Jumps and Information Asymmetry in the US Treasury Market *

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This paper analyses the informational role of the trading activity when jumps occur in the US Treasury market. As jumps mark the arrival of new information to the market, we explore the contribution of jumps in reducing the informational asymmetry. We identify jumps using a combination of jump detection techniques. For all maturities, the trading activity is more informative in the proximity of jumps. For the 2- and 5-year maturities, there is a lower level of information asymmetry before the jump, followed by a high level during the jump window and up to 20 minutes after the jump occurs. Thus, the incorporation of new information in prices is not instantaneous but several transactions are needed for the market to completely acknowledge the new information. Finally, we propose the use of the estimated integrated volatility as an exogenous predictor of jump occurrence in addition to announcement surprises.

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JEL classification numbers: G12, G14, C01, C51

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Jumps and Information Asymmetry in the US Treasury Market

Abstract. This paper analyses the informational role of the trading activity when jumps occur in the US Treasury market. As jumps mark the arrival of new information to the market, we explore the contribution of jumps in reducing the informational asymmetry. We identify jumps using a combination of jump detection techniques. For all maturities, the trading activity is more informative in the proximity of jumps. For the 2- and 5-year maturities, there is a lower level of information asymmetry before the jump, followed by a high level during the jump window and up to 20 minutes after the jump occurs. Thus, the incorporation of new information in prices is not instantaneous but several transactions are needed for the market to completely acknowledge the new information. Finally, we propose the use of the estimated integrated volatility as an exogenous predictor of jump occurrence in addition to announcement surprises.

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1 Introduction

Jumps can be defined as big and unexpected changes in the prices of financial securities. The unanticipative nature of jumps stems from the fact that they are informational events, i.e. the result of new information reaching the market. Once this new information arrives to the market and the jump occurs, information is homogeneously distributed to all market participants. If before the jump there are agents with some degree of private information, after the jump, everyone should have the same information. Thus, jumps should reduce the degree of informational asymmetry in the markets.

The main objective of this present paper is to investigate the role of jumps, as informational events, in dissipating informational asymmetry in the US Treasury bond market. We identify jumps in bond prices using high frequency data and combinations of nonparametric jump detection procedures. Then, we measure the informational asymmetry in the proximity of jumps, modifying the approach proposed in Green (2004). We consider various time windows before, at the time and after a jump takes place, as well as in situations when no jumps occur. For the 2- and 5-year maturities, we find that information asymmetry increases dramatically in the time window when the jump occurs, and then stays relatively high for up to 20 minutes after the jump has occurred. Moreover, information asymmetry reaches a minimum immediately before the jump. Given that most of the jumps take place as a result of macroeconomic announcements, this finding is consistent with a low degree of information leakage before announcements. On the contrary, for the 10-year bond, there is evidence of higher levels of informational asymmetry before jumps occur. This is very likely due to the higher degree of uncertainty attached to bonds with longer maturities.

Our analysis builds upon Green (2004) who considers the release of macroeconomic news as informational events. Indeed, in the US Treasury market, the main source of information resides in macroeconomic news announcements (Fleming and Remolona, 1997; Balduzzi et al., 2001; Altavilla et al., 2014). Moreover, in Section 2.2, we show that the vast majority of jumps occur on days with macroeconomic news announcements. At the same time, we show that only a small proportion of announcements (less than 13%) leads to jumps in prices and is thus relevant. In this paper, we propose "jumps occurrence" as a natural way to discriminate between relevant and irrelevant information: information is relevant if it leads to jumps in prices.

In addition, this paper brings several novel contributions to the recent empirical literature on jump identification and determination, previously developed by Jiang et al. (2011), Lahaye et al. (2011), Boudt and Petitjean (2014), Dungey et al. (2009) and Gilder et al. (2014). First, based on Dumitru and Urga (2012), we use a combination of testing procedures and sampling frequencies to identify jumps in prices, the combination of tests being more robust than the use of the single procedure as applied in the above mentioned papers. Second, we find that in the US Treasury market jumps mainly occur as a result of macroeconomic news releases. Third, we show that due to the simultaneity of jumps and news announcements, jumps are almost always preceded by a significant liquidity withdrawal. Thus, while previous research considers liquidity shocks as an important determinant of the probability of jump occurrence, we argue that liquidity shocks and jumps are endogenously jointly determined. As a consequence, we show that a major cause of jump occurrence in the US Treasury market is still the release of macroeconomic news. Finally, we further complement the literature on determinants of jumps by proposing the use of the estimated integrated volatility as an additional exogenous predictor of jump occurrence.

The paper is structured in the following way. Section 2 describes the data, the interdealer market for the US Treasury bonds, the jump detection procedures and the empirical results on jump detection. Section 3 reports and discusses the bulk of our findings on the informational role of the order flow when jumps occur. Section 4 concludes.

2 Preliminary analysis

2.1 Data and market description

Our analysis is based on high frequency data for four US Treasury bonds, namely the 2-, 5-, 10- and 30-year bonds. The data was provided by BrokerTec, an interdealer electronic trading platform and is made up of trade records, quotations and order cancellations, as well as a work-up part. Due to the complexity and scarcity of the data set, we include a short but insightful description of the market and the data.

The interdealer brokerage market The secondary market for US Treasury bonds is an interdealer over-the -counter market, where, as shown in Fleming and Mizrach (2009) and Fleming (1997), there are 22-23 hours of trading activity per day, with most of it being placed during New-York hours, that is between 7:30 am and 5:00 pm. There are some trading peaks between 10:00 and 10:30 am and between 14:30 and 15:00.

The largest part of the transactions in the interdealer market for the US Treasury bonds takes place through two large interdealer brokerage firms, ICAP PLC with about 60% of market share and Cantor Fitzgerald with 28% (Mizrach and Neely, 2006). Before 2000, both the actors on the marketplace provided voice-assisted brokerage services. All the market data from ICAP was collected in the GovPX database and was customarily used for the studies concerning the US Treasury bonds. However, as noted by Mizrach and Neely (2006), Boni and Leach (2004), Fleming (2003) and Barclay et al. (2006), with the foundation of electronic trading platforms, most of the trading with US Treasury bonds migrated from the voice-assisted to the electronic platforms. Thus, as shown in Barclay et al. (2006), e-Speed, the electronic platform of Cantor Fitzgerald was inaugurated in March 1999, while its main competitor, BrokerTec, was set up in June 2000 and was purchased by ICAP in 2003. These electronic trading platforms are characterized by lower transaction costs and by a higher level of liquidity, also due to the fact that electronic systems match opposite orders automatically, making the whole trading process more fluid. The voice-assisted platforms remain though important for their use for more "customized", complex transactions that require human intermediaries to perform negotiations between parties. Mizrach and Neely (2006) show that after the introduction of the electronic trading platforms, the average trading volume almost tripled from $200 billion in 1999 to $ 575 billion in 2005 .

Market characteristics The interdealer market is an expandable limit order one, where transactions typically pass through three different phases (Boni and Leach, 2004, see). Traders post limit orders, that can be automatically matched by the electronic system. They can also respond to an already existing order (becoming "aggressive"). However, as noted by Boni and Leach (2004), there is an incentive on the market to provide liquidity through limit orders, as commissions are paid only for responding orders.

The next phase of a transaction is the so-called "work-up" process. This type of market provides the traders with the right of refusal to trade additional quantities, provided that the other party desires this. Thus, traders usually enter limit orders in order to find counter-parties and then increase quantities during the work-up process. Moreover, there is the possibility to post "iceberg" orders, that have hidden quantities.

Once the parties agree on quantities, the trades are perfected and they appear in the Trade section. Boni and Leach (2004) show that the right and not the obligation to further increase traded quantities reduces the costs associated with information leakage and stale limit orders, unlike the usual limit order markets, where large orders might cause free-riding on the signal. Fleming and Mizrach (2009), use BrokerTec data to reveal that liquidity is greater than the one reported by studies using data from voice-assisted brokerage platforms. Moreover, the iceberg orders are sparse and are mostly used during volatile periods.

Dataset The data contains intraday observations covering the order book, with both order submissions and cancellations, the trade section and the work-up process for the 2-, 5-, 10- and 30-year bonds and covering a period between January 2003 and March 2004. The choice of the period is related to its relative calmness in comparison to other intervals during the last decade. All nonparamentric tests for jumps identify excessive returns by comparison to a local volatility measure. If volatility is very high, as during financial crises, the tests are not able to pick up jumps anymore. While the first three bonds are very liquid, for the 30-year one the competitor brokerage platform, E-Speed, owns a bigger market share.

Prices are reported in 256th of a point and are maintained under this form throughout the analysis, as they do not influence the results, given that we work with log-returns.

For each trading day, we keep in our sample just the data comprised between 7:30 a.m. EST and 5:00 p.m. EST, when trading is more active.

Sampling is done every 5 and 15 minutes. Based on the information in the order book , we compute mid-quotes, spread and depth of the market at the best bid and ask quotes. We rely on information in the trade section to compute orderflow and trade volumes.

2.2 Jump detection

During the last decade, high frequency econometrics has seen several contributions developing tests for jumps in the prices of financial assets (see Barndorff-Nielsen and Shephard, 2006; Andersen et al., 2007; Lee and Mykland, 2008; Jiang and Oomen, 2008; Podolskij and Ziggel, 2010).

Dumitru and Urga (2012) show that the combination of detection procedures and/or sampling frequencies improve the results of jumps tests when prices are contaminated with microstructure noise. More precisely, unions and intersections of the results of various testing procedures applied for different sampling frequencies lead to improvements in the power of tests, without impending on the size.

In this paper, we simultaneously rely on the results of the following jump identification procedures: 1. the Barndorff-Nielsen and Shephard (2006) applied on 5 minutes data (denoted BNS5); 2. the Barndorff-Nielsen and Shephard (2006) applied on 15 minutes data (denoted BNS15); 3. the Andersen et al. (2007)-Lee and Mykland (2008) test applied on 15 minutes data (denoted ABDLM15). To decide whether jumps occur at a certain day, we consider as final test for jumps the following combination through unions of intersections of the above tests:

$$(ABDLM15 \cap BNS5) \cup (ABDLM15 \cap BNS15)$$

Thus, the final days with jumps are the ones identified with the Lee and Mykland (2008)- Andersen et al. (2007) test, if they were also detected by the Barndorff-Nielsen and Shephard (2006) procedure on either 5 or 15 minutes data.

