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Empirical evidence on jumps in the term structure of the US Treasury Market ☆

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ABSTRACT

The dynamics of US Treasury prices may be interrupted by jumps, and cojumps — where these occur simultaneously across the term structure. This paper finds significant evidence of jumps and cojumps in the US term structure using the Cantor-Fitzgerald tick dataset sampled over the period 2002–2006. While cojumping is frequently found in response to scheduled macroeconomic news announcement, around one-fifth of cojumps occur independently of news. The results are discussed in relation to term structure theories, day of the week effects, asymmetric news effects and trading volume.

1. Introduction

Understanding the process by which bond prices evolve is fundamental to our knowledge of this market. In particular, the characterisation of disruptions to the underlying price process, or jumps, represents an important piece of the temporal dynamics puzzle. For example, Piazzesi (2005) and Johannes (2004) demonstrate the improvements in bond pricing, and Andersen, Bollerslev and Diebold (2007a) the gains in forecasting, which result from taking into account jump behaviour. Despite its importance however, relatively little is known about the jump behaviour of bond prices. Das (2002) examines daily Federal Funds Rate data and finds that Federal Open Market Committee (FOMC) meetings are an important factor in explaining jumps. Johannes (2004) focuses on daily 3 month Treasury bill data and identifies 12 large rate changes (termed jumps) that coincide with economic and political news as well as Federal Reserve announcements. In the high frequency domain, Tauchen and Zhou (2006) estimate the jump intensity, mean and variance of 10 year US Treasury bond rates sampled at a 5 minute interval. They use this information to parameterise a jump risk measure, which they relate to movements in credit spreads.

The purpose of this paper is to identify and characterise jumps in the US Treasury bond market. To this end, we first establish the presence of jumps by applying a test proposed by Barndorff-Neilsen and Shephard (2004a, 2006) and Andersen, Bollerslev and Diebold (2007a) to individual bond maturities. A recent innovation in the literature has been to extend this univariate concept of

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jumping to the multivariate domain, whereby two or more assets simultaneously jump. For example, Bollerslev, Law and Tauchen (2007) consider the issue of cojumping in the context of an index and its constituent stocks, while Jacod and Todorov (2007) develop a test to distinguish common jumping in a two asset environment and Lahaye, Laurent and Neely (2007) consider the relationship between jumps and news across a range of asset types. The bond market presents an interesting and unique opportunity to extend this cojumping literature. Unlike other asset markets, the US Government Treasury markets trade a range of near identical assets, which are distinguished only by maturity and coupon. As such, it is interesting to consider the extent to which jumps occur simultaneously across the term structure. This distinction is potentially important as the detection of concurrent jumps across different maturities has very different implications for bond market dynamics compared to the situation where individual bond maturities jump in isolation.

Having established the presence (or otherwise) of jumps in the data, the second objective of this paper is to characterise these jumps. Specifically, our focus is on understanding jumps that disrupt the entire term structure, which we argue represent the most interesting and significant jump events. To explain these term structure wide disruptions, we draw from the news announcement literature which shows that the unexpected component of scheduled macroeconomic news has a significant effect on the US Treasury market (see Ederington and Lee, 1993; Becker et al., 1996; Fleming and Remolona, 1997, 1999a,b; Jones et al., 1998; Goldberg and Leonard, 2003; Green, 2004; Simpson and Ramchander, 2004; Pasquariello and Vega, 2007). Further, recent forays into the high frequency domain have shown the reaction times to news surprises are very short (see Balduzzi et al., 2001; Gurkaynak and Wolfers, 2006; Andersen et al., 2007b). This literature suggests that macroeconomic news announcements may be responsible for generating jumps in high-frequency bond price dynamics. As such, our paper is related to that of Piazzesi (2005), who finds considerable improvements in pricing across the yield curve when the potential for jumps associated with FOMC decisions is included. Andersson (2007) also notes the effects of FOMC decisions on bond markets using high frequency data.

The results of this study produce significant evidence of frequent jumps in bond prices. Further, cojumping across two or more maturities is also common, including a large number of cases where the entire term structure jumps. For the latter, jumps across the term structure typically occur in association with a scheduled news release, although not all news releases generate jumps. Where a news release does generate a jump however, the observed return is significantly larger than where news is released that does not generate a jump. Further, news related cojumping is usually associated with a shift in the term structure consistent with the sign of the news announcement surprise. This is not the entire story however, as a number of jumps in the term structure are observed where there is no news surprise and conversely, news surprises do not always generate a jump. These anomalies remain the subject of ongoing research.

The remainder of this paper proceeds as follows. Section 2 discusses the theoretical relationship between the term structure and the arrival of news to the market. Section 3 describes the price process and the econometric methods used in testing for univariate jumps. Section 4 introduces and summarises the data. The empirical application of jump tests to the Treasury bonds data is considered in Section 5, with formal univariate tests and the application of a coexceedance measure of cojumping. These cojumps are subsequently related to news using intradaily analysis in Section 6. Finally, Section 7 concludes.

2. News and the term structure of the yield curve

The expectations theory of the term structure of interest rates attributes the shape of the yield curve to a consensus forecast of future interest rates. In this context, any macroeconomic news that impacts on bond prices should affect all maturities and simultaneous jumps should be observed. This pure expectations theory of the term structure assumes risk neutrality, which is generally regarded as unrealistic. As a result, this theory has long been discounted as a possible explanation for the term structure. A number of alternative explanations have been proposed, which focus on some form of liquidity preference theory or preferred habitat behaviour based explanation for the term structure.

The liquidity preference theory of the term structure assumes that longer term rates are higher than the average of expected future rates by an amount equal to a liquidity risk premium. This premium reflects the relatively higher risk of long bonds, given their greater potential for capital loss before maturity. The liquidity premium hypothesis suggests that long bond prices should be more responsive to the arrival of sensitive news than shorter maturities, so that information driven jumps may be more frequent at the long end of the yield curve.

The liquidity preference theory implies a risk premium which rises uniformly with maturity, which is unrealistic (albeit technically possible). Market segmentation theory also augments the expectations theory with a risk premium, but in this model the premium is not linked to maturity. Instead, investors are assumed to operate solely within particular segments of the yield curve and local supply and demand ultimately determine the equilibrium price for a bond at any given maturity. Investor preference for a particular maturity range may be a function of market characteristics (investors may prefer short-term instruments for reasons of liquidity) or reflect asset-liability management constraints. For example, insurance companies and pension funds typically have predictable long term liabilities, which they hedge by matching to long dated bonds. Commercial banks however, have a portfolio of short and medium term loans which prudent banking practice dictates should be funded by liabilities of a similar maturity. Thus, the segmented market theory assumes that bonds are not substitutable and the supply and demand for short-term and long-term instruments are independent. Modigliani and Sutch (1966) extend this model by removing the assumption of rigid market segmentation. Their preferred habitat theory argues that investors may be induced to move out of their chosen segment of the yield curve, where a risk premium is paid that reflects the marginal investors aversion to reinvestment risk.

The market segmentation/preferred habitat model suggests that speculators may be more active at the short end of the yield curve (where liquidity is higher) compared to the long maturity markets, which are dominated by institutional investors hedging long dated liabilities. In this case, news may generate a relatively greater response in short maturity bond prices as speculators alter their portfolio holdings whereas fund managers do not (unless that news happens to impact on the liability position of their portfolio). Thus, under a preferred habitat theory, jumps may be more prevalent in short maturity bonds compared with longer maturities.

As discussed in the introduction, the empirical evidence on the importance of macroeconomic news announcements on bond pricing is well established; see inter alia Ederington and Lee (1993) Becker, Finnerty and Kopecky (1996), Fleming and Remolona (1997, 1999a,b), Li and Engle (1998), Jones, Lamont and Lumsdaine (1998), Goldberg and Leonard (2003), Green (2004) and Simpson, and Ramchander (2004), Pérignon and Villa (2006) and Pasquariello and Vega (2007).

A relatively small number of papers have considered the responses of different bond maturities to the arrival of macroeconomic news. Barrett, Gosnell and Heuson (2004) found that the unexpected news component of four announcements had the same impact across the maturity spectrum using zero coupon yields. In contrast, de Goeij and Marquering (2006) find that macroeconomic announcements are more influential at the intermediate and long end of the yield curve, while monetary policy changes affect short-term bonds most. Both of these papers consider daily data which may mask intraday effects. Using high frequency data Campbell and Sharpe (2007) find relatively little difference in the news impact for 2 and 10 year bonds, while Balduzzi, Elton and Green (2001) and Gurkaynak, Sack and Swanson (2005) find that news impact is generally increasing with maturity for most macroeconomic announcements. This latter result is supported by Gurkayanak and Wolfers (2006) who use improved data on expectations, based on the relatively new options contracts on future data announcements, and also find that the news impact is broadly increasing from the short end to the longer end of the curve.

