Jumps in interest rates: To what extent do news surprises matter?[1]

Ángel León[2]
University of Alicante

Szabolcs Sebestyén[3]
Catholic University of Portugal

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[2]Ángel León is an Associate Professor at the Departamento Economía Financiera, Facultad de Ciencias Económicas, Universidad de Alicante. E-mail: aleon@ua.es.

[3]Szabolcs Sebestyén is an Assistant Professor at the Faculdade Ciências Económicas e Empresariais, Catholic University of Portugal. E-mail: szsebe@fcee.ucp.pt

Abstract

This paper studies to what extent news surprises are responsible for jumps in euro area interest rates. We find that the day-of-the-week effects of jumps can be associated with the seasonal pattern of announcements. Monetary policy surprises cause jumps in almost all rates, while US labour market variables affect medium and long-term rates, showing the high sensitivity of the euro area yield curve to US employment data. We also propose a parsimonious model for latent factors that characterise the level, slope and curvature of the yield curve. Our model also provides good forecasts for the yield curve on announcement days.

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1 Introduction

A well-known characteristic of financial time series is that jumps occur occasionally. According to the standard view, the most important factor causing price movements is the news arrival process. In other words, financial prices change if new, *unexpected* information appears in the market. This is because unexpected news induce revisions in investors' expectations regarding future prices, leading to adjustments in current prices. Surprises occur despite the fact that there has been a growing amount of information available to market participants. However, all the information regarding the state of the economy is inherently uncertain; thus it is impossible to perfectly forecast the behaviour of economic variables, leading to uncertainty when pricing assets.

In this paper we study the extent to which macroeconomic and monetary policy announcements matter in inducing jumps in euro area interest rates. As new economic figures should result in revised investor expectations and changed market prices only if the actual numbers are different from the expected ones, we define a surprise component for each release, and examine whether announcement surprises induce jumps in interest rates, and of what size. This issue is of great interest also from the point of view of central banks, since they operate via the interest rate market and prefer smooth changes in interest rates to abrupt movements. Hence, identifying the sources of jumps in interest rates may help central banks to pursue a more transparent and efficient monetary policy.

Das (2002) studies whether jumps are more likely to occur on specific weekdays. However, we do not stop at that point, and try to uncover the factors that lie behind the day-of-the-week impacts. Our perception is that public information plays a crucial role in financial markets. Therefore, we examine whether unexpected economic news, grouped by weekdays, are responsible for the day-of-the-week effects. We find that the intraweek seasonalities of jumps can be very well explained by the pronounced seasonal pattern of economic announcements. Afterwards, we turn to the possible impacts of individual releases, and we also allow previously realised jumps to affect the conditional volatility of daily differences in interest rates.

A strength of this paper is that we work with interest rates from the whole euro area term structure. Yield curve models that incorporate macroeconomic factors are relatively new in the literature, since most models only impose a no-arbitrage restriction and care little about economic linkages. The majority of papers that explicitly incorporate macro variables into multi-factor term structure models only consider a unidirectional linkage, that is, either macroeconomic

factors affect yield curve dynamics (Ang and Piazzesi 2003, Hördahl, Tristani and Vestin 2006, and Wu 2002), or vice versa (Estrella and Hardouvelis 1991, and Estrella and Mishkin 1998). Only a few studies allow for a bidirectional linkage, see Kozicki and Tinsley (2001), Rudebusch and Wu (2003), Dewachter and Lyrio (2006), and Diebold, Rudebusch and Aruoba (2006). A significant shortcoming of these papers is that they only involve a few macroeconomic variables (usually inflation and output), and that because the realised values of the variables are used, the fact that only unexpected news are likely to affect the yield curve is ignored. Therefore, we consider a broad group of releases, both from the US and from the euro area, and take the surprise component of the variables instead of their mere realised values.

Methodologically, the work closest to ours is Diebold et al. (2006), since it is also based on the Nelson-Siegel framework. Particularly, a dynamised version of the framework (Diebold and Li 2006) requires the estimation of three latent dynamic factors, interpreted as level, slope and curvature components of the term structure. However, we depart from their approach in several aspects. Diebold et al. (2006) employ a simple VAR(1) representation of the variables (the three latent factors and three macroeconomic variables), and estimate the model by Kalman filter. They also study the linkages between yield curve factors and macroeconomic variables via impulse response functions and variance decomposition. However, this method involves the estimation of a large number of parameters, making it very cumbersome. Furthermore, the choice of macro variables seems arbitrary, as it is based on visual inspection: whether their values co-move with the particular yield curve factors.

Instead, we model the three latent factors individually as jump-diffusion processes. This specification seems appropriate since it allows for modelling smooth changes via the diffusion part of the process, and is also able to capture abrupt movements in the factors through jumps. The statistical properties of the latent factors also support our modelling framework. Jump intensities are supposed to be determined by macroeconomic and monetary news surprises, suggesting that sharp changes in yield curve factors can be associated with unexpected news. Our model is parsimonious, and it also allows for an accurate modelling of the conditional volatility of the factors, leading to a better understanding the dynamics of the yield curve over time. Previous models only considered simple models for the factors with homoskedastic errors,[1] whereas they evidently inherit the time-series properties of individual yields, such as

[1] To our knowledge, there are only three papers in the literature that consider time-varying volatility for the factors, Christiansen and Lund (2005), Koopman, Mallee and van der Wel (2007), and Bianchi, Mumtaz and Surico (2008), although the first is not based on the Nelson-Siegel framework.

conditional heteroskedasticity. We assume a GARCH structure on the latent factors, which is of great importance from the point of view of bond derivative pricing and risk management. Of course, our approach only considers a unidirectional linkage between the term structure and macroeconomic variables, but, as Diebold et al. (2006) also mentions, the "yields-to-macro" link is less important than the opposite direction.

As a robustness check, we carry out a simple forecasting exercise. In particular, we study whether our model is able to predict the yield curve on announcement days, given information up until the previous day. We choose the US non-farm payrolls release since it appears to affect almost all individual rates and all the three yield curve factors. Evidently, forecasting the term structure implicitly implies forecasting the individual rates that constitute the curve. Hence, we also predict daily interest rates and compare them to the observed rates. Our forecasting results are encouraging, since the predicted yield curves are very close to the actual ones, suggesting that our specification is appropriate. Of course, forecasting should involve the evaluation of the forecasting performance of our model against other alternative specifications. However, this is beyond the scope of our paper, and we leave it for future research.

This study is also in line with the work of Li and Engle (1998), Jones, Lamont and Lumsdaine (1998), Christiansen (2000), De Goeij and Marquering (2006), and Beber and Brandt (2007), among others, in terms of measuring the impacts of macroeconomic announcements on both the conditional mean and variance of interest rates. However, although these studies examine either bond or T-bond futures returns in the US, whereas we focus on euro area markets and study a substantial part of the benchmark euro area yield curve, analysing maturities from two weeks to ten years. A main shortcoming of these papers is that they primarily analyse the impacts of releases on volatility, while paying less attention to level effects. A problem with this approach is that, as high-frequency studies show,[2] return variability returns to its normal level usually about one hour after the announcement, thus making it difficult to detect significant volatility impacts on a daily basis. Furthermore, the inclusion of dummy variables to capture the effects of releases fails to identify the fact that only unexpected news makes investors revise their expectations and causes jumps. Finally, these studies rely on a relatively small set of announcements, while our work is based on a broad group of releases, which includes not only aggregated euro area macroeconomic announcements, but also member states numbers and US variables, as well as the European Central Bank (ECB)'s monetary decisions, 43 variables in total.

[2]See Andersen and Bollerslev (1998) and Andersen, Bollerslev, Diebold and Vega (2003) for US data, and Sebestyén (2006) and Andersson, Hansen and Sebestyén (2006) for euro area data, among others.

The paper is structured as follows. Section 2 introduces the interest rate data and provides preliminary data analysis. In Section 3 the basic econometric model is described and some preliminary empirical results are presented. These results support the superiority of our model over various alternatives. In Section 4 we turn to the effects of announcements, and introduce the modified model, as well the empirical findings. Section 5 provides the specification and the results of the analysis on the impacts of news surprises on the entire yield curve, and also forecasting results. Finally, Section 6 concludes with a summary of our findings.

2 Interest rate data and descriptive statistics

The interest rate data analysed here consist of daily observations in euro area interest rates. The sample covers the period from January 4, 1999 (introduction of the euro) through December 30, 2005. Both money market rates and bond yields are considered, thus providing the basis for this analysis from a substantial part of the benchmark yield curve in the euro area. Short rates are taken from the derivative markets, namely, EONIA swap rates with maturities of 2 weeks, and 1, 3, 6 and 12 months. The reason for using swap rates is that the EONIA swap market is currently one of the largest and most liquid financial markets in the world (see BIS, 2005). Indeed, the swap curve has become the pre-eminent benchmark yield curve in the euro area. The medium and long-term rates are German government bond yields with 3, 5 and 10 years of maturity. German bonds fulfill a benchmark status in the long-term segment of the euro area bond market, showing high liquidity and price transparency.

Weekends and holidays are excluded from the data set, providing 1805 useful daily observations. Table 1 contains some descriptive statistics of the interest rate levels (panel A) and the corresponding first differences (panel B). They are denoted, respectively, by r_t and Δr_t.

[Insert Table 1]

For the sample period, the average term structure exhibits an upward-sloping pattern; that is, long-term rates are higher than short-term rates. Thus, the average yield curve has a normal shape. Looking at the variation coefficient (VC), the volatilities of money market rates are of approximately the same magnitude, but are higher than those of bond yields. For the latter, there can be identified a decreasing pattern in volatility the longer the maturity. The usual augmented Dickey-Fuller (ADF) test shows that the null hypothesis of a unit root cannot be rejected at any significance level for the level of all interest rates. This test, however, rejects the

presence of a unit root for all the Δr_t series. Hence, it is a good approximation to model the daily differences in interest rates as they are stationary.