Once a day with jump is identified as above, we rely on the results of the ABDLM15 for that day to identify the time of the jump. As shown below, the Andersen et al. (2007)-Lee and Mykland (2008) test, based on standardized intraday returns, offers information not only on the day of the jump, but also on the timing of the jump or jumps in that day, up to the length of the sampling interval (15 minutes here). Moreover, the size of the standardized return corresponding to the time of the jump gives us the jump size. If more than one jump is detected within one day, all of them are taken into consideration.

To further control for the impact of microstructure noise, the realized bipower variation over 5 minutes data is based on staggered returns (Andersen et al., 2007). We rely on 99% critical values for all tests applied here. Below, we report a short description of the jump detection procedures implemented.

2.2.1 Jump tests

Barndorff-Nielsen and Shephard (2006) test This procedure tests the null hypothesis of continuity of the sample path during a trading day. It relies on comparing a robust to jumps volatility estimator, the realized bipower variation (BV_t), with a non-robust to jumps estimator, the realized variance (RV_t). Based on the results of the simulation in Huang and Tauchen (2005), we employ the ratio test statistic:

$$\frac{1-\frac{BV_t}{RV_t}}{\sqrt{0.61\,\delta\,\max\left(1,\frac{TQ_t}{BV_t^2}\right)}} \xrightarrow{L} \mathcal{N}(0,1) \tag{1}$$

where t is the end of the time interval of interest, $[0,t]$, and TP_t denotes the realized tripower variation. To define RV_t, BV_t and TP_t, the time interval $[0,t]$ is split into n equal subintervals of length δ. The j-th intraday return r_j on day t is $r_j = p_{t-1+j\delta} - p_{t-1+(j-1)\delta}$, where $p_{t-1+j\delta}$ is the j-th logarithmic price observed on day t, $j = 1 \ldots n$. We then have:

$$RV_t = \sum_{j=1}^{n} r_j^2 \tag{2}$$

$$BV_t = 1.57 \sum_{j=2}^{n} |r_j r_{j-1}| \tag{3}$$

$$TP_t = n\,1.74\left(\frac{n}{n-2}\right)\sum_{j=3}^{n} |r_{j-2}|^{4/3}|r_{j-1}|^{4/3}|r_j|^{4/3} \tag{4}$$

Lee and Mykland (2008)-Andersen et al. (2007) test Lee and Mykland (2007) and Andersen et al. (2007) concurrently develop tests for jumps based on the standardization of the intraday returns by the square root of the realized bipower variation. While Andersen et al. (2007) use observations of the whole trading day to compute BV_t, Lee and Mykland (2008) estimate it on a local window that precedes the time when the test is performed. Both tests have the null hypothesis of continuity of the sample path at a certain time, t_j. This allows users to identify both the exact time of a jump as well as the number of jumps within a trading day. The following statistic is considered:

$$z_j = \frac{|r_j|}{\sqrt{BV_t/n}} \xrightarrow{L} \mathscr{N}(0,1), \qquad j = 1 \dots n, \tag{5}$$

Both papers point out that the usual normal critical values (95% and 99% percentiles) are too permissive. To address this issue, Andersen et al. (2007) treat it as a multpiple testing problem and use the Sidak correction leading to a test size $\beta = 1-(1-\alpha)^{\delta}$, where α is the daily size. Lee and Mykland (2008) propose using the distribution of the maximum of the above statistic over the trading day. The new properly standardized statistic will display an extreme value distribution (Gumbel distribution):

$$\frac{\max z_j - C_n}{S_n} \to \xi, \qquad \mathbf{P}(\xi) = \exp(-e^{-x}), \qquad \forall j = 1, 2, \dots, n \tag{6}$$

where $C_n = \frac{(2\log n)^{1/2}}{\mu_1} - \frac{\log \pi + \log(\log n)}{2\mu_1(2\log n)^{1/2}}$ and $S_n = \frac{1}{\mu_1(2\log n)^{1/2}}$. In this paper, we rely on critical values as in Lee and Mykland (2008).

Boudt et al. (2011) notice that the volatility estimator used to standardize the returns in (5) changes very slowly, while intraday volatility tends to cluster and peak during the same time intervals within a trading day. They propose parametric and nonparametric estimators of the periodicity factor that are robust to the presence of jumps. Here, we only describe the nonparametric approach that we use to correct the test statistic in (5). Let the intraday returns be described by the following discrete model:

$$y_j = f_j s_j u_j + a_j, \qquad j = 1 \dots n, \tag{7}$$

where s_j is the average bipower variation, estimated on a local window around j, $f_j = \sigma_j / s_j$, the periodicity factor, with σ_j the spot volatility, $u_j \sim i.i.d.\mathscr{N}(0,1)$.

The periodicity factor is estimated as follows. First, we standardize all intraday returns by the squared root of the properly scaled realized bipower variations estimated on a local window around j. Let $r_{(1),j} \leq r_{(2),j} \leq \ldots \leq r_{(n_j),j}$ be the ordered standardized returns in a window around time j. Second, we compute Rousseeuw and Leroy (1988)' "shortest half scale estimator" on these returns.

$$ShortH_j = 0.741 \min\{r_{(h_j),j} - r_{(1),j}, \ldots, r_{(n_j),j} - r_{(n_j-h_j+1),j}\}, \tag{8}$$

where $h_j = [n_j/2] + 1$. This estimator can be subsequently standardized to $f_j^{ShortH} = \frac{ShortH_j}{\frac{1}{n}\sqrt{ShortH_j^2}}$.

The final periodicity estimator is the standardized Weighted Standard Deviation (WSD):

$$f_j^{WSD} = \frac{WSD_j}{\frac{1}{n}\sqrt{WSD_j^2}}, \tag{9}$$

with $WSD_j = \sqrt{1.081\frac{\sum_{l=1}^{n_j} w_{l,j} r_{l,j}^2}{\sum_{l=1}^{n_j} w_{l,j}}}$, where the weights $w_{l,j}$ are given by:

$$w_{l,j} = \begin{cases} 1, & \text{if} \quad \left(\frac{r_{l,j}}{\hat{f}_j^{ShortH}}\right)^2 \leq 6.635 \\ 0, & \text{otherwise} \end{cases}$$

2.2.2 Detected jumps

We find that the 2-year bonds jump in 14.5% of the days, the 5-year in 10.6%, the 10-year in 9.6% and finally the 30-year in 17.91% of the days. As expected, if we do not consider the result for the 30-year bond, we observe a decrease in the proportion of identified jumps with the increase in the maturity. The 30-year bond is highly illiquid during the period we considered in our sample and thus we expect the high proportion of detected jumps is spuriously generated.

Table 1 reports some descriptive statistics on the estimated jump sizes for all the maturities, while Table 2 reports the same indicators but for jump sizes that were previously standardized by a local volatility estimator. The biggest size is encountered in the case of the 30-year bond, but we suspect this finding is due to liquidity issues, just as the high proportion of jumps identified for this maturity. If we ignore this maturity, when we look at all central tendency parameters in Table 1, we observe that the 10-year bond displays the highest jump size, followed by the 5-year and the 2-year. It seems that the latter jumps more frequently, but less abruptly than the other bonds. However, if we standardize these jumps by robust to jumps local volatility estimators, we observe (see Table 2) that the previous hierarchy disappears, indicating that the shorter maturity bonds are less volatile than the others.

	Size			
	Mean	Median	Mode	Std
Y2	0.081%	0.063%	0.023%	0.052%
Y5	1.787%	0.181%	0.000%	10.394%
Y10	1.795%	0.292%	0.000%	9.814%
Y30	2.127%	0.474%	0.211%	9.639%

Table 1: Summary statistics for the estimated jump size for the 2-, 5-, 10- and 30-year US Treasury bonds

	Standardized Size			
	Mean	Median	Mode	Std
Y2	31.15	23.57	16	19.39
Y5	28.38	22.25	16.07	15.67
Y10	28.36	24.19	15.91	13.24
Y30	30.19	21.8	16.04	30.15

Table 2: Summary statistics for the standardized jump size for the 2-, 5-, 10- and 30-year US Treasury bonds

Table 3 reports the number of common jumps between maturities, when taken two by two. We observe a clear prevalence of common jumps at the shorter end of the term structure. Thus, we have the largest number of co-jumps for combinations of the 2-year maturity with the other bonds.

The main conclusion is that the shorter maturity bonds jump more frequently than the others. This suggests that they react to a larger proportion of macroeconomic announcements than the others, meaning that they are more sensitive to events occurring in the economic environment. The other

	Y2	Y5	Y10	Y30
Y2	44	28	24	23
Y5		32	21	17
Y10			29	17
Y30				53

Table 3: Number of jumps (diagonal elements) and co-jumps (off-diagonal elements) for the 2-, 5-, 10- and 30-year US Treasury bonds

	Y2		Y5		Y10		Y30	
Match	94	92.16%	79	100.00%	60	93.75%	72	83.72%
No match	8	7.84%			4	6.25%	14	16.28%
Total	102	100.00%	79	100.00%	64	100.00%	86	100.00%

Table 4: Number and percentages of jumps matched with macroeconomic announcements

bonds are less sensitive, displaying a lower probability of jump occurrence, but, given the long maturity, they transpose the environment uncertainty to larger moves in the prices.

2.2.3 Determinants of jumps

For each maturity and for each jump, we check whether on the day and around the time of the jump there were any macroeconomic announcements. Data on announcements is taken from Yahoo! Finance, which reports some of the data provided by Briefing.com. A complete list of all relevant announcements is included in Appendix A.

For each maturity, we compute the number and percentage of jumps to which macroeconomic announcements can be associated, as well as jumps which cannot be matched with any news releases. Results are summarized in Table 4. For the 2-, 5- and 10-year bonds, more than 90% of the jumps can be associated with the release of public information to the market. For the 30-year bond, this percentage equals only 83.73%, which we believe is due to the spurious detection of jumps that cannot be matched with announcements.

Once we identified all news releases that can impact on bond prices, we

	Y2		Y5		Y10		Y30	
Big surprise	64		64		64		64	
Big surprise & no jump	57	89.06%	57	89.06%	56	87.50%	64	100.00%

Table 5: Number of big announcement surprises and number and percentages of those not associated with any jump (big surprises are defined as larger than the 95% quantile of the normal distribution).

compute the absolute value of the announcement surprise, provided data on this is available. We standardize each surprise by the standard deviation of all surprises available for the same announcement during the period considered in our sample. We select all standardized surprises larger than the 95% quantile of the normal distribution and examine whether jumps took place on the corresponding days and times. Surprisingly, for all maturities, we identify a very low percentage of 'big' surprises associated with jumps. The results are summarized in Table 5.

