section II describes the data and jump test. Section III presents empirical results of identified price jumps in the U.S. Treasury market, and market activities around jumps. Section IV examines the role of liquidity shocks in bond price jumps as well as post-jump price discovery process. Section V concludes.

II. Data and Methodology

A. Data

The U.S. Treasury securities data are obtained from BrokerTec, an interdealer electronic trading platform in the secondary wholesale U.S. Treasury securities market. Since 2003, the majority of secondary trading has gone through electronic platforms with over 95% of active issue treasury occurring on electronic platforms.[5] Two platforms dominate the U.S. treasuries market: BrokerTec and E-speed. BrokerTec has a market share of 60-65% on the active issues and is more active in the trading of 2-year, 3-year, 5-year and 10-year Treasury notes. The data also include the 30-year bond, although E-speed has a larger market share for this maturity. There has been a strong growth in trading volume on the BrokerTec platform in recent years. The average daily trading volume of all maturities goes up from \$30.9 billion in 2003, \$53.0 billion in 2004, \$80.2 billion in 2005, to \$103.4 billion in 2006. The BrokerTec platform functions as a limit order book. Traders can submit limit orders, i.e., orders that specify both price and quantity posted on the book, or they can submit marketable limit orders, i.e., orders with a better price than or equal to the best price on the opposite side of the market, to ensure immediate execution. Limit order submitters can post "iceburg" orders, where only part of their order are visible to the market and the remaining part is hidden. All orders on the book except the hidden part of the orders are observed by market participants. The orders remain in the market until matched, deleted, inactivated, loss of connectivity, or market close. The market operates more than 22 hours a day from Monday to Friday. After the market closes at 5:30 p.m. (EST), it opens again at 7:00 p.m. (EST). The data set contains the tick-by-tick observations of transactions, order submissions and or-

[5]See "Speech to the Bond Market Association", December 8, 2004 by Michael Spencer, founder and chief executive of ICAP, one of the world's largest interdealer broker.

der cancellations. It includes the time stamp of the observations, the quote, the quantity entered and deleted, the side of the market and, in the case of a transaction, an aggressor indicator.

We use data from 7:30 a.m. EST to 5:00 p.m. EST since trading is more active during this time interval. This interval also contains all pre-scheduled U.S. news announcements, and it provides us with 9.5 hours of trading and 114 five-minute return observations each day. The choice of working on five-minute returns follows Fleming and Remolona (1999), Balduzzi, Elton and Green (2001), and others. Since liquidity has changed drastically over time, we restrict our sample period to the most recent years, i.e., from January 2, 2005 to December 29, 2006. Days with early closing before public holidays are also excluded as liquidity is typically low for these days. The dataset consists of over 465.5 million observations and 10.9 million transactions.

Table I provides descriptive statistics of the data. Since the order book contains the price schedule on both sides of the market, there are multiple ways to measure liquidity. We compute and report the bid-ask spread, daily trading volume (in \$billions), trading duration (in seconds), daily return volatility, depth at the best quote, depth of the entire book, and hidden depth. Spread is defined both in relative terms and in ticks. Relative spread is defined as

$$\text{relative spread} = (\text{best bid price} - \text{best ask price})/\text{mid-quote} \tag{1}$$

and measured at the end of each 5-minute interval and averaged over the trading day. Tick spread is also measured at the end of each 5-minute interval and averaged over the trading day. As mentioned in Fleming and Mizrach (2008), the tick size differs for different maturities. The tick size of the 2-year, 3-year and 5-year note is 1/128, whereas that of the 10-year note and 30-year bond is 1/64. Daily return volatility is calculated as the square-root of the sum of squared log mid-quote difference sampled at 5-minute intervals

$$\text{return volatiilty} = (\sum_{i=1}^{114}(\ln p_i - \ln p_{i-1})^2)^{1/2} \tag{2}$$

where the mid-quote is defined as $p_i = (\text{best bid price} + \text{best ask price})/2$. The average (hidden) depth (in millions) at the best bid/ask is the total (hidden) observed depth at the best price on both the bid and ask side of the market measured at the end of each 5-minute interval and averaged over the trading day. The average depth and average hidden depth in the entire order book are defined similarly.

BrokerTec is a highly liquid platform over our sample period from 2005 to 2006. As shown in Table I, relative spread is smallest for the 2-year note with a sample mean of less than 0.0083% among the actively traded securities, followed by the 5-year note (0.0119%) and 10-year note (0.0179%). The tick spread is consistent with the relative spread. Trading volume is heaviest for the 2-year note ($27.45 billion per day), followed by the 5-year note ($24.69 billion per day), and 10-year note ($22.76 billion per day). In terms of trading duration, the 10-year note is most frequently traded, with an average duration of 6.59 seconds. This is closely followed by the 5-year note at 6.74 seconds. The trading duration of the most heavily traded 2-year note is on average 15.99 seconds. The result suggests that the average trade size is larger for the 2-year note than the 5-year and the 10-year note.

Return volatility is generally increasing with maturity. The trend seems related to where the depth accumulates on the order book. The mode of depth for the 2-year note locates closest to the best price, on average around 1.18 ticks away from the best price on both sides of the market. As maturity increases, depth mode locates further away from the best price: 1.25 ticks for the 3-year note, 1.67 ticks for the 5-year note, 1.53 ticks for the 10-year note, and 2.68 ticks for the 30-year bond. Thus normal price movements are more likely to be restricted by depth aggregated at the mode. The finding is consistent with Kavajecz and Odders-White (2004) in the equity market where accumulation of depth at a price level restricts the range of normal price changes.

The 2-year note has the deepest book both at the best price ($637.72 million) and entire book ($5,122 million). Hidden depth is low in general: hidden orders at the best price consist of less than 5% of the observed depth at the best price for the 2-year, 5-year, and 10-year notes.

Figure 1 presents the intra-day activities in the 2-year note. The intraday patterns for other bonds are similar and thus not reported for brevity. Consistent with the findings in Fleming (1997), trading volume peaks first in the 8:30 to 10:00 EST interval and goes up again from 13:00 to 14:00 EST. These two intervals overlap with major macroeconomic announcements. Trading duration shows the reverse pattern of trading volume. The time between transactions is longer at the end of the day, averaging over 40 seconds. At the most hectic interval from 8:30 to 9:00 EST, there are on average fewer than 5 seconds between transactions. Relative spread is higher at the beginning (before 8:30 EST)) and the end of the trading day (after 16:00 EST). The depth at the best price is thinner before 8:30 EST and after 15:00 EST. For the rest of the day, the book is on average over $600 millions. The level of hidden depth is higher at noon and it goes up again after 15:00 EST. This finding suggests that market participants hide more of their orders when there is less total depth in the market.

Data on macroeconomic news announcements and the survey of market participants comes from Bloomberg and Briefing.com economic calendar. We cover an extensive list of announcements and include both announcements used in previous literature and announcements where jumps are detected. To ensure the list of announcements is comprehensive, we start with the 25 announcements from Pasquariello and Vega (2007). We then check whether the timing of each jump coincides with any other announcements using information from the Briefing.com economic calendar, which features a comprehensive list of pre-scheduled announcements. This way, we include 7 additional economic announcements: FOMC minutes, ISM service, NY Empire State Index, Chicago PMI, Existing Home Sales, Philadelphia Fed Index, and ADP National Employment report. In addition to pre-scheduled news announcement, we also collect the auction result release times for 2-year, 3-year, 5-year and 10-year notes. Lastly, we collect the release of the testimony of Semiannual Monetary Policy Report and Economic Outlook. The full list of announcements can be found in Table II. Following Balduzzi, Elton and Green (2001) and Andersen Bollerslev, Diebold and Vega (2007), the standardized announcement surprise is defined as

$$S_{kt} = \frac{A_{kt} - E_{kt}}{\hat{\sigma_k}} \tag{3}$$

where A_{kt} is the actual announcement, E_{kt} is the median forecast for news k on day t, and $\hat{\sigma_k}$ is the standard deviation of $A_{kt} - E_{kt}, t = 1, 2, \cdots, T$.

B. Statistical Tests of Jumps

A number of statistical tests have been proposed in recent literature to detect whether there are jumps in asset prices. For instance, Aït-Sahalia (2002) exploits the restrictions on the transition density of diffusion processes to assess the likelihood of jumps. Carr and Wu (2003) make use of the decay of the time value of an option with respect to the option's maturity. Barndorff-Nielsen and Shephard (2004,

2006) propose a bi-power variation (BPV) measure to separate the jump variance and diffusive variance. Lee and Mykland (2007) exploit the properties of BPV and develop a rolling-based nonparametric test of jumps. Aït-Sahalia and Jacod (2007) propose a family of statistical tests of jumps using power variations of returns. Jiang and Oomen (2008) propose a jump test based on the idea of "variance swap" and explicitly take into account market microstructure noise.

In this study, we employ two of the aforementioned jump tests, namely, the "bi-power variation" (hereafter BPV) approach and the "variance swap" (hereafter SWV) approach. Both tests are developed using high frequency data to test for the presence of jumps during a particular time period, e.g., a day. In addition, both BPV and SWV jump tests are developed in a model-free framework and apply to a very general asset price process specified as follows:

$$dS_t/S_t = \mu_t dt + \sqrt{V_t} dW_t + (\exp(J_t) - 1)\, dq_t. \tag{4}$$

where μ_t is the instantaneous drift, V_t is the instantaneous variance when there is no random jump, W_t is a standard Brownian motion, q_t is a counting process with finite instantaneous intensity λ_t ($0 \leq \lambda_t < \infty$), and J_t is the random jump. Note that for the process specified in (4), there are no particular structures imposed on the drift term, the diffusive volatility component, or jump component.[6]

Throughout the paper, we assume that bond prices are observed at regular time intervals $\delta = 1/N$ over the period $[0, 1]$. The conventional realized variance (RV) is defined as:

$$RV_N = \sum_{i=1}^{N} r_{\delta,i}^2,$$

where $r_{\delta,j} = \ln(S_{j\delta}/S_{(j-1)\delta})$. It is well known (see, e.g., Jacod and Shiryaev (1987), Andersen, Bollerslev, Diebold, and Labys (2003)) that $\operatorname*{plim}_{N\to\infty} RV_N = V_{(0,1)} + \int_0^1 J_u^2 dq_u$, where $V_{(0,1)} \equiv \int_0^1 V_u du$. In words, RV is a consistent estimator of the total variance, including both the continuous diffusive component and the discontinuous jump component.

[6] Technically, the process in Eq. (4) represents a general semi-martingale process in the probability space $(\Omega, \mathcal{F}, P)$ with an information filtration $(\mathcal{F}_t) = \{\mathcal{F}_t : t \geq 0\}$. As a result, the demeaned asset price process is a local martingale and can be decomposed canonically into two orthogonal components: a purely continuous martingale and a purely discontinuous martingale, see Theorem 4.18 in Jacod and Shiryaev (2003).

The bi-power variation (BPV) measure defined in normalized form is given by:

$$BPV_N = \frac{1}{\mu_1^2} \sum_{i=1}^{N-1} |r_{\delta,i+1}| \, |r_{\delta,i}| \, ,$$

where $\mu_p = 2^{p/2}\Gamma\left((p+1)/2\right)/\sqrt{\pi}$ for $p > 0$. Barndorff-Nielsen and Shephard (2004) show that $\operatorname*{plim}_{N\to\infty} BPV_N = V_{(0,1)}$, i.e., the BPV captures the diffusive variance component. Based on the difference between RV and BPV, Barndorff-Nielsen and Shephard (2006) propose the following jump test:

$$\frac{V_{(0,1)}\sqrt{N}}{\sqrt{\Omega_{BPV}}} \left(1 - \frac{BPV_N}{RV_N}\right) \xrightarrow{d} \mathcal{N}(0,1). \tag{5}$$

where $\Omega_{BPV} = (\pi^2/4 + \pi - 5)Q_{(0,1)}$ and $Q_{(0,1)} = \int_0^1 V_u^2 du$.