The statistical properties of Δr_t are reported in panel B of Table 1. The null hypothesis of normality can clearly be rejected as the sample skewness and kurtosis values are far away from those of the Gaussian distribution. The p-values of the Jarque-Bera (JB) test, though not reported, are essentially zero in all cases. Note that the skewness is negative for very short-term rates (2-week, 1-month and 3-month) while it is positive for longer maturities. Meanwhile, the kurtosis is considerably higher for money market rates. The graphical analysis of Figure 1 may provide a possible explanation for the very high values of kurtosis of money market rates. It is evident that the series of 2-week to 6-month interest rate differences are relatively smooth with extremely sharp jumps, while the 1-year rate and the bond yields seem inherently more volatile with jumps of lower size. Note that the very large jumps in money market rates mainly occurred in the first half of the sample period. Finally, the Ljung-Box statistics for the squares of Δr_t — denoted as LB in panel B — show strong autocorrelation for all series. This may suggest modelling the conditional variance, for instance, under the well-known GARCH family framework.

[Insert Figure 1]

3 Model specification

This section is divided into two parts: first, we introduce our benchmark model, the corresponding likelihood function, and some conditional moments. Second, we show some preliminary empirical results.

3.1 The econometric model

A mean reverting Poisson-Gaussian process with GARCH volatility is chosen for modelling the dynamics of daily changes in euro area interest rates. This process seems suitable due to the empirical characteristics of Δr_t, mentioned in the previous section. The discrete-time version of the corresponding continuous-time jump-diffusion specification is given by

$$\Delta r_t = \alpha_0 + \alpha_1 r_{t-1} + \sigma_t \Delta z_t + J_t \Delta n_t \tag{1}$$

where α_1 should be negative in order to guarantee mean-reversion, Δz_t is an iid standard normal variable, and J_t is the jump size which is also assumed to be normally distributed with constant

mean and variance denoted by μ_J and σ_J^2, respectively. We assume that Δz_t and J_t are independent. Moreover, Δn_t refers to a Poisson process with mean λ_t as the time-varying intensity parameter for the number of jumps, occurring in the interval $(t-1, t]$, and Δn_t is also assumed to be independent of the other two random variables. We approximate the Poisson process with a Bernoulli distribution — originally proposed by Ball and Torous (1983) and applied by Das (2002) and Benito, León and Nave (2007) — with probability λ_t when there is a jump and hence, with probability $1-\lambda_t$ when no jump occurs. This means that in a given interval either only one jump occurs or no jump occurs, which seems reasonable for data at the daily frequency. The conditional variance σ_t^2 of Δr_t is assumed to follow a GARCH (1,1) process, i.e.

$$\sigma_t^2 = \omega_0 + \omega_1 \left[\Delta r_{t-1} - \mathrm{E}_{t-2}\left(\Delta r_{t-1}\right)\right]^2 + \omega_2 \sigma_{t-1}^2 \tag{2}$$

The hypotheses underlying equation (1) imply that the distribution of Δr_t, conditional to the most recent information set, denoted as Φ_{t-1}[3], and to j jumps, is normal,

$$f\left(\Delta r_t \mid \Delta n_t = j, \Phi_{t-1}\right) = \frac{1}{\sqrt{2\pi\left(\sigma_t^2 + j\sigma_J^2\right)}} \exp\left[-\frac{\left(\Delta r_t - \alpha_0 - \alpha_1 r_{t-1} - j\mu_J\right)^2}{2\left(\sigma_t^2 + j\sigma_J^2\right)}\right] \tag{3}$$

where j takes on either the value 0 or 1 and hence, the conditional density function of Δr_t is given by

$$f\left(\Delta r_t \mid \Phi_{t-1}\right) = \left(1-\lambda_t\right) f\left(\Delta r_t \mid \Delta n_t = 0, \Phi_{t-1}\right) + \lambda_t f\left(\Delta r_t \mid \Delta n_t = 1, \Phi_{t-1}\right) \tag{4}$$

Therefore, in order to obtain estimates for the unknown parameters, the log-likelihood function, given by $\sum_{t=1}^{T} \ln f\left(\Delta r_t \mid \Phi_{t-1}\right)$, has to be maximised.

It is straightforward to see that the conditional mean and variance of Δr_t are

$$\begin{aligned} \mathrm{E}_{t-1}\left(\Delta r_t\right) &= \alpha_0 + \alpha_1 r_{t-1} + \lambda_t \mu_J \\ \mathrm{Var}_{t-1}\left(\Delta r_t\right) &= \sigma_t^2 + \lambda_t\left[\sigma_J^2 + \left(1-\lambda_t\right)\mu_J^2\right] \end{aligned} \tag{5}$$

where $\mathrm{E}_{t-1}(\cdot)$ and $\mathrm{Var}_{t-1}(\cdot)$ indicate the expectation and variance conditional to the information set Φ_{t-1}. Note that $\lambda_t \mu_J$ and $\lambda_t\left[\sigma_J^2 + \left(1-\lambda_t\right)\mu_J^2\right]$ are the jump contributions to the conditional mean and variance in (5), respectively. Also, observe that equation (2) includes both the jump and no jump effects through the square of past innovations. In order to disentangle these two different innovations from observed returns, a proxy for the jump component will be implemented in the next section.

[3]Note that the information set may contain events that occur between time $t-1$ and time t. Specifically, it is the amount of information available at the closing time of date t.

As regards modelling λ_t, we first follow Das (2002) in examining whether jumps are more likely to happen on specific days of the week. This analysis will be important for understanding the role of macroeconomic releases in causing jumps, studied in the next section. We assume a step function for the intensity of jump arrivals:

$$\lambda_t = \delta_0 + \delta_1 D_{1t} + \delta_2 D_{2t} + \delta_3 D_{3t} + \delta_4 D_{4t} \tag{6}$$

where δ_0 is the arrival probability of a jump on Monday and δ_k $(k = 1, 2, 3, 4)$, corresponding to Tuesday to Friday respectively, denote the incremental jump intensity (either positive or negative) of day k over Monday's level. Finally, D_{kt} stand for dummy variables, indicating day k of the week. Note that equation (6) nests the case of a constant intensity under the restriction $\delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$.

3.2 Empirical results

Some simpler models, though not reported here[4], have been estimated by quasi-maximum likelihood procedure. These models are: (i) a pure Gaussian model, (ii) a GARCH-Gaussian model, (iii) a Poisson-Gaussian structure with constant intensity parameter and (iv) a GARCH-Poisson-Gaussian model with constant intensity. We also implement for all these models a mean-reverting process for the no-jump component. According to these models, we may conclude the following results.

First, the Poisson-Gaussian model outperforms the pure Gaussian one. This superiority of the specifications with jumps also holds when adding GARCH structure to the models. The large differences in the Schwarz criterion (SIC) values are striking when comparing models with and without jumps in most cases. Second, the GARCH structure is significant and it leads to a noteworthy increase in the SIC values. GARCH-Gaussian models for money market rates turn out to be non-stationary, i.e. $\omega_1 + \omega_2 > 1$, but the introduction of jumps eliminates this feature. A similar behaviour is reported by Benito et al. (2007) and Das (2002) in modelling the overnight EONIA rate and the overnight Fed Funds rate, respectively. This finding indicates that jumps account for a considerable component of interest rate volatility. We will study this issue in more detail later in Section 4.2. Finally, the mean reversion, captured by the parameter α_1 in equation (1), is insignificant in all models, though it is always negative once we introduce jumps; that is, the sign of α_1 becomes more unstable when jumps are not incorporated.[5]

[4]The estimation results for these models are available upon request.

[5]We have also estimated a non-linear structure for the mean, in particular, both a polynomial of order three

[Insert Table 2]

Now we turn to the model presented in the previous subsection, i.e. the GARCH-Poisson-Gaussian model with mean reversion and λ_t specified by equation (6). The estimation results are presented in Table 2. As expected, the findings of the previous models also hold here. The likelihood ratio test (LRT), see the last row of Table 2, for testing the null hypothesis of a constant intensity parameter against equation (6), leads to a clear rejection of the null hypothesis in almost all cases except for the 1-month and 3-month rates. Therefore, there is compelling evidence of day-of-the-week effects for jumps in all interest rates, since even for the 1-month and 3-month rates at least one δ_i is significant. It is noteworthy that Thursday (δ_3) and Friday (δ_4) appear to be the most important days, since they are significant for most interest rates, primarily for maturities over one year. Figure 2A exhibits the probabilities across the different weekdays for all the interest rates where δ_0 is the jump probability for Monday and $\delta_0 + \delta_k$ with $k = 1, 2, 3, 4$ denote the jump probabilities for Tuesday to Friday, respectively. This probabilities for the different weekdays are roughly: 4% (Monday), 10% (Tuesday), 8% (Wednesday), 20% (Thursday) and 15% (Friday). It is clear from the figure that the longer the maturity the higher the probability of a jump, suggesting that jumps are more likely to occur in the level of longer-term yields.

Figure 2B is also obtained via the parameter estimates in Table 2, and shows the contributions of the jump component of the conditional variance, defined as $\lambda_t \left[\sigma_J^2 + (1 - \lambda_t)\, \mu_J^2\right]$, over the total variance given in equation (5), per weekday. It is evident from the figure that the size of jump-implied volatility is much more important for money market rates than for bond yields. Therefore, whereas jumps contribute mainly to the volatility of short rates, they affect the level of long-term yields. The means of these jump contributions across the different weekdays are: 33% (Monday), 43% (Tuesday), 40% (Wednesday), 56% (Thursday) and 49% (Friday).