3. Identifying and measuring jumps

Analysis of high frequency asset market data focuses on measures of the underlying volatility of the data generating process. The price of the asset is assumed to evolve as a continuous process of the form

$$p_t = \int_0^t a_s ds + \int_0^t \sigma_s dW_s \tag{1}$$

where p_t represents the price of the bond at time t, and the right hand side terms represent a continuous, locally bounded variation process, a_s, a strictly positive stochastic volatility process with well defined limits, σ_s, and W_s is Brownian motion. Returns in this process are defined as $r_t = p_t - p_0$ and the associated quadratic variation is given by

$$[r,r]_t = \int_0^t \sigma_s^2 ds \tag{2}$$

where the notation $[r,r]_t$ is taken to denote the equivalent of variance at time t (and commensurately $[r,q]_t$ represents a covariance between r and q). It is well known that asymptotically the quadratic variation in Eq. (2) can be approximated by realized variance, that is the sum of n squared returns sampled at frequency δ. The subscript δ is used to identify the sampling frequency such that in expressing the realized variance,

$$RV_{t+1}(\delta) = \sum_{j=1}^{1/\delta} r_{t+j\delta,\delta}^2 \tag{3}$$

$r_{t+j\delta,\delta} = p_t + j_\delta - p_{t+(j-1)\delta}$ are the δ period returns within the day.

Although realized variance has proven to be a useful concept in high frequency analysis, it is also apparent that there are spikes in the daily realized variance potentially due to underlying events affecting the markets. The search for a means of identifying these spikes led to a literature on jumps in realized variance; see particularly Barndorff-Neilsen and Shephard (2004a) and Andersen, Bollerslev and Diebold (2007a). This consists of augmenting the continuous process given in Eq. (1) with a potentially discontinuous jump component as follows

$$p_t = \int_0^t a_u du + \int_0^t \sigma_u dW_u + \sum_{j=1}^{N} c_{jt} \tag{4}$$

where the final term is the jump process with c_{jt} a non-zero random number, and N is a count variable, representing the number of jumps.

The quadratic variation associated with this equation is given by

$$[r,r]_t = \int_0^t \sigma_s^2 ds + \sum_{j=1}^{N} c_j^2. \tag{5}$$

Barndorff-Nielsen and Shephard (2006) show how to separate the jumps using bi-power variation.[1] This technique for separating jumps relies on the observation that forms other than realized variance also converge to the true quadratic variation

[1] This turns out to be a special case of the more general testing framework for jumps recently proposed by Aït-Sahalia and Jacod (2009), however, their new tests require extremely high numbers of observations to produce good sampling properties. The authors recommend less than one minute sampling, and are hence unsuited to the current data set.

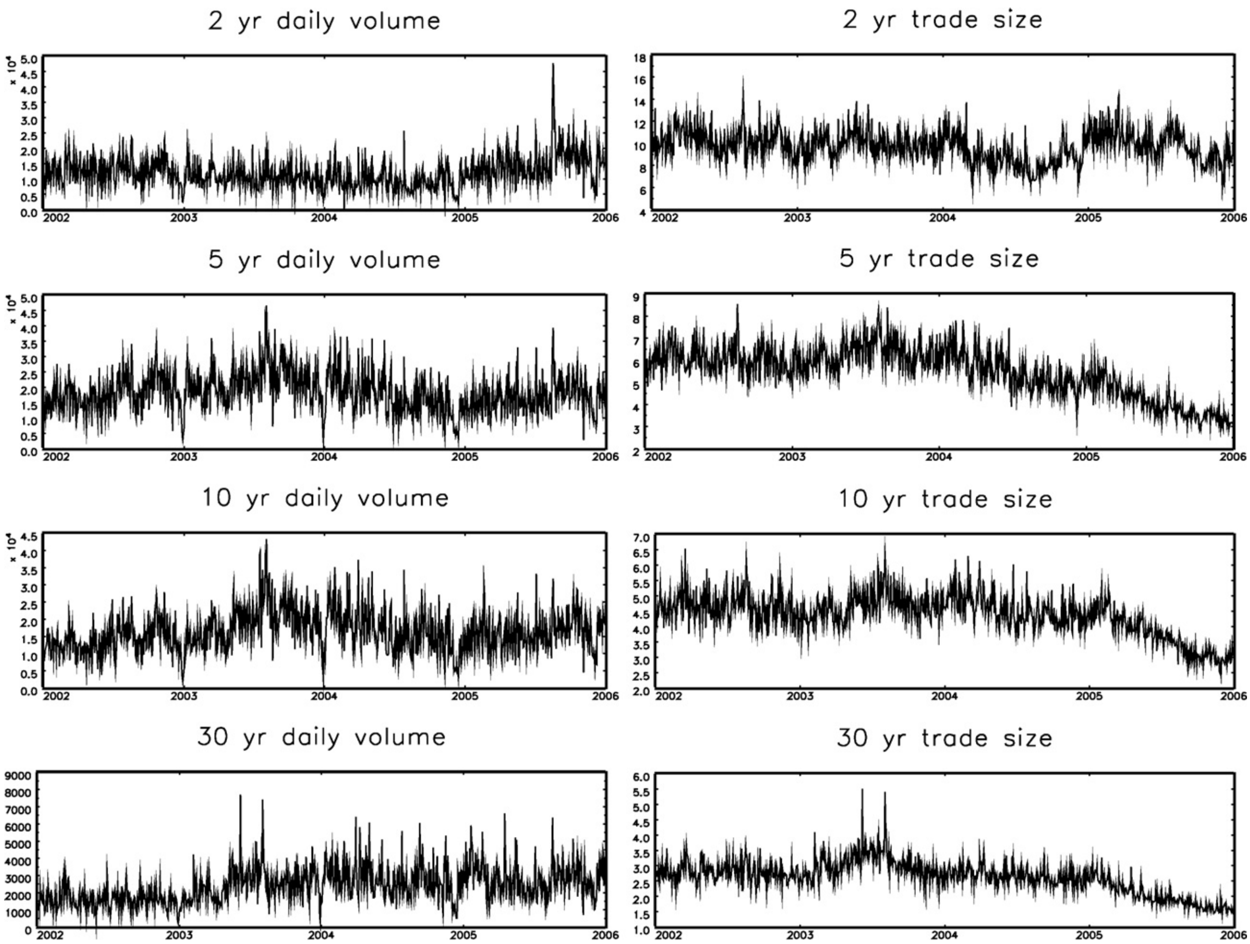

Fig. 1. Average daily volume and trade size by maturity 2002–2006.

given in Eq. (2). In particular the Barndorff-Neilsen and Shephard (2004a) test exploits realized bi-power variation, which consists of the standardized sum of the product of consecutive returns given by

$$BV_{t+1}(\delta) = \mu_1^{-2} \sum_{j=2}^{1/\delta} |r_{t+j\delta,\delta}|\,|r_{t+(j-1)\delta,\delta}|.$$

The coefficient of standardization is the mean of the absolute value of the standard normally distributed random variable, $\mu_1 = \sqrt{2/\pi}$. Bi-power variation has the property that

$$BV_{t+1}(\delta) \rightarrow \int_0^t \sigma_s^2 ds. \tag{6}$$

It follows that asymptotically as $\delta \rightarrow 0$

$$RV_{t+1}(\delta) - BV_{t+1}(\delta) \rightarrow \sum_{0<<s\leq t} c_s^2$$

where the difference between realized variance and bi-power variation provides a consistent estimate of a jump. In a finite sample it is possible that the sample bi-power variation may be negative, so it is convenient to truncate the measure of jumps at zero and define the jumps $J_{t+1}(\delta)$ as

$$J_{t+1}(\delta) = max\left[RV_{t+1}(\delta) - BV_{t+1}(\delta), 0\right].$$

In order to select statistically significant jumps the jumps test statistic under the null hypothesis of no jump is defined as

$$JS_{t+1}(\delta) = \frac{RV_{t+1}(\delta) - BV_{t+1}(\delta)}{\sqrt{(\mu_1^{-4} + 2\mu_1^{-2} - 5)\delta \int_t^{t+1} \sigma^4(s)ds}} \rightarrow N(0,1). \tag{7}$$

An estimate of $\int_t^{t+1}\sigma^4(s)ds$ is provided by the realized tri-power quarticity, $TQ_{t+1}(\delta)$. For $\delta\to 0$

$$TQ_{t+1}(\delta) = \delta^{-1}\mu_{4/3}^{-3}\sum_{j=3}^{1/\Delta}|r_{t+j\delta,\delta}|^{4/3}|r_{t+(j-1)\delta,\delta}|^{4/3}|r_{t+(j-2)\delta,\delta}|^{4/3}\to\int_t^{t+1}\sigma^4(s)ds,$$

where $\mu_{4/3}=2^{2/3}\Gamma(7/6)\Gamma(1/2)^{-1}$. Huang and Tauchen (2005) however, have shown that a statistic based on substituting $TQ_{t+1}(\delta)$ into Eq. (7) tends to over-reject the null. As such, the test statistic implemented in this paper contains a correction based on modifying the denominator of Eq. (7) (see also Andersen et al., 2007a) as follows

$$JS_{t+1}(\delta) = \frac{RV_{t+1}(\delta)-BV_{t+1}(\delta)}{\sqrt{(\mu_1^{-4}+2\mu_1^{-2}-5)\max\{1,TQ_{t+1}(\delta)BV_{t+1}(\delta)^{-2}\}}}\to N(0,1). \tag{8}$$

The test is then implemented for chosen significance levels. In practice, the significance level chosen has to be quite high as the test tends to find rather a large number of jumps — see Beine et al. (2007). Pending the discovery of a formal solution to this problem, we limit the number of jumps by specifying a significance level of 0.05.