The "variance swap" jump test developed in Jiang and Oomen (2008) is based on an intuition long established in the finance literature: in the continuous-time limit, the difference between simple return and log return equals one half of the instantaneous variance. To see this, a direct application of Itô's lemma to the price process in Eq. (4) leads to:

$$d\ln S_t = (\mu_t - \lambda_t \eta_t - \frac{1}{2}V_t)dt + \sqrt{V_t}dW_t + J_t dq_t, \tag{6}$$

Taking the difference between Eq. (6) and Eq. (4), and integrating over $[0,1]$, we have:

$$2\int_0^1 (dS_t/S_t - d\ln S_t) = V_{(0,1)} + 2\int_0^1 \left(\exp\left(J_t\right) - J_t - 1\right) dq_t. \tag{7}$$

It is clear that when there are no jumps, the left hand side captures the realized variance of asset returns. This idea has been explored in the "variance swap" literature. Specifically, Neuberger (1994) proposes a strategy to perfectly replicate "variance swap" by dynamically trading on "log-price" contracts. However, when there are jumps in the price process, this replication strategy fails, and the gain/loss of the replication strategy is a function of jumps.

Based on the discretized version of the left-hand side of Eq. (7), Jiang and Oomen (2008) constructs "variance swap" measure:

$$SWV_N = 2\sum_{j=1}^{N} (R_{\delta,j} - r_{\delta,j}) = 2\sum_{j=1}^{N} R_{\delta,j} - 2\ln\left(S_1/S_0\right), \tag{8}$$

where $R_{\delta,j} = (S_{j\delta} - S_{(j-1)\delta})/S_{(j-1)\delta}$. Based on the difference between RV and SWV, the "variance swap" jump test is proposed as follows:

$$\frac{V_{(0,1)}N}{\sqrt{\Omega_{SWV}}}\left(1 - \frac{RV_N}{SWV_N}\right) \xrightarrow{d} \mathcal{N}(0,1) \tag{9}$$

where $\Omega_{SWV} = \frac{1}{9}\mu_6 X_{(0,1)}$ and $X_{(0,1)} = \int_0^T V_u^3 du$.

Simulations performed in Jiang and Oomen (2008) show the "bi-power variation" and "variance swap" tests have similar finite sample properties in size but different finite sample properties in power. Both tests tend to over-reject the null hypothesis of no jumps. In general, the SWV test has more power in detecting infrequent large jumps while the BPV test can pick up frequent small jumps. Thus, we combine both tests in our empirical analysis for more desirable finite sample properties.[7] In addition, simulations in Lee and Mykland (2007) show that the SWV test and their proposed approach share similar powers of identifying jumps in most common settings.

When the test statistics of both BPV and SWV approaches are significant (at the 1% critical level), we reject the null hypothesis of no jumps. We then follow a sequential approach to identify jump returns. As acknowledged in the literature, pinpointing exactly which return is a jump is a difficult task. This is because volatility is time-varying and clustered, and returns of the largest magnitude are not necessarily jumps. In this paper, we propose a sequential approach to identify jump returns during a day. Details of the procedure are given in Appendix A. In a concurrent study, Andersen, Bollerslev, Federiksen, and Nielsen (2007) propose a similar procedure for identifying intraday jump returns. In addition, as noted earlier, since high frequency intraday returns are used, the data is likely subject to significant market microstructure effects. In both jump testing and jump return identification, we take into account potential market microstructure effects. Specifically, in the first step we allow for measurement error (i.e. asset price is observed with noise) in the SWV test, whereas in the second step we take into account discrete price changes due to tick-size and bid-ask spread. Details can be found in Appendix A.

[7] Simulations in Huang and Tauchen (2005) for the BPV test and Jiang and Oomen (2008) for the SWV test show that among various versions of test statistics, the ratio tests of both approaches have the best finite sample performance. As a result, our empirical analysis is based on the ratio tests. As detailed in Jiang and Oomen (2008), the feasible BPV and SWV tests are obtained by consistent and robust estimators of $V_{(0,1)}$, Ω_{BPV}, and Ω_{SWV}.

We evaluate the performance of jump tests using simulations. Each "day" we simulate the sample path of a jump-diffusion process with stochastic volatility, and then implement the jump tests. We examine the size and power of the BPV test, the SWV test and the joint-test under different jump sizes and different sets of parameter values for the mean reversion of volatility, volatility-of-volatility and "leverage effect". The design of the simulation is described in detail in Appendix B. The simulation is performed with 10,000 replications. The results in Table A show that at the 1% critical level, both the BPV and SWV tests tend to over reject the null hypothesis of no jumps with the size clearly above 1%. However, the size of the joint BPV and SWV tests is much improved, generally below but much closer to 1%. Thus, the joint approach substantially mitigates the size problem. As expected, the combined test has lower power. However, when the jump size is large (more than 4 times of return standard deviation), the joint test procedure does not sacrifice much of the power and works well in picking up large jumps. The conservativeness of the joint test approach suits our purpose as we are interested in large price changes in the U.S. Treasury security market.

III. Empirical Results

In this section, we first present summary statistics of all jumps. Then we identify how often jumps are associated with pre-scheduled news announcements/events.

A. Jumps in Bond Prices

Table III reports the jump frequency, the statistics of jump size for different maturities and the number of concurrent jumps across maturities. Among the three most liquid securities, the 5-year note has the highest jump frequency with 72 jumps, followed by the 2-year note with 69 jumps, and the 10-year note with 63 jumps. The jump size generally increases with maturity and the mean absolute jump size goes up from 0.08% for the 2-year note, 0.16% for the 5-year note, to 0.28% for the 10-year note. This pattern is consistent with Balduzzi, Elton and Green (2001) who find that the size of the price change as a result of announcement surprise is increasing with maturity. Considering the level of daily return volatility reported in Table I, jumps represent dramatic price changes over 5-minute interval. Separating positive jumps from negative ones, there is no clear difference in terms of frequency and size.

How often do jumps happen at the same time across different maturities? The last panel of Table III shows the concurrent jumps across maturities. Jumps across two different maturities are defined as concurrent if they are less than 5-minute apart from each other. Across maturities, there is a strong concurrence of jumps in bond prices. For example, out of the 69 jumps at the 2-year note prices, 70% of them have concurring jumps at the 3-year maturity. We note that here we simply document whether jumps for different maturities overlap with each other in time. The issue of co-jumps across maturities is formally examined in Dungey, MacKenzie and Smith (2007) and Lahaye, Laurent and Neely (2007). Dungey, MacKenzie and Smith (2007) examine co-jumps across maturities using the E-speed data. Lahaye, Laurent and Neely (2007) examine co-jumps across asset markets.

B. Jumps and Macroeconomic News Announcements

We further examine how often jumps occur at pre-scheduled news announcement time. A jump is identified as occurring at an announcement time if the 10-minute window centered around the announcement time overlaps with the 5-minute jump return interval. With a 10-minute window, we allow for potential variations (such as recording errors) in announcement time.

Table IV shows that a large majority of jumps occur during the time of announcement. For example, more than 90% of jumps of the 2-year note occur during pre-scheduled announcements. Although the number of jumps outside of announcement time is small, the median jump sizes are overall comparable to those at pre-scheduled announcement time. Panels C and D of Table IV report the number of concurrent jumps across maturities according to whether they occur at announcement time or not. The frequency of concurrent jumps is higher for jumps occurring at announcement time.

The left column of Figure 2 plots the distribution of the jump frequency throughout the day for the most liquid 2-, 5-, and 10-year notes. The frequency spikes around 8:30, 10:00, and 14:00, corresponding to standard pre-scheduled announcement time. The right column plots the distribution of jumps occurring outside announcement time. The distribution is, in general, flat over the day, conforming to the intuition that these jumps are generally unanticipated.

To pinpoint exactly what drives jumps in bond prices, we first focus on jumps occurring at announcement time. Panel A of Table V reports the top 15 announcements associated with the highest number of jumps. Among them, the following news announcements are identified as mostly frequently associated with bond price jumps: Initial Jobless Claims, Consumer Price Index, Change in Nonfarm Payroll, Retail Sales, Producer Price Index, Consumer Confidence, and ISM index. These announcements are generally consistent with those considered in the existing literature, such as Balduzzi, Elton and Green (2001), Green (2004), Pasquariello and Vega (2007), and Menkveld, Sarkar and van der Wel (2008). In addition, we also identify news items that have not been examined in the previous studies but are potential causes of jumps in bond prices. They include the announcement of NY Empire State Index, ISM service, Chicago PMI, Existing Home Sales, Philadelphia Fed Index, ADP National Employment report, and the release of the testimony of Semiannual Monetary Policy Report and Economic Outlook.

Is announcement surprise indicative of jumps? Existing literature documents empirical evidence that a larger surprise tends to have a bigger impact on bond prices. In this paper, we focus on jumps in bond prices and are interested in whether announcement surprise has a strong explanatory power of jumps. As a preliminary analysis, we sort jumps on announcement days to form 5 equal groups (quintiles) according to the absolute jump return and examine the patterns of announcement surprises across groups. Panel B of Table V reports the mean absolute jump return, mean absolute announcement surprise, and the number of significant surprises (i.e., survey error larger than 1 standard deviation) for each group. When there are multiple news announcements associated with a jump, news with the biggest announcement surprise is used in the calculation of average announcement surprise. The results show a rather non-monotonic relation between announcement surprise and jump magnitude. In fact, for the 5-year note the group with the highest absolute mean jump return has the lowest mean announcement surprise. The finding offers initial evidence that announcement surprise have a limited power in explaining jumps.

Now we turn to jumps outside announcement time. While these jumps could be attributed to unexpected information arrival or liquidity shocks in general, it turns out that to pinpoint the exact cause, even as an *ex post* check, is not always so easy. For each of the jumps, we search the news archive FACTIVA for potentially related news/events.[8] The following four cases illustrate a variety of unanticipated news/events as potential cause of jumps in the 10-year note prices.

- 02/28/2005 – 10-year note slid 22/32 in price, driving yields up to 4.36 percent from 4.27 percent. No specific news found.
- 05/04/2005 – Longer-dated Treasury debt prices plummeted after the government startled investors by saying it was considering resuming issuance of 30-year bonds.
- 03/28/2006 – U.S. Treasury bond investors digest a Federal Reserve policy statement, crafted with new Fed Chairman Ben Bernanke, suggesting more interest rate hikes.
- 09/19/2006 – Bond investors bet heavily on a Federal Reserve interest rate cut soon.

Figure 3 plots the return pattern and trading volume around the above jumps. The jump on March 28, 2006, which occurs 15 minutes after the FOMC decision, represents a reversal of the initial drop in bond price. Overall, post-jump returns represent no immediate reversal in price changes. In addition, trading volume increases around jumps.

C. Market Activities Around Jumps

In this section, we examine in more detail market activities around jumps and the differences between jumps occurring at pre-scheduled news announcement time and those outside pre-scheduled news announcement time. Figure 4 plots market activities around jumps in the 2-year note. The plots for other maturities have similar patterns. The left column focuses on announcement days, contrasting days with jumps at announcement versus those without. For clean comparison, our analysis excludes days with multiple jumps. The right column plots market activities around jumps outside pre-scheduled announcement time. The following summarizes the findings.

[8]FACTIVA offers a comprehensive news collection from the Wall Street Journal, the Financial Times, Dow Jones, Reuters newswires and the Associated Press.

- *The Announcement Effect* Consistent with Fleming and Remolona (1999), Balduzzi, Elton and Green (2001), and Green (2004), trading volume is low during the pre-announcement period and increases sharply after the announcement. Consistent with findings in Fleming and Piazzesi (2008) around FOMC announcements, our results show that return volatility, defined as the average of absolute change in logarithmic price, starts to rise in the 5-minute interval before announcements and then peaks at the announcement time. Bid-ask spread peaks in the 5-minute interval before the announcement.

  Both the depth at the best quotes and overall market depth drop before announcement, to the lowest level in the 5-minute interval prior to announcement, and climb back to the normal level after the announcement. Hidden depth at the best quotes shows a similar pattern as the observed depth. The results suggest that market participants withdraw orders when facing information uncertainty.

- *The Jump Effect* When a jump occurs at an announcement time, the increase in trading volume is even more dramatic. Compared to announcements without jumps, trading volume around announcement time nearly doubles. Similarly, there is a more pronounced pre-announcement increase in volatility and widening of the bid-ask spread on announcement days with jumps. This suggests that before jumps occur, market participants withdraw existing orders at the best quotes and place their orders further out. A subsequent large price change occurs either (i) when a market order hits the existing limit orders following the announcement or (ii) new limit orders come in and set a new price moving the existing mid-quote up/down. This mechanism could be at play with or without significant announcement surprises. This finding offers a plausible explanation for the imperfect relation between announcement surprises and price jumps.