[Insert Figure 2]

As a summary, our estimation results suggest that jumps are most likely to occur on Thursdays, followed by Fridays and Tuesdays. Moreover, Monday shows by far the smallest jump intensities. In the next section we study whether these seasonalities can be associated with macroeconomic and monetary policy announcements.

and the function proposed by Ait-Sahalia (1996) — i.e., a polynomial of order two plus the inverse of the interest rate level — but the mean reverting parameter was not significant in any of the cases either with or without jumps. The same occurred for those parameters in the drift capturing the non-linear behaviour.

4 The role of announcements

4.1 Description of releases

In the previous section it has been shown that clear weekday effects are present in the jump intensity of euro area interest rates. It is widely known that perhaps the most important motive for changes in financial prices is news arrival, that is, when new information appears in the market. In this paper we only consider public information, since it is available to all investors and it is likely to have stronger and more measurable impacts than private information. Perhaps the most relevant information in interest rate determination are decisions and statements of central banks. Although monetary policy only directly affects the very short rates, it may also affect long-term yields through the expectation hypothesis.

Another important source of information relates to the state of the economy, i.e., macroeconomic data releases. Nominal interest rates can be affected by information about the economy as new economic figures can impact both the real interest rate component and the expected inflation component of the nominal rate. This effect is likely to be stronger the longer the maturity of interest rates. Moreover, bond yields react to macroeconomic announcements because of their implication for future monetary decisions.

Hence, we collected all monetary policy decisions of the ECB[6], and the most important macroeconomic announcements both from the euro area and from the US over the sample period. Note that the 50 basis point cut in September 17, 2001 was omitted as it occurred in a non-scheduled meeting; thus, no market expectations were available. Therefore, the inclusion of such a substantial surprise would distort our estimations.

Moreover, in addition to the aggregated euro area variables, numbers from the three biggest European economies (Germany, France and Italy) were also gathered. In total, 43 announcements are considered here. The variables are displayed in Table A1 in the Appendix, where they are also grouped into three categories: activity and employment, forward-looking and prices.

In order to study whether jumps are more likely to occur on certain weekdays due to releases, the weekly distribution of the announcements needs to be examined. Table 3 shows statistics on announcements for each weekday. It is evident from the table, unsurprisingly, that the

[6]The Federal Reserve's decisions are also widely monitored by market participants as changes in the US monetary policy rate may affect all financial markets in the world. However, the Fed publishes its decisions when the European markets are already closed, thus we omitted them from the analysis. This problem does not arise with US macroeconomic announcements, as they are released during European trading hours.

distribution of weekdays is almost uniform, see second column. What is noticeable at first sight is that announcements occurred very frequently over the sample period: on 1374 days out of 1805 at least one release took place (third column), i.e. about the three-quarter of days are characterised by announcements. Moreover, unlike the distribution of all weekdays, the distribution of weekdays with at least one release is far from uniform. On Mondays there were far fewer announcements than would be implied by the uniform distribution, while on Tuesdays, Thursdays and Fridays more releases occurred in the sample period.

This is even more striking if the total number of announcements for each weekday are taken, see fifth column. About 80% of the releases took place on Tuesdays, Thursdays or Fridays, and the dominance of Thursday is striking. However, it has to be noted that the distribution of announcements is biased due to the large number of US initial jobless claims releases which are weekly announcements and are almost always published on Thursdays. Hence, the same statistics are also calculated without taking into account the initial jobless claims variable, and are displayed in the fourth and sixth columns. The results are similar, although the dominance of Thursday is somewhat weaker.

[Insert Table 3]

Our results suggest that jumps in interest rates can be explained by the weekly seasonality of public information announcements. It means that news in macroeconomic and monetary policy releases may be mainly responsible for the presence of jumps in interest rates. This is even more convincing if we look at the weekly distributions of particular announcements (see shaded lines in Table A1 in the Appendix).

For interest rates, perhaps the most important source of public information is monetary policy decisions. There were 112 ECB decisions in the sample period among which 105 were announced on a Thursday, while the remaining ones were announced on a Wednesday. In addition to the monetary policy announcements, there are two macroeconomic variables, which are also released mainly on Thursdays: the US Philadelphia Fed index (all of the 84 announcements took place on a Thursday) and the US initial jobless claims (348/362). Both are considered by investors as very important indicators of the US economy. These results may explain the far largest jump intensity of euro area interest rates on Thursdays.

Regarding the other weekdays with high jump probabilities, in the case of Tuesday two very relevant variables arise: the ZEW index (45/45), which is thought of as one of the most important economic sentiment index for the euro area, and the US consumer confidence index

(81/84), which is a good indicator of the household sentiments about the US economy. The most important announcement for Fridays is the US non-farm payrolls release (83/84). It is considered by some studies as the "king of announcements" as it contains useful information about the US job market, and is widely monitored by market participants. Another important release, which is generally published on a Friday, is the University of Michigan consumer sentiment index (74/79). For the remaining weekdays it is not possible to find such a clear pattern of announcement distribution, supporting our hypothesis that jumps might be linked to a certain macroeconomic policy release.

To study whether monetary policy and macroeconomic announcements are responsible for the clear day-of-the-week effects in the jump intensity of euro area interest rates, the data releases are first grouped by weekdays. It is reasonable to suggest that rather than an announcement itself, it is the surprise contained in an announcement that moves financial prices. Hence for each variable, a surprise component, proposed by Balduzzi et al. (2001), is defined as

$$S_t^k = \frac{A_t^k - E_t^k}{\sigma_k} \tag{7}$$

where A_t^k and E_t^k are the actual and expected[7] values of variable k, respectively, and σ_k denotes the standard deviation of the difference between the two values. Hence, if on day t an announcement occurs in variable k, S_t^k takes on the value given in equation (7), and zero otherwise. The advantage of this normalisation is that all variables are in terms of the standard deviation of the corresponding surprise, allowing for an easy comparison of the responses of variables measured in different units.

4.2 The effects of surprises

Our first analysis consists of grouping the surprises by weekday, and for each weekday, the sum of absolute surprises is calculated for the whole sample. The reason for taking absolute values is that our main interest is in studying the impacts of surprises on the intensity of jumps, which is likely to be related to the *size* of the surprises. In this way one time series for each weekday has been obtained, denoted by SW_t^i, $i = 1 \ldots, 5$. Then, a modified version of equation (6) is used to estimate our GARCH-Poisson-Gaussian model. In particular, the jump intensity is now

[7] The median expectation values taken from surveys conducted by Bloomberg are used as expectations for the macro variables, whereas for the monetary policy surprise the mean of analysts' expectations, collected by Reuters are taken.

defined as

$$\lambda_t = \frac{\exp(u_t)}{1 + \exp(u_t)} \tag{8}$$

where

$$u_t = \gamma_0 + \sum_{i=1}^{5} \gamma_i SW_t^i \tag{9}$$

The exponential transformation in equation (8) guarantees that λ_t, being a probability, is between zero and one. In equation (9), γ_0 is related to the probability of a jump on any weekday without announcement (or with announcement but with zero surprise). This probability, denoted by λ^0, is computed as $\lambda^0 = \exp(\gamma_0) / [1 + \exp(\gamma_0)]$, and it is of great interest, since it provides a "benchmark" jump intensity value for days without data release (or with zero surprise). On the other hand, γ_i $(i = 1, \ldots, 5)$ measures the sensitivity of jump intensity to surprises on weekday i. The corresponding probability is obtained as the mean of all λ_t's, where t refers to days on which at least one announcement occurred, and is given by

$$\overline{\lambda}^i = \frac{1}{N_i} \sum_{t=1}^{N_i} \frac{\exp\left(\gamma_0 + \gamma_i SW_t^i\right)}{1 + \exp\left(\gamma_0 + \gamma_i SW_t^i\right)} \tag{10}$$

for weekday i, where N_i denotes the total number of weekdays with at least one release for weekday i (see third column of Table 3). These estimated probabilities are displayed in Table 4. The results support our belief that surprises in macroeconomic variables and monetary policy decisions can be responsible for the day-of-the-week effects found in the jump intensity of euro area interest rates. The highest probabilities of jumps — and significant through the corresponding γ_i's — appear on Thursdays. Friday becomes the next important day, while Tuesday and Wednesday show similar jump intensities. The probability of a jump on a Monday is usually much lower than on any other day. Moreover, long-term interest rates tend to exhibit higher jump probabilities than money market rates. Summing up, the intraweek seasonality of jumps is similar to that plotted in Figure 2A.