4. Data

Previous research on US bond markets has typically focussed on the GovPX dataset, which brings with it a number of issues related to identifying trades, matching the actual bid-ask spread to trades and correctly calculating the volume of trade. While one approach would be to ignore these problems, see Andersen and Benzoni (2007), most researchers have undertaken complicated sample manipulation, see Boni and Leach (2004), Brandt and Kavajecz (2004), and Dungey, Goodhart and Tambakis (2008).

Since 2000, the US Treasury market has undergone a significant number of changes (for details, see Mizrach and Neely, 2006). This resulted in a serious drop in the coverage of the GovPX database and the emergence of two new US bond data vendors: Cantor Fitzgerald who provides the eSpeed database and ICAP who provide the BrokerTec database. Mizrach and Neely (2006) report that on-the-run trading is now almost completely electronic, with eSpeed (BrokerTec) capturing 40% (60%) of trading volume. They compare the two databases and find there are qualitatively few differences, which suggests that any empirical results are unlikely to be source dependent.

In this paper, we sample data from the Cantor trades database beginning with the first available observation on January 2, 2002 to September 29, 2006. These 1168 trading days provide over 13.5 million trades in on-the-run bonds, an average of over 11.7 thousand trades each day. While the dataset covers the 2, 3, 5, 10 and 30 year maturities, the 3 year bond data is only available from April 30, 2003 and so is excluded here. A trading day is defined as starting at 07:30 and finishing at 17:30 (all time references refer to New York trading time). The data have been filtered to remove all US public holidays.

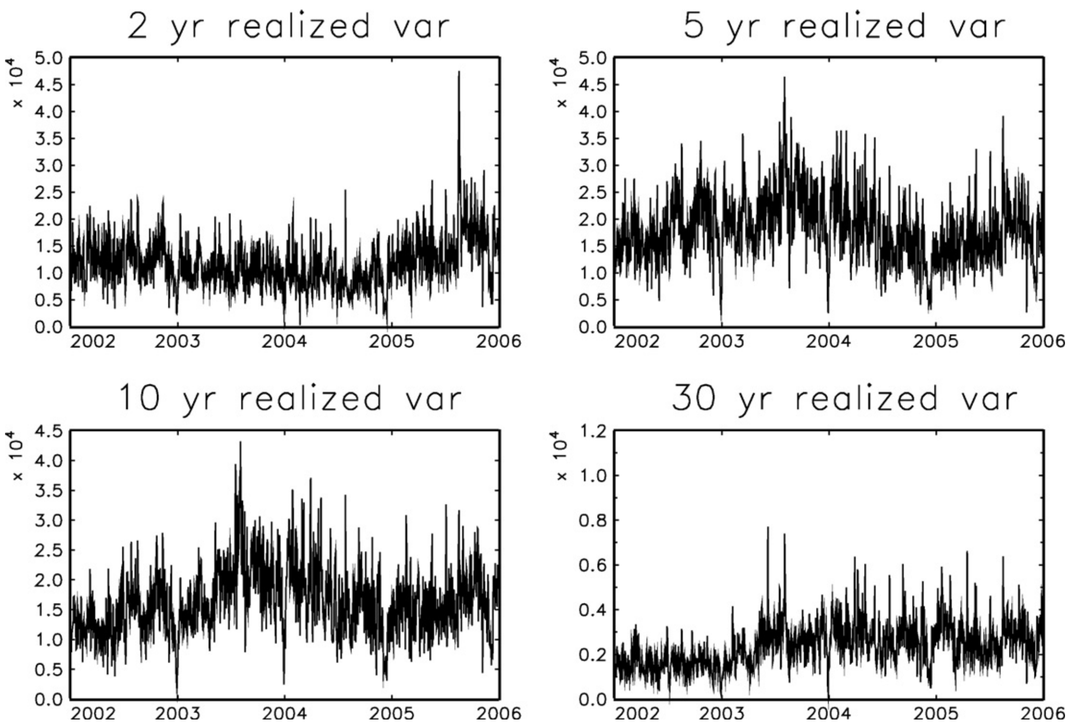

Fig. 2. Realized variance calculated from 5 minute sampling frequency.

Table 1
Rejection frequency of univariate jumps test and number of jump days identified.

Maturity	Total days	Rejection frequency	No. of jump days	Rejection frequency	No. of jump days
		30 minute sampling		15 minute sampling	
2 year	1168	0.277	324	0.381	445
5 year	1168	0.200	234	0.264	264
10 year	1168	0.205	239	0.239	279
30 year	1168	0.191	223	0.235	275
		10 minute sampling		5 minute sampling	
2 year	1168	0.509	594	0.763	891
5 year	1168	0.281	328	0.403	471
10 year	1168	0.267	312	0.429	501
30 year	1168	0.266	311	0.531	620

Fig. 1 presents average daily volumes and trade size for each maturity. The average daily trading volume is highest in the 5 and 10 year bonds. The 30 year bond however, has a much lower trading volume and averages around 1000 trades per day. The average trade size for the 2 year bond is highest (averaging $US12 million) and this falls progressively as the bond maturity increases to the 30 year bond which has an average trade size of just under $US2.5 million. We omit a more detailed discussion of the volume and trade flow properties of this data in the interests of brevity.

In order to apply the univariate jump testing procedures described in Section 3, the trade by trade data must be sampled at discrete and equal time intervals. There is a lively debate in the high frequency literature about the nature of this sampling interval, including the advantages and disadvantages of sampling at higher frequencies and resampling (see Aït-Sahalia et al., 2005; Oomen, 2006; Griffin and Oomen, 2008). In general, a trade-off exists between sampling as frequently as possible to obtain maximum information and sampling from a noisy price signal. Selecting a sampling frequency is further complicated by issues surrounding the choice of sampling method. The usual approach is to take the last trade price in the δ interval as representative of all traded prices in that interval. This potentially leads to the problem of scrambling, where information is assigned in a way that distorts the true time interval between the observations. Sheppard (2006) shows that scrambling problems can bias the covariance and may be used to justify lower sample frequencies.

While univariate tests of optimal sampling frequency do exist, the results are not consistent across different maturities.[2] As such, we choose to consider a range of different sampling intervals (5, 10, 15 and 30 minutes) to ensure the robustness of our results. By way of comparison, a wide range of intervals has been used in the previous literature. Fleming (1997) uses 30 minute samples in his study of the US bond spot market, Lahaye, Laurent and Neely (2007) settle for 15 minutes, while Andersen, Bollerslev, Diebold and Vega (2007b), Mizrach and Neely (2008) and Bollerslev, Cai and Song (2000) sample at 5 minute intervals in their studies of bond futures data (although none of these authors apply an optimal sampling frequency test). Other asset markets currently used 5 minute intervals, see Andersen and Bollerslev (1998) for foreign exchange and Bandi and Russell (2006) for equities.

The daily realized variance for each of the four maturities sampled at a 5 minute frequency are presented in Fig. 2. The realized variance for the other sampling frequencies are qualitatively consistent with those presented. Realized variance is lowest in the 30 year contract and highest in the 5 year maturity. As indicated in Section 3 the tests for jumps focuses upon comparisons of realized variance with bi-power variation and we proceed to investigate this issue in the next section.

5. Empirical results

5.1. Univariate jumping

Table 1 shows the rejection frequency of the univariate jumps test given in Eq. (8)) for the different maturities at the 5% significance level — that is the proportion of total observations which are jumps. Where the data is sampled at a 5 minute frequency, jumps are found in the 2 year bond price series on 891 days in a sample of 1168, or 76.3% of the time. The 30 year bond exhibits the second highest number of jumps (620), that is, a jump occurs on 53.1% of the days in the sample.[3] The intermediate 5 and 10 year bonds jump the least, generating a significant test score 40.3% and 42.9% of the time respectively. Where the other sampling intervals are considered, the test results indicate that the 2 year bond consistently generates the highest number of jumps, although the 30 year bond is no longer the second highest number of jumps. The proportion of jumps identified in each maturity increases with the sampling frequency, possibly reflecting increasing noise in the data (see Bandi and Russell, 2006).