  Both the depth at the best quotes and overall market depth are slightly lower during the pre-announcement period on announcement days with jumps. Again, withdrawal of depth at the best quotes before announcements could lead to large price changes when market orders erode the thin book after the news announcement. The hidden depth, however, is larger during the pre-announcement period. That is, market participants place more hidden depth at the best quotes to protect their positions when facing more uncertainty.

- *Jumps Outside Announcement Time* Similar to jumps at announcement time, trading volume increases at jumps outside announcement time. However, we do not observe any volatility increase before jumps outside announcement time. Also, spread fluctuates around a stable level before and after jumps outside announcement time. This is further evidence that these jumps are triggered by the arrival of unanticipated information or events.

  Unlike the case of jumps at announcement time where both depth at the best quote and the overall depth increase after jumps, depth actually drops to a lower level in the 5-minute interval after jumps outside announcement time. The pattern seems to suggest that after the jumps, market participants either withdraw depth from the market or do not replenish the depth in the midst of uncertainty due to the nature of jumps. Interestingly, the depth of hidden orders at the best bid and ask quotes are virtually zero around jumps outside announcement time. The complete withdrawal of hidden depth at the best quotes and the lower level of observed depth before these jumps may hint information asymmetry in the U.S. Treasury market. Some market participants withdraw their orders in anticipation of the upcoming events. After the jump, hidden depth at the best quotes does not come back to the market immediately. It is likely that information uncertainty is not immediately resolved, and market participants refrain from submitting hidden depth at the best quotes.

- *Post-Jump Price Reversal?* One important question is whether jumps are followed immediately by price reversal. To answer this question, we calculate and plot a variable of post-jump return reversal/momentum. The variable is defined as $CRet_{[t,t+\tau]}/Ret_{j,t}$ where $Ret_{j,t}$ denotes jump return and $CRet_{[t,t+\tau]}$ denotes the post-jump cumulative return over the interval $[t, t+\tau], 5 \leq \tau \leq 30$. A negative value of the variable indicates a reversal of jumps in prices, whereas a positive value indicates momentum. Results reported in Figure 4 show that there is neither a clear reversal nor momentum after jumps.

IV. Further Analysis

A. Information Shocks vs. Liquidity Shocks

In this section, we assess the role of information shocks and liquidity shocks in price jumps. Again, information shocks are measured by announcement surprises. In our analysis, liquidity shock carries a broad meaning and it could arise due to pure trading imbalance or order withdrawal as a result of information uncertainty. An example of the later case is the drop of market depth before an announcement. Motivated by findings on bid-ask spread and market depth before jumps, we define the following two variables to capture liquidity shocks:

- Standardized shock to overall depth, $dpthshk_{t-1}$, is defined as the difference between overall depth in 5-minute interval $t-1$ and the mean of overall depth from $t-6$ to $t-2$, scaled by the standard deviation of the difference:

  $$dpthshk_{t-1} = \frac{depth_{t-1} - \frac{1}{5}\sum_{j=2}^{6} depth_{t-j}}{\sigma_{depth}}, \tag{10}$$

  where $depth_{t-j}$ is the overall observed market depth measured at the end of $t-j$. This measure captures the withdrawal of orders or drop in overall observed market depth.

- Standardized shock to spread, $sprdshk_{t-1}$, is defined similarly as:

  $$sprdshk_{t-1} = \frac{spread_{t-1} - \frac{1}{5}\sum_{j=2}^{6} spread_{t-j}}{\sigma_{spread}}, \tag{11}$$

  where $spread_{t-j}$ is the spread at the end of interval $t-j$. This measure captures the withdrawal of best quotes and thus changes in bid-ask spread prior to announcements.

To examine the interaction between information shocks and liquidity shocks, we focus on announcement days. We first sort all announcements to form 3 equal groups (terciles) according to pre-announcement liquidity shocks defined above. Then within each group, we further sort the announcements to form 3 equal subgroups according to announcement surprise. Panel A of Table VI reports the results based on depth shock and Panel B reports the results based on spread shock. The findings are overall consistent based on both measures and are summarized as follows. First, examining the patterns across liquidity groups, it is clear that pre-announcement liquidity shock is positively related to subsequent absolute return and number of jumps. The fact that announcement surprises are of similar magnitude across liquidity groups makes it even easier to interpret the results. That is, holding announcement surprise as a constant or controlling for the announcement surprise effect, there is a positive relation between pre-announcement liquidity shock and post-announcement absolute return as well as jumps. We also perform a double sort by first sorting on announcement surprise and then liquidity shocks, and the above conclusion is confirmed. The results are not tabulated for brevity. Second, examining the patterns within each liquidity subgroup, absolute return is positively correlated with announcement surprise. This is consistent with the findings in existing literature that larger announcement surprises or unexpected macroeconomic shocks have a stronger impact on bond prices. For example, Green (2004) groups cumulative transaction returns based on announcement surprise and shows that a larger surprise is associated with a bigger change in return in purchase transactions. Third and more interestingly, the overall monotonic relation between announcement surprise and the number of jumps is observed only in the first two liquidity groups with low and medium liquidity shocks. In the third group with the largest liquidity shock, there is a less consistent positive relation between announcement surprise and the number of jumps. In this case, jumps occur regularly regardless whether or not news announcements come with surprises. These findings suggest that pre-announcement liquidity shocks in general precede jumps in bond prices and play an important role in bond price jumps.

We further estimate a Probit model to directly examine how announcement surprise and liquidity shock contribute to the likelihood of jumps. Several additional measures of liquidity shocks are constructed in our analysis:

- Standardized shock to hidden depth, $hidshk_{t-1}$, is defined similarly as the shock to observed depth and captures the withdrawal of hidden depth.
- Realized volatility, $Vola_{t-1}$, is calculated as square-root of the sum of squared 5-minute log return during the 30-minute interval before the jump. Realized volatility proxies for market uncertainty.

- Order flow imbalance, OF_{t-1}, is the volume of buy trades minus that of sell trades during the 5-minute interval before jump, reflecting excess buying or selling pressure. As shown in previous literature, such as Evans (2002), Evans and Lyons (2002), Green (2004), and Brandt and Kavajecz (2004), order flow carries significant information of price change. Given that we are interested in whether information embedded in order flow predicts price change but not the direction of price change, we use the absolute value of order flow (scaled by its sample mean).

- The last measure is order imbalance, OB_{t-1}, which is calculated as $depth_{ask,t-1} - depth_{bid,t-1}$ at the end of $t-1$. Order imbalance is shown to be informative about future price movements in Cao, Hansch and Wang (2008) and Harris and Panchapagesan (2005). Similar to order flow imbalance, we test whether the absolute value of order imbalance (scaled by its sample mean) precipitates price jumps.

We first estimate the following model to examine whether pre-announcement liquidity shocks are predictive of jumps:

$$\begin{aligned} P(jump_t|announcement) &= f(\alpha + \beta_{dpthshk} dpthshk_{t-1} + \beta_{Hidshk} Hidshk_{t-1} \\ &\quad + \beta_{sprdshk} sprdshk_{t-1} + \beta_{|OF|}|OF_{t-1}| + \beta_{|OB|}|OB_{t-1}| \\ &\quad + \beta_{vola} Vola_{t-1}) \end{aligned} \tag{12}$$

where $P(\cdot)$ denotes the probability that a jump occurs, which *ex post* takes a value of 1 when there is a jump at the announcement time t and 0 when there is no jump at the announcement time. To keep the analysis clean, only announcement days with a single jump at the announcement time are included.

The first column of Table VII reports the estimation results of the above model for the most liquid 2-year, 5-year and 10-year notes. The null hypothesis that the coefficients of all liquidity variables are jointly zero is strongly rejected for all three maturities. In particular, realized volatility is significant at the 5% level, and shocks to overall market depth are significant at the 10% level for all maturities. In addition, the shock to spread, $sprdshk$, is significantly positive at the 5% level for the 5-year and 10-year notes.

Next, we estimate a similar model with only information shocks to examine how well announcement surprises explain jumps:

$$P(jump_t|announcement) \quad = \quad f(\alpha + \Sigma_{j=1}^{J}\gamma_j|sur_{j,t}|) \tag{13}$$

where $|sur_{j,t}|$ is the absolute value of the standardized announcement surprise for news item j where $j = 1, 2, \cdots, J$. Note that whereas liquidity shocks are measured during the pre-announcement period, announcement surprise is only available at the time of announcement. Since we have more than 30 pre-scheduled announcements, it is infeasible to include all of them in the estimation. Based on the evidence in Table V, we include six important announcements in our benchmark model: Consumer Price Index, Change in Nonfarm Payrolls, Retail Sales, New Home Sales, ISM index and Initial Jobless Claims. The rest of the announcements are added into the regression one by one, and is kept in the model only if its coefficient is significant. The second column of Table VII reports the estimation results of the above model. For brevity, only the coefficient estimates of the above six announcements are reported. As gauged by the value of the likelihood function, the model with information shocks fairs slightly better than the model with liquidity shocks, except for the 10-year note where the likelihood functions have comparable values.

Finally, we estimate the following model with both announcement surprises and liquidity variables as explanatory variables:

$$\begin{aligned} P(jump_t|announcement) \quad = \quad & f(\alpha + \beta_{dpthshk}dpthshk_{t-1} + \beta_{Hidshk}Hidshk_{t-1} \\ & +\beta_{sprdshk}sprdshk_{t-1} + \beta_{|OF|}|OF_{t-1}| + \beta_{|OB|}|OB_{t-1}| \\ & +\beta_{vola}Vola_{t-1} + \Sigma_{j=1}^{J}\gamma_j|sur_{j,t}|) \end{aligned} \tag{14}$$

The purpose here is to test whether the predictive power of liquidity shocks is subsumed by information contained in announcement surprise. Estimation results are reported in the third column of Table VII. Interestingly, adding announcement surprise does not reduce the significance of market volatility and shocks to overall depth. The null hypothesis that the coefficients of all liquidity variables are jointly zero remains strongly rejected. In other words, the predictive power of these variables about upcoming jumps is not subsumed by surprises in macroeconomic news announcements. The results suggest that liquidity shocks contribute to bond price jumps beyond the effect of information shocks.

B. Post-Jump Price Discovery

In this subsection, we examine the price discovery process after jumps in bond prices. The literature, e.g., Green (2004), Brandt and Kavajecz (2004), Pasquariello and Vega (2007) and Menkveld, Sarkar and van der Wel (2008), compares the impact of order flow on prices on announcement versus non-announcement days. Green (2004) and Menkveld, Sarkar and van der Wel (2008) find that order flow is more informative post announcement. Brandt and Kavajecz (2004) find that order flow imbalances account for up to 26% of the day-to-day variation in yields on days without major macroeconomic announcements. The effect of order flow on yields is permanent and strongest when liquidity is low. The literature, however, is relatively silent on how informative order flow is after a significantly large change in bond prices. We extend the literature and address the following questions: what is the impact of jumps on the price discovery process in the bond market? In particular, do jumps tend to increase or reduce the informativeness of subsequent order flow in the bond market?

We first examine the post-jump price discovery process for all jump days, using non-jumps days as a control sample. On jump days, order flows are observed every 5 minutes over the 60-minute interval after the jump. To avoid the effect of multiple jumps, we only include days with a single jump in our analysis.[9] For non-jump days, order flows are observed every 5 minutes during the most active trading period from 8:30 EST to 15:00 EST. Specifically, let $j = 0$ denote the 5-minute interval where a jump occurs, the post jump period starts at the 5-minute interval $j = 1$, i.e., the interval right after the jump. We estimate the following model:

$$p_{j+1} - p_j = \alpha + \alpha_{jump} d_{jump} + \beta^{OF} OF_{j+1} + \beta^{OF}_{jump} OF_{j+1} d_{jump} + \varepsilon_{j+1} \tag{15}$$

where p_j denotes the logarithmic mid-quote at the end of interval j, and OF_j is the cumulative order flow imbalance calculated from transactions during interval j. The dummy variable d_{jump} takes a value of 1 for jump days, and 0 for non-jump days. Thus, the coefficient β^{OF} captures the price impact of order flow during non-jump days, whereas β^{OF}_{jump} captures the post-jump price impact of order flow.

[9]The results are robust when multiple-jumps days are included in the analysis.

Results reported in the first column of Table VIII show that β^{OF} is significantly positive for all three maturities, indicating that order flow is positively related to price. This finding is consistent with the previous literature. The coefficient β^{OF}_{jump} is generally negative, suggesting that post-jump order flow has a lesser effect on bond prices. However, the coefficient estimate is only significant at the 5% level for the 2-year note. Note that the above results are based on all days with jumps, using non-jump days as a control sample. It is likely that there is significant information flow to the market even on days without price jumps, e.g., days with news announcement. As a result, simply separating days according to whether there are jumps or not may potentially reduce the power of our analysis.