After studying the aggregated impacts of releases on each weekday, we now turn to the effects of individual announcements.[8] The objective is to analyse whether jumps can be linked to certain releases. This means that equation (9) is now substituted by the expression $u_t = \theta_0 + \theta_k \left|S_t^k\right|$, where S_t^k is defined in equation (7). Moreover, we also allow the mean of the jump (μ_J) to be

[8] As we mentioned in the previous subsection, each of the selected individual announcements is usually released on a specific weekday (Tuesday, Thursday or Friday). Note that there are no important variables with announcements concentrated on Wednesdays, see Table A1 in the Appendix. It may suggest that the significant jump probabilities for Wednesday found above might be due to different releases occurred on Wednesdays.

time-varying and to capture asymmetries, that is, it is defined as

$$\mu_{J,t} = \beta_0 + \beta_1 D_t^{k-} + \beta_2 D_t^{k+}, \tag{11}$$

where D_t^{k-} and D_t^{k+} are dummies for positive and negative surprises for variable k, respectively.[9]

So far we have assumed that jumps affect the conditional variance of daily interest rate differences only through the time-varying jump probabilities. However, it is reasonable to think that previously realised jumps may also have some impact on the GARCH component of the conditional volatility. This effect is realised via the squared past innovations $\varepsilon_{t-1}^2 = [\Delta r_{t-1} - \mathrm{E}_{t-2}(\Delta r_{t-1})]^2$ in the GARCH structure, and is captured by the parameter ω_1 in equation (2). The problem is that it is difficult to decompose the total feedback impact into normal and jump components. Maheu and McCurdy (2004) propose the use of a proxy for the jump contribution.[10] We thus estimate the ex-post expected number of jumps and allow this estimate to affect the feedback of past innovations on future volatility. Hence, we rewrite equation (2) as

$$\sigma_t^2 = \omega_0 + g(\Phi_{t-1})\,\varepsilon_{t-1}^2 + \omega_2 \sigma_t^2 \tag{12}$$

with

$$g(\Phi_{t-1}) = \exp\left[\omega_1 + \omega_{1,J} E(\Delta n_{t-1} \mid \Phi_{t-1}) + \omega_1^- I(\varepsilon_{t-1}) + \omega_{1,J}^- I(\varepsilon_{t-1}) E(\Delta n_{t-1} \mid \Phi_{t-1})\right] \tag{13}$$

where $I(\varepsilon_{t-1})$ is an indicator variable equal to 1 when $\varepsilon_{t-1} < 0$ and zero otherwise, and $E(\Delta n_{t-1} \mid \Phi_{t-1})$ is the ex-post estimate of the expected number of jumps occurred between time $t-2$ and $t-1$, using period $t-1$ information. This estimate can be calculated via Bayes' rule,

$$E(\Delta n_{t-1} \mid \Phi_{t-1}) = \frac{f(\Delta r_{t-1} \mid \Delta n_{t-1} = 1, \Phi_{t-2}) \cdot \mathrm{P}(\Delta n_{t-1} = 1 \mid \Phi_{t-2})}{f(\Delta r_{t-1} \mid \Phi_{t-2})}. \tag{14}$$

Because the function $g(\Phi_{t-1})$ needs to be positive for a well-specified GARCH process, it is defined in terms of an exponential function. To illustrate this specification: if for the last day news ε_{t-1} is positive and no jump occurs, the feedback coefficient to σ_t^2 becomes $g(\Phi_{t-1}) = \exp(\omega_1)$; while for $\varepsilon_{t-1} > 0$ with one jump occurring, $g(\Phi_{t-1}) = \exp(\omega_1 + \omega_{1,J})$. On the other hand, if $\varepsilon_{t-1} < 0$ and no jump occurs, then $g(\Phi_{t-1}) = \exp\left(\omega_1 + \omega_1^-\right)$; and finally, if $\varepsilon_{t-1} < 0$ and one jump occurs, it follows that $g(\Phi_{t-1}) = \exp\left(\omega_1 + \omega_{1,J} + \omega_1^- + \omega_{1,J}^-\right)$.

[9] Note that, instead of dummy variables, we also experimented with the negative and positive surprises themselves, but the results are very similar.

[10] See also Beber and Brandt (2007) for an application.

4.2.1 Results for the monetary policy surprise

We estimate this model for all the seven selected individual announcements. Let us discuss first the results for the ECB's monetary policy release, since it is likely to be the most important source of information for interest rate markets. From Panel A of Table 5 it is evident that the implied jump intensities are significant for maturities up to 5 years. A one standard deviation surprise in the monetary decision (about 6 basis points) has the biggest effect, as expected, on the very short rates. The implied probabilities for the 2-week and 1-month rates are 0.61 and 0.49, respectively. These are the rates which are directly affected by the current monetary decision, whereas the rates with longer maturities are instead driven by expectations regarding future decisions and by other factors. For the 3-month rate the jump intensity reduces to 0.22, then it starts to increase up to the 1-year horizon, where it begins to decline again, leading to a hump-shaped impact curve.

The highly significant jump intensities point to some lack of predictability of the ECB's monetary policy because of the finding that *surprises* matter, not mere decisions (see Kuttner, 2001, Poole and Raasche, 2001, and Poole, Raasche and Thornton, 2002). However, the estimated jump probabilities are relatively low, and are usually below 0.3 (except for the very short rates). It is also noteworthy that the mean of the (absolute) monetary surprise variable is considerably lower than that of macro surprises, whereas its standard deviation is much higher. This is because, among the 112 monetary decisions of the ECB over the sample period, 54 were perfectly anticipated according to Reuters surprise measure and therefore resulted in zero surprises.

It is useful to discuss separately the periods before and after November 8, 2001, the date on which the ECB switched from bimonthly monetary meetings to monthly ones. Prior to that date, 24 zero surprises occurred out of 63, while afterwards 30 out of 49 were zeroes. This can be explained by the fact that, with bimonthly monetary meetings, market participants could not anticipate the exact timing (and magnitude) of the policy rate changes.[11] This is clearly reflected by the average absolute surprise, since for the first sub-sample it is 0.69 (without zeroes 1.12), while for the second one is only 0.21 (without zeroes 0.55). Furthermore, the biggest surprise before November 8, 2001 was more than 4 standard deviations, whereas after it was only 1.75 standard deviations.

[11] This issue is studied by the ECB, see ECB (2002). We also have to note that another reason for the many zero surprises after November 8, 2001 is that, during the period June 5, 2003 through December 1, 2005, the ECB did not change its policy rate, and all these no-change decisions were perfectly anticipated by financial markets according to Reuters' polls.

Because of this duality of the sample period in terms of the frequency of monetary policy meetings, we estimate a GARCH-Poisson-Gaussian model in which the jump intensity is modelled as a function of a constant, the absolute monetary policy surprise variable, and the latter multiplied by a dummy, which takes the value 1 before November 8, 2001, and zero otherwise.[12] Our results (not reported here) clearly show that the estimated coefficients for the first period are much larger than for the latter period for all rates. These results support our belief that the ECB's monetary policy decisions have become more predictable after switching to monthly discussions of the Governing Council, and also indicate that the significant jump probabilities in Panel A of Table 5 can mainly be associated with the pre-November 8, 2001 period.

Concerning the estimated coefficients of equation (11), Panel A of Table 5 provides clear evidence not only for time-varying jump means, but also for asymmetric responses. In particular, negative surprises induce much higher jumps than positive ones. That is, when the ECB raises its key interest rate less (or lowers it more) than the market expected, euro area interest rates fall more than they increase in the case of positive surprises. This could be easily explained if there were more negative surprises in the sample and if they were of greater magnitude. But neither is the case here. Indeed, there occurred 35 positive surprises compared to the 23 negative ones over the sample period, and the mean of positive surprises is also bigger (1.02 against 0.79 in absolute value). Thus, our results indicate that market participants reacted more sharply to negative monetary policy surprises than to positive ones.

As we will show below, the asymmetry can be related to the way we calculate the monetary policy surprise rather than to particular economic factors. Several studies use market interest rates to define the surprise component of monetary policy. Kuttner (2001) proposes to use federal funds futures to measure surprises in the Federal Open Market Committee (FOMC) decisions, and his approach is followed by various authors (Cochrane and Piazzesi, 2002, and Bernanke and Kuttner, 2005, among others). For the euro area no such futures rates are available, thus Pérez-Quirós and Sicilia (2002) propose to use very short-term EONIA swap rates, since it can be assumed that, on days of monetary meetings, the ECB's decisions are the main drivers of these rates. Moreover, EONIA swaps are less subject to liquidity considerations than cash EONIA rates, and there is no need to control for risk premia, see Durré, Evjen and Pilegaard (2002).

Pérez-Quirós and Sicilia (2002) find that the 2-week rate predicts well the monetary policy decisions before November 2001, while afterwards the 1-month rate is preferable. After inves-

[12] To simplify our model, the conditional variance is modelled again as a GARCH(1,1) process instead of the specification in equation (12), and the mean of the jump size is assumed to be a constant.

tigating several alternatives,[13] we found that the 1-month rate provides the highest likelihood value for almost all cases, therefore we define the market-based monetary policy surprise as the standardised daily difference in the 1-month rate on meeting days, and zero otherwise.

The difference between the two surprise measures is that our expectations dataset was collected by Reuters some days prior to the decision, and it only contains investors' expectations regarding the *current* decision, while not saying anything about the expected *future* path of the ECB's key interest rate. Hence, even if the current decision differs considerably from the one expected by market participants, the ECB in its Introductory Statement may hint that the future stance of monetary policy may be in line with market expectations, resulting in smooth changes in money market rates. On the other hand, the choice of the 1-month rate has the advantage that, due to its maturity, it provides expectations not only regarding the current decision, but also regarding the next decision.

[Insert Table 5]

The results are displayed in Panel B of Table 5 where the estimated coefficients for the 1-month rate are not presented, since that variable was used in the construction of the surprise component. The pattern now is different. The implied jump intensities are somewhat smaller than in Panel A (except for the 10-year rate), suggesting that market interest rates were better predictors of monetary decisions than the Reuters surprise over the sample period. The considerable difference between the estimated jump probabilities for the 10-year rate may stem from the distinct nature of the surprise measures. The market-based surprise contains information regarding the press conference held after the announcement of the decision, thus possibly reflecting hints by the president at the future stance of monetary policy.