While more than 90% of the jumps are generated by announcements, it seems that approximately 90% of the announcements do not cause jumps. These results can be explained by several factors. First, given our sample of just 15 months, for each type of news release, we have just a few surprises. Thus, the standard deviation of each type of surprise is computed on a very small sample and thus, subject to biases. Second, there are certain announcements that are more important than others and jumps can occur even if surprises are not very big. Third, as suggested by Hess (2004), the "timeliness" of the news releases might be important, as well. If several announcements reveal similar information, the earlier ones should have a greater impact on the prices.

The liquidity around jump times puzzle Previous research identifying determinants of jumps in the prices of financial assets find that liquidity shocks preceding jumps are very good predictors of jump occurrence (Jiang et al., 2011; Boudt and Petitjean, 2014). Jiang et al. (2011), who use the same data set as us but a slightly different sample, find that when liquidity shocks and news surprises are jointly considered as determinants of jump occurrence, news surprises tend to lose their significance. Our descriptive analysis above, though, shows that in the US Treasury market, the vast majority of jumps (over 90%) can be matched to macroeconomic announcements. The above statements give rise to what we call here the “liquidity around jump times puzzle”, which we explain below.

Macroeconomic announcements have long been documented to constitute the main source of information concerning the fundamental value of government bonds (Balduzzi et al., 2001; Andersen et al., 2003; Hess, 2004; Green, 2004; Dungey et al., 2009). Consequently, US Treasury bond prices were shown to react to news releases. This abundant evidence in addition to our own descriptive evidence in the previous paragraph prove beyond no doubt that news releases are the main drive for jumps in bond prices. Moreover, we show below that the simultaneity of jumps and macroeconomic announcements can generate liquidity shocks preceding jumps.

We measure several liquidity indicators on a window of -/+ 25 minutes around the time of the jump and examine their behavior within this interval. We consider the depth of the market at the best bid and ask quotes, the spread and the trading volume. Figure 1 illustrates these different measures for the 2-year bond. The corresponding figures for the other maturities are comprised in Appendix B. As the depth indicators refer to the best bid and ask quotes, they are both expressed in number of contracts.

Both the depth at the best ask quote and the one at the best bid quote fall in the 5-10 minutes that precede the jump. Spread peaks within the 5 minutes interval before the occurrence of the jump, while the trade volume falls in the 5-10 minutes before the jump and then experiences an abrupt increase. Thus, all these liquidity measures show a severe withdrawal of liquidity before the jump occurrence.

The observed liquidity withdrawal can be explained by the simultaneity of most jumps with macroeconomic announcements. Before macroeconomic announcements, market participants limit their trading activity waiting to

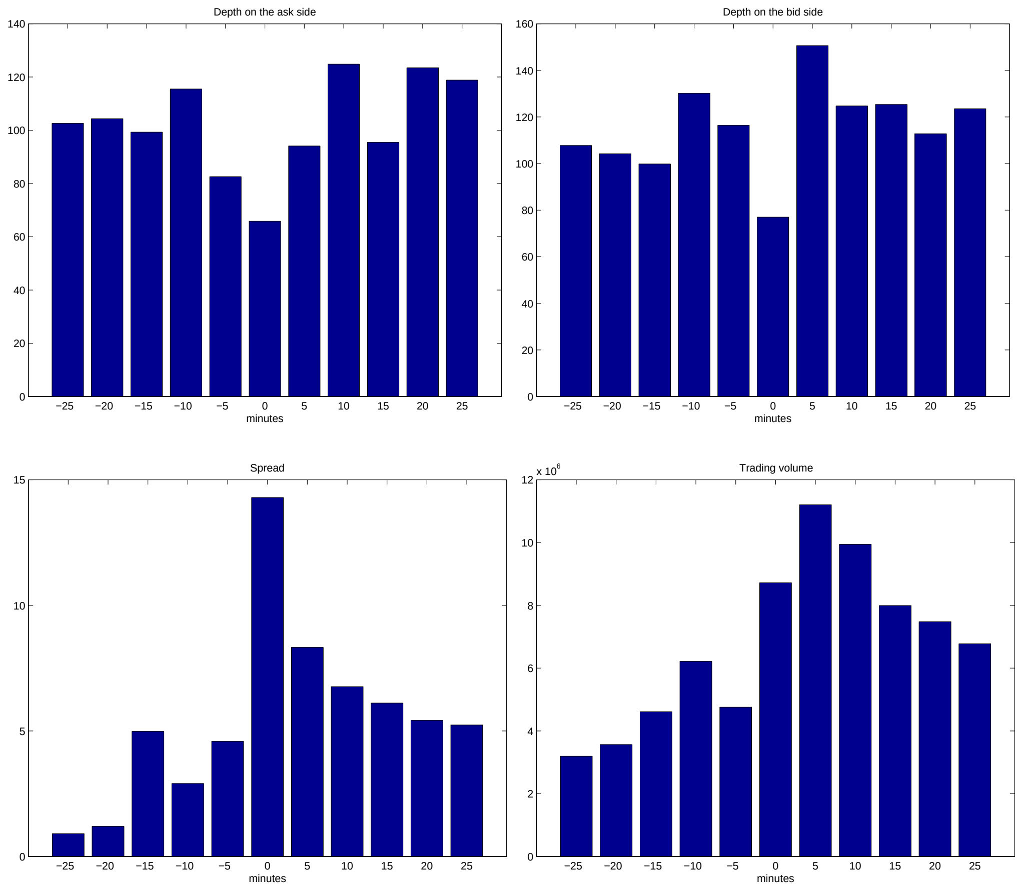

Figure 1: Alternative liquidity measures around the time of jump for the 2-year bond

find out the content of the news release. As most jumps occur after news releases, they will always be accompanied by the observed liquidity withdrawal. This makes us believe that jumps and liquidity shocks before jumps are endogenously determined, being both caused by the release of macroeconomic information.

A simple regression model explaining the jump occurrence in the US Treasury market. In order to quantify the impact of announcement surprises on jumps, we estimate an extreme value (Gumbel) binary choice model in which we consider as determinants of the probability of jump occurrence the announcement surprise and the square root of the bipower variation estimate for the corresponding trading day, based on 5 minutes staggered returns. The inclusion of the volatility estimator has two major rationales. First, it is sensible to believe that if jumps occurred within one day, volatility increased as well. To avoid endogeneity issues, we consider here just the volatility coming from the continuous part of the price process and not the one including the jumps. Second, we believe that a volatility proxy might capture other unknown factors that could contribute to the price dynamics but which might be hard to identify and observe. In our analysis, we take into consideration all the days in our sample, independent of whether news were released or not on that day. The dependent variable is set to 1 if at least one jump occurred on a certain day and to 0 otherwise.

Table 6 includes the estimation output for these binary choice regressions. The choice of the extreme value distribution is based on the reported Akaike, Schwartz and Hannan-Quinn information criteria.

We observe that the surprise is significant at a 1% significance level for the 2-, 5- and 10-year bonds and at a 5% significance level for the less liquid 30 -year bond. Our proxy for volatility is also found highly significant (1%) for the 2-, 5- and 30-year bonds, while for the 10-year one we have significance only at a 5% significance level. In the same table we report results for the Hosmer-Lemeshow goodness-of-fit test for binary choice models, which

		Coefficient	p-value	Goodness of fit	
Y2	C	-2.53	0.0000	H-L Statistic	5.74
	Surprise	0.29	0.0021	Prob. Chi-Sq(8)	0.68
	Volatility (BV)	1881.19	0.0000		
Y5	C	-2.37	0.0000	H-L Statistic	4.36
	Surprise	0.40	0.0002	Prob. Chi-Sq(8)	0.82
	Volatility (BV)	432.54	0.0002		
Y10	C	-1.62	0.0000	H-L Statistic	8.28
	Surprise	0.30	0.0014	Prob. Chi-Sq(8)	0.41
	Volatility (BV)	107.26	0.0262		
Y30	C	-1.33	0.0000	H-L Statistic	11.91
	Surprise	0.18	0.0284	Prob. Chi-Sq(8)	0.16
	Volatility (BV)	88.96	0.0066		

Table 6: Results from regressing the probability of a jump on a constant (C), the announcement surprise and volatility, measured as the realized bipower variation (BV)

compares values predicted by the model with the real values of the dependent variable. Results in Table 6 suggest that differences between actual and predicted values are not significant, indicating a good fit.

3 Informativeness of the order flow when jumps occur

Jumps are unanticipated sized changes in prices. They are related to fundamentals of financial assets and reflect new information coming to the market. Because of their role in marking the incorporation of new information in the price, one would expect a significant decrease in informational asymmetry following jump occurrence. Thus, once information is released and a jump takes place, the trading process should gradually become less and less informative. The first objective of this section is to test the validity of this intuitive hypothesis.

In the US Treasury market, new information is customarily related to the release of macroeconomic news. Whenever the content of such news is unanticipated by the market, we expect to observe a jump. The unanticipative nature of new information when prices jump implies a low degree of informational asymmetry in the interval preceding the jump. This is congruent with the absence of informational leakage before jumps occur. Testing the validity of this hypothesis is the second objective of this section.

Our analysis follows the framework of Green (2004), who examines the impact of trading on bond prices around news releases. The author finds a very low degree of informational asymmetry before announcements, accompanied by a significant increase in the informational role of trading following announcements. However, as observed in the previous section, while the majority of jumps in this market are caused by macroeconomic announcements, not all announcements lead to jump occurrence. Jumps occur if and only if information is relevant. For this very reason, it is worthwhile introducing into analysis a new category of informational events: jumps themselves. This is made possible by the recent advances in the econometrics of jump detection based on high frequency data which followed Green (2004)'s seminal work.

Green (2004)'s analysis relies on data for the 5-year bond. Here, we use data for the 2-, 5-, 10- and 30-year maturities. This gives us the opportunity to explore whether the behaviour of various maturities in terms of informativeness of the order flow when jumps occur is similar or not. This constitutes a third objective of this section.

The starting point of our analysis is Madhavan et al. (1997)' model of price formation (denoted as MRR):

$$p_{t_i} - p_{t_{i-1}} = (\phi + \theta)x_{t_i} - (\phi + \rho\theta)x_{t_{i-1}} + e_{t_i}, \tag{10}$$

where t_i are the times when trades take place, $i = 1 \dots N$, with N the total number of trades, x_{t_i} is the order flow at time t_i, with $x_{t_i} = 1$ if the transaction is buyer initiated and $x_{t_i} = -1$ if the initiator was the seller, ϕ captures the compensation for providing liquidity, including all order processing costs, but also the effects of dealer inventories, ρ is the autocorrelation in the order flow, while θ measures the information asymmetry. The latter is the most important parameter in our analysis and assesses the impact of the surprise in the order flow $(x_{t_i} - \rho x_{t_{i-1}})$ on price changes.