To sharpen our analysis, we next restrict our analysis only to days with pre-scheduled macroeconomic news announcements. As order flows are shown in the previous literature to carry more information on announcement days, we examine whether jumps has any impact on the informativeness of order flow. We estimate model (15) using order flow imbalance observed on announcement days with price jumps, whereas announcement days without jumps are used as a control sample. To keep the analysis clean, announcement days with jumps occurring outside announcement time are excluded. To examine the post-jump effect over different time horizons, we estimate the model using order flows observed during 15-minute, 30-minute, and 60-minute time periods after jumps.

The results are reported in the second to fourth columns of Table VIII. Similar to the results in the first column, β^{OF} is significantly positive for all three maturities. Since we now focus on news announcement days, β^{OF} tends to have a larger magnitude than those in the first column, indicating that order flow has a stronger price effect on announcement days. Also similar to the results in the first column, the coefficient β^{OF}_{jump} is negative for all maturities. Note that the coefficients β^{OF}_{jump} are now statistically significant for all maturities. This suggests that the post-jump order flow imbalance has significantly less effect on bond prices compared to announcement days with no jumps. The results are largely consistent over the 15-minute, 30-minute, and 60-minute post-jump horizons, except that β^{OF}_{jump} decreases in magnitude as time horizon increases from 15-minute to 60-minute. A direct interpretation of the finding is that when a jump occurs, information flow contained in the news announcement is incorporated quickly into bond prices. Thus, subsequent order flows tend to have less impact on bond prices. Of course, it is also possible that price discovery could slow down after jumps if there is a lack of trading. However, as reported in Figure 4 we observe a surge in trading volume after jumps. This evidence provides further support that jumps serve as a dramatic form of price discovery and post-jump order flow has less informational role. On the other hand, when information arrives at the news announcement with no price jumps, smooth price changes serve as a gradual way of incorporating information into bond prices.

V. Conclusion

Using the intraday data from the BrokerTec electronic trading platform, in this paper we identify jumps in bond prices in the U.S. Treasury market. We examine to what extent jumps are associated with pre-scheduled macroeconomic news announcements. Our results show that a majority of jumps occur around macroeconomic news announcements. Nevertheless, announcement surprises have limited explanatory power of bond price jumps.

We further examine whether jumps are also driven by other market variables, in particular liquidity shocks. We document some significantly different patterns between announcement days with jumps and those with no jumps. Noticeably, we observe a more dramatic widening of the bid-ask spread and a more significant drop in market depth prior to announcements with jumps. Our analysis further shows that liquidity shocks during the pre-announcement period play an important role for jumps in the U.S. Treasury market. Moreover, the predictive power of liquidity shocks for upcoming jumps is not subsumed by the effect of unexpected information shocks.

Finally, examining post-jump price discovery process, we find that order flow is in general less informative immediately after jumps compared to the case where there is no jump at announcement. This finding, coupled with a post-jump surge of trading volume, suggests that jumps serve as a dramatic form of price discovery and post-jump order flow tends to have less impact on bond prices.

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Appendix A: Identification of Jump Returns

When the null hypothesis of no jump is rejected, the following procedure is used to identify jump returns.

- Step 1: Let $\{r_1, r_2, \cdots r_N\}$ be log return observations during the testing period. If the jump test statistic JS_0 is significant, we record JS_0 and continue to Step 2.
- Step 2: We replace each of the return observations $r_i (i = 1, \cdots, N)$ by the median return of the sample (denoted by r_{md}), and perform jump test on $\{r_1, \cdots, r_{i-1}, r_{md}, r_{i+1}, \cdots, r_N\}$. The test statistics $JS^{(i)}, i = 1, 2, \cdots, N$ are recorded.
- Step 3: We compute the differences of the jump test statistic in Step 1 with those in Step 2, i.e., $JS_0 - JS^{(i)}, i = 1, 2, \cdots, N$. Return j is identified as a jump return if $JS_0 - JS^{(j)}$ has the highest value. This criterion is in the spirit of the likelihood ratio test since r_j is the return that contributes most to the jump test to reject the null hypothesis.
- Step 4: Replace the identified jump, r_j, by the median of returns, and we have a new sample of return observations $\{r_1, \cdots, r_{j-1}, r_{md}, r_{j+1}, \cdots, r_N\}$. Then start over again from Step 1.

The above procedure continues until all jumps are identified. Andersen, Bollerslev, Federiksen and Nielsen (2007) propose a similar procedure for identifying intraday jump returns. The main difference is that instead of using the median of sample to replace each single return in Step 2 of the sequential procedure, they use the mean of remaining $N - 1$ returns. To take into account of the market microstructure effect, we modify the SWV jump test by allowing measurement error in the observed asset prices, i.e., $\hat{P}_t = P_t + \epsilon_t$ where P_t is the intrinsic price of the asset and ϵ_t is the noise. The standard error of ϵ_t is estimated based on the first-order autocorrelation of the return process. Details can be found in Jiang and Oomen (2008). In addition, to ensure that identified jump returns are not the result of discrete tick size or bid-ask bounce, we also impose a condition that the absolute jump return has to be more than twice the tick size. We find that this restriction virtually has no effect on our identified jump returns.

Appendix B: Monte Carlo Simulations of the Jump Tests

In our simulation, the following stochastic volatility jump-diffusion model is used as the data generating process (DGP):

$$\begin{aligned} dS_t/S_t &= \mu dt + \sqrt{V_t} dW_t^s + J_t dq_t, \\ dV_t &= \beta(\alpha - V_t) dt + \sigma \sqrt{V_t} dW_t^v, \end{aligned} \tag{16}$$

where $dW_t^s dW_t^v = \rho dt$.

For the benchmark case, the model parameter values are set as $\mu = 0, \rho = 0$, α=mean of daily variance of the 2-year note, the value of β is determined by $e^{-\beta}$=first order autocorrelation of daily variance, σ is set from $\frac{\alpha\sigma^2}{2\beta}$=variance of daily return variance. That is:

Benchmark parameter values: $\mu = 0, \rho = 0, \alpha = 0.005, \beta = 0.8, \sigma = 0.10$

We also consider 7 alternative set of parameter values as follows:

Alternative I parameter values: $\mu = 0, \rho = 0, \alpha = 0.005, \beta = 0.2, \sigma = 0.10$

Alternative II parameter values: $\mu = 0, \rho = 0, \alpha = 0.005, \beta = 1.6, \sigma = 0.10$

Alternative III parameter values: $\mu = 0, \rho = 0, \alpha = 0.005, \beta = 0.8, \sigma = 0.05$

Alternative IV parameter values: $\mu = 0, \rho = 0, \alpha = 0.005, \beta = 0.8, \sigma = 0.20$

Alternative V parameter values: $\mu = 0, \rho = 0.50, \alpha = 0.005, \beta = 0.8, \sigma = 0.10$

Alternative VI parameter values: $\mu = 0, \rho = -0.50, \alpha = 0.005, \beta = 0.8, \sigma = 0.10$

Each "day", we simulate a sample path of the return process specified in (16) using the Euler scheme with 1 minute discretization interval over a total of 9.5 hours. Then we sample returns at 5-minute interval. To examine size, we set jump return as zero (i.e., J=0). To examine power, jumps (J) are added to the 30th observation of 5-minute returns, and we set $J = 4 \times \sqrt{\alpha}, 7 \times \sqrt{\alpha}, 10 \times \sqrt{\alpha}$ respectively in our simulation. Jump tests are performed on the 5-minute return observations at 1% critical level. The procedure is repeated 10,000 times. Simulation results for both size and power are summarized in the following table for different sets of parameter values and jump sizes:

Table A: Size and Power of Jump Tests (%)

		Scenarios						
Jump Size	Jump Test	Benchmark	A1	A2	A3	A4	A5	A6
$0 \times \sqrt{\alpha}$	BPV	3.4	3.01	2.8	2.75	4.13	3.3	3.18
	SWV	4.65	4.5	4.34	2.99	6.34	4.44	4.13
	Joint	0.75	0.72	0.48	0.32	1.29	0.62	0.57
$4 \times \sqrt{\alpha}$	BPV	54.25	55.27	51.62	49.49	53.17	53.9	53.9
	SWV	73.65	72.21	75.5	82.81	63.49	75.46	72.9
	Joint	51.12	52.49	48.58	46.87	48.97	51.38	50.49
$7 \times \sqrt{\alpha}$	BPV	93.72	90.97	94.42	97.23	85.45	92.45	92.99
	SWV	99.13	98.4	99.72	99.96	93.21	99.49	98.65
	Joint	93.56	90.65	94.4	97.22	84.36	92.39	92.71
$10 \times \sqrt{\alpha}$	BPV	99.42	98.98	99.7	99.92	95.97	99.41	99.43
	SWV	100	99.97	100	100	99.14	100	99.98
	Joint	99.42	98.96	99.7	99.92	95.81	99.41	99.42

Table I. Summary Statistics of Market Activities

This table reports the summary statistics of daily trading volume ($ billions), daily return volatility (%) of 5-minute returns based on the mid bid-ask quote from 7:00 a.m. to 5:00 p.m., trade durations (seconds), relative spread ($\times 10,000$) and spread in ticks, average depth at the best bid and ask ($ millions), average depth in the entire order book ($ millions), average hidden depth at the best bid and ask ($ millions), and average hidden depth in the entire book during the sample period from 2005 to 2006. Spread and depth variables are averaged over 5-minute intervals of the trading day.

Variable	Mean	Median	StDev	Max	Min	Skewness	Kurtosis
Panel A: 2-year note)							
Spread (in ticks)	1.06	1.05	0.05	1.59	0.99	4.50	39.24
Relative spread ($\times 10,000$)	0.83	0.83	0.04	1.29	0.78	5.02	47.35
Trading volume ($ billions)	27.45	26.55	10.12	79.50	6.05	0.97	5.08
Trading durations (seconds)	15.99	14.61	6.76	48.21	3.48	0.98	4.09
Return volatility (%)	0.07	0.06	0.03	0.28	0.03	2.61	13.60
Depth at the best bid and ask ($ mil)	637.72	593.14	254.17	1567.41	190.25	0.44	2.46
Hidden depth at the best bid and ask($mil)	32.64	25.77	22.56	173.68	1.82	2.04	10.21
Depth of the entire order book ($ mil)	5122.56	4227.90	2416.23	10305.34	899.38	0.34	1.77
Hidden depth of the entire order book ($ mil)	99.83	81.71	73.53	526.09	9.25	2.04	9.08
Panel B: 3-year note							
Spread (in ticks)	1.19	1.17	0.10	1.90	1.04	2.17	10.88
Relative spread ($\times 10,000$)	0.94	0.92	0.08	1.50	0.82	2.12	10.47
Trading volume ($ billions)	9.60	9.05	3.65	22.92	1.70	0.72	3.34
Trading durations (seconds)	27.47	21.73	16.76	104.33	6.13	1.52	5.18
Return volatility (%)	0.10	0.09	0.04	0.33	0.04	2.24	9.44
Depth at the best bid and ask ($ mil)	167.49	164.22	75.12	406.70	39.24	0.31	2.27
Hidden depth at the best bid and ask($mil)	8.83	6.66	8.46	111.75	0.08	4.86	49.94
Depth of the entire order book ($ mil)	1260.76	1025.58	686.90	3141.09	198.15	0.57	2.06
Hidden depth of the entire order book ($ mil)	29.01	18.33	30.73	272.72	0.61	3.46	21.20
Panel C: 5-year note							
Spread (in ticks)	1.18	1.16	0.10	2.30	1.04	4.65	42.55
Relative spread ($\times 10,000$)	0.93	0.92	0.08	1.87	0.83	4.93	47.01
Trading volume ($ billions)	24.69	24.17	7.48	50.31	7.71	0.55	3.36
Trading durations (seconds)	6.74	6.02	3.13	23.94	2.20	1.41	5.97
Return volatility (%)	0.17	0.15	0.06	0.45	0.07	1.71	6.90
Depth at the best bid and ask ($ mil)	119.30	118.22	33.46	213.12	54.86	0.47	2.71
Hidden depth at the best bid and ask($mil)	6.83	5.90	4.25	39.37	0.22	1.90	10.92
Depth of the entire order book ($ mil)	1238.48	1154.73	485.39	2522.77	442.96	0.43	2.01
Hidden depth of the entire order book ($ mil)	40.36	29.48	133.01	2885.68	4.18	20.66	441.77