Therefore, our findings show that measuring monetary surprises only from current decisions leads to more likely jumps than when market expectations on future decisions are also taken into account. According to the Reuters measure, the ECB's decisions implied sharp movements in market interest rates on meeting days. Moreover, the size of jumps is not constant, but rather time-varying. However, clear conclusions cannot be drawn about asymmetric responses, since they depend considerably on the way the monetary surprise variable is constructed. Whereas negative surprise matter when using the Reuters surprise, positive ones prevail in the case of

[13] We have tried both the 2-week and the 1-month rates, as well as a mixture series where the 2-week rate were used until November 8, 2001, and the 1-month rate thereafter.

the market based surprise.[14] Our results suggest that further, intraday analysis of this issue is called for.

We also calculated the time series of ex post and ex ante jumps probabilities, $E(\Delta n_{t-1} \mid \Phi_{t-1})$ and λ_t respectively, for all series.[15] Our model seems well specified, since the monetary policy surprises are well anticipated by both measures of jump intensity. Furthermore, the 50 basis point cut on September 17, 2001 in an unscheduled Governing Council meeting is not anticipated ex ante, but is fully anticipated ex post.

4.2.2 Results for macroeconomic surprises

Regarding the macroeconomic variables, the US non-farm payrolls release seems to considerably affect euro area interest rates with maturities over 6 months, see Panel C of Table 5. The estimated jump intensities are also characterised by the above described hump-shaped response curve, although the peak can now be observed at the 5 year maturity. The jump probabilities range from 0.4127 (6 months) to 0.8069 (5 years), suggesting that news surprises from the US labour market have strong impacts on euro area interest rates. Turning to the parameters of equation (11), what is striking is that bad news matters more; that is, negative surprises relate to jumps of greater magnitude than do positive surprises. Moreover, only negative surprises significantly affect jump size. The magnitude of effects ranges from -0.0220 (6 months) to -0.1005 (5 years), indicating that a one standard deviation surprise in non-farm payrolls (about 100.000 payrolls) induces a sharp decrease in the 5-year rate of about 10 basis points. These are quite strong effects, which are about the same size as the impacts of monetary decisions. However, whereas monetary policy mainly affects the short end of the yield curve, non-farm payrolls has its biggest effect on long rates, in line with expectations. This result is in accordance with previous empirical findings that the non-farm payrolls release is among the most important

[14] The only exception is the 3-month rate, where the dominance of negative surprises is still substantial. After checking the rates of other maturities, it seems that a small number of unusual observations occurred probably due to technical errors, mainly at the beginning of the sample period. We are grateful to Rasmus Pilegaard for calling our attention to this issue. One of them occurred on a meeting day (October 7, 1999), causing a big negative surprise (indeed, the biggest surprise in the series). Hence, the estimation results probably reflect the impact of this outlier rather than the real effects of surprises. This is also supported by the fact that replacing these unusual observations with the average of the preceding and following rates, the estimated β_1 becomes much smaller in absolute value.

[15] The results are available upon request.

macroeconomic data to investors.[16]

For the other variables we cannot report significant results. Although the US initial jobless claims variable has some impact on medium-term yields, the implied probabilities are not very large. These results suggest that euro area interest rates are very sensitive to news surprises from the US labour market, which may reflect investors' concerns about the so-called "jobless recovery" in the last couple of years of the sample.

[Insert Figure 3]

Figure 3 depicts the evolution of the feedback coefficients explained above for the interest rates across the yield curve and for some individual releases, specifically the monetary policy release and 3 macroeconomic announcements: the German ZEW index, the US non-farm payrolls, and the US initial jobless claims variables. It is evident from the figures that jumps result in smaller feedback coefficients than do normal innovations. This implies that news associated with jump innovations are incorporated more quickly into current interest rates. This pattern is in line with previous findings for stock returns, see Maheu and McCurdy (2004). There is also evidence of asymmetry, in that the feedback depends on the sign of past return innovations. Considering the case of $\varepsilon_{t-1} < 0$, after normal (jump) innovations news is incorporated more slowly (faster). Finally, we should remark that, although not reported, the above conclusions hold for the other individual releases.

5 Modelling the term structure

So far we have estimated GARCH-Poisson-Gaussian models for individual interest rates. However, when interest rates for a substantial part of the yield curve are available, it is advisable to carry out a multivariate analysis which takes into account the relationship between interest rates of different maturities. Building a multivariate model with eight interest rates, with jumps and conditional volatilities, however, would result in a huge model with plenty of parameters, thus we rather seek a more parsimonious modelling framework.

This section aims, at first, to fit daily euro area yield curves by using a slight variation of the popular Nelson-Siegel (1987) model, modified by Diebold and Li (2006).[17] Three time-varying

[16] See Barrett et al. (2004), among others.

[17] Similarly to Diebold and Li (2006), we use neither a no-arbitrage approach nor an equilibrium approach since we are not interested here in pricing fixed income securities. In Christensen, Diebold and Rudebusch (2007), it is reconciled the Nelson-Siegel model with the absence of arbitrage.

parameters, which summarise information about the whole term structure, are obtained, and they can be interpreted as factors corresponding to level, slope and curvature. Then, we study the impact of surprises through jumps on these factors. Finally, for model robustness checking, we examine the forecasting performance of our model.

5.1 Yield curve estimations

We fit the yield curve, where the interest rates are now denoted by $r_t(\tau)$ with τ standing for maturity (2 weeks, 1 month and so forth) in years, by using the following three-factor model:

$$r_t(\tau) = \beta_{1t} + \beta_{2t}F_{2t} + \beta_{3t}F_{3t}, \tag{15}$$

with

$$\begin{aligned} F_{2t} &= \frac{1-e^{-\eta_t\tau}}{\eta_t\tau} \\ F_{3t} &= \frac{1-e^{-\eta_t\tau}}{\eta_t\tau} - e^{-\eta_t\tau} \end{aligned} \tag{16}$$

where the time-varying parameter η_t governs the exponential decay rate. The time-varying parameters, β_{1t}, β_{2t} and β_{3t}, are called latent dynamic factors and, as Diebold and Li (2006) show, have an economic interpretation in terms of the term structure. The parameters $F_{1t} = 1$, F_{2t} and F_{3t} are called "loadings". The loading on β_{1t} equals one and it may be viewed as a long-term factor or level factor. It holds that $r_t(\infty) = \beta_{1t} > 0$. We compare this factor with the empirical 10-year yield. The loading on β_{2t} is F_{2t}, which is a decreasing function starting at 1 for $\tau = 0$ and then it decreases quickly to 0. Hence, it may be considered a short-term factor. The factor β_{2t} is related to the slope of the yield curve that can be defined as $r_t(\infty) - r_t(0) = -\beta_{2t}$ (see Frankel and Lown 1994), and we compare it with the 10-year yield minus the 3-month rate. Note that $r_t(0) = \beta_{1t} + \beta_{2t} > 0$, that is, the instantaneous interest rate hinges on both the level and the slope of the yield curve. The loading on β_{3t} is F_{3t}, which starts at 0, then increases, and finally decays to 0. Therefore, it may be viewed as a medium-term factor. The factor β_{3t} is closely related to the empirical yield curve curvature that is defined as $2r_t(\text{2-year}) - r_t(\text{3-year}) - r_t(\text{10-year})$.[18]

We estimate the parameters β_{jt}, by fixing η_t at a pre-specified value[19], by ordinary least

[18] The selected theoretical and empirical levels, slopes and curvatures are the same as in Diebold and Li (2006).

[19] In a first stage, we estimated the four parameters by non-linear least squares for each day. The median for the estimated series of η_t turned out to be 0.6. This value for η_t was kept fixed while we estimated again equation (15) by ordinary least squares, and obtained the daily β_{jt} estimates. We adopted this methodology since the β_{jt} values have an economic meaning, while the value of η_t is irrelevant for our analysis.

squares for each day t. That is, a total of 1805 estimates are obtained, denoted by $\hat{\beta}_{jt}$. The pairwise correlations between the estimated factors are not very large: $\rho\left(\hat{\beta}_{1t}, \hat{\beta}_{2t}\right) = -0.25$, $\rho\left(\hat{\beta}_{1t}, \hat{\beta}_{3t}\right) = -0.03$ and $\rho\left(\hat{\beta}_{2t}, \hat{\beta}_{3t}\right) = -0.43$.[20] Figure 4 compares the model-based level, slope and curvature (obtained by the estimated factors) with the empirical level, slope and curvature defined earlier. The associated pairwise correlations between the theoretical and empirical measures are: 0.82 (level), 0.97 (slope) and 0.98 (curvature). Finally, the ADF tests suggest, though not reported here, that all $\hat{\beta}_{jt}$ series are non-stationary. This implies that it is reasonable to work with these series in daily difference, $\Delta\hat{\beta}_{jt}$.

[Insert Figure 4]

5.2 Impact of surprises on the yield curve

The literature does not provide a "benchmark" model for studying the effects of macroeconomic factors on the yield curve. Diebold et al. (2006) propose a simple VAR(1) framework for the three latent factors and three macro variables (inflation rate, capacity utilisation and the Fed funds rate), and then estimate the model by Kalman filter techniques. However, the statistical characteristics of the latent factors, namely, the high kurtosis and non-zero skewness[21] rather point to the presence of jumps in the series. Moreover, analysis of serial correlation exhibits evidence on volatility clustering, suggesting the modelling of the conditional volatilities of the factors as GARCH processes. This is an important contribution to the existing modelling frameworks, because yield curve factors evidently inherit the dynamic properties of individual rates which are clearly conditionally heteroskedastic. Therefore, we estimate for the $\Delta\hat{\beta}_{jt}$ series our benchmark GARCH-Poisson-Gaussian model, although with constant mean instead of a mean reverting process. The results suggest that this specification is appropriate for modelling these series.