3.1 Models

In order to analyze how the parameters of the above model change in the presence of jumps, we transform equation (10), by adding several dummies, resulting in the following five models:

Model 1

$$\begin{aligned} p_{t_i} - p_{t_{i-1}} =& (\phi_J + \theta_J) I_{J,t_i} x_{t_i} - (\phi_J + \rho\theta_J) I_{J,t_i} x_{t_{i-1}} + (\phi_{NJ} + \theta_{NJ}) I_{NJ,t_i} x_{t_i} - \\ & (\phi_{NJ} + \rho\theta_{NJ}) I_{NJ,t_i} x_{t_{i-1}} + e_{t_i}, \end{aligned} \tag{11}$$

where the parameters are estimated separately for the days with jumps $(I_{J,t_i} = 1)$ and for those without jumps $(I_{NJ,t_i} = 1)$.

Model 2

$$\begin{aligned} p_{t_i} - p_{t_{i-1}} =& (\phi_{J0} + \theta_{J0}) I_{J,t_i} I_{J0,t_i} x_{t_i} - (\phi_{J0} + \rho\theta_{J0}) I_{J,t_i} I_{J0,t_i} x_{t_{i-1}} + (\phi_B + \theta_B) I_{J,t_i} I_{B,t_i} x_{t_i} - \\ & (\phi_B + \rho\theta_B) I_{J,t_i} I_{B,t_i} x_{t_{i-1}} + (\phi_A + \theta_A) I_{J,t_i} I_{A,t_i} x_{t_i} - (\phi_A + \rho\theta_A) I_{J,t_i} I_{A,t_i} x_{t_{i-1}} + \\ & (\phi_{NJ} + \theta_{NJ}) I_{NJ,t_i} x_{t_i} - (\phi_{NJ} + \rho\theta_{NJ}) I_{NJ,t_i} x_{t_i - 1} + e_{t_i}, \end{aligned} \tag{12}$$

where, for the days with jumps, we differentiate between the moment of the jump, J0 and the periods before (B) and after (A) the jump.

Model 3

$$
\begin{aligned}
p_{t_i} - p_{t_{i-1}} =& (\phi_{J0} + \theta_{J0}) I_{J,t_i} I_{J0,t_i} x_{t_i} - (\phi_{J0} + \rho\theta_{J0}) I_{J,t_i} I_{J0,t_i} x_{t_{i-1}} + \\
& (\phi_{B5} + \theta_{B5}) I_{J,t_i} I_{B5,t_i} x_{t_i} - (\phi_{B5} + \rho\theta_{B5}) I_{J,t_i} I_{B5,t_i} x_{t_{i-1}} + \\
& (\phi_{A5} + \theta_{A5}) I_{J,t_i} I_{A5,t_i} x_{t_i} - (\phi_{A5} + \rho\theta_{A5}) I_{J,t_i} I_{A5,t_i} x_{t_{i-1}} + \\
& (\phi_{other} + \theta_{other}) I_{other,t_i} x_{t_i} - (\phi_{other} + \rho\theta_{other}) I_{other,t_i} x_{t_{i-1}} + e_{t_i}
\end{aligned} \tag{13}
$$

where, for the days with jumps we consider a window of -/+ 5 minutes around the jump and estimate parameters at the jump time (J0), for the 5 minutes that precede the jump (B5), for the 5 minutes after the jump (A5) and for the rest of the data (other).

Model 4

$$
\begin{aligned}
p_{t_i} - p_{t_{i-1}} =& (\phi_{J0} + \theta_{J0}) I_{J,t_i} I_{J0,t_i} x_{t_i} - (\phi_{J0} + \rho\theta_{J0}) I_{J,t_i} I_{J0,t_i} x_{t_{i-1}} + \\
& (\phi_{B10} + \theta_{B10}) I_{J,t_i} I_{B10,t_i} x_{t_i} - (\phi_{B10} + \rho\theta_{B10}) I_{J,t_i} I_{B10,t_i} x_{t_{i-1}} + \\
& (\phi_{A10} + \theta_{A10}) I_{J,t_i} I_{A10,t_i} x_{t_i} - (\phi_{A10} + \rho\theta_{A10}) I_{J,t_i} I_{A10,t_i} x_{t_{i-1}} + \\
& (\phi_{other} + \theta_{other}) I_{other,t_i} x_{t_i} - (\phi_{other} + \rho\theta_{other}) I_{other,t_i} x_{t_{i-1}} + e_{t_i},
\end{aligned} \tag{14}
$$

just as model 3, but the window is of -/+ 10 minutes around the jump time.

Model 5

$$
\begin{aligned}
p_{t_i} - p_{t_{i-1}} =& (\phi_{J0} + \theta_{J0}) I_{J,t_i} I_{J0,t_i} x_{t_i} - (\phi_{J0} + \rho\theta_{J0}) I_{J,t_i} I_{J0,t_i} x_{t_{i-1}} + \\
& (\phi_{B20} + \theta_{B20}) I_{J,t_i} I_{B20,t_i} x_{t_i} - (\phi_{B20} + \rho\theta_{B20}) I_{J,t_i} I_{B20,t_i} x_{t_{i-1}} + \\
& (\phi_{A20} + \theta_{A20}) I_{J,t_i} I_{A20,t_i} x_{t_i} - (\phi_{A20} + \rho\theta_{A20}) I_{J,t_i} I_{A20,t_i} x_{t_{i-1}} + \\
& (\phi_{other} + \theta_{other}) I_{other,t_i} x_{t_i} - (\phi_{other} + \rho\theta_{other}) I_{other,t_i} x_{t_{i-1}} + e_{t_i},
\end{aligned} \tag{15}
$$

just as model 3, but the window is of -/+ 20 minutes around the jump time.

To estimate the above models, we use all the transaction data available. Given that jumps are identified based on 5/15 minutes data, we cannot perfectly match the times of the jumps with the times of the trades. Thus, the indicator function I_{J0,t_i} selects a window of +/- 2 minutes around the jump time. All the other indicator functions that select observations around the times of the jumps are adapted accordingly. For instance, I_{B10,t_i} selects all observations preceding a certain jump time with 12 to 2 minutes.

The Generalized Method of Moments is employed to estimate the coefficients of the above equations. We exemplify here only the estimation of model 1, as the estimation for the others is very similar. Let $\beta = (\alpha, \rho, \phi_J, \theta_J, \phi_{NJ}, \theta_{NJ})$ be the vector of parameters to estimate for model 1, with α the intercept added to the model. In order to find the estimates for the components of this vector, the following moment conditions are used:

$$E \begin{bmatrix} x_{t_i} x_{t_{i-1}} - x_{t_i}^2 \rho \\ e_{t_i} - \alpha \\ (e_{t_i} - \alpha) I_{J,t_i} x_{t_i} \\ (e_{t_i} - \alpha) I_{J,t_i} x_{t_{i-1}} \\ (e_{t_i} - \alpha) I_{NJ,t_i} x_{t_i} \\ (e_{t_i} - \alpha) I_{NJ,t_i} x_{t_{i-1}} \end{bmatrix} = 0 \qquad (16)$$

The estimates are robust to ARCH-type heteroskedasticity.

3.2 Empirical results

Results for the 2-, 5- and 10-year bonds are summarized in Tables 7-9. Results for the 30-year maturity may be affected by the low liquidity that characterizes the data for this maturity. Consequently, for completeness we report them only in the Appendix C, Table 11. The estimated coefficients for this maturity behave, in terms of size, for all models, very similarly to the estimates for the 2- and 5-year maturities. However, for the days with jumps, coefficients are usually insignificant, probably due to the low number of observations used to estimate them.

As already mentioned, the focus of our analysis are the θ parameters.

Model 1

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0035	0.0012	2.94	0.0032
ϕ_J	0.0310	0.0141	2.20	0.0275
θ_J	0.3759	0.0118	31.81	0.0000
ϕ_{NJ}	0.0456	0.0040	11.33	0.0000
θ_{NJ}	0.3258	0.0036	90.58	0.0000

Model 2

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0034	0.0012	2.90	0.0037
ϕ_{J0}	-0.8520	0.5397	-1.58	0.1144
θ_{J0}	1.3779	0.4303	3.20	0.0014
ϕ_B	0.0653	0.0246	2.66	0.0079
θ_B	0.2858	0.0194	14.76	0.0000
ϕ_A	0.0316	0.0125	2.53	0.0112
θ_A	0.3595	0.0111	32.43	0.0000
ϕ_{NJ}	0.0456	0.0040	11.33	0.0000
θ_{NJ}	0.3258	0.0036	90.58	0.0000

Model 3

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0034	0.0012	2.88	0.0039
ϕ_{J0}	-0.8421	0.5381	-1.57	0.1176
θ_{J0}	1.5269	0.4259	3.59	0.0003
ϕ_{B5}	0.1910	0.1397	1.37	0.1716
θ_{B5}	0.3446	0.0605	5.70	0.0000
ϕ_{A5}	-0.1346	0.1262	-1.07	0.2860
θ_{A5}	0.6672	0.0944	7.07	0.0000
ϕ_{other}	0.0460	0.0038	12.19	0.0000
θ_{other}	0.3292	0.0034	97.70	0.0000

Model 4

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0034	0.0012	2.87	0.0041
ϕ_{J0}	-0.8421	0.5381	-1.56	0.1176
θ_{J0}	1.5276	0.4259	3.59	0.0003
ϕ_{B10}	0.1536	0.0797	1.93	0.0541
θ_{B10}	0.2460	0.0476	5.16	0.0000
ϕ_{A10}	-0.0834	0.0770	-1.08	0.2789
θ_{A10}	0.5729	0.0614	9.33	0.0000
ϕ_{other}	0.0465	0.0038	12.30	0.0000
θ_{other}	0.3279	0.0034	97.58	0.0000

Model 5

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0034	0.0012	2.88	0.0039
ϕ_{J0}	-0.8420	0.5403	-1.56	0.1192
θ_{J0}	1.4193	0.4316	3.29	0.0010
ϕ_{B20}	0.1235	0.0618	2.00	0.0455
θ_{B20}	0.2660	0.0424	6.27	0.0000
ϕ_{A20}	-0.0559	0.0472	-1.18	0.2364
θ_{A20}	0.5064	0.0400	12.65	0.0000
ϕ_{other}	0.0473	0.0038	12.47	0.0000
θ_{other}	0.3262	0.0034	96.68	0.0000