Variable	Mean	Median	StDev	Max	Min	Skewness	Kurtosis
Panel D: 10-year note							
Spread (in ticks)	1.13	1.11	0.07	1.82	0.99	3.27	28.19
Relative spread ($\times 10,000$)	1.79	1.77	0.11	2.93	1.60	3.16	25.69
Trading volume ($ billions)	22.76	22.62	6.93	43.68	5.32	0.38	2.84
Trading durations (seconds)	6.59	5.59	3.35	22.49	2.23	1.32	4.82
Return volatility (%)	0.29	0.26	0.10	0.77	0.11	1.67	7.43
Depth at the best bid and ask ($ mil)	120.93	118.37	32.11	227.99	50.96	0.55	3.10
Hidden depth at the best bid and ask($mil)	5.50	4.82	3.24	28.60	0.88	2.12	11.88
Depth of the entire order book ($ mil)	1520.08	1376.26	657.52	3459.07	439.77	0.75	2.69
Hidden depth of the entire order book ($ mil)	36.43	31.22	24.07	233.61	2.52	2.88	20.97
Panel E: 30-year bond							
Spread (in ticks)	2.05	2.02	0.37	6.47	1.48	3.80	43.37
Relative spread ($\times 10,000$)	3.10	3.02	0.46	9.23	2.41	5.23	64.89
Trading volume ($ billions)	2.72	2.52	1.08	8.42	0.87	1.00	4.52
Trading durations (seconds)	52.97	27.59	67.33	612.96	8.88	3.55	19.01
Return volatility (%)	0.53	0.50	0.23	4.26	0.23	8.77	135.06
Depth at the best bid and ask ($ mil)	11.96	11.54	2.41	21.75	6.15	0.68	3.45
Hidden depth at the best bid and ask($mil)	1.14	0.92	1.01	11.31	0.03	4.56	38.50
Depth of the entire order book ($ mil)	133.42	118.88	52.45	312.63	46.50	1.45	4.58
Hidden depth of the entire order book ($ mil)	6.29	4.84	5.91	51.60	0.15	2.98	16.65

Table II. Macroeconomic News with Pre-Scheduled Announcements

This table reports the list of macroeconomic news included in our analysis. N denotes the total number of announcements during the period from January 2005 to December 2006. Day and Time denote, respectively, the weekday or day of the month and time (EST) of announcement. σ_{surprise} denotes the standard deviation of announcement surprises. $N_{|\text{surprise}|>k\sigma_{\text{surprise}}}$ denotes the number of announcements where the announcement surprise is more than k standard deviation.

News/Event	N	Day	Time	σ_{surprise}	$N_{\lvert\text{surprise}\rvert>\sigma_{\text{surprise}}}$	$N_{\lvert\text{surprise}\rvert>2\sigma_{\text{surprise}}}$
Business Inventories	24	Around the 15th of the month	8:30[a]	0.002	5	1
Capacity Utilization	24	Two weeks after month end	9:15	0.003	6	1
Change in Nonfarm Payrolls	24	First Friday of the month	8:30	59.228	9	0
Chicago PMI	24	Last business day of the month	10:00	5.094	8	1
Construction Spending	24	Two weeks after month-end	10:00	0.245	1	1
Consumer Confidence	24	Last Tuesday of Month	10:00	3.860	6	2
Consumer Credit	24	5th business day of the month	15:00	125.82	1	1
Consumer Price Index	24	Around the 13th of the month	8:30	0.002	9	0
Current Account	8	10 to 11 weeks after quarter-end	8:30	7.687	2	0
Durable Orders	24	Around the 26th of the month	8:30	0.031	9	1
Economic outlook	6	According to schedule	10:00[b]	n.a.	n.a.	n.a.
Existing Home Sales	24	On the 25th of the month	10:00	0.160	7	1
FOMC Minutes	16	Thursday following the next FOMC meeting date	14:15	n.a.	n.a.	n.a.
FOMC rate decision expected	16	According to schedule	14:10	0.000	0	0
Factory Orders	24	Around the first business day of the month	10:00	0.006	6	2
GDP Advance	8	3rd / 4th week of the month for prior quarter	8:30	0.006	1	1
GDP Final	8	3rd / 4th week of second month following the quarter	8:30	0.001	4	1
GDP Preliminary	8	3rd / 4th week of first month following the quarter	8:30	0.003	3	0
Housing Starts	24	Two or three weeks after the reporting month	8:30	124.26	6	2

Event	N	Day	Time	σ_{surprise}	$N_{\lvert\text{surprise}\rvert>\sigma_{\text{surprise}}}$	$N_{\lvert\text{surprise}\rvert>2\sigma_{\text{surprise}}}$
ISM Services	24	On the third business day of the month	10:00	2.834	9	1
ISM index	24	First business day of the month	10:00	2.332	6	1
Industrial Production	24	Around the 15th of the month	9:15	0.003	8	1
Initial Jobless Claims	104	Thursday weekly	8:30	17.499	23	6
Leading Indicators	24	around the first few business days of the month	8:30	0.002	7	2
Monthly Treasury Budget	24	about the third week of the month	14:00	5.239	4	2
NY Empire State Index	24	15th/16th of the month	8:30	9.738	9	1
New Home Sales	24	Around the last business day of the month	10:00	92.492	6	2
PCE	24	Around the first business day of the month	8:30	0.046	5	5
Personal Income	24	Around the first business day of the month	8:30	0.003	2	1
Philadelphia Fed	24	Third Thursday of the month	12:00	7.960	10	0
Producer Price Index	24	Around the 11th of each month	8:30	0.307	2	1
Retail Sales	24	Around the 12th of the month	8:30	0.121	1	1
Semiannual Monetary Policy Report	4	February and July annually	10:00	n.a.	n.a.	n.a.
Trade Balance	24	Around the 20th of the month	8:30	3.225	7	1
ADP National Employment Report	8	2 days before Change in Nonfarm Payrolls	8:15	n.a.	n.a.	n.a.

[a] – Business inventories are announced at either 10:00 a.m. or 8:30 a.m. During 2005-2006, 17 announcements took place at 10:00 a.m. and 7 announcements took place at 8:30 a.m.

[b] – One testimony of Economic Outlook is released at 14:30 on 5th June, 2006.

Table III. Summary Statistics of Bond Price Jumps

This table, Panels A to C, reports the number of days identified as having jumps (N_d), the number of jumps (N) and summary statistics of jump size, including the mean, absolute mean, absolute median, maximum, minimum, standard deviation ($StdDev$), skewness and kurtosis. Panel D reports the number of concurrent jumps across maturities, where jumps of two different maturities occurring at the same or adjacent 5-minute interval are defined as concurrent jumps.

Bond	N_d	N	Mean	Mean (abs.)	Median (abs.)	Max	Min	StdDev	Skewness	Kurtosis
Panel A: All Jumps										
2-year note	60	69	0.00	0.08	0.07	0.24	-0.17	0.09	0.44	2.69
3-year note	66	74	0.01	0.12	0.11	0.28	-0.28	0.14	-0.21	2.00
5-year note	65	72	-0.01	0.16	0.14	0.40	-0.41	0.18	0.17	2.12
10-year note	58	63	-0.01	0.28	0.24	0.70	-0.64	0.31	-0.02	2.04
30-year bond	69	76	-0.09	0.50	0.40	2.13	-3.55	0.67	-1.20	11.69
Panel B: Positive Jumps										
2-year note	31	32	0.08	0.08	0.06	0.24	0.04	0.05	1.71	5.57
3-year note	40	41	0.12	0.12	0.11	0.28	0.05	0.05	1.06	3.59
5-year note	30	31	0.17	0.17	0.15	0.40	0.08	0.08	1.11	3.79
10-year note	31	32	0.27	0.27	0.24	0.70	0.15	0.12	1.71	5.85
30-year bond	30	30	0.52	0.52	0.41	2.13	0.24	0.36	2.94	13.36
Panel C: Negative Jumps										
2-year note	34	37	-0.07	0.07	0.07	-0.04	-0.17	0.03	-1.22	3.78
3-year note	31	33	-0.12	0.12	0.10	-0.06	-0.28	0.06	-1.11	3.28
5-year note	37	41	-0.16	0.16	0.13	-0.09	-0.41	0.08	-1.47	4.92
10-year note	28	31	-0.29	0.29	0.24	-0.16	-0.64	0.13	-1.47	4.55
30-year bond	43	46	-0.49	0.49	0.37	-0.21	-3.55	0.50	-5.11	31.59

	2-year note	3-year note	5-year note	10-year note	30-year bond
Panel D: Concurrent jumps across maturities					
2-year note	69				
3-year note	48	74			
5-year note	43	50	72		
10-year note	36	42	44	63	
30-year bond	30	33	39	47	76

Table IV. Jumps and Pre-Scheduled News Announcements

This table, Panels A and B, reports the number of jumps, N, and summary statistics of jumps associated with a pre-scheduled news announcement and those not directly associated with a pre-scheduled news announcement. A jump is referred to as associated with a news announcement if the 5-minute jump return interval overlaps with the 10-minute window centered around the announcement time. Panels C and D report the number of concurrent jumps across maturities, where concurrent jumps are defined in the same way as in Table III.

Bond	N	Mean	Mean (abs.)	Median (abs.)	Max	Min	StdDev	Skewness	Kurtosis
Panel A: Jumps Associated with Pre-Scheduled Announcement									
2-year note	63	0.00	0.08	0.07	0.24	-0.17	0.09	0.45	2.62
3-year note	70	0.01	0.13	0.11	0.28	-0.28	0.14	-0.22	1.99
5-year note	65	-0.01	0.17	0.14	0.40	-0.41	0.19	0.08	2.03
10-year note	58	-0.01	0.28	0.24	0.70	-0.64	0.31	0.00	2.05
30-year bond	59	-0.07	0.47	0.42	0.94	-1.01	0.51	0.28	1.89
Panel B: Jumps Not Associated with Pre-Scheduled Announcement									
2-year note	6	0.00	0.05	0.05	0.07	-0.07	0.05	0.02	1.19
3-year note	4	0.01	0.09	0.09	0.12	-0.09	0.09	0.05	1.07
5-year note	7	-0.06	0.11	0.10	0.18	-0.12	0.10	1.98	5.04
10-year note	5	0.00	0.24	0.24	0.26	-0.35	0.25	-0.41	1.33
30-year bond	17	-0.16	0.61	0.27	2.13	-3.55	1.04	-1.36	8.04

	2-year note	3-year note	5-year note	10-year note	30-year bond
Panel C: Concurrent Jumps Associated with Pre-Scheduled Announcement					
2-year note	63				
3-year note	46	70			
5-year note	41	47	65		
10-year note	35	41	42	58	
30-year bond	29	32	37	41	59
Panel D: Concurrent Jumps Not Associated with Pre-Scheduled Announcement					
2-year note	6				
3-year note	2	4			
5-year note	2	3	7		
10-year note	1	1	2	5	
30-year bond	1	1	2	6	17

Table V. Jumps, Macroeconomic News, and Announcement Surprises

Panel A reports the top 15 news announcements with the largest number of jumps. It reports the number of jumps (N_J) and mean absolute jump returns ($|ret_j|$) associated with each macroeconomic news announcement for relatively liquid notes with 2-, 5- and 10-year maturities. Total N_J is the number of unique jumps (excluding concurrent jumps) among all maturities. In Panel B, we sort jumps in each maturity into 5 groups (quintiles) according to absolute jump return. For each group, we then calculate and report the mean absolute jump return ($|ret_j|$), mean absolute surprise $|sur|$, and the number of significant announcement surprises (N^*).