Furthermore, instead of the somewhat arbitrarily chosen macro variables, as in Diebold et al. (2006), we study the impact of surprises on the three latent factors by estimating our GARCH-Poisson-Gaussian model for each of the 43 variables. Hence, the model is given by equations (1)—(4), where the dependent variables are now $\Delta\hat{\beta}_{jt}$'s ($j = 1, 2, 3$). The jump intensity is modelled

[20] Diebold et al. (2006) also find that the interaction between the factors is negligible.

[21] Preliminary estimations and descriptive statistics for the estimated factor difference series are not reported here to save place, but they are available upon request.

as in equation (8), but equation (9) is replaced with

$$u_t = \phi_0 + \sum_{k=1}^{n} \phi_k \left| S_t^k \right|, \tag{17}$$

where S_t^k is defined in equation (7) and n denotes the total number of different releases taken for the estimation. We estimated this specification for each surprise one by one, the insignificant ones were then dropped out, and finally the model was re-estimated with all the individually significant variables. The monetary policy surprise, as a crucial announcement for interest rate markets, was always included in the model, even if it was insignificant. Moreover, the model was estimated with both monetary surprise measures.

It is noteworthy that, since the US initial jobless claims numbers are almost always released on a Thursday and on a weekly basis, they are almost always concurrent with the ECB's monetary policy decisions. Therefore, to analyse the impacts of these variables, we carry out two different estimations: the first does not contain the initial jobless claims variable, while the second contains both the monetary policy surprise and the initial jobless claims surprise. As the results are quite similar, we only report those with both surprise variables. Note that ϕ_0 in equation (17) is related to those days without any release of the given variables, while the ϕ_k's represent the incremental jump probability after a surprise in variable k.

We can report the following important findings. First, Reuters monetary policy surprises affect none of the components of the yield curve, see Panel A of Table 6. Although the estimated coefficients are relatively large for slope (short-term) and curvature (medium-term), mimicking the hump-shaped responses of individual rates, neither are significant. Nonetheless, when using the market-based monetary policy surprise, see Panel B of Table 6, the estimated effect of the monetary policy surprise on the medium-term component, $\Delta\hat{\beta}_{3t}$, becomes significant. The estimated coefficient is very large, implying a very likely jump in medium-term interest rates on days of monetary meetings. This may suggest that investors are aware of the medium-term policy orientation of the ECB.

Regarding the macroeconomic variables, different releases turn out to be relevant for different segments of the term structure. The medium-term component is affected by the most macro surprises, namely, US non-farm payrolls, US initial jobless claims, US retail sales, as well as US ISM manufacturing and non-manufacturing confidence indices. Non-farm payrolls news surprises appear to have the strongest impact on euro area interest rates, the implied jump probabilities are over 0.75 in every case. The previously mentioned hump-shaped pattern can also be observed, implying the highest jump intensity for medium-term yields. The other macro

variable which also affects all the three latent factors is the US initial jobless claims. The jump probabilities are lower than those for non-farm payrolls, but are still quite high. These findings are in accordance with the results of Section 4.2, that is, that euro area interest rates are highly sensitive to US employment variables, apparently reflecting market participants' concerns about the jobless recovery.

In addition to these two releases, US retail sales induce significant jumps in short and medium-term interest rates, while two forward-looking variables, the US ISM manufacturing and non-manufacturing confidence indices only affect the medium-term component of the yield curve, although the former only barely. This suggests that euro area interest rates are not only determined by real economy variables, but also by expectations on the business cycle of the US.

[Insert Table 6]

To analyse the impact of announcements on each component of the term structure, it is straightforward to show that the derivative, $\partial\lambda_t^j/\partial\left|S_t^k\right| = \lambda_t^j\left(1-\lambda_t^j\right)\phi_k^j$, becomes positive if and only if $\phi_k^j > 0$ where j denotes the component of the term structure with (1 = level, 2 = slope, 3 = curvature). The sign of ϕ_k^j remains the same across the three components of the term structure for each release k. According to the above derivative, the jump probabilities of $\Delta\hat{\beta}_{jt}$ increase for the releases with positive values for ϕ_k^j. This holds for all announcements in our model.

This sign effect can be better understood if we compute the probabilities implied by each release for the three factors. Figure 5 plots the median probabilities, obtained by simulating 10000 samples of the size of each standardised surprise series and computing the probabilities according to the triangular distribution, by using the parameter estimates given in Table 6. The parameters that define the triangular distribution are the minimum, maximum and mode which are obtained from the descriptive statistics of the selected announcement surprises. We again find that the most relevant releases are the ECB's monetary policy surprise, the US non-farm payrolls and the US initial jobless claims with probabilities close to one, and these are the variables that show significant parameters across the whole yield curve except the monetary surprise.

5.3 Forecasting the yield curve

In order to check the accuracy of the model we proposed for the latent factors in the previous subsection, we carry out a simple forecasting exercise. This is done by making forecasts for the

factors and from the predicted factors we can also derive predicted individual interest rates and compare them to the observed rates. Evaluation of the forecasting performance of our model against other alternative specifications is beyond the scope of this paper, and is subject to future research.

We focus on announcement days, that is, we want to examine how our model predicts the yield curve on days when releases occur. Since we have a broad set of announcements, it would be counter-productive to study each of them. Instead, we choose US non-farm payrolls, which appeared to be the most important macroeconomic variable both for individual interest rates and for yield curve latent factors. The forecasting period is the last year of the sample, 2005. As non-farm payrolls are released on a monthly basis, we make forecasts for 12 announcement days. The predictions are based on the following specification:

$$\hat{r}_{t+1|t}(\tau) = \hat{\beta}_{1,t+1|t} + \hat{\beta}_{2,t+1|t}\left(\frac{1-e^{-\eta\tau}}{\eta\tau}\right) + \hat{\beta}_{3,t+1|t}\left(\frac{1-e^{-\eta\tau}}{\eta\tau} - e^{-\eta\tau}\right), \tag{18}$$

where

$$\hat{\beta}_{j,t+1|t} = \hat{\beta}_{j,t} + \hat{\alpha}_0 + \hat{\mu}_J\hat{\lambda}_t, \tag{19}$$

and $\hat{\alpha}_0$ and $\hat{\mu}_J$ are obtained by estimating our GARCH-Poisson-Gaussian model for the latent factors. As regards $\hat{\lambda}_t$, it is estimated by equation (8), where $\hat{u}_t$ is now $\hat{u}_t = \hat{\phi}_0 + \hat{\phi}_{\text{NFP}}\left|S_t^{\text{NFP}}\right|$, and S_t^{NFP} is the standardised surprise for the non-farm payroll release. Therefore, given the surprises and appropriate parameter values, the forecasts can be easily calculated.

We start our forecasting exercise with studying the in-sample fit of our model. Hence, the estimated parameters result from the estimation of the model for the entire sample period (the estimates of the jump intensity parameters are displayed in Table 6), and the realised surprises are taken. The results (not reported here) show that the model accuracy is very good, both the predicted latent factors and the implied individual rates are very close to the actual values.

Evidently, a good fit of yield curve dynamics should be observed not only in-sample, but also out-of-sample. To carry out out-of-sample forecasts, we re-estimate our model given in the previous subsection up until the days before each of the non-farm payroll releases occurred in 2005, and predict the yield curve for the announcement days. The only remaining question is how to forecast the surprise? We can choose between three approaches. First, we can take the true surprises. Of course, these can only be used for robustness checking, since the true values of surprises are not known on the day before the release. Second, we can take the historical average of (absolute) surprises occurred just before the day to forecast as a proxy for the expected

surprise. And finally, we can simulate surprises by the triangular distribution as in the previous subsection.

Forecasts from these approaches result in very similar outcomes, thus we only report those obtained by using the historical average of surprises. The predicted interest rates and the actual ones for the 12 announcement days in 2005 are depicted in Figure 6. It is evident from the figure that our model's forecasting accuracy is very good, since the estimated yield curves are very close to the observed ones. The difference between the predicted and observed rates is usually some basis points, and the shape of the predicted yield curves is always equivalent to that of the actual curves.

6 Conclusions

This paper provides an econometric model for the daily behaviour of euro area interest rates, across the yield curve. The specification captures not only the stylised facts of financial time series, such as mean reversion and volatility clustering, but also takes into account the jumps that can be observed in the series. Our simple GARCH-Poisson-Gaussian model appears to outperform other specifications, suggesting that jumps are relevant factors in interest rates.

The existing literature provides few and incomplete answers to the question which particular economic factors induce jumps in interest rates. Das (2002) describes the day-of-the-week effects of jumps in US short-term interest rates. We find that these weekday impacts can be linked to the seasonal pattern of monetary policy announcements and certain macroeconomic data releases.

We have extended our model to one that allows jumps to affect future volatility through past innovations. Our results suggest that jumps result in smaller feedback coefficients than do normal innovations. The most relevant variables appear to be the ECB's monetary policy surprise, and employment variables from the US. The latter seems to reflect investors' concerns about the so-called "jobless recovery" in the last couple of years of the sample. We also find some asymmetry: positive and negative past innovations have different impacts on the future conditional variance. However, this hinges considerably on the way we define the monetary policy surprise.

After analysing individual interest rates, we carry out a multivariate analysis in a parsimonious way. We estimate three latent dynamic factors that contain useful information regarding the term structure of interest rates. In particular, the three factors can be interpreted as level,

slope and curvature of the yield curve. After studying the statistical properties of these factors, we employ our GARCH-Poisson-Gaussian model for these series, where the jump intensity is modelled as a function of macroeconomic and monetary policy surprises.