There is some evidence in the literature to suggest that jumps may exhibit daily seasonality. For example, Das (2002) finds that jumps are more likely to occur on Wednesdays, which are attributed to option expiry effects. While it is not possible to incorporate day of the week effects in the jump testing procedure, it is possible to comment on the frequency with which jumps occur across the various days of the week. For example, consider the 471 jumps detected in the 5 year bond sampled at a 5 minute frequency.

[2] Zhang, Mykland and Aït-Sahalia (2005) and Bandi and Russell, (2006) develop a means of estimating the optimal sampling frequency. These methods applied to the data used in this paper produce a range of 2 to 19 minutes and vary across maturity and year.

[3] The high proportion of jumps is usual in the application of these jumps tests in the literature, but contrasts with Johannes (2004) method which identifies only 10 jumps in Treasury bills in the period 1991 to 1993.

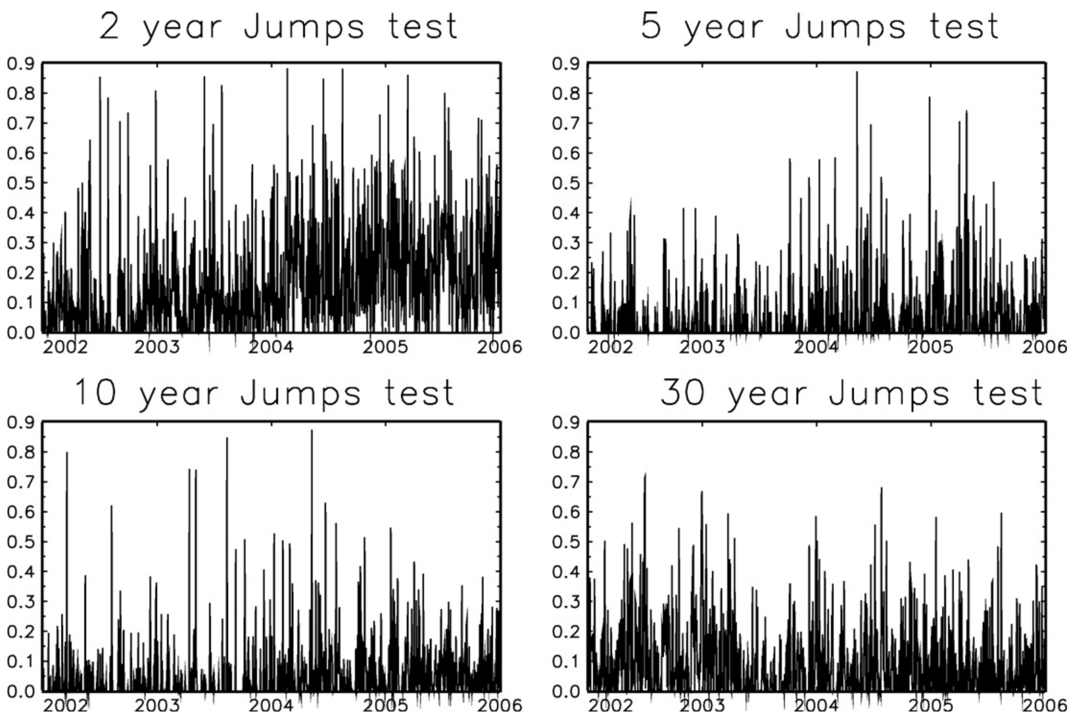

Fig. 3. Barndorff-Neilsen and Shephard Univariate Jumps test by maturity for the data sampled at 5 minute intervals. Each figure presents the excess of the sample Jump statistic over its critical value.

The percentage of jumps occurring on each of the days of the week is 20.4%, 20.4%, 18.5%, 19.5% and 21.2% from Monday to Friday respectively. Similar results are found when the other maturities are considered as well as longer sampling intervals. Thus, there does not appear to be any evidence of any daily seasonality in the univariate jump test results.

Fig. 3 shows the jumps tests results for each of the maturities for the 5 minute sampling interval as the exceedance of the sample statistic over the critical value, and provides visual confirmation of the prevalence of jumps in each of the maturities and the 30 year bond in particular. Casual observation of these plots suggests a degree of coincidence in observed jumps, as many of the large critical values appear contemporaneously across maturities and clustering in jump activity also appears common. In the next section, we consider this issue more fully and introduce a formal measure of cojumping.

5.2. Cojumping

In addition to applying univariate tests to identify jumps in the prices of individual bonds, the extent to which bonds of different maturities cojump may also be considered. To identify cojump events in the data, we use a technique that is based on the identification of co-exceedances, as introduced by Bae, Karolyi and Stulz (2003) in the context of financial market contagion and extreme events.[4]

The coexceedance approach to identifying cojumping counts the number of times the estimated jump test score exceeds a pre-determined threshold across different maturities. The threshold is given by the critical value of the jump statistic, which will be determined independently for each series under consideration. More formally, denote $d_{i,t,\delta}$ as a binary variable taking the value 1 when returns in bond of varying maturity subscripted i, where $i=1\ldots n$, (sampled at frequency δ) contain a jump as indicated by the univariate jumps test,

$$d_{i,t} = \begin{cases} 1 & JS_{i,t}(\delta) > JS_{i,t}(\delta)_{critical} \\ 0 & \text{otherwise} \end{cases}. \tag{9}$$

The number of co-exceedances for a jump in bond of maturity j recorded at time t can then be calculated as a simple sum of $d_{i,t}$ over all $i \neq j$,

$$E_{j,t\,|\,d_{j,t}=1} = \sum_{i=1,i\neq j}^{n} d_{i,t}$$

which in the current application of 4 maturities, $n=4$, means that $E_{j,t}$ varies discretely between 0 and 3.[5]

[4] A useful multivariate jump test is yet to be operationalised (see Barndorff-Neilsen and Shephard, 2004b).

[5] An alternative approach to identifying and measuring cojumping events may be to apply the univariate jump test to spreads. Such an approach is not feasible however, as unlike prices, the spread data do not exhibit discontinuities. This means that the jump test applied to the spread at any reasonable level of significance will fail to detect any such events. The authors would like to thank the anonymous referee for suggesting this approach.

Table 2
Number of co-exceedances in jumps by maturity.

Maturity	Co-exceedances				Total number of jumps
	0	1	2	3	
30 minute sampling					
2 year	123	79	56	66	324
5 year	32	68	66	66	234
10 year	39	64	70	66	239
30 year	67	47	43	66	223
15 minute sampling					
2 year	177	99	70	99	445
5 year	23	67	75	99	264
10 year	34	69	77	99	279
30 year	65	63	48	99	275
10 minute sampling					
2 year	226	156	103	109	594
5 year	31	95	93	109	328
10 year	24	85	94	109	312
30 year	60	78	64	109	311
5 minute sampling					
2 year	204	236	227	224	891
5 year	10	68	169	224	471
10 year	13	82	182	224	501
30 year	76	160	160	224	620

Table 2 presents the number of co-exceedances associated with an observed jump in the maturity shown in the first column. With 15 minute sampling, the 2 year bond is observed to jump uniquely (the number of co-exceedances is 0) on 177 occasions, and with one other bond of unspecified maturity 99 times, and contemporaneously with all the maturities in the sample 99 times (3 co-exceedances). The final column in the table gives the total number of jumps recorded across all maturities and sampling frequencies.

Table 2 reveals that cojumping across all 4 maturities is clearly the most frequent event. It is interesting to note that while the univariate jump output did not exhibit any daily seasonality, the same cannot be said of these cojumping data. For example, in the 30 minute data, the entire term structure jumped on 66 days. The percentage of cojumps across the term structure occurring on each of the days of the week is 9.1%, 23.0%, 20.0%, 12.0% and 36.0% from Monday to Friday respectively. Thus, cojumps are less likely to occur on Mondays or Thursdays and more likely to occur on Fridays. The same pattern is evident in the data sampled at a higher frequency, although the differences between the days of the week becomes less pronounced as the sampling interval shortens.

The results in Table 2 allow some characterisation of jumps by maturity structure. The 2 year maturity has more jumps than other maturities and a relatively high proportion that are unique jumps. The proportions of unique jumps in the 5 and 10 year maturities are relatively low, which means that they are more likely to jump in conjunction with other bonds. The 30 year bond exhibits fewer unique jumps than the 2 year bond, but more than the middle maturity bonds at all sampling frequencies. The 15 minute sample data highlights these aspects of our results: 177 (40%) of the 2 year jumps are unique, only 23 (9%) and 34 (12%) of the 5 and 10 year jumps are unique, and 65 (23%) of the 30 year jumps are unique. In the 5 minute sample data the corresponding figures for the unique jumps in the 2, 5, 10 and 30 year bonds are 24%, 2%, 4% and 12%. Overall, these results tend to suggest a stylized representation of the yield curve jumping more at both ends than the middle, consistent with elements of both the liquidity preference and preferred habitat theory.