Panel A: Macroeconomic News and Jumps

	2-year note		5-year note		10-year note		
News/Event	N_j	$\|ret_j\|$	N_j	$\|ret_j\|$	N_j	$\|ret_j\|$	Total N_j
Initial Jobless Claims	9	0.054	7	0.151	7	0.233	15
Consumer Price Index	13	0.073	8	0.195	11	0.319	15
Change in Nonfarm Payrolls	10	0.122	9	0.284	11	0.380	14
Retail Sales	9	0.070	6	0.174	7	0.255	12
Producer Price Index	3	0.065	6	0.167	4	0.324	8
ISM index	1	0.062	4	0.127	4	0.206	8
Construction Spending	1	0.062	4	0.127	4	0.206	8
Durable Orders	3	0.064	5	0.159	2	0.373	7
New Home Sales	4	0.047	4	0.110	2	0.216	6
Housing Starts	3	0.063	4	0.152	1	0.405	6
FOMC rate decision expected	4	0.088	0		1	0.240	6
Consumer Confidence	3	0.047	3	0.104	3	0.235	6
NY Empire State Index	4	0.043	5	0.158	5	0.225	5
FOMC Minutes	4	0.098	4	0.182	3	0.280	5
GDP Advance	1	0.106	3	0.135	3	0.245	4

Panel B: Jumps and Announcement Surprises

	2-year note			5-year note			10-year note		
	$\|ret_j\|$	$\|Sur\|$	N^*	$\|ret_j\|$	$\|Sur\|$	N^*	$\|ret_j\|$	$\|Sur\|$	N^*
Q1 (low)	0.037	1.005	5	0.090	1.058	4	0.166	0.722	3
Q2	0.047	0.976	4	0.110	1.154	4	0.203	1.108	4
Q3	0.059	1.055	3	0.139	0.923	5	0.247	1.247	5
Q4	0.076	0.942	4	0.192	0.963	3	0.314	0.651	2
Q5 (high)	0.142	0.846	4	0.280	0.793	5	0.501	1.043	5

Table VI. Jumps, Announcement Surprises, and Liquidity Shocks

This table reports how jumps are related to announcement surprises and liquidity shocks. We first sort announcements into 3 groups (terciles) according to liquidity shocks (shocks in overall depth ($depshk$) and shocks in spread ($sprdshk$)) in the 5-minute pre-announcement period. Within each group, we further sort announcements into 3 sub-groups according to announcement surprise. Panel A (Panel B) reports the mean of shocks in overall depth (shocks in spread), announcement surprise ($|sur|$), mean absolute return ($|ret|$), and the number of jumps (N_j) for each subgroup.

Panel A: Results sorted on $depshk$

	2-year note				5-year note				10-year note			
	$depshk$	$\|sur\|$	$\|ret\|$	N_j	$depshk$	$\|sur\|$	$\|ret\|$	N_j	$depshk$	$\|sur\|$	$\|ret\|$	N_j
T1(low)	0.739	0.168	0.012	1	0.898	0.176	0.035	3	0.852	0.192	0.056	0
	0.694	0.647	0.023	3	0.841	0.629	0.059	5	0.832	0.685	0.069	1
	0.695	1.635	0.030	6	0.762	1.531	0.063	4	0.863	1.728	0.099	4
T2	1.412	0.193	0.014	1	1.631	0.203	0.034	1	1.484	0.203	0.056	5
	1.441	0.682	0.017	3	1.618	0.720	0.045	4	1.484	0.654	0.086	5
	1.424	1.751	0.023	7	1.646	1.792	0.061	6	1.500	1.541	0.089	5
T3 (high)	2.872	0.176	0.026	8	3.045	0.162	0.058	8	2.748	0.140	0.087	5
	2.899	0.653	0.028	7	3.055	0.657	0.069	11	2.744	0.623	0.106	8
	2.747	1.421	0.029	5	2.952	1.495	0.072	8	2.795	1.524	0.133	13

Panel B: Results sorted on $sprdshk$

	2-year note				5-year note				10-year note			
	$sprdshk$	$\|sur\|$	$\|ret\|$	N_j	$sprdshk$	$\|sur\|$	$\|ret\|$	N_j	$sprdshk$	$\|sur\|$	$\|ret\|$	N_j
T1(low)	0.0082	0.163	0.012	1	0.0101	0.216	0.028	1	0.0124	0.165	0.047	0
	0.0079	0.584	0.016	3	0.0096	0.679	0.031	3	0.0124	0.614	0.050	2
	0.0088	1.389	0.017	3	0.0099	1.714	0.045	7	0.0120	1.657	0.071	4
T2	0.0640	0.205	0.016	3	0.0863	0.181	0.036	3	0.1327	0.183	0.058	2
	0.0534	0.738	0.017	3	0.0829	0.626	0.040	4	0.1355	0.675	0.053	1
	0.0522	1.741	0.021	6	0.0835	1.510	0.051	5	0.1341	1.532	0.085	6
T3(high)	0.8085	0.173	0.024	6	0.6252	0.147	0.061	8	0.7884	0.186	0.101	8
	0.9110	0.692	0.039	7	1.1991	0.686	0.099	9	1.2127	0.672	0.158	13
	0.8480	1.646	0.040	9	1.2794	1.606	0.105	10	0.9285	1.607	0.158	10

Table VII. Jumps, Information Shocks and Liquidity Shocks

This table reports the estimation results of the Probit model for bond price jumps associated with pre-scheduled news announcement. The explanatory variables include return volatility ($vola$), spread shock ($sprdshk$), absolute order flow (OF), absolute order imbalance (OB), overall depth shock ($dpthshk$), overall hidden depth shock ($hidshk$) and announcement surprises of major macroeconomic news.

	Liquidity Shocks: Eq. (12)			Information Shocks: Eq. (13)			Information vs. Liquidity Shocks: Eq. (14)		
	Estimate	Standard Error	P-Value	Estimate	Standard Error	P-Value	Estimate	Standard Error	P-Value
Panel A: 2-year note									
Intercept	-1.811	0.307	<.0001	-1.300	0.196	<.0001	-2.508	0.444	<.0001
$vola$	1.902	0.864	0.028				2.346	0.956	0.014
$sprdshk$	0.132	0.121	0.277				0.227	0.156	0.146
OF	0.165	0.123	0.181				0.207	0.135	0.126
OB	-0.135	0.127	0.288				-0.007	0.138	0.959
$dpthshk$	-0.433	0.232	0.063				-0.500	0.276	0.070
$hidshk$	0.127	0.147	0.385				0.265	0.171	0.120
Consumer Price Index				0.889	0.311	0.004	0.928	0.321	0.004
Initial Jobless Claims				-0.092	0.245	0.707	0.150	0.284	0.598
ISM index				-0.290	0.578	0.616	-0.449	0.680	0.509
Change in Nonfarm Payrolls				0.267	0.436	0.541	-0.027	0.548	0.960
Retail Sales				12.982	6.957	0.062	20.912	7.827	0.008
New Home Sales				0.470	0.376	0.211	0.758	0.422	0.072
Likelihood	-67.685			-64.916			-56.404		
Joint test: $\beta_{liquidty} = 0$	13.290		0.04				17.024		0.010

	Liquidity Shocks: Eq. (12)			Information Shocks: Eq. (13)			Information vs. Liquidity Shocks: Eq. (14)		
	Estimate	Standard Error	P-Value	Estimate	Standard Error	P-Value	Estimate	Standard Error	P-Value
Panel B: 5-year note									
Intercept	-1.766	0.350	<.0001	-1.259	0.187	<.0001	-2.473	0.492	<.0001
$vola$	0.852	0.282	0.003				1.254	0.329	0.000
$sprdshk$	0.210	0.107	0.050				0.139	0.157	0.375
OF	0.003	0.121	0.977				-0.369	0.194	0.057
OB	-0.041	0.149	0.782				-0.076	0.170	0.656
$dpthshk$	-0.416	0.227	0.067				-0.929	0.287	0.001
$hidshk$	0.056	0.127	0.656				0.101	0.149	0.498
Consumer Price Index				0.043	0.380	0.909	-0.015	0.467	0.974
Initial Jobless Claims				-0.004	0.206	0.985	0.119	0.230	0.604
ISM index				0.634	0.335	0.058	0.684	0.358	0.056
Change in Nonfarm Payrolls				0.897	0.334	0.007	1.207	0.448	0.007
Retail Sales				9.935	7.183	0.167	14.742	8.117	0.069
New Home Sales				0.103	0.435	0.814	0.505	0.479	0.292
Likelihood	-74.270			-72.258			-59.832		
Joint $\beta_{liquidty} = 0$	14.760		0.03				24.853		0.0004
Panel C: 10-year note									
Intercept	-1.731	0.332	<.0001	-1.373	0.194	<.0001	-2.635	0.472	<.0001
$vola$	0.788	0.159	<.0001				0.838	0.178	<.0001
$sprdshk$	0.250	0.118	0.034				0.160	0.168	0.340
OF	0.007	0.161	0.968				0.029	0.190	0.881
OB	-0.382	0.176	0.030				-0.445	0.221	0.044
$dpthshk$	-0.457	0.235	0.052				-0.818	0.300	0.006
$hidshk$	0.031	0.121	0.798				0.021	0.141	0.880
Consumer Price Index				0.678	0.305	0.026	0.460	0.365	0.208
Initial Jobless Claims				-0.106	0.242	0.662	0.114	0.261	0.664
ISM index				0.721	0.345	0.037	0.907	0.422	0.031
Change in Nonfarm Payrolls				1.085	0.324	0.001	1.017	0.462	0.028
Retail Sales				19.091	7.349	0.009	21.637	7.937	0.006
New Home Sales				0.462	0.312	0.138	0.551	0.353	0.118
Likelihood	-69.883			-70.679			-53.672		
Joint $\beta_{liquidty} = 0$	37.560		0.0001				34.014		0.0001

Table VIII. Post-Jump Price Discovery: Order Flow

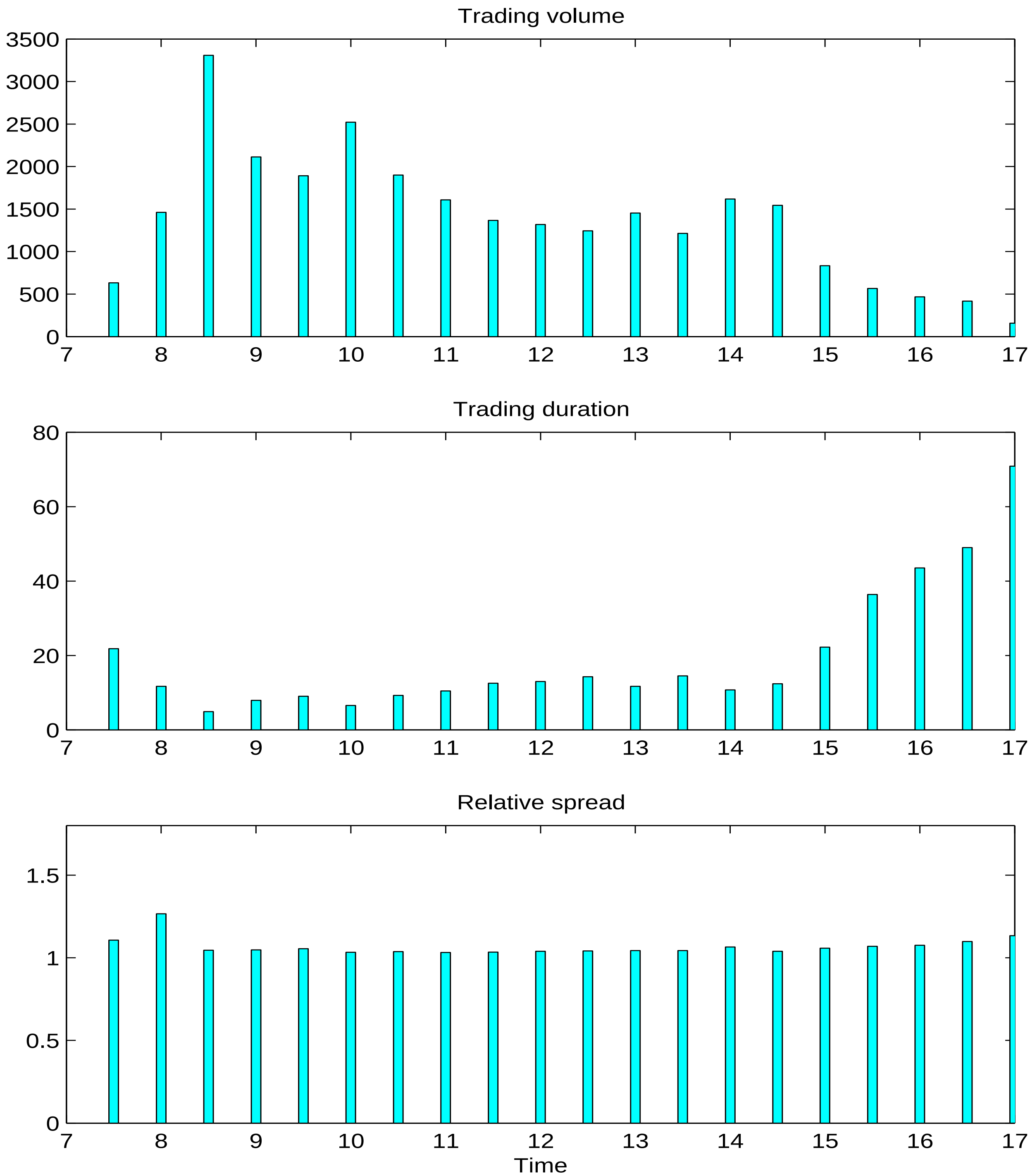
This table reports the coefficient estimates, standard errors and p-values for the post-jump price discovery process specified in Eq. (15). The first set of columns contrasts the price discovery process after jumps vs. days with no jumps. For jump days, the order flows (OF) are observed every 5-minute over the 60-minute horizon after jumps. For non-jump days, the order flows (OF) are observed every 5-minute from 8:30 to 15:00 EST. The second, third and fourth set of columns restrict our analysis to the days with pre-scheduled news announcements and contrasts the price discovery process after jumps vs. days with no jumps. The model is estimated over 15-minute, 30-minute, and 60-minute horizon after jumps. Results for 2-year note, 5-year note, and 10-year note are reported in Panels A, B, and C respectively.