The results are in line with our previous findings, although now the monetary policy surprise lost most of its significance. The two US employment variable still seem very important, mainly in the medium and long-term segment of the term structure, and we also find three other US macroeconomic releases that significantly affect the yield curve.

As a robustness check, we studied whether our model is able to forecast the yield curve on announcement days. The results show that the GARCH-Poisson-Gaussian model has a good forecasting performance, since the predicted term structures are very close to the observed ones. Comparing the predictions of our model with those of other alternative specifications are left for future research.

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Tables

Table 1: Descriptive statistics of daily euro area interest rates (r_t) and first differences (Δr_t)

Descriptive statistics for daily euro area interest rates both in levels and in daily differences over the period January 4, 1999 through December 30, 2005. Weekends and holidays are excluded from the data set, providing 1805 usable observations. Mean, Median, Max, Min, and Std denote the sample mean, median, maximum, minimum, and standard deviation, respectively. VC denotes the sample variation coefficient (i.e., Std/Mean). Skew and Kurt stand for skewness and kurtosis, respectively. ADF denotes t-statistic (unit root as null hypothesis) of the Augmented Dickey-Fuller test without constant (since the constant was not significant) and lag difference terms (the selected length order is based on the SIC criterion). LB stands for the Ljung-Box test statistic for serial correlation up to the 42th order for the squared first differences of daily interest rates. Significance at the 1% level is denoted by the symbol *.

	EONIA swaps					German bond yields		
	2-week	1-month	3-month	6-month	1-year	3-year	5-year	10-year
PANEL A: Interest rate level (r_t)								
Mean	2.990	2.993	3.001	3.026	3.125	3.497	3.850	4.412
Median	2.790	2.790	2.775	2.855	2.910	3.208	3.659	4.6932
Max	4.945	4.935	5.065	5.128	5.275	5.321	5.287	5.648
Min	1.960	1.960	1.890	1.845	1.830	2.186	2.473	3.019
Std	0.938	0.940	0.947	0.956	0.969	0.867	0.775	0.648
VC	0.314	0.314	0.316	0.316	0.310	0.248	0.201	0.147
ADF (p-value)	−0.76 (0.386)	−0.79 (0.373)	−0.74 (0.395)	−0.48 (0.508)	−0.38 (0.546)	−0.39 (0.544)	−0.34 (0.561)	−0.41 (0.538)
PANEL B: Interest rate difference (Δr_t)								
Mean	-5×10^{-4}	-4×10^{-4}	-4×10^{-4}	-3×10^{-4}	-1×10^{-4}	-1×10^{-4}	-1×10^{-4}	-3×10^{-4}
Median	0.000	0.000	0.000	0.000	0.000	−0.002	−0.002	−0.002
Max	0.268	0.265	0.370	0.285	0.240	0.388	0.222	0.210
Min	−0.420	−0.367	−0.415	−0.245	−0.210	−0.292	−0.234	−0.152
Std	0.034	0.027	0.032	0.033	0.038	0.049	0.049	0.042
Skew	−1.180	−1.196	−0.815	0.175	0.376	0.592	0.394	0.369
Kurt	33.532	36.997	54.687	22.324	8.234	6.609	4.532	4.048
LB	94.17*	94.86*	397.77*	1470.4*	695.55*	91.45*	296.38*	368.25*
ADF	−46.53*	−29.02*	−54.53*	−12.54*	−45.84*	−43.34*	−43.19*	−43.27*

Table 2: GARCH-Poisson-Gaussian process with time varying jump intensity

Daily data of euro area interest rates for the period January 5, 1999 to December 30, 2005. The table contains the results for the GARCH-Poisson-Gaussian model with time-varying jump intensity parameter and mean reversion. The model is defined as $\Delta r_t = \alpha_0 + \alpha_1 r_{t-1} + \sigma_t \Delta z_t + J_t \Delta n_t$ where $\Delta z_t \sim N(0,1)$, $J_t \sim N\left(\mu_J, \sigma_J^2\right)$, and Δn_t is a Poisson increment, approximated by a Bernoulli distribution with probability of a jump equal to λ_t, which is modelled as a step function, $\lambda_t = \delta_0 + \delta_1 D_{1t} + \delta_2 D_{2t} + \delta_3 D_{3t} + \delta_4 D_{4t}$, where δ_0 is the arrival probability of a jump on Monday and δ_k, $k = 1,2,3,4$ corresponding to Tuesday to Friday, respectively, denote the incremental jump intensity of day k over Monday's level. D_{kt} denote dummy variables indicating day k of the week. The conditional variance is a GARCH(1,1) process, $\sigma_t^2 = \omega_0 + \omega_1 \left[\Delta r_{t-1} - E_{t-2}\left(\Delta r_{t-1}\right)\right]^2 + \omega_2 \sigma_{t-1}^2$. It is assumed that Δz_t, J_t and Δn_t are independent.

	EONIA swaps					German bond yields		
	2-week	1-month	3-month	6-month	1-year	3-year	5-year	10-year
ω_0	6.9×10^{-6} (1.75)	1.3×10^{-6} (1.01)	4.1×10^{-6} (0.87)	4.8×10^{-6} (2.28)	8.6×10^{-6} (2.44)	1.4×10^{-5} (1.67)	1.8×10^{-5} (1.68)	3.9×10^{-6} (0.54)
ω_1	0.3071 (4.11)	0.1068 (0.74)	0.2410 (5.39)	0.1213 (4.90)	0.0595 (4.80)	0.0277 (3.44)	0.0302 (3.52)	0.0324 (4.92)
ω_2	0.5799 (6.59)	0.8119 (4.77)	0.7006 (15.15)	0.8217 (23.06)	0.9027 (49.81)	0.9526 (68.11)	0.9497 (65.71)	0.9548 (102.91)
α_0	0.0020 (1.41)	0.0002 (0.19)	0.0009 (0.66)	0.0015 (1.11)	0.0011 (0.55)	0.0020 (1.41)	0.0020 (1.41)	0.0020 (1.41)
α_1	−0.0010 (−1.66)	−0.0002 (−0.29)	−0.0004 (−0.66)	−0.0007 (−1.24)	−0.0009 (−1.29)	−0.0012 (−1.17)	−0.0015 (−1.29)	−0.0011 (−0.83)
μ_J	0.0060 (1.07)	0.0064 (0.55)	0.0023 (0.21)	0.0043 (0.66)	0.0147 (2.60)	0.0227 (1.86)	0.0188 (1.30)	0.0041 (0.43)
σ_J	0.0813 (4.78)	0.0724 (5.93)	0.0928 (3.44)	0.0628 (4.81)	0.0585 (8.32)	0.0715 (5.65)	0.0622 (6.09)	0.0422 (4.46)
δ_0	0.0553 (2.12)	0.0630 (3.08)	0.0506 (1.90)	0.0635 (2.14)	0.0356 (1.29)	0.0000 (0.04)	0.0285 (1.08)	0.0000 (0.09)
δ_1	0.0315 (1.12)	0.0081 (0.31)	−0.0222 (−0.93)	−0.0037 (−0.12)	0.0728 (1.75)	0.0917 (1.56)	0.1211 (1.49)	0.1903 (1.34)
δ_2	0.0227 (0.80)	0.0183 (0.60)	−0.0127 (−0.59)	−0.0286 (−1.02)	0.0204 (0.59)	0.0964 (1.73)	0.0459 (0.66)	0.1680 (1.08)
δ_3	0.1176 (2.86)	0.0637 (1.04)	0.0380 (1.37)	0.0608 (1.53)	0.1918 (3.34)	0.2143 (2.33)	0.2165 (2.08)	0.3644 (2.13)
δ_4	−0.0067 (−0.27)	−0.0050 (−0.21)	−0.0070 (−0.29)	0.0235 (0.71)	0.1439 (2.71)	0.2133 (2.29)	0.1575 (1.20)	0.3725 (1.41)
Log-L	4577.34	5005.49	4775.83	4362.54	3605.69	2992.29	2964.15	3235.88
SIC	4532.35	4960.51	4730.84	4317.55	3560.70	2947.30	2919.17	3190.89
LRT (p-value)	18.96 (0.001)	5.72 (0.221)	7.36 (0.118)	8.86 (0.065)	22.12 (0.000)	24.00 (0.000)	13.56 (0.009)	16.65 (0.002)

Note: Quasi-maximum likelihood estimates with Bollerslev-Wooldridge (1992) robust t-statistics in parentheses. Log-L stands for the log-likelihood function. SIC is the Schwarz information criterion. LRT $= 2\left(LL_U - LL_R\right)$, where LL_U and LL_R denote the unrestricted and restricted Log-L values, respectively. LRT follows under $H_0 : \delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$ a χ^2 distribution with 4 degrees of freedom. p-values in parentheses.