To explore further the term structure of these jumps we refine the co-exceedances reported in Table 2 by maturity structure. Table 3 reports the frequency of cojumping in combinations of bonds denoted as (2,5,10) for example, which gives the number of observations for which the 2, 5 and 10 year bonds record jumps on the same day. The numbers reported are mutually exclusive, meaning that the numbers of jumps recorded in the 2 year and 5 year pair, denoted (2,5), for example, is not a subset of the 2 year, 5 year and 10 year maturity triplet, denoted (2,5,10) in the Table. The results are consistent with Table 2 in that combinations involving the shorter maturity bonds display more cojumping behaviour.

The most frequent type of cojumping is where all assets jump on the same day. The next most frequent event is a jump involving three assets at the shorter end of the maturity structure (2,5,10) and the pair at the short end consisting of the 2 year and 5 year (2,5). There is then a mixture of results. On the one hand, pairs and triplets involving both ends of the maturity structure examined here (that is including the 2 and 30 year bonds) jump relatively frequently, supporting the earlier supposition that information may enter from both ends of the term structure. The least frequent cojumping events occur when only one end of the maturity structure is involved, for example the middle pair (5,10) and the non-contiguous pair (5,30).

5.3. Intraday timing of jumps

While the discussion of the previous section has identified evidence of jumps occurring simultaneously across the term structure on a given day, it cannot be assumed that these episodes occur contemporaneously.[6] To investigate this possibility, the precise timing of

[6] Jacod and Todorov (2007) distinguish between disjointed jumps - which occur on the same day but at different times - and common jumps on a pairwise basis.

Table 3
Maturity structure of multiple jumps.

	Sampling frequency			
	30 minute	15 minute	10 minute	5 minute
Maturity pairs				
(2,5)	38	41	71	53
(2,10)	20	28	41	57
(2,30)	21	30	44	126
(5,10)	24	17	17	3
(5,30)	6	9	7	12
(10,30)	20	24	30	19
Maturity triples				
(2,5,10)	36	42	54	86
(2,5,30)	9	13	24	64
(2,10,30)	11	15	25	77
(5,10,30)	23	20	15	19
All jump	66	99	109	224

any given jump is determined using an approach motivated by Beine et al. (2007). Specifically, on a day in which a jump is identified, the returns for each sampling interval in the day are ranked in terms of their absolute value for each maturity. This ranking is then compared across maturities to identify the time period during which the largest absolute return is observed. To limit the scope of the reported results, we only formally consider the case where all 4 maturities cojump within the exact same interval of a given day.[7]

Table 4 provides a detailed breakdown of the intraday timings and shows that the majority of the cojumps across all maturities (henceforth cojumps) occur in the interval beginning at 8:30am regardless of the sampling frequency. The left most column gives the start period for the interval under consideration, and the different columns represent the number of jump days on which the largest absolute movement in returns occurs in the period immediately following the start time for the different sampling frequencies. For example, all four maturities cojumped on 68 occasions in the interval 8:30 to 8:35 for the 5 minute data. The 10 minute column shows that on 52 occasions a cojump occurred in the interval 8:30–8:40 and so forth. Nesting the results across the different sampling frequencies is not straightforward, in part due to issues with selecting the representative price as the last recorded trade in the interval.

These results clearly show that most cojumping occurs in the periods immediately following 8:30 and 10:00, which are the two most common times for scheduled US news releases. The cojumps at 14:15 also coincide with news releases, in this case FOMC announcements. Boukus and Rosenberg (2006) show that FOMC announcements contain important information that is relevant for the bond market. Further, Piazzesi (2005) found that including potential jumps for FOMC decisions improves fitting of the yield curve. Our results show that FOMC decisions generate jumps less often than other scheduled news events in the sample (which suggests that the results of Piazzesi (2005) may be further improved with the inclusion of other news events). Table 4 also contains a row labelled ‘other’, which records the number of times cojumps occur within a time interval that is not associated with these three major news release times. The row labelled ‘unallocated’ summarises the number of instances in which common jumps were recorded on a given day across maturities, but the intraday returns did not correspond to a particular time period.

6. Sources of Jumps

The evidence of Section 3 suggests that most jumps in the term structure of the yield curve coincide with times when macroeconomic news is commonly released to the market.[8] To investigate this further, we gather information on the timing and content of 23 major macroeconomic announcements over the sample period.[9] Knowledge of the markets expectations is potentially important in this context as the literature suggests that it may not be the act of releasing information to the market, nor the estimate itself, that is important. Rather, it may be the extent to which the actual announcement differs from the expected, i.e. the surprise content of each announcement, that determines the response of the market to the information release. Expectations are captured using the Bloomberg median survey forecast estimate for each news item. The surprise in each series is described as

[7] We tested the sensitivity of these results to other options and found they are qualitatively unchanged. For example, where we consider the case where 3 maturities experienced their largest intradaily return in the same interval, and the remaining maturity experienced its second largest intradaily return in that interval.

[8] It is evident that a number of jumps occur in the absence of scheduled news events. One possible explanation would be that these jumps are in response to news events other than scheduled macroeconomic announcements. For example, at all sampling frequencies a jump is detected on 20 April 2005, which is the date on which US Secretary to Treasury McClellan held a press conference in which he commented on reissuance of 30 year Treasury bonds. Jiang, Lo and Verdelhan (2007) have found evidence relating jumps to liquidity pressures captured in the order book. Another possibility is that the jumps in the bond market are in response to events in other asset markets. For example, Dungey and Martin (2007) provide evidence of spillovers from equity to bond markets. Explaining jumps in the absence of scheduled news events and their causes is beyond the focus of this paper, but remains an area of ongoing investigation by the authors.

[9] Simpson and Ramchander (2004) and Ramchander, Simpson and Chaudhry (2005) use the same set of 23 announcements, which are Auto Sales, Business Inventory, Capacity Utilization, Construction Spending, Consumer Credit, CPI, Durable Good Orders, Factory Orders, Hourly Earnings, Housing Starts, Industrial Production, Leading Indicators, New Home Sales, Non-Farm Payroll, Personal Consumption, Personal Income, PPI, Real GDP, Retail Sales, Trade Balance, Treasury Budget, Unemployment and U.S. Purchasing Managers Index.

Table 4
Jump timings.

Period start time	Sampling frequency			
	30 min	15 min	10 min	5 min
8:30	27	40	52	68
10:00	15	14	14	17
14:15	5	1	1	2
Other	7	24	13	25
Total allocated	54	79	80	112
Unallocated	12	20	29	112
Total jump days	66	99	109	224
Unallocated as proportion of jump days (%)	18	20	27	50

'above' ('below') expectations, when the announced outcome is greater (smaller) than expected. A 'no surprise' result is recorded when expectations accord with the actual release. To account for the different units of measurement across the various news items, each surprise is standardized by the corresponding standard deviation of all surprises for that particular news release over the sample period. In cases where more than one news release occurred on the same day, the sum of the standardized surprises was recorded as the net surprise for that day.[10]

Table 5 summarises this data. Of the 1168 days in the sample period, news is released to the market on 684 of these days and 312 of these releases are above expectations and 329 are below expectations. On only 43 days did the median survey forecast accord to the actual news item released. The remaining rows of data in Table 5 record the number of jumps associated with news announcements for different sampling frequencies. The numbers recorded differ from those in Table 4 as not all news releases occur at the times shown. For example, the 5 minute data reveals that of the 224 days on which cojumping is observed, one or more news items are released to the market on 153 days. The news surprise is above expectations on 71 days, below expectations on 75 days and meets with the markets expectations on only 7 days. Overall, these results show that the proportion of news days on which there are jumps is relatively low, between 8% for the 30 minute sample and 22% for the 5 minute sample. Negative news was more likely to record a jump than positive news, even after controlling for the higher prevalence of negative news items in the sample data.

The direction of the jumps in the term structure may relate to the surprise content of the news release. For example, Fig. 4 provides a snapshot of the shift in the term structure for an above and below expectations non-farm payroll news event drawn from the 5 minute data sample. The three lines describe the shift in the yield curve at time t, $t+1$ and $t+2$ (which correspond to 5,10 and 15 minutes respectively) from the prevailing price at the time of the news event. Note that sensitivity analysis to the return as calculated from a starting point 5 minutes prior to the news release showed no discernible difference in the results.

The left hand panel in Fig. 4 is for December 6, 2002 on which day non-farm payrolls were released with an expected figure of +35,500 and an actual figure of −40,000. In response to this news, bond prices rose which is consistent with a downward revision of the outlook for the economy. The right hand panel relates to May 11, 2004 when non-farm payrolls were expected to be +175,000, while the actual release was much higher than expected at +337,000. Bond prices fell across the maturity structure consistent with stronger expectations for economic growth (and higher inflation).