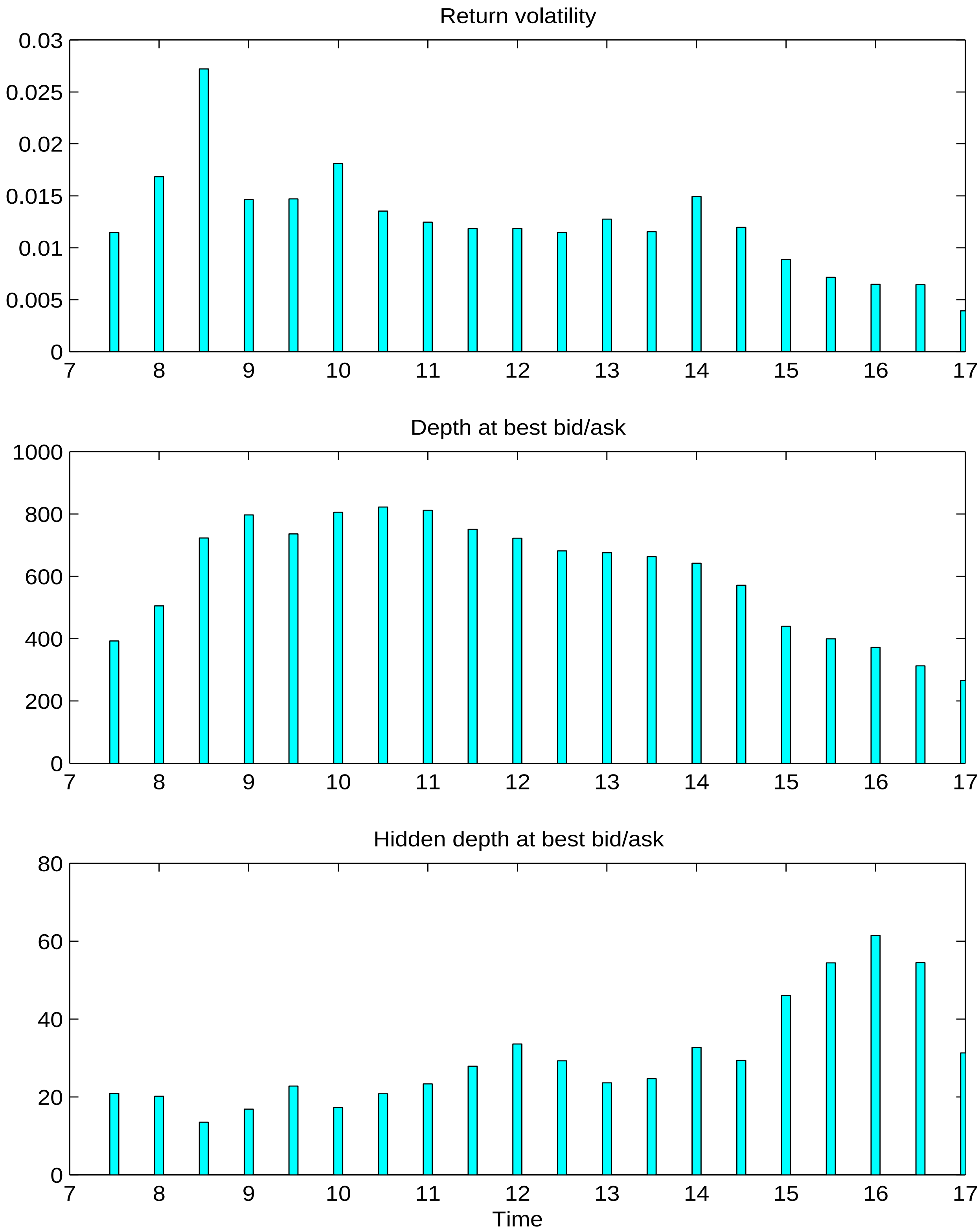
	All: Jump vs. No Jump (60-m)			News: Jump vs. No Jump (15-m)			News: Jump vs. No Jump (30-m)			News: Jump vs. No Jump (60-m)		
	Estimate	Std Error	P-value	Estimate	Std Error	P-value	Estimate	Std Error	P-value	Estimate	Std Error	P-value
Panel A: 2-year note												
α	0.040	0.036	0.272	0.223	0.540	0.680	0.032	0.315	0.920	0.214	0.183	0.242
α_{jump}	-0.943	0.256	0.000	-0.002	1.277	0.999	-0.497	0.731	0.497	-0.250	0.416	0.549
β^{OF}	0.014	0.000	$<.0001$	0.019	0.002	$<.0001$	0.018	0.001	$<.0001$	0.016	0.001	$<.0001$
β^{OF}_{jump}	-0.002	0.001	0.008	-0.007	0.003	0.016	-0.005	0.002	0.013	-0.004	0.001	0.002
$adj-R^2$	0.189			0.124			0.145			0.151		
Panel B: 5-year note												
α	0.506	0.080	$<.0001$	0.474	0.926	0.609	0.447	0.568	0.431	0.685	0.342	0.045
α_{jump}	0.683	0.570	0.234	3.045	2.255	0.177	0.947	1.387	0.495	1.351	0.835	0.106
β^{OF}	0.060	0.001	$<.0001$	0.081	0.005	$<.0001$	0.079	0.003	$<.0001$	0.070	0.002	$<.0001$
β^{OF}_{jump}	-0.002	0.001	0.179	-0.035	0.010	0.000	-0.026	0.006	$<.0001$	-0.018	0.004	$<.0001$
$adj-R^2$	0.227			0.230			0.250			0.244		
Panel C: 10-year note												
α	0.459	0.133	0.001	0.837	1.433	0.559	0.221	0.909	0.808	0.710	0.567	0.211
α_{jump}	0.545	0.941	0.562	-1.049	3.696	0.777	-0.325	2.351	0.890	0.196	1.466	0.894
β^{OF}	0.128	0.001	$<.0001$	0.178	0.008	$<.0001$	0.160	0.006	$<.0001$	0.134	0.004	$<.0001$
β^{OF}_{jump}	-0.004	0.003	0.146	-0.065	0.018	0.001	-0.038	0.012	0.002	-0.018	0.008	0.022
$adj-R^2$	0.288			0.341			0.324			0.292		

FIGURE 1

Intraday Market Activities

This figure plots market activities in each half-hour window during the day from 7:30 a.m. to 5:00 p.m.. Variables include trading volume ($ millions), trading duration (seconds), relative bid-ask spread ($\times 10,000$), return volatility (%) calculated from 5-minute returns based on the mid bid-ask quote, average depth at the best bid and ask ($ millions) calculated over each 5-minute interval, and average hidden depth at the best bid and ask ($ millions) calculated over each 5-minute interval.





Return volatility
0.03
0.025
0.02
0.015
0.01
0.005
0
7
8
9
10
11
12
13
14
15
16
17
Depth at best bid/ask
1000
800
600
400
200
0
Hidden depth at best bid/ask
80
60
40
20
Time

FIGURE 2

Intraday Frequency of Jumps

This figure plots intra-day distribution of jump frequency (number of jumps over each 5-minute interval) for 2-, 5-, and 10-year notes. The intra-day distribution of jump frequency is plotted for all jumps as well as jumps outside pre-scheduled news announcement time.

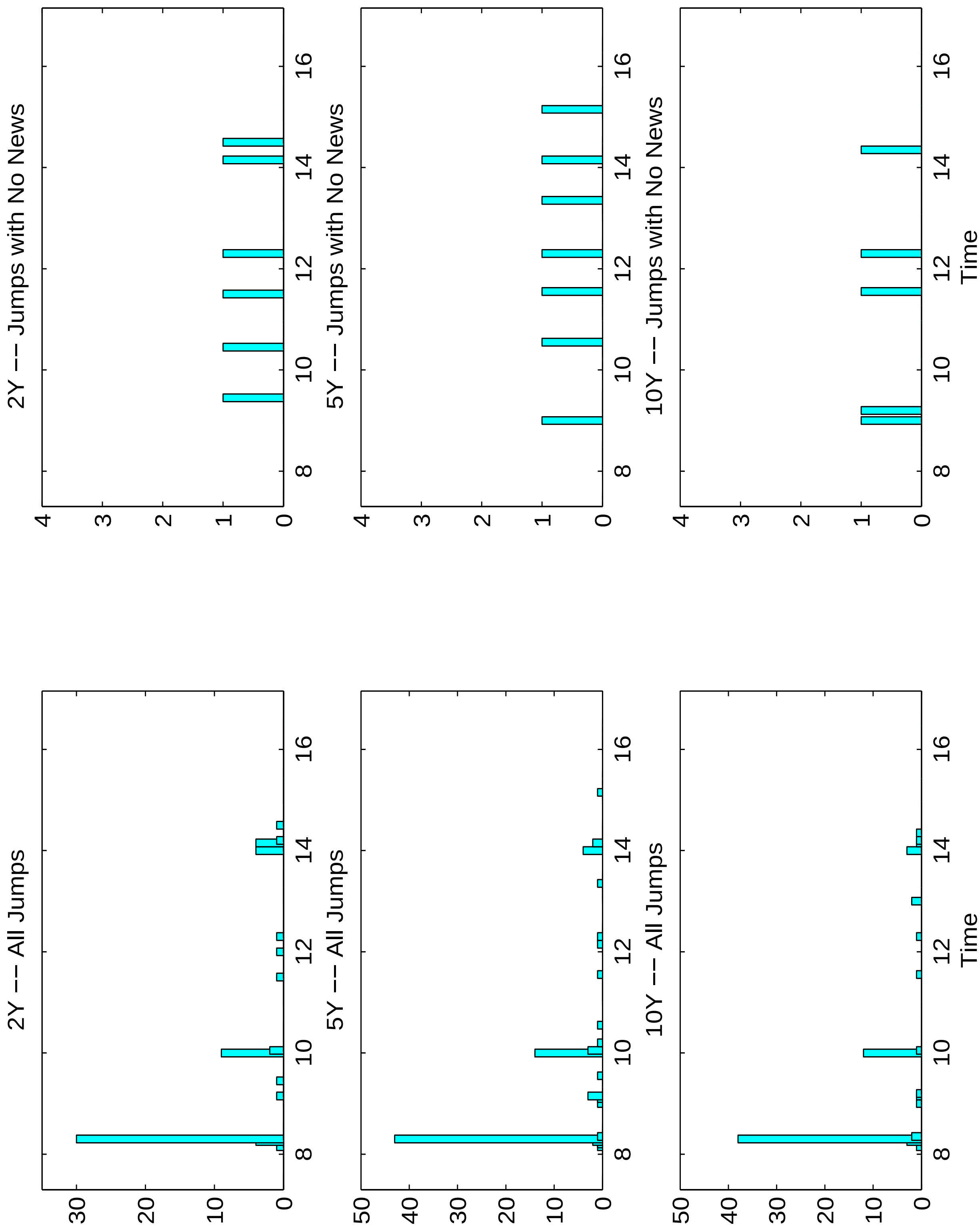


FIGURE 3

Return and Trading Volume

– Jumps outside announcement time (10-year note)

This figure plots market activities, return and trading volume, for four representative cases of jumps in the 10-year note price occurred outside announcement time. The legend in each plot indicates the date that jumps occur.