Table 7: Estimated coefficients, standard errors, t-statistics and p-values, respectively, for Models 1-5 for the 2-year bond. For all models, the value of the correlation coefficient for the order flow is $\widehat{\rho} = 0.6609$

Model 1

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0044	0.0017	2.58	0.0098
ϕ_J	-0.1710	0.0216	-7.92	0.0000
θ_J	0.8575	0.0197	43.63	0.0000
ϕ_{NJ}	-0.1767	0.0056	-31.29	0.0000
θ_{NJ}	0.8454	0.0073	115.18	0.0000

Model 2

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0044	0.0017	2.56	0.0106
ϕ_{J0}	-1.6179	0.9121	-1.77	0.0761
θ_{J0}	2.9582	0.8663	3.41	0.0006
ϕ_B	-0.1746	0.0421	-4.15	0.0000
θ_B	0.7612	0.0336	22.64	0.0000
ϕ_A	-0.1303	0.0208	-6.26	0.0000
θ_A	0.7883	0.0179	44.14	0.0000
ϕ_{NJ}	-0.1767	0.0056	-31.29	0.0000
θ_{NJ}	0.8454	0.0073	115.18	0.0000

Model 3

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0044	0.0017	2.56	0.0105
ϕ_{J0}	-1.6712	0.9138	-1.83	0.0674
θ_{J0}	3.2768	0.8655	3.79	0.0002
ϕ_{B5}	-0.2157	0.1475	-1.46	0.1435
θ_{B5}	0.7726	0.1386	5.57	0.0000
ϕ_{A5}	-0.0168	0.2863	-0.06	0.9533
θ_{A5}	1.1441	0.1336	8.57	0.0000
ϕ_{other}	-0.1731	0.0053	-32.63	0.0000
θ_{other}	0.8410	0.0067	125.50	0.0000

Model 4

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0043	0.0017	2.53	0.0113
ϕ_{J0}	-1.6698	0.9138	-1.83	0.0676
θ_{J0}	3.2773	0.8655	3.79	0.0002
ϕ_{B10}	-0.2633	0.1051	-2.51	0.0122
θ_{B10}	0.7290	0.1034	7.05	0.0000
ϕ_{A10}	-0.1813	0.1683	-1.08	0.2813
θ_{A10}	0.9441	0.0836	11.29	0.0000
ϕ_{other}	-0.1721	0.0053	-32.48	0.0000
θ_{other}	0.8404	0.0067	125.03	0.0000

Model 5

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0043	0.0017	2.54	0.0112
ϕ_{J0}	-1.6072	0.9128	-1.76	0.0783
θ_{J0}	3.0325	0.8731	3.47	0.0005
ϕ_{B20}	-0.3145	0.1502	-2.09	0.0363
θ_{B20}	0.8049	0.1085	7.42	0.0000
ϕ_{A20}	-0.1205	0.1018	-1.18	0.2366
θ_{A20}	0.8408	0.0639	13.16	0.0000
ϕ_{other}	-0.1718	0.0053	-32.37	0.0000
θ_{other}	0.8397	0.0068	124.32	0.0000

Table 8: Estimated coefficients, standard errors, t-statistics and p-values, respectively, for Models 1-5 for the 5-year bond. For all models, the value of the correlation coefficient for the order flow is $\widehat{\rho} = 0.6928$

Model 1

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0034	0.0033	1.02	0.3101
ϕ_J	-0.1040	0.0430	-2.42	0.0155
θ_J	1.3216	0.0419	31.55	0.0000
ϕ_{NJ}	-0.2017	0.0119	-16.93	0.0000
θ_{NJ}	1.3647	0.0104	130.61	0.0000

Model 2

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0035	0.0033	1.04	0.2988
ϕ_{J0}	-0.8359	1.7737	-0.47	0.6374
θ_{J0}	0.0004	1.5499	0.00	0.9998
ϕ_B	-0.0302	0.0803	-0.38	0.7073
θ_B	1.0373	0.0964	10.76	0.0000
ϕ_A	-0.0882	0.0418	-2.11	0.0347
θ_A	1.2630	0.0410	30.82	0.0000
ϕ_{NJ}	-0.2017	0.0119	-16.93	0.0000
θ_{NJ}	1.3647	0.0104	130.61	0.0000

Model 3

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0034	0.0033	1.02	0.3061
ϕ_{J0}	-0.9096	1.7708	-0.51	0.6075
θ_{J0}	0.5169	1.5494	0.33	0.7387
ϕ_{B5}	0.5159	1.2391	0.42	0.6772
θ_{B5}	2.3117	0.9639	2.40	0.0165
ϕ_{A5}	0.1530	0.2963	0.52	0.6056
θ_{A5}	1.7152	0.2743	6.25	0.0000
ϕ_{other}	-0.1902	0.0112	-16.92	0.0000
θ_{other}	1.3566	0.0099	136.74	0.0000

Model 4

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0034	0.0033	1.03	0.3049
ϕ_{J0}	-0.9097	1.7711	-0.51	0.6075
θ_{J0}	0.5198	1.5496	0.34	0.7373
ϕ_{B10}	0.2787	0.4956	0.56	0.5739
θ_{B10}	1.5666	0.6596	2.37	0.0176
ϕ_{A10}	-0.0195	0.2731	-0.07	0.9430
θ_{A10}	1.5090	0.2892	5.22	0.0000
ϕ_{other}	-0.1909	0.0112	-17.05	0.0000
θ_{other}	1.3562	0.0098	137.85	0.0000

Model 5

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0036	0.0033	1.07	0.2864
ϕ_{J0}	-0.8725	1.7801	-0.49	0.6240
θ_{J0}	-0.0529	1.5444	-0.03	0.9727
ϕ_{B20}	-0.3082	0.4060	-0.76	0.4478
θ_{B20}	1.9321	0.5167	3.74	0.0002
ϕ_{A20}	0.1541	0.1648	0.94	0.3498
θ_{A20}	1.3630	0.1551	8.79	0.0000
ϕ_{other}	-0.1951	0.0115	-17.00	0.0000
θ_{other}	1.3591	0.0103	132.20	0.0000

Table 9: Estimated coefficients, standard errors, t-statistics and p-values, respectively. for Models 1-5 for the 10-year bond. For all models, the value of the correlation coefficient for the order flow is $\widehat{\rho} = 0.6725$

Below, we discuss the values of the $\widehat{\theta}$s for Model 1 and Model 2 separately and then for Models 3-5 jointly. We complete this section with some brief discussions of the estimates of the ϕs and ρs for all models considered.

Model 1. In general, if we look at results for Model 1 for all maturities, we observe that the estimates of θ tend to increase with maturity. Thus, for the 2-year bond, $\widehat{\theta}$ takes the value .38 for days with jumps and .33 for days without jumps. For the 5-year bond, the same estimated parameters are about .85 and .84, while for the 10-year bond the values are 1.32 and 1.36. This increase in the coefficients with the maturity is due to the fact that price changes tend to be higher for longer maturities, which is also consistent with the fact that jump sizes are bigger for higher maturities.

The results for Model 1 in Tables 7 - 9 indicate that the estimates of θ do not vary much between days with jumps and days without jumps. For the 2- and 5-year maturities, estimates for θ_J are bigger than those for θ_{NJ}, while for the 10-year maturity, the results are reversed. The close values of θs for jump days and days without jumps are not surprising. As these coefficients are measured for data within a whole day, they confer an average value for information asymmetry. This suggests that the order flow informativeness is transitory. Results for the more complex models below will confirm this fact, showing that trading can become informative for a certain period in the proximity of a jump, but then this effect dissipates.

Model 2. In this model, we separately estimate coefficients for the 'jump window', which is -/+ 2 minutes around the jump time. Moreover, we split the days with jumps in intervals that precede jumps and periods that follow them. Evidence for all maturities indicate that θ takes higher values after the jump than before. For instance, for the 2-year maturity, we have $\widehat{\theta_B} = 0.29$ and $\widehat{\theta_A} = 0.36$. Moreover, for the 2- and 5-year bonds, information asymmetry dramatically increases when jumps occur ($\widehat{\theta_{J0}} = 1.38$ for the 2-year bond and $\widehat{\theta_{J0}} = 2.96$ for the 5-year bond).

The low levels of $\widehat{\theta_B}$ are consistent with the absence of informational leakage before a jump occurs. After a jump occurs, for the first two maturities,the degree of informativeness of the orderflow jumps also to a very high level and then decreases again. This high levels can be explained by the fact that after the jump, the trading activity significantly intensifies and thus, also becomes more informative. $\widehat{\theta_A}$ is higher for all maturities than $\widehat{\theta_B}$ and has relatively close levels to $\widehat{\theta_{NJ}}$. This indicates that after a jump, θ returns to what are considered to be "normal" values.

For the 10-year maturity, the coefficient that captures information asymmetry for the 'jump window' is not significant at 1% or 5% significance levels (see Table 9 on page 24). We believe this might be because the 'jump window' (-/+ 2 minutes around the jump time) we used was too narrow. Consequently, we extend this window to -/+ 5 minutes around the jump time and widen all the other windows accordingly. Estimates of all the models for the 10-year maturity are reported in Table 12 in Appendix C. If we look at results for Model 2, we observe that the estimate of θ_{J0} increases to 1.14 and is significant at a 5% significance level, but is still lower than $\widehat{\theta_A}$ and $\widehat{\theta_{NJ}}$.

Models 3-5. In these models, we narrow our analysis to those intervals of time that are very close to the time of the jump. We maintain the 'jump window' of -/+ 2 minutes around the identified time of the jump and build windows of 5 (Model 3), 10 (Model 4) and 20 (Model 5) minutes before and after the jump.

The 2- and 5-year maturities exhibit a similar behavior. $\widehat{\theta}$s are very high at the jump time, they are quite low before the jump and remain at higher levels after the jump. For the 2-year bond, for instance, $\widehat{\theta_{J0}} = 1.52$ for all the three models, $\widehat{\theta_B}$ is quite low, varying from 0.12 for Model 5 to 0.34 for Model 3, while $\widehat{\theta_A}$, with values between 0.51 and 0.66 is considerably higher than $\widehat{\theta_{other}}$ and $\widehat{\theta_B}$. A similar scaling between $\widehat{\theta_B}$ and $\widehat{\theta_A}$ is maintained for the 30-year bond, as shown in Appendix C, Table 11.