This example for the release of non-farm payroll news is typical for the majority of news releases that are associated with jumps in bond prices. That is to say, where the release of news generates a jump in prices, the move in term structure generally corresponds to the direction of the news surprise.

Further insights into the sources of bond price cojump behaviour can be obtained by distinguishing between the different types of announcements. As days with multiple news releases are problematic when trying to identify the source of a cojump, only days on which one announcement is made are considered. Further, the focus is limited to the 5 minute data, which provides the greatest number of days for analysis. Recall from Table 4 that there are 112 days on which all maturities jump simultaneously within the day. Multiple news announcements are observed on 61 of these days and 16 days had no scheduled news releases. Thus, there are 35 days on which all the maturities simultaneously cojumped and only one scheduled macroeconomic news announcement occurs. Table 6 lists the different announcement types that are associated with these 35 cojump days. Note that these measures of surprise are in units appropriate to that release and are not comparable. For example, the average surprise component across all housing starts announcements is 89,830 houses, with a maximum recorded surprise of 256,000 and minimum of 7,500. Retail sales on the other hand is measured as the total monthly percentage change, with an average surprise across all announcements of 0.39% and a maximum (minimum) surprise of 1.5% (0.0%).

Table 6 summarises the number of occasions each of the news items is associated with a jump, as well as the nature of the surprise component of each announcement. For example, of the 57 retail sales announcements, 7 generated a jump - two of these are associated with an above expectations surprise, 4 with a below expectations surprise and 1 with no surprise. The maximum absolute surprise that generated a cojump is 0.6%, which is less than the maximum surprise across all of the announcements. The average surprise associated with these cojumps is 0.3%, which is below the average announcement value.

Summarising the results across the ten different announcements, the average surprise is typically larger where jumps occur, but the largest surprises may not be associated with jumps. For example, there are large surprises in the GDP, retail sales and trade

[10] The average of the standardized surprises was also considered and the results are qualitatively unchanged from those discussed here.

Table 5
Summary of above and below expectations macroeconomic news releases and the relationship with jumps.

	News release days	Type of news surprise		
		Above expectations	Below expectations	No surprise
Total days	684	312	329	43
Days with jumps				
30 min	54	25	27	2
15 min	79	36	40	3
10 min	83	42	37	4
5 min	153	71	75	7

balance announcements that are not associated with jumps. The exceptions are factory orders and housing starts where jumps occur at the maximum surprise. On the other hand, jumps also occur at the minimum surprise, which is zero in most cases.

Thus, the size of the surprise component in the announcement does not necessarily relate to the likelihood of a jump.[11] In the context of the existing literature, the current results extend the association between jumps and scheduled news (Piazzesi, 2005) and jumps and surprise events (Johannes 2004), to include the existence of both large surprises without jumps and jumps with no surprise information.

6.1. The determinants of bond price jumps

To provide a more formal context in which to assess the relationship between jumps and news, a panel logit model is specified where the probability of a jump is specified as a function of the release of news to the market. Further, drawing from the previous analysis that suggests the possibility of daily seasonality in the cojump data, day of the week dummy variables are also included. Thus, the model to be estimated is of the form

$$J_{it}^{*} = a_0 + \sum_{k=1}^{4} \alpha_k D_{kt} + \beta D_{NEWS,t} + \varepsilon_{it},\ J_{it} = \mathbf{I}\left(J_{it}^{*} > 0\right),\ i = 2, 5, 10, 30;\ t = 1, \ldots, 1168 \tag{10}$$

where $\mathbf{I}(J_{it}^{*} > 0)$ is an indicator function that transforms the latent continuous variable J_{it}^{*} for maturity i in trading day t into the binary variable J_{it}, indicating the occurrence of a jump, D_k is a dummy variable for the day of the week for Monday through to Thursday and D_{NEWS} is a common variable across maturities that captures the release of news to the market. We estimate a random effects model where

$$\varepsilon_{it} = \tau_i + e_{it},\ e_{it} \sim iidN\left(0, \sigma_e^2\right),\ \tau_i \sim iidN\left(0, \sigma_\tau^2\right)$$

which captures the unobserved heterogeneity across the propensity of different maturities to jump. The 'correct' specification of D_{NEWS} is not obvious and a number of different possibilities are considered. In the first instance, a news dummy is constructed that takes a value of unity on days on which news announcements are made and zero otherwise (D_{NEWS}). While it is possible that the action of releasing news may cause price discontinuities, it may be argued that jumps are more likely to result from the markets response to the content of the announcement. One possibility is that the market garners information from changes in the macroeconomic variable. To capture this possibility, a news dummy is constructed that takes a value of unity where the macroeconomic variable has increased (D_{NEWS}^2) or decreased (D_{NEWS}^3) from the prior estimate and zero otherwise.

The more recent macroeconomic announcement literature has focused on the difference between the markets expectation of the release and the actual release itself, i.e. the surprise component of the release. To this end, a news variable is specified that takes the value of the surprise component of the news release where an announcement is made on that day and zero otherwise (D_{NEWS}^4). This variable may be further refined by distinguishing between above and below expectations surprises in which case the news variable takes the value of the surprise where the actual announcement is greater than the expected (D_{NEWS}^5) or less than expected (D_{NEWS}^6) and zero otherwise.

The estimation results for Eq. (10) for the data sampled at the 5 minute frequency are presented in Panel A of Table 7. The first line of the results in Panel A corresponds to a model in which the news variable is specified as D_{NEWS}. The constant term in the model is not significantly different from zero and both the Monday and the Thursday dummy variables are significant, albeit of opposite sign. The news release dummy variable is positive and significant, indicating that the release of news has a positive impact on the probability of observing a jump. To assess the significance of this effect, the marginal effects of news releases on jump probability are presented in the final column. In this model, the marginal effect of news releases is to increase the probability of observing a jump by 5%.

Where the alternative specifications for the news variable are considered, the estimated results reveal that the day of the week dummy variables are unchanged in terms of their sign and significance. Further discussion is therefore omitted for the sake of brevity. Where the news variable is respecified to capture positive or negative changes in the macroeconomic variable (i.e. D_{NEWS}^2 or D_{NEWS}^3), the results find that only positive increases in the announced item have a significant impact on the probability of observing a jump. The marginal contribution of a positive one unit change in a macro news variables is estimated to be 5%. Where the surprise component of

[11] The possibility that the expectations data are stale may account for some of the recorded discrepancies. Gurkaynak and Wolfers (2006) use options based estimates of major news release expectations and find that they are slightly more accurate than survey based forecasts.

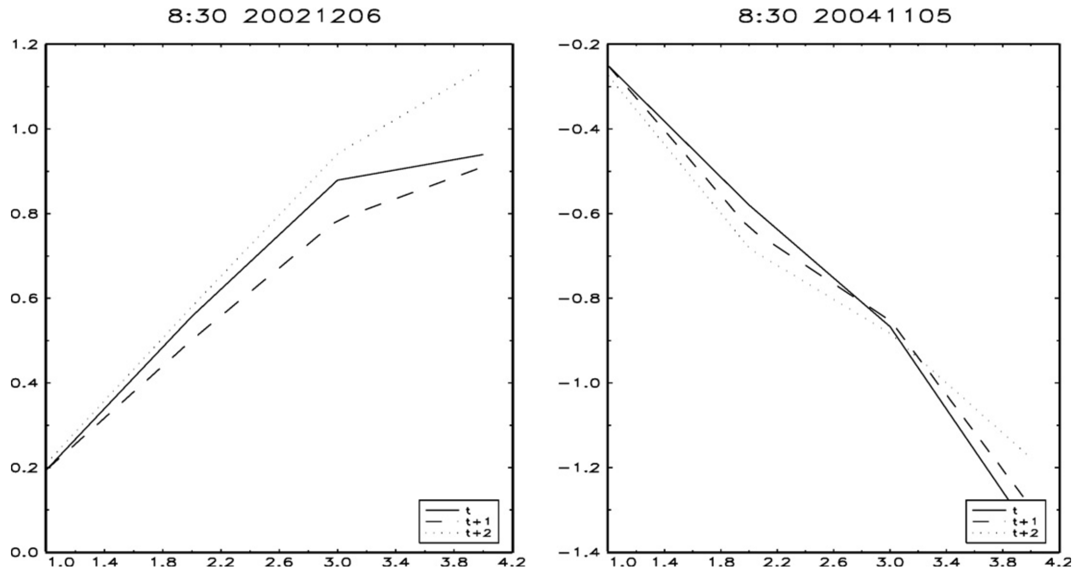

Fig. 4. Shift in the term structure associated with a non-farm payrolls announcement. The left panel is the response to payrolls being −75,500 less than expected, the right panel is the response to payrolls being 162,000 more than expected. The release dates are given as YYYYMMDD.

the news is considered (D^4_{NEWS}), the results are insignificant. This could possibly be because the above and below expectations news effects cancel each other out. To test this proposition, above expectations releases are considered on their own (D^5_{NEWS}) and the results reveal a positive and significant news coefficient. The marginal contribution of an above expectations news release is a 5% jump in the probability of observing a jump. The final row of panel A, presents the logit model where the news variable captures announcements that are below expectations (D^6_{NEWS}). The estimated coefficient is negative and significant, indicating that below expectations news increases the probability of observing a jump. The marginal effect of a below expectations news release is estimated to be a 4% increase in the probability of observing a jump.