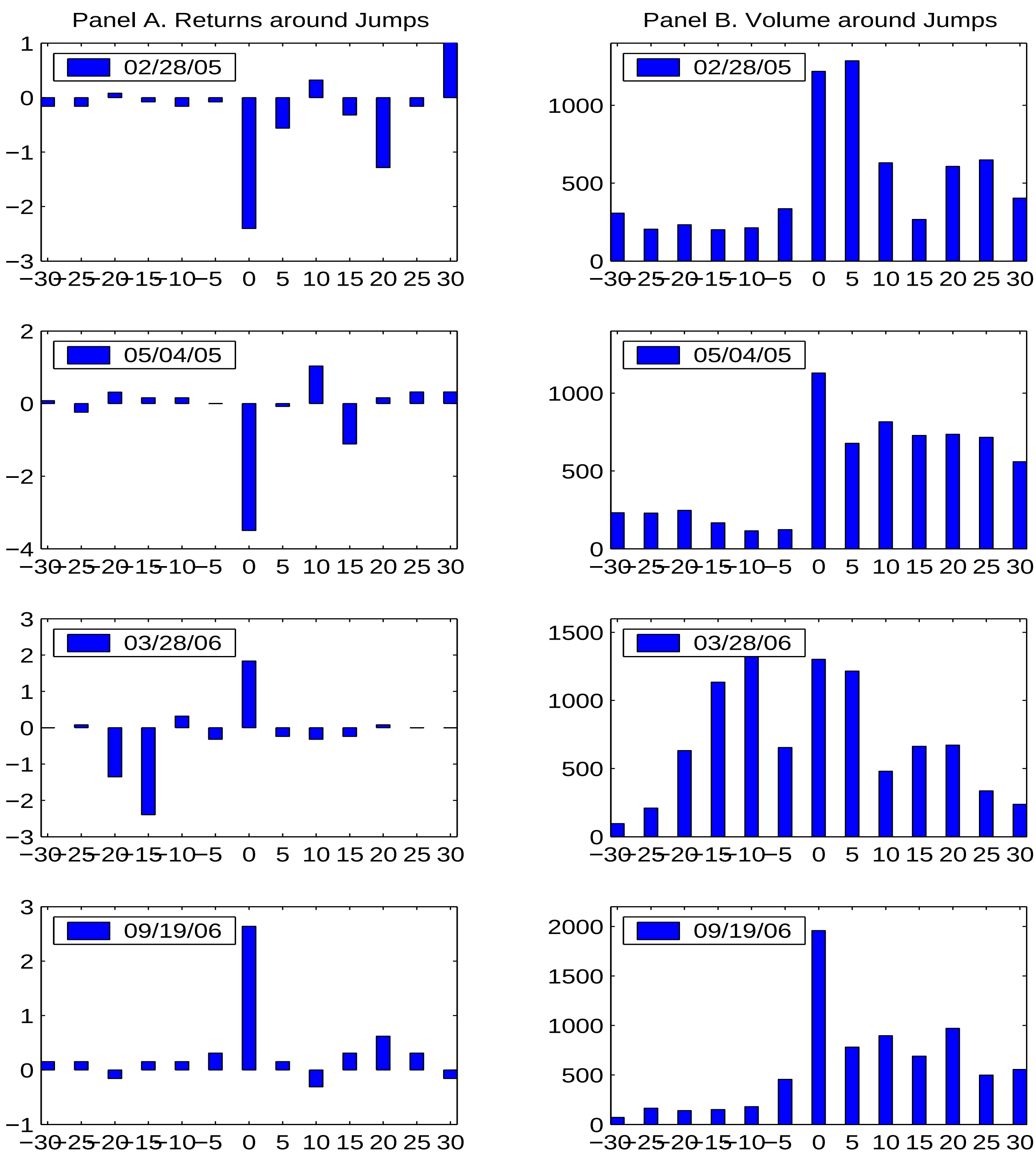
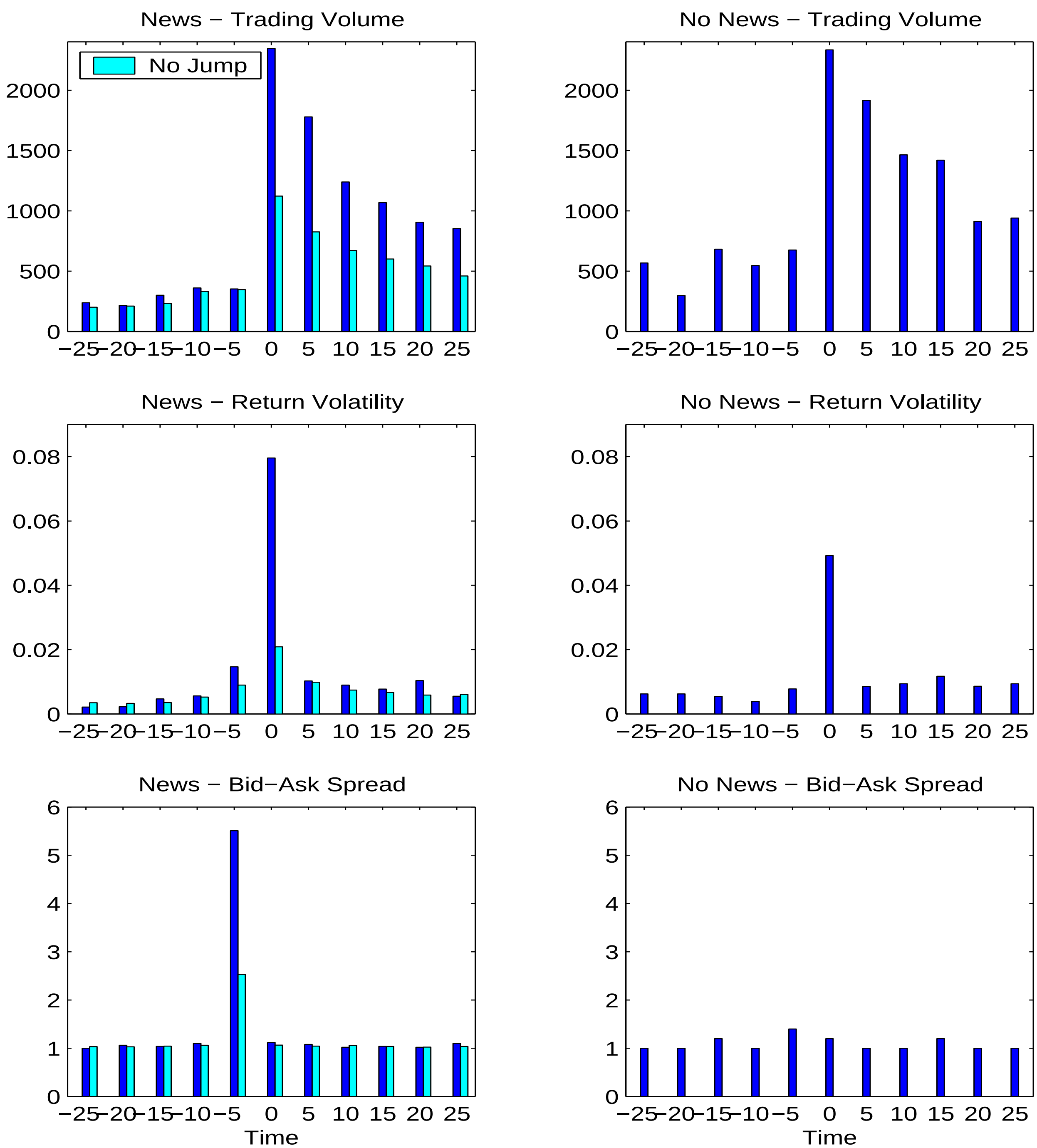
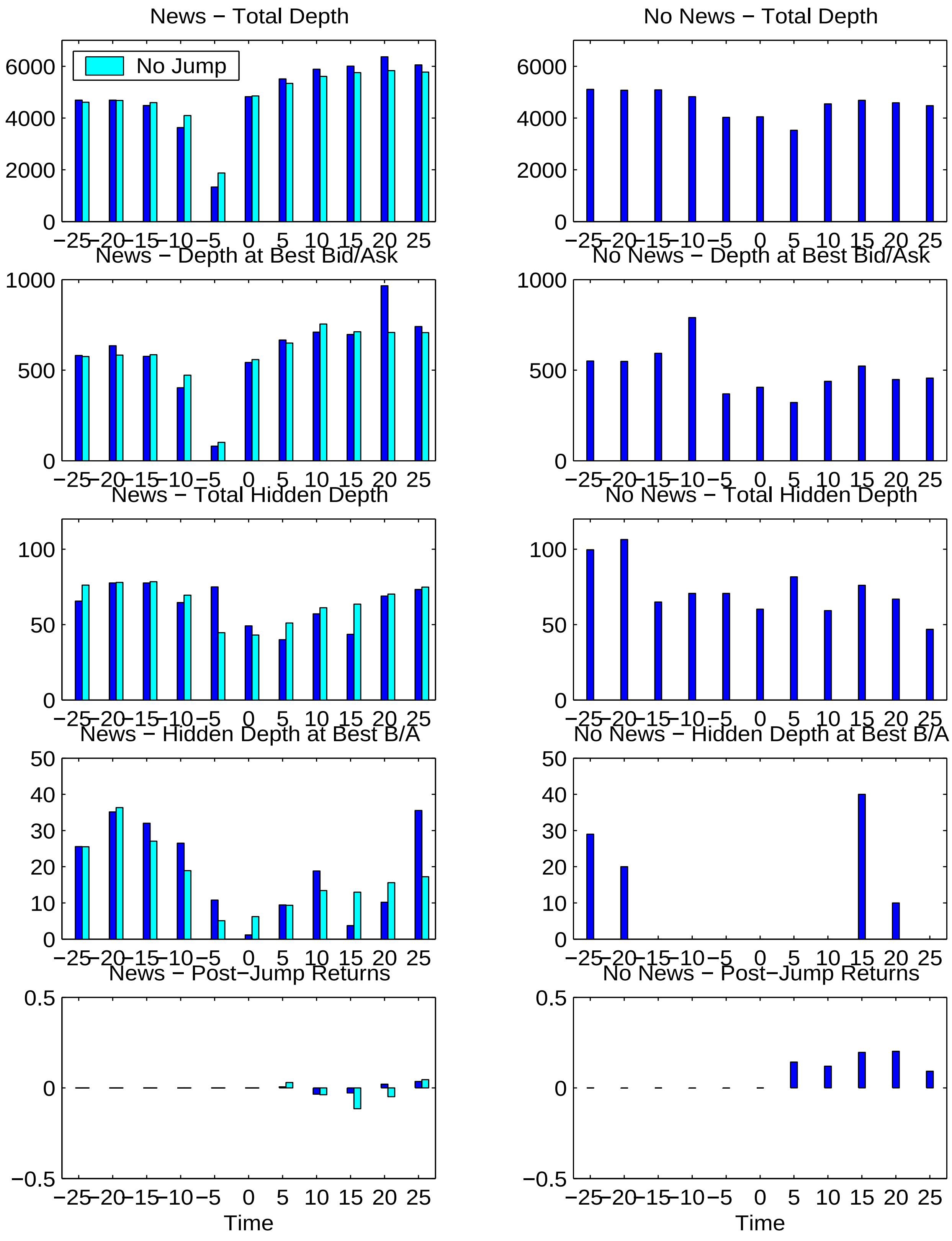


FIGURE 4

Market Activities Around Jumps (2-year note)

This figure plots market activities before and after jumps. The left column contrasts market activities around jumps occurring at announcement time to announcements with no jumps. The right column plots market activities around jumps outside pre-scheduled news announcement time. Variables include trading volume ($ millions), return volatility (%), relative bid-ask spread ($\times 10,000$), depth of the entire order book ($ millions), depth at the best bid and ask ($ millions), total hidden depth ($ millions), hidden depth at the best bid and ask ($ millions), and an indicator of post-jump return reversal/momentum.




News − Total Depth
No Jump
No News − Total Depth
News − Depth at Best Bid/Ask
No News − Depth at Best Bid/Ask
News − Total Hidden Depth
No News − Total Hidden Depth
News − Hidden Depth at Best B/A
No News − Hidden Depth at Best B/A
News − Post−Jump Returns
No News − Post−Jump Returns
Time
Time