The estimator of θ_B has the lowest value of all the θs, reflecting again the no leakage hypothesis. In addition, as shown in the previous section, the trading activity decreases before the jump and there is a significant liquidity withdrawal. Thus, it is possible that in the immediate window preceding the jump, the trading activity is not very informative because there is not much trading going on. In fact, as we move from Model 3 to 5 and increase the window before the jump, $\widehat{\theta_B}$ also increases, as more trading is likely to occur in a wider time window.

$\widehat{\theta_A}$ is higher than the values of θs before the jump and for all other observations. After the jump, trading intensifies for a certain time interval and then moves back to normal levels. This is reflected by the fact that $\widehat{\theta_A}$ is higher for the 5 minute after jump window (Model 1) and lowest for the 20 minute window (Model 3).

For the 10-year bond, results are contradictory to the ones for the first two maturities and to results obtained for Model 2 for the same maturity. θ_{J0} is again insignificant, while $\widehat{\theta_A}$ is lower than $\widehat{\theta_B}$ for all models. We offer here two sets of explanations for the inconsistency of results for this maturity with results for shorter maturities. A combination of the two could also be possible.

1. These results are sample dependent and could potentially change if the analysis were repeated on a much larger sample. The limitations in terms of sample size for this analysis do not regard the number of transactions, but the number of identified jumps. For the 10-year bond, we only observe 29 jumps, a lower number than for shorter maturities. Moreover, jump identification is a statistical procedure, subject to error. Given the low number of jumps, if the right timing of some jumps was not identified correctly, it could potentially affect the estimates for all coefficients of interest, θ_{J0}, θ_A and θ_B.

2. Longer maturity bonds are well known to carry more uncertainty and to be less tied to macroenomic policy. The high informational asymmetry found before a jump takes place could potentially reflect this higher degree of uncertainty. Market participants do not know whether the

following news release would be relevant or not and thus, every trade occurring is perceived as informative. At the same time, once information arrives to the market, its content needs to be of extreme relevance in order to impact prices of longer maturity bonds. Thus, a very limited number of the very dense macroeconomic news releases will impact the longer maturity bonds. Due to this limited responsiveness of longer maturities to news releases, there is a mutual agreement in the market about the price level after the correction induced by the jump. Thus, even if trading intensifies after the jump, the price changes induced by trades are not substantial.

For all maturities, θ increases dramatically in a window after or before the jump. This suggests that the incorporation of new information in prices is not instantaneous. It takes several transactions for the market to completely acknowledge the new information. The length of this process of incorporating new information into the transaction prices depends on the depth of the order book, which undergoes several changes once new information is released. More precisely, following the release of information, market participants re-adjust their orders, which will then be executed in the order of submission. The transaction prices will experience several "re-adjustment jumps" to acknowledge the new state of the world. Thus, one jump in the efficient, unobserved price can translate into a series of "re-adjustment jumps" in the transaction prices.

Some results on $\widehat{\phi}$. The order processing cost parameter, ϕ , captures dealers' compensation for providing liquidity and theory suggests it should be positive. However, our results are mixed. For the 5-year bond, estimates are negative for all the models, just as in Green (2004). For the other maturities, coefficients are sometimes positive and sometimes negative. Green (2004) suggests that a $\phi < 0$ indicates that dealers consume liquidity in the interdealer market and thus exhibit a sub-optimal behavior, which can be due to the fact that they are sufficiently compensated in the retail market. We argue here that in a world where most dealers practice high frequency trading, their compensation is obtained over several transactions. ϕ in the MRR model captures the average compensation over subsequent transactions.

If we look at all maturities and all models, we observe that the $\widehat{\phi}$-s are not significant not even at a 5% significance levels for the jump windows, as well as for the windows that precede or follow jumps. We find mixed evidence when comparing the ϕ estimates before and after the jump. $\widehat{\phi}$ before the jump is consistently higher than the estimate after the jump for the 2- and 10-year maturities, but the situation is reversed for the 5-year bond.

Some results on $\widehat{\rho}$. The above estimation procedure assumes and computes a constant correlation of the order flow throughout the sample, which is reported within the caption for each table. In Table 10 on the next page we report the order flow autocorrelation coefficients for groups of observations formed on the basis of the indicator functions from Models 1 - 5. When such data groups are considered, we notice some variations in the correlation coefficients between the different sets of observations. Results for Model 1 for the 2-, 5- and 10-year maturities indicate that order flow seems to be more autocorrelated in days with jumps than in days without jumps. If we split the days with jumps in before and after intervals, as in Models 2 - 5, we notice that in all cases autocorrelation within the 'jump window' is lower than before and after the jump, and is highest after the jump. This is consistent with the fact that once relevant information arrives on the market, the trading activity explodes, with traders interpreting news based on the observed order flow. This is why high levels of autocorrelation are also associated with high levels of information asymmetry.

Given the differences in the autocorrelation of the order flow between different time windows considered, we wondered whether this could affect the results of the estimations of Models 1 - 5. Consequently, for the 2-year bond, we re-estimated all the models, by considering varying autocorrelation coefficients, as reported in Table 10. The estimation output is included

		2-Year	5-Year	10-Year	30-Year
Model 1	$I_{J,t}$	0.671	0.711	0.689	0.428
	$I_{NJ,t}$	0.659	0.690	0.671	0.446
Model 2	$I_{J,t}I_{J0,t}$	0.638	0.731	0.725	0.680
	$I_{J,t}I_{B,t}$	0.670	0.702	0.690	0.461
	$I_{J,t}I_{A,t}$	0.673	0.717	0.692	0.416
	$I_{NJ,t}$	0.659	0.690	0.671	0.446
Model 3	$I_{J,t}I_{J0,t}$	0.638	0.731	0.725	0.680
	$I_{J,t}I_{B5,t}$	0.656	0.740	0.770	0.438
	$I_{J,t}I_{A5,t}$	0.716	0.800	0.795	0.312
	$I_{other,t}$	0.661	0.692	0.672	0.443
Model 4	$I_{J,t}I_{J0,t}$	0.638	0.731	0.725	0.680
	$I_{J,t}I_{B10,t}$	0.677	0.741	0.745	0.433
	$I_{J,t}I_{A10,t}$	0.725	0.796	0.794	0.374
	$I_{other,t}$	0.660	0.692	0.671	0.443
Model 5	$I_{J,t}I_{J0,t}$	0.638	0.731	0.725	0.680
	$I_{J,t}I_{B20,t}$	0.670	0.721	0.711	0.386
	$I_{J,t}I_{A20,t}$	0.713	0.790	0.778	0.421
	$I_{other,t}$	0.660	0.691	0.671	0.443

Table 10: Autocorrelation coefficients of the signed order flow. The coefficients are estimated for different groups of observations. The grouping criteria in column 2 are given by the indicator operators used in equations (11)-(15)

in Table 13 in Appendix C. The main consequence of considering different correlation coefficients is that for the 'jump window', the information asymmetry parameter slightly decreases. For instance, for Model 2, $\widehat{\theta_{J0}}$ was 1.37 when we used a unique autocorrelation coefficient in the estimation and 1.29 when different correlation coefficients are used. Apart from this, within each model, the hierarchy of the coefficients in terms of size does not change.

4 Conclusions

In this paper, we analyzed the role of jumps in incorporating new information in prices and reducing the informational asymmetry in the US Treasury market.

We started by detecting jumps in the US Treasury 2-, 5-, 10- and 30-year bonds both on a daily basis, using a combination of the Barndorff-Nielsen and Shephard (2004) test for jumps applied on data sampled every 5 and 15 minutes, with the Andersen et al. (2007)-Lee and Mykland (2008) procedure corrected for periodicity. We found that the 2-year bonds jump in 14.5% of the days, the 5-year in 10.6%, the 10-year in 9.6% and finally, the 30-year in 17.91% of the days.

The release of macroeconomic news is found to be the major cause of jumps in the bond prices. 90% of jumps are shown to occur at the same time or soon after an announcement. Moreover, the standardized announcement surprise is found to be an important determinant of the probability of jump occurrence. We argued that the liquidity measures, previously used in the literature to explain jumps, could suffer of endogeneity. We proposed using the estimated integrated volatility as an exogenous predictor of jump occurrence in addition to announcement surprises.

Further and most importantly, we examined the impact of trading on bond prices in the nearness of jumps. We found that for the 2- and 5- year maturities, the level of information asymmetry increased immediately after jumps occured, due to the arrival of new information to the market, and then remained at a high level up to 20 minutes after the jump. Before a jump takes place, there was a low degree of informational asymmetry, consistent with a low extent of information leakage.

For the 10-year bond, the results contradicted the ones for the shorter maturities, as we detected a higher level of information asymmetry before rather than after the jump. However, this parameter always remained higher for the windows around the jump times than when no jumps occured. We explained this result by the higher degree of riskiness of longer maturity bonds, as well as the shortness of the jump sample for this maturity.

The findings in this paper suggest further developments. It would be interesting to explore the differences in the maturities when new information reaches the market and how these differences may be subject to turmoil periods like the ones we have experienced over the last few years. It would also be interesting to analyze the informational role of trading for alternative classes of assets. We leave this to future work.

References

Altavilla, C., D. Giannone, and M. Modugno (2014). The low frequency effects of macroeconomic news on government bond yields. working paper, Finance and Economics Discussion Series, Federal Reserve Board, Washington, D.C.

Andersen, T. G., T. Bollerslev, and F. X. Diebold (2007). Roughing it up: Including jump components in the measurement, modeling and forecasting of return volatility. *Review of Economics and Statistics 89*, 701–720.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and C. Vega (2003). Micro effects of macro announcements: Real-time price discovery in foreign exchange. *The American Economic Review 93*(1), 38–62.

Andersen, T. G., T. Bollerslev, and D. Dobrev (2007). No-arbitrage semimartingale restrictions for continuous-time volatility models subject to leverage effects, jumps and i.i.d. noise: Theory and testable distributional implications. *Journal of Econometrics 138*, 125–180.

Balduzzi, P., E. J. Elton, and T. C. Green (2001). Economic news and bond prices: Evidence from the u.s. treasury market. *The Journal of Financial and Quantitative Analysis 36*(4), 523–543.

Barclay, M. J., T. Hendershott, and K. Kotz (2006). Automation versus intermediation: Evidence from treasuries going off the run. *The Journal of Finance 61*, 2395–2414.

Barndorff-Nielsen, O. and N. Shephard (2004). Power and bipower variation with stochastic volatility and jumps. *Journal of Financial Econometrics 2*, 1–48.