Table 6
Major scheduled news announcement summary and incidence of jumps.

	CPI	Durable Goods	Factory Orders	GDP	Housing Starts
Number of announcements	57	57	56	57	57
Surprise characteristics					
Max abs(surprise)	0.30	8.20	3.23	1.70	256.0
Min abs(surprise)	0	0	0	0	7.5
Average abs(surprise)	0.10	1.89	0.49	0.37	89.8
Jumps matching announcements	5	4	4	4	3
Positive surprise	4	3	2	1	1
Negative surprise	0	1	2	3	2
Zero surprise	1	0	0	0	0
Surprises and jump Characteristics					
max abs(surprise)	0.1	7.2	3.2	0.6	256.0
Min abs(surprise)	0.0	0.8	0.2	0.1	102.0
Average abs(surprise)	0.1	3.5	1.3	0.3	189.0
	Leading Indicators	PPI	Retail Sales	Trade Balance	US NAPM
Number of announcements	57	57	57	57	57
Surprise Characteristics					
Max abs(surprise)	0.5	1.2	1.5	32.0	7.4
Min abs(surprise)	0	0	0	0	0
Average abs(surprise)	0.11	0.36	0.39	2.98	1.66
Jumps matching announcements	2	3	7	1	2
Positive surprise	0	1	2	1	2
Negative surprise	2	1	4	0	0
Zero surprise	0	1	1	0	0
Surprises and jump Characteristics					
Max abs(surprise)	0.2	1.1	0.6	1.6	5.2
Min abs(surprise)	0.1	0.0	0.0	1.6	4.7
Average abs(surprise)	0.2	0.5	0.3	1.6	5.0

Table 7
Logit regression results of the impact of news on jumps.

Constant	D_{MON}	D_{TUE}	D_{WED}	D_{THU}	D_{NEWS}	D_{NEWS} Specification	Marginal News effect
Panel A: 5 minute							
0.019	0.385*	−0.022	−0.104	−0.196*	0.219*	(1)	0.05*
(0.320)	(0.101)	(0.096)	(0.096)	(0.096)	(0.064)		(0.016)
0.127	0.326*	−0.063	−0.146	−0.202*	0.215*	(2)	0.05*
(0.317)	(0.099)	(0.095)	(0.096)	(0.096)	(0.072)		(0.017)
0.159	0.323*	−0.059	−0.137	−0.198*	0.060	(3)	0.01
(0.317)	(0.099)	(0.096)	(0.096)	(0.096)	(0.071)		(0.017)
0.182	0.309*	−0.073	−0.148	−0.196*	0.019	(4)	0.00
(0.316)	(0.099)	(0.096)	(0.096)	(0.096)	(0.029)		(0.007)
0.111	0.351*	−0.055	−0.122	−0.165	0.184*	(5)	0.05*
(0.317)	(0.099)	(0.096)	(0.096)	(0.097)	(0.047)		(0.011)
0.096	0.377*	−0.020	−0.095	−0.163	−0.153*	(6)	−0.04*
(0.317)	(0.101)	(0.097)	(0.097)	(0.097)	(0.047)		(0.011)
Panel B: 10 minute							
−0.771*	−0.110	−0.043	−0.262*	−0.299*	0.300*	(1)	0.07*
(0.237)	(0.103)	(0.099)	(0.100)	(0.100)	(0.067)		(0.015)
−0.563*	−0.203*	−0.104	−0.317*	−0.299*	0.056	(2)	0.01
(0.232)	(0.101)	(0.097)	(0.099)	(0.100)	(0.075)		(0.016)
−0.620*	−0.171	−0.076	−0.290*	−0.308*	0.209*	(3)	0.05*
(0.233)	(0.102)	(0.098)	(0.100)	(0.100)	(0.073)		(0.016)
−0.545*	−0.213*	−0.113	−0.322*	−0.299*	0.031	(4)	0.01
(0.231)	(0.101)	(0.098)	(0.100)	(0.100)	(0.030)		(0.006)
−0.652*	−0.151	−0.087	−0.284*	−0.251*	0.262*	(5)	0.06*
(0.233)	(0.102)	(0.098)	(0.100)	(0.101)	(0.045)		(0.010)
−0.676*	−0.108	−0.031	−0.240*	−0.248*	−0.223*	(6)	−0.05*
(0.234)	(0.103)	(0.099)	(0.101)	(0.101)	(0.047)		(0.010)
Panel C: 15 minute							
−1.161*	−0.346*	0.053	−0.249*	−0.197	0.466*	(1)	0.09*
(0.177)	(0.111)	(0.101)	(0.105)	(0.103)	(0.072)		(0.014)
−0.866*	−0.478*	−0.038	−0.333*	−0.201	0.213*	(2)	0.04*
(0.168)	(0.109)	(0.100)	(0.104)	(0.103)	(0.077)		(0.016)
−0.864*	−0.465*	−0.021	−0.312*	−0.201	0.152*	(3)	0.03*
(0.169)	(0.110)	(0.101)	(0.104)	(0.103)	(0.076)		(0.015)
−0.802*	−0.506*	−0.061	−0.345*	−0.196	0.076*	(4)	0.01*
(0.167)	(0.109)	(0.100)	(0.104)	(0.103)	(0.031)		(0.006)
−0.939*	−0.425*	−0.020	−0.291*	−0.135	0.311*	(5)	0.06*
(0.170)	(0.110)	(0.101)	(0.104)	(0.103)	(0.045)		(0.009)
−0.917*	−0.409*	0.019	−0.267*	−0.152	−0.183*	(6)	−0.04*
(0.170)	(0.111)	(0.102)	(0.105)	(0.103)	(0.047)		(0.009)
Panel D: 30 minute							
−1.345*	−0.350*	−0.200	−0.127	−0.419*	0.437*	(1)	0.07*
(0.132)	(0.117)	(0.109)	(0.107)	(0.111)	(0.077)		(0.012)
−1.082*	−0.471*	−0.282*	−0.207	−0.424*	0.255*	(2)	0.04*
(0.119)	(0.114)	(0.107)	(0.106)	(0.111)	(0.081)		(0.014)
−1.085*	−0.453*	−0.259*	−0.180	−0.426*	0.199*	(3)	0.03*
(0.121)	(0.115)	(0.108)	(0.107)	(0.111)	(0.081)		(0.014)
−1.007*	−0.502*	−0.307*	−0.219*	−0.418*	0.082*	(4)	0.01*
(0.117)	(0.114)	(0.108)	(0.107)	(0.111)	(0.033)		(0.005)
−1.137*	−0.423*	−0.270*	−0.165	−0.359*	0.290*	(5)	0.05*
(0.120)	(0.115)	(0.108)	(0.107)	(0.112)	(0.045)		(0.008)
−1.110*	−0.414*	−0.233*	−0.148	−0.379*	−0.160*	(6)	−0.03*
(0.121)	(0.117)	(0.109)	(0.108)	(0.112)	(0.049)		(0.008)

Note:
(1) D_{NEWS} takes a value of unity where news occurs and zero otherwise.
(2) D_{NEWS} takes the value of the change in the news item where it has increased and zero otherwise.
(3) D_{NEWS} takes the value of the change in the news item where it has decreased and zero otherwise.
(4) D_{NEWS} takes the value of the surprise component of the news item and zero otherwise.
(5) D_{NEWS} takes the value of the surprise component of the news item where actual exceeds expectations and zero otherwise.
(6) D_{NEWS} takes the value of the surprise component of the news item where actual is less than expectations and zero otherwise.

To test the robustness of these results to the sampling frequency of the data, the logit model with each of the six different specifications for the news variable are reestimated for the 10, 15 and 30 minute data. These results may be compactly summarised as follows. For the 10 minute data (Panel B of Table 7), a Wednesday day of the week effect is found. Further, the news event dummy is positive, significant and generates a marginal effect estimate of 7%. Of the two news variables capturing the change in the estimate, only the negative change coefficient is significant and the marginal effect is 5%. Both the above and below expectations news series are found to be significant with signs that are consistent with the 5 minute data. The marginal effect estimates are 2% lower than previously estimated however, and take the values of 35 and −2% respectively.

Table 8
Returns, surprises and jumps, results of estimating Eq. (11) across maturities and different sampling frequencies, (standard errors), *indicates statistically significant at 5% level.