Barndorff-Nielsen, O. and N. Shephard (2006). Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics 4*, 1–30.

Boni, L. and C. Leach (2004). Expandable limit order markets. *Journal of Financial Markets 7*, 145–185.

Boudt, K., C. Croux, and S. Laurent (2011). Robust estimation of intraweek periodicity in volatility and jump detection. *Journal of Empirical Finance 18*, 353–367.

Boudt, K. and M. Petitjean (2014). Intraday liquidity dynamics and news releases around price jumps: Evidence from the djia stocks. *Journal of Financial Markets 17*, 121–149.

Dumitru, A.-M. and G. Urga (2012). Identifying jumps in financial assets: a comparison between nonparametric jump tests. *Journal of Business and Economic Statistics 30*(2), 242–255.

Dungey, M., M. McKenzie, and V. Smith (2009). Empirical evidence on jumps in the term structure of the us treasury market. *Journal of Empirical Finance 16*(3), 430 – 445.

Fleming, M. J. (1997). The round-the-clock market for u.s. treasury securities. *Federal Reserve Bank of New York Economic Policy Review 3*(2), 9–32.

Fleming, M. J. (2003). Measuring treasury market liquidity. *Federal Reserve Bank of New York Economic Policy Review 9*(3), 83–108.

Fleming, M. J. and B. Mizrach (2009). The microstructure of a us treasury ecn: the brokertec platform. working paper, Federal Reserve Bank of New York.

Fleming, M. J. and E. M. Remolona (1997). What moves the bond market? *Federal Reserve Bank of New York Economic Policy Review 3*(4), 31–50.

Gilder, D., M. B. Shackleton, and S. J. Taylor (2014). Cojumps in stock prices: Empirical evidence. *Journal of Banking & Finance 40*, 443–459.

Green, T. C. (2004). Economic news and the impact of trading on bond prices. *The Journal of Finance 59*(3), 1201–1233.

Hess, D. (2004). Determinants of the relative price impact of unanticipated information in u.s. macroeconomic releases. *The Journal of Futures Markets 24*(7), 609–629.

Huang, X. and G. Tauchen (2005). The relative contribution of jumps to total price variance. *Journal of Financial Econometrics 3*(4), 456–499.

Jiang, G. J., I. Lo, and A. Verdelhan (2011). Information shocks, jumps, and price discovery. evidence from the us treasury market. *Journal of Financial and Quantitative Analysis 46*(22), 527–551.

Jiang, G. J. and R. Oomen (2008). Testing for jumps when asset prices are observed with noise- a "swap variance" approach. *Journal of Econometrics 144*, 352–370.

Lahaye, J., S. Laurent, and C. J. Neely (2011). Jumps, cojumps and macro announcements. *Journal of Applied Econometrics 26*(6), 893–921.

Lee, S. S. and P. A. Mykland (2008). Jumps in financial markets: a new nonparametric test and jump dynamics. *Review of Financial studies 21*, 2535–2563.

Madhavan, A., M. Richardson, and M. Roomans (1997). Why do security prices change? a transaction-level analysis of nyse stocks. *Review of Financial Studies 10*(4), 1035–1064.

Mizrach, B. and C. J. Neely (2006). The transition to electronic communications networks in the secondary treasury market. *Federal Reserve Bank of St. Louis Review 88*(6), 527–541.

Podolskij, M. and D. Ziggel (2010). New tests for jumps in semimartingale models. *Statistical Inference for Stochastic Processes 13*, 15–41.

Rousseeuw, P. and A. Leroy (1988). A robust scale estimator based on the shortest half. *Statistica Neerlandica 42*, 103–116.

Appendix A Macroeconomic announcements that generate jumps in the term structure

Auto Sales	Factory Orders	Nonfarm Payrolls
Average Workweek	Fed's Beige Book	NY Empire State Index
Building Permits	FOMC Meeting	Personal Income
Business Inventories	FOMC Minutes	Personal Spending
Capacity Utilization	GDP-Adv & Final	Philadelphia Fed
Chain Deflator-Adv & final	Help-Wanted Index	PPI
Construction Spending	Hourly Earnings	Productivity-Prel
Consumer Confidence	Housing Starts	Retail Sales
Consumer Credit	Industrial Production	Retail Sales ex-auto
CPI & Core CPI	Initial Claims	Trade Balance
Current Account	ISM Index	Treasury Budget
Durable Orders	ISM Services	Truck Sales
Employment Cost Index	Leading Indicators	Unemployment Rate
Existing Home Sales	Mich Sentiment-Prel	Wholesale Inventories
Export Prices ex-ag	New Home Sales	

Appendix B Liquidity measures around the time of the jump for the 5-, 10- and 30-year US Treasury bonds

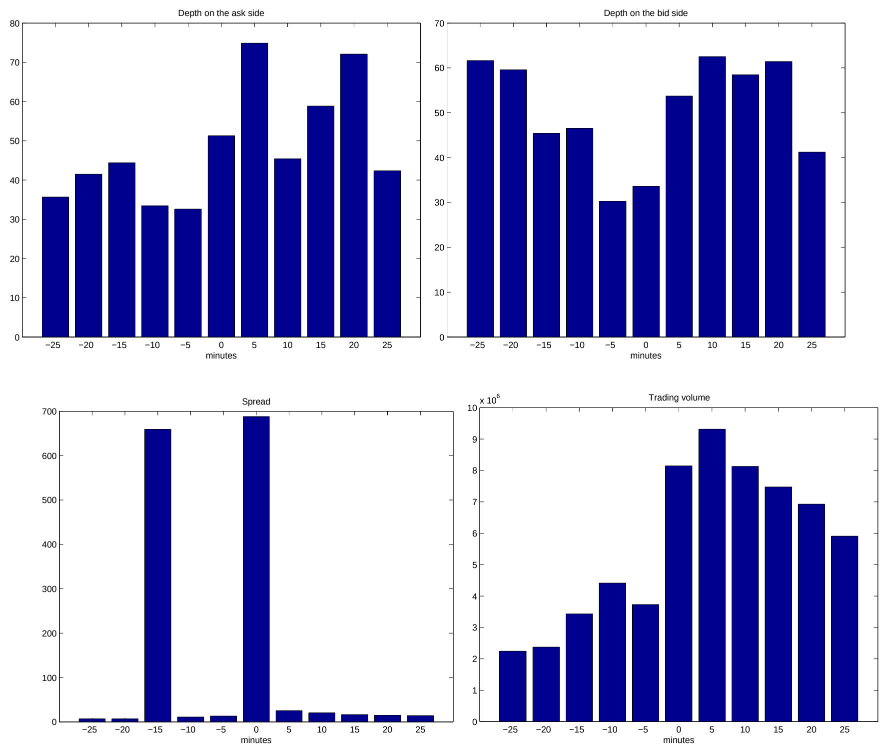

Figure 2: Alternative liquidity measures around the time of jump for the 5-year bond

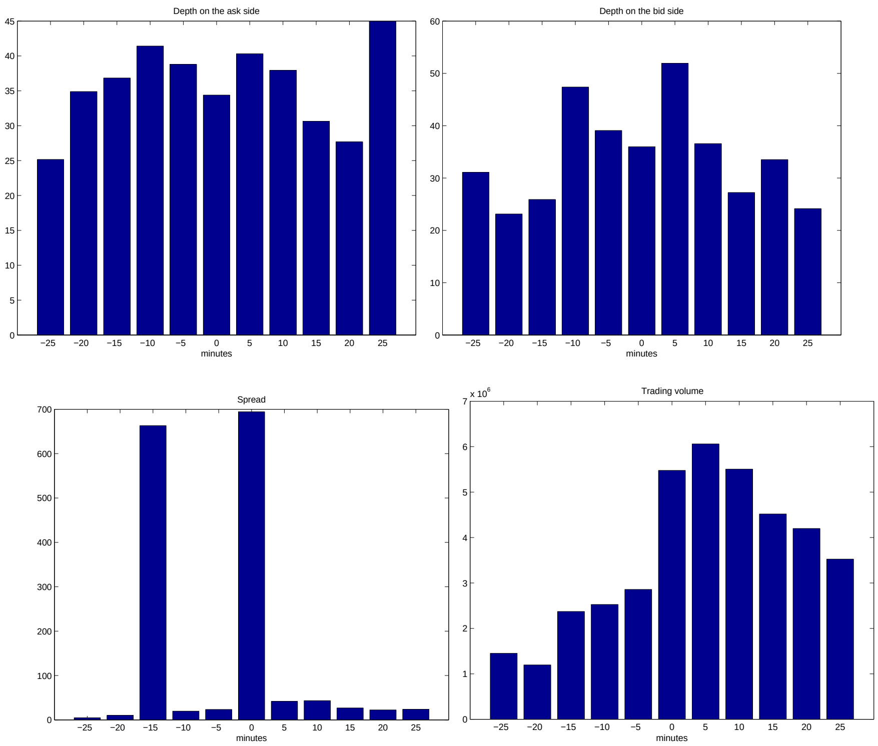

Figure 3: Alternative liquidity measures around the time of jump for the 10-year bond

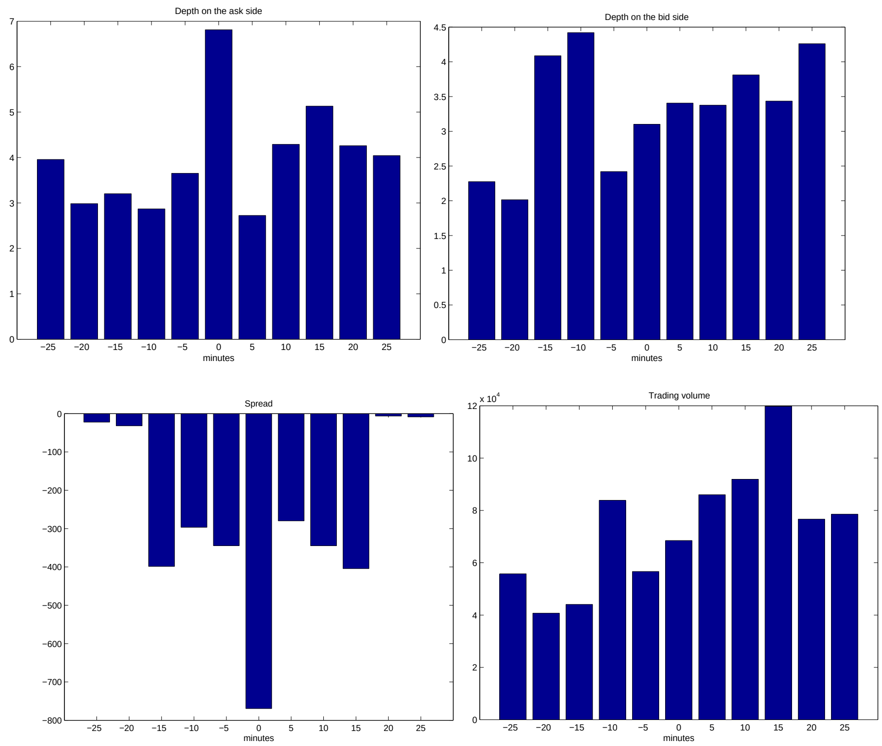

Figure 4: Alternative liquidity measures around the time of jump for the 30-year bond

Appendix C More results on the price formation process when jumps occur

Model 1

	Coefficient	Std. Error	t-Statistic	p-value
α	-0.0257	0.1051	-0.24	0.8069
ϕ_J	-0.7431	0.5968	-1.25	0.2131
θ_J	3.8223	0.5850	6.53	0.0000
ϕ_{NJ}	-1.1816	0.2124	-5.56	0.0000
θ_{NJ}	3.4496	0.2053	16.80	0.0000

Model 2

	Coefficient	Std. Error	t-Statistic	p-value
α	-0.0237	0.1049	-0.23	0.8215
ϕ_{J0}	-24.9491	17.4855	-1.43	0.1536
θ_{J0}	16.9362	13.7566	1.23	0.2183
ϕ_B	0.6611	1.1087	0.60	0.5510
θ_B	2.9124	1.0484	2.78	0.0055
ϕ_A	-0.8181	0.7015	-1.17	0.2436
θ_A	3.7285	0.6788	5.49	0.0000
ϕ_{NJ}	-1.1817	0.2124	-5.56	0.0000
θ_{NJ}	3.4497	0.2053	16.80	0.0000

Model 3

	Coefficient	Std. Error	t-Statistic	p-value
α	-0.0273	0.1045	-0.26	0.7938
ϕ_{J0}	-24.9511	17.7134	-1.41	0.1590
θ_{J0}	19.1459	13.8811	1.38	0.1678
ϕ_{B5}	-0.2331	6.8353	-0.03	0.9728
θ_{B5}	6.5974	2.3795	2.77	0.0056
ϕ_{A5}	-4.7729	15.2462	-0.31	0.7542
θ_{A5}	23.9930	15.0539	1.59	0.1110
ϕ_{other}	-1.0746	0.1983	-5.42	0.0000
θ_{other}	3.4392	0.1918	17.93	0.0000

Model 4

	Coefficient	Std. Error	t-Statistic	p-value
α	-0.0239	0.1044	-0.23	0.8190
ϕ_{J0}	-24.9523	17.7136	-1.41	0.1589
θ_{J0}	19.1466	13.8809	1.38	0.1678
ϕ_{B10}	2.6739	5.4653	0.49	0.6247
θ_{B10}	6.1792	4.3859	1.41	0.1589
ϕ_{A10}	-6.7657	7.8044	-0.87	0.3860
θ_{A10}	14.4657	7.3015	1.98	0.0476
ϕ_{other}	-1.0610	0.1986	-5.34	0.0000
θ_{other}	3.4417	0.1917	17.96	0.0000

Model 5

	Coefficient	Std. Error	t-Statistic	p-value
α	-0.0282	0.1045	-0.27	0.7875
ϕ_{J0}	-24.0574	17.2641	-1.39	0.1635
θ_{J0}	14.9826	13.0245	1.15	0.2500
ϕ_{B20}	3.0304	3.7612	0.81	0.4204
θ_{B20}	5.3797	2.9308	1.84	0.0664
ϕ_{A20}	-5.7990	4.7319	-1.23	0.2204
θ_{A20}	8.6947	4.4831	1.94	0.0525
ϕ_{other}	-1.0608	0.1986	-5.34	0.0000
θ_{other}	3.4414	0.1917	17.96	0.0000

Table 11: Estimated coefficients, standard errors, t-statistics and p-values, respectively, for Models 1-5 for the 30-year bond. For all models, the value of the correlation coefficient for the order flow is $\widehat{\rho} = 0.4430$

	Model 2					Model 3			
	Coefficient	Std. Error	t-Statistic	p-value		Coefficient	Std. Error	t-Statistic	p-value
α	0.0035	0.0033	1.04	0.2988	α	0.0034	0.0033	1.02	0.3076
ϕ_{J0}	-0.1817	0.7828	-0.23	0.8164	ϕ_{J0}	-0.1950	0.7817	-0.25	0.8030
θ_{J0}	1.1431	0.5225	2.19	0.0287	θ_{J0}	1.6079	0.5288	3.04	0.0024
ϕ_B	-0.0606	0.0870	-0.70	0.4865	ϕ_{B5}	-0.6672	0.9869	-0.68	0.4990
θ_B	1.0102	0.0911	11.09	0.0000	θ_{B5}	2.1253	1.1136	1.91	0.0563
ϕ_A	-0.0927	0.0413	-2.25	0.0247	ϕ_{A5}	0.0205	0.3248	0.06	0.9497
θ_A	1.2527	0.0402	31.15	0.0000	θ_{A5}	1.3736	0.3089	4.45	0.0000
ϕ_{NJ}	-0.2017	0.0119	-16.93	0.0000	ϕ_{other}	-0.1906	0.0112	-17.04	0.0000
θ_{NJ}	1.3647	0.0104	130.61	0.0000	θ_{other}	1.3562	0.0098	137.98	0.0000

	Model 4					Model 5			
	Coefficient	Std. Error	t-Statistic	p-value		Coefficient	Std. Error	t-Statistic	p-value
α	0.0035	0.0033	1.05	0.2914	α	0.0036	0.0033	1.07	0.2852
ϕ_{J0}	-0.1597	0.7964	-0.20	0.8411	ϕ_{J0}	-0.1475	0.8011	-0.18	0.8540
θ_{J0}	1.2609	0.5186	2.43	0.0151	θ_{J0}	1.0923	0.5119	2.13	0.0328
ϕ_{B10}	-0.3350	0.7356	-0.46	0.6488	ϕ_{B20}	-0.6106	0.4776	-1.28	0.2010
θ_{B10}	1.7748	0.6770	2.62	0.0088	θ_{B20}	1.8977	0.5145	3.69	0.0002
ϕ_{A10}	0.0997	0.2567	0.39	0.6978	ϕ_{A20}	0.1240	0.1614	0.77	0.4422
θ_{A10}	1.3958	0.2513	5.55	0.0000	θ_{A20}	1.3062	0.1535	8.51	0.0000
ϕ_{other}	-0.1928	0.0112	-17.25	0.0000	ϕ_{other}	-0.1934	0.0112	-17.22	0.0000
θ_{other}	1.3567	0.0098	137.98	0.0000	θ_{other}	1.3570	0.0099	137.44	0.0000

Table 12: Estimated coefficients, standard errors, t-statistics and p-values, respectively, for Models 2-5 for the 10-year bond, for a 'jump window' of -/+ 5 minutes. The other time windows around the jump time are adjusted accordingly to the 'jump window'. For instance, for Model 3, which considers a -/+ 5 minutes window around the jumps, the before and after windows are of -/+ 10 minutes around the jump time, as identified in Section 2.2.2. For all models, the value of the correlation coefficient for the order flow is $\widehat{\rho} = 0.6609$.

Model 1

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0035	0.0012	2.94	0.0032
ϕ_J	0.0189	0.0143	1.32	0.1872
θ_J	0.3880	0.0122	31.81	0.0000
ϕ_{NJ}	0.0478	0.0040	11.91	0.0000
θ_{NJ}	0.3237	0.0036	90.58	0.0000

Model 2

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0034	0.0012	2.90	0.0037
ϕ_{J0}	-0.7647	0.5206	-1.47	0.1419
θ_{J0}	1.2906	0.4030	3.20	0.0014
ϕ_B	0.0576	0.0249	2.31	0.0209
θ_B	0.2935	0.0199	14.76	0.0000
ϕ_A	0.0178	0.0127	1.39	0.1635
θ_A	0.3734	0.0115	32.43	0.0000
ϕ_{NJ}	0.0478	0.0040	11.91	0.0000
θ_{NJ}	0.3236	0.0036	90.58	0.0000

Model 3

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0034	0.0012	2.88	0.0039
ϕ_{J0}	-0.7454	0.5193	-1.44	0.1512
θ_{J0}	1.4301	0.3989	3.59	0.0003
ϕ_{B5}	0.1959	0.1394	1.40	0.1600
θ_{B5}	0.3398	0.0596	5.70	0.0000
ϕ_{A5}	-0.2651	0.1397	-1.90	0.0577
θ_{A5}	0.7977	0.1128	7.07	0.0000
ϕ_{other}	0.0463	0.0038	12.26	0.0000
θ_{other}	0.3290	0.0034	97.70	0.0000

Model 4

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0034	0.0012	2.87	0.0041
ϕ_{J0}	-0.7453	0.5193	-1.44	0.1512
θ_{J0}	1.4308	0.3989	3.59	0.0003
ϕ_{B10}	0.1415	0.0809	1.75	0.0802
θ_{B10}	0.2581	0.0500	5.16	0.0000
ϕ_{A10}	-0.2156	0.0871	-2.48	0.0133
θ_{A10}	0.7051	0.0756	9.33	0.0000
ϕ_{other}	0.0472	0.0038	12.50	0.0000
θ_{other}	0.3273	0.0034	97.58	0.0000

Model 5

	Coefficient	Std. Error	t-Statistic	p-value
α	0.0034	0.0012	2.88	0.0039
ϕ_{J0}	-0.7520	0.5212	-1.44	0.1491
θ_{J0}	1.3293	0.4043	3.29	0.0010
ϕ_{B20}	0.1160	0.0624	1.86	0.0629
θ_{B20}	0.2735	0.0436	6.27	0.0000
ϕ_{A20}	-0.1471	0.0523	-2.81	0.0049
θ_{A20}	0.5976	0.0472	12.65	0.0000
ϕ_{other}	0.0483	0.0038	12.74	0.0000
θ_{other}	0.3252	0.0034	96.68	0.0000

Table 13: Estimated coefficients, standard errors, t-statistics and p-values, respectively, for Models 1-5 for the 2-year bond. We use different values for the autocorrelation coefficient for the order flow, as resulting from Table 10.