	2 year	5 year	10 year	30 year	2 year	5 year	10 year	30 year
	30 minute sampling				15 minute sampling			
α	−0.000	0.000	0.001	0.003	0.001	0.001	0.003	0.007*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
β	−0.006*	−0.019*	−0.030*	−0.043*	−0.005*	−0.016*	−0.023*	−0.030*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
γ	−0.065*	−0.157*	−0.217*	−0.300*	−0.069*	−0.177*	−0.259*	−0.367*
	(0.008)	(0.009)	(0.010)	(0.012)	(0.007)	(0.008)	(0.010)	(0.012)
	10 minute sampling				5 minute sampling			
α	0.001	0.002	0.004	0.007*	0.000	0.002	0.004*	0.004*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
β	−0.007*	−0.020*	−0.030*	−0.040*	−0.008*	−0.020*	−0.031*	−0.040*
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
γ	−0.047*	−0.121*	−0.168*	−0.252*	−0.024*	−0.068*	−0.090*	−0.128*
	(0.007)	(0.007)	(0.008)	(0.010)	(0.005)	(0.006)	(0.006)	(0.007)

For the 15 minute data (Panel C of Table 7), a Monday and a Wednesday effect are present in the data. All of the news variables are significant and, with the exception of the below expectations series, positive. The marginal effect of these news series is the highest of all the different frequencies tested so far. In particular, the marginal contribution of a news release is the highest observed so far and is estimated to be 9%. Finally, where the results for the 30 minute data are considered (Panel D of Table 7), Monday, Tuesday and Thursday are all found to exhibit a lower probability of observing a jump. For the news variables, the results are remarkably similar to the 15 minute data, except that the estimated marginal effects are slightly lower in some cases.

While the range of macroeconomic news announcements considered in this paper is extensive, there may be other sources of news to the bond market. To account for this possibility, trading volume is frequently used in the finance literature to proxy for unidentified news. The logit equation is augmented to include the (log) total trading volume in each sampling interval and estimated for the data sampled at each of the different intervals allowing for the six different news specifications. The results are not presented to conserve space and may be summarised as follows. The trading volume estimate is universally negative and significant in the 5 minute data, insignificant in the 10 minute data and positive and significant in the 15 and 30 minute results. The change in sign in the lower frequency data could reflect the possibility that the 5 minute data does not allow sufficient time for accumulated volume to fully reflect the impact of the news release on the market. In the longer trading intervals however, the traded volume estimate does capture the full extent of the markets response to the news and possible jump in prices. Most importantly, the estimated news variables are robust to the inclusion of trading volume: their signs, significant and marginal effect estimates are consistent with those previously discussed. The logit equations were reestimated where traded volume is included and the news variables are omitted. In this case, the trading volume coefficients are consistent with those observed in the presence of the news terms, which suggests that news and volume are picking up different marginal effects.

6.2. Bond returns and news announcements

Further insights into the impact of news on bond prices are obtained by following Balduzzi, Elton and Green (2001), who regress the return from five minutes prior to the news announcement to 30 minutes afterwards on the size of the news surprise. In light of the discussion that links jumps to news releases, this model is augmented to include an interaction term for the presence of jumps. Thus, the regression equation takes the form:

$$r_t = \alpha + \beta S_t + \gamma D_t S_t + \varepsilon_t, \tag{11}$$

where r_t is the return (log price difference of traded prices sampled immediately prior to the news release to the next sampling period), S_t is the standardized news surprise, D_t is a one-zero dummy indicating whether the news event was associated with a jump in the term structure and ε_t is the error term.

Table 8 reports the estimation results for each maturity and sampling frequency. These results indicate that above expectations news for the economy decreases bond prices, as indicated by the negative β coefficients. These results are consistent with the significant negative relationship between news surprises and returns found in the earlier literature (for example, in Balduzzi, Elton and Green (2001), virtually all of the significant coefficients across their sample of news announcements are negative). Consistent with Balduzzi, Elton and Green (2001), Gurkaynak, Sack and Swanson (2005) and Gurkayanak and Wolfers (2006), the estimation results also show that the effects of news surprises from scheduled releases are increasing across the maturity structure. The effect of news surprises is not particularly sensitive to the sampling frequency of the data.

The γ coefficient indicates whether the relationship between returns and the surprise component of scheduled news differs significantly in the presence of jumps. The estimated results show that γ is negative in all cases, which suggests that surprises on jump days have a significantly greater negative price impact than on non-jump days. Lahaye, Laurent and Neely (2007) also show a

Table 9
Returns, surprises and jumps, results of estimating Eq. (11) across maturities and different sampling frequencies, (standard errors), *indicates statistically significant at 5% level.

	2 year	5 year	10 year	30 year	2 year	5 year	10 year	30 year
	30 minute sampling				15 minute sampling			
α	−0.002	−0.003	0.008*	0.003	0.002	−0.011*	0.002	0.015*
	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)
β	−0.006*	−0.019*	−0.030*	−0.043*	−0.005*	−0.015*	−0.023*	−0.030*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
γ	−0.065*	−0.156*	−0.218*	−0.300*	−0.068*	−0.179*	−0.259*	−0.366*
	(0.008)	(0.009)	(0.010)	(0.012)	(0.007)	(0.008)	(0.010)	(0.012)
δ	−0.001	−0.001	−0.005*	0.005	−0.001	0.011*	−0.001	−0.074*
	(0.001)	(0.001)	(0.002)	(0.014)	(0.002)	(0.002)	(0.003)	(0.027)
	10 minute sampling				5 minute sampling			
α	0.001	−0.010*	0.005	0.008*	0.001	−0.009*	0.003	0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
β	−0.007*	−0.019*	−0.030*	−0.040*	−0.008*	−0.019*	−0.031*	−0.040*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
γ	−0.047*	−0.120*	−0.169*	−0.252*	−0.024*	−0.067*	−0.090*	−0.128*
	(0.007)	(0.007)	(0.008)	(0.010)	(0.005)	(0.006)	(0.006)	(0.007)
δ	−0.001	0.016*	−0.002	−0.010	0.001	0.028*	0.002	0.085
	(0.002)	(0.003)	(0.003)	(0.031)	(0.004)	(0.004)	(0.005)	(0.048)

significant impact of news surprises on jump days across a range of assets, although they do not distinguish the increment from non-jump surprise days. The estimated γ coefficients decrease as the sampling frequency increases, which suggests that the effect of jumps at lower frequencies is substantially greater than those only detectable at high frequency. This may tie directly to the persistence of the price effects from the news surprise and is an ongoing area of research.

The list of macroeconomic news announcements considered in this paper is by no means exhaustive of all news that is relevant to pricing in this market. To control for the arrival of other forms of news, we respecify the test equation to include trading volume, i.e.

$$r_t = \alpha + \beta S_t + \gamma D_t S_t + \delta V_t + \varepsilon_t, \tag{12}$$

where δ represents the impact of a $US1 billion trade on the return for the given interval. Table 9 reports the estimation results for each maturity and sampling frequency. The results reveal that the estimated volume coefficients are typically insignificant for all maturities and sampling intervals, except the 5 year bond where δ is significant and positive for the 5, 10 and 15 minute sampled data. Thus, for the 5 year bond, higher trading volume is associated with higher returns. Most importantly, the estimated β and γ coefficients are virtually unchanged compared to those estimated for the regressions that omitted the volume control at all maturities and all sampling frequencies.

7. Conclusion

This paper builds on an emerging literature which attempts to understand the process by which bond prices evolve. We first identified significant disruptions to the price dynamics for US Treasury bonds using univariate jumps tests across a variety of sampling intervals. The concept of cojumping was introduced as a means of exploring whether jumps occurred together across the maturity structure, consistent with expectations theory of term structure, or were predominantly associated with short term assets, consistent with preferred habitat theory, or longer term assets, consistent with liquidity theory. The empirical results showed that the US Treasuries tended to cojump across maturities, but that there were also more unique jumps at both ends of the curve, providing some support for both liquidity and preferred habitat behaviour.

In around two-thirds of the sample, cojumping across the maturity structure coincided with a scheduled US news release, confirming earlier results that news has a significant impact on Treasury bonds. However, not all news was associated with a significant disruption in the price process, and the size of surprise in the news is not necessarily directly related to the existence of a jump. The direction of the shift in the term structure in response to news was consistent with expectations: news which added to inflationary pressures decreased bond prices. Additionally, the presence of jumps was associated with a stronger response to a news surprise than where no jump is observed. Jumps which occurred without any identifiable news event were not readily distinguishable from the jumps associated with news, although they tended to be somewhat more likely to be associated with negative news. The evidence on jumps in bond prices explored in this paper indicates the complexity of the dynamics in this market, stimulating future research into the transmission of shocks, the response of the term structure and interactions with other asset markets.

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