Table 3: Weekly distribution of announcements

Weekdays	Total number of weekdays	Weekdays with at least one release	Weekdays with at least one release (without initial jobless claims)	Total number of releases	Total number of releases (without initial jobless claims)
Monday	358	153	153	229	229
Tuesday	361	298	298	607	606
Wednesday	361	254	253	487	474
Thursday	364	359	324	1037	689
Friday	361	310	310	754	754
Total	*1805*	*1374*	*1338*	*3114*	*2752*

Table 4: Jump probabilities of absolute aggregated surprises per weekday

Daily data of euro area interest rates for the period January 5, 1999 to December 30, 2005. The table contains the results for the GARCH-Poisson-Gaussian model with time varying jump intensity parameter and mean reversion. The model is defined as $\Delta r_t = \alpha_0 + \alpha_1 r_{t-1} + \sigma_t \Delta z_t + J_t \Delta n_t$ where $\Delta z_t \sim N(0,1)$, $J_t \sim N\left(\mu_J, \sigma_J^2\right)$, and Δn_t is the Poisson increment, approximated by a Bernoulli distribution with probability of a jump equal to λ_t, which is modelled as $\lambda_t = \exp(u_t) / [1 + \exp(u_t)]$ with $u_t = \gamma_0 + \sum_{i=1}^{5} \gamma_i SW_t^i$, where SW_t^i denotes the aggregated absolute macroeconomic and monetary surprises for weekday i. The conditional variance is a GARCH(1,1) process, $\sigma_t^2 = \omega_0 + \omega_1 \left[\Delta r_{t-1} - E_{t-2}(\Delta r_{t-1})\right]^2 + \omega_2 \sigma_{t-1}^2$. It is assumed that Δz_t, J_t and Δn_t are independent. The probability of a jump on days without any release is given by $\lambda^0 = \exp(\gamma_0) / [1 + \exp(\gamma_0)]$. The probability of a jump for each weekday when at least one release occurred is the mean of all λ_t's where t refers to days on which at least one announcement occurred, and is given by $\overline{\lambda}^i = (1/n_i) \sum_{t=1}^{n_i} \exp\left(\gamma_0 + \gamma_i SW_t^i\right) / \left[1 + \exp\left(\gamma_0 + \gamma_i SW_t^i\right)\right]$ for weekday i, where n_i denotes the total number of weekdays with at least one release for weekday i.

	EONIA swaps					German bond yields		
	2-week	1-month	3-month	6-month	1-year	3-year	5-year	10-year
λ^0	0.0706***	0.0715***	0.0497***	0.0501***	0.0691***	0.0867***	0.0843***	0.0748***
$\overline{\lambda}^1$	0.0019	0.0648	0.0046	0.0477	0.0509	0.0133	0.0077	0.0068
$\overline{\lambda}^2$	0.0726	0.0591	0.0022**	0.0814*	0.1591***	0.1468	0.1808*	0.3599
$\overline{\lambda}^3$	0.0598	0.0970	0.0637	0.0765	0.1178*	0.1396	0.1617**	0.2353**
$\overline{\lambda}^4$	0.1233***	0.1138***	0.0646	0.1132***	0.2393***	0.2015***	0.2090**	0.5190
$\overline{\lambda}^5$	0.0289***	0.0468	0.0350	0.0813*	0.1584***	0.1781**	0.1969	0.7447

Note: Quasi-maximum likelihood estimates with Bollerslev-Wooldridge (1992) standard errors. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 5: Estimated jump intensities and jump sizes for some news surprises

Daily data of euro area interest rates for the period January 5, 1999 to December 30, 2005. The table contains some important estimation results from a GARCH-Poisson-Gaussian model with time varying jump intensity and time-varying jump size. The model is defined as $\Delta r_t = \alpha_0 + \alpha_1 r_{t-1} + \sigma_t \Delta z_t + J_t \Delta n_t$ where $\Delta z_t \sim N(0,1)$, $J_t \sim N\left(\mu_{J,t}, \sigma_J^2\right)$, and Δn_t is the Poisson increment, approximated by a Bernoulli distribution with probability of a jump equal to λ_t, which is modelled as $\lambda_t = \exp(u_t) / [1 + \exp(u_t)]$ with $u_t = \theta_0 + \theta_k \left|S_t^k\right|$, where S_t^k denotes surprise component of variable k. The conditional variance is a GARCH(1,1) process, $\sigma_t^2 = \omega_0 + g(\Phi_{t-1})\varepsilon_{t-1}^2 + \omega_2 \sigma_t^2$, with $g(\Phi_{t-1}) = \exp\left[\omega_1 + \omega_{1,J} E(\Delta n_{t-1} \mid \Phi_{t-1}) + \omega_1^- I(\varepsilon_{t-1}) + \omega_{1,J}^- I(\varepsilon_{t-1}) E(\Delta n_{t-1} \mid \Phi_{t-1})\right]$, where $I(\varepsilon_{t-1})$ is an indicator variable equal to 1 when $\varepsilon_{t-1} < 0$ and zero otherwise, and $E(\Delta n_{t-1} \mid \Phi_{t-1})$ is the ex-post estimate of the expected number of jumps occurred between time $t-2$ and $t-1$, using period $t-1$ information. The jumps size is modelled as $\mu_{J,t} = \beta_0 + \beta_1 D_t^{k-} + \beta_2 D_t^{k+}$, where D_t^{k-} and D_t^{k+} are dummies for positive and negative surprises of variable k, respectively. It is assumed that Δz_t, J_t and Δn_t are independent. The probability of a jump when at least one surprise in variable k occurred is the mean of all λ_t's where t refers to days on which at least one surprise occurred, and is given by $\overline{\lambda}_k = (1/n_k) \sum_{t=1}^{n_k} \exp\left(\theta_0 + \theta_k \left|S_t^k\right|\right) / \left[1 + \exp\left(\theta_0 + \theta_k \left|S_t^k\right|\right)\right]$, where n_k denotes the total number of releases for variable k. Panel A displays the results for the monetary policy surprise (subscript "MON") defined by using the Reuters measure, Panel B shows the estimated coefficients for the monetary policy surprise (subscript "MON") defined as daily differences in the 1-month EONIA swap rate on meeting days and zero otherwise, while Panel C presents the results for US non-farm payrolls surprises (subscript "NFP").

	EONIA swaps					German bond yields		
	2-week	1-month	3-month	6-month	1-year	3-year	5-year	10-year
PANEL A: Reuters monetary surprise								
$\overline{\lambda}_{\text{MON}}$	0.6117***	0.4853***	0.2184***	0.2625***	0.3258***	0.2452**	0.1371**	0.2210
β_1	−0.0571**	−0.0424***	−0.1409***	−0.0963**	−0.0830**	−0.0448	0.0584**	−0.0346
β_2	0.0424	0.0361**	0.0331	0.0240	0.0272	0.0435	0.0609	0.0311
PANEL B: EONIA monetary surprise (1-month)								
$\overline{\lambda}_{\text{MON}}$	0.3577***	—	0.2110***	0.2307***	0.3212**	0.2226**	0.1090*	0.4558***
β_1	−0.0542**	—	−0.0917***	−0.0322	−0.0377*	−0.0207	0.0721**	−0.0152
β_2	0.0582**	—	0.0105	0.0519**	0.0373*	0.0574**	0.0599**	0.0342***
PANEL C: US non-farm payrolls								
$\overline{\lambda}_{\text{NFP}}$	0.0474	0.0758	0.0931**	0.4127***	0.6704***	0.7878***	0.8069***	0.7565*
β_1	−0.0019	0.0138	0.0108	−0.0220	−0.0393***	−0.0879***	−0.1005***	−0.0927**
β_2	−0.0764	−0.0146	−0.0350	0.0166	0.0047	−0.0410**	−0.0388	−0.0377

Note: Quasi-maximum likelihood estimates with Bollerslev-Wooldridge (1992) standard errors. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 6: Estimated effects of news surprises on the jump intensity of yield curve factors

Daily data of euro area interest rates for the period January 5, 1999 to December 30, 2005. The table contains the results for the GARCH-Poisson-Gaussian model with time-varying jump intensity parameter. The model is defined as $\Delta\hat{\beta}_{jt} = \alpha_0 + \sigma_t \Delta z_t + J_t \Delta n_t$ where $\Delta\hat{\beta}_{jt}$ measures the daily changes in the level, slope and curvature of the term structure ($j = 1, 2, 3$ respectively), $\Delta z_t \sim N(0,1)$, $J_t \sim N\left(\mu_J, \sigma_J^2\right)$, and Δn_t is the Poisson increment, approximated by a Bernoulli distribution with probability of a jump equal to λ_t, which is modelled as $\lambda_t = \exp(u_t) / [1 + \exp(u_t)]$ with $u_t = \phi_0 + \sum_{k=1}^{n} \phi_k \left|S_t^k\right|$, where S_t^k denotes the standardised surprise of release k. It is assumed that Δz_t, J_t and Δn_t are independent. The conditional variance is a GARCH(1,1) process, $\sigma_t^2 = \omega_0 + \omega_1 \left[\Delta r_{t-1} - E_{t-2}(\Delta r_{t-1})\right]^2 + \omega_2 \sigma_{t-1}^2$. "MON" stands for the ECB's monetary policy surprise, "NFP" denotes US non-farm payroll, "IJC" is US initial jobless claims, "RS" is US retails sales, "MAN" is US ISM manufacturing confidence index, and "NMAN" is US ISM non-manufacturing confidence index. Panel A displays the results for the monetary policy surprise defined by using the Reuters measure, Panel B shows the estimated coefficients for the monetary policy surprise defined as standardised daily differences in the 1-month EONIA swap rate on meeting days and zero otherwise.

	$\Delta\hat{\beta}_{1t}$	$\Delta\hat{\beta}_{2t}$	$\Delta\hat{\beta}_{3t}$
Panel A: Reuters monetary surprise			
ϕ_0	-0.9748^{***}	-1.0306^{***}	-1.9184^{***}
ϕ_{MON}	-0.0654	1.1253	5.2557
ϕ_{NFP}	2.9343^{**}	2.2685^{**}	5.3696^{***}
ϕ_{IJC}	1.2026^{**}	0.7970^{**}	1.0435^{***}
ϕ_{RS}	—	1.6965^{*}	2.0066^{***}
ϕ_{MAN}	—	—	0.8592^{*}
ϕ_{NMAN}	—	—	1.2945^{**}
Panel B: EONIA monetary surprise (1-month)			
ϕ_0	-0.9840^{***}	-1.0586^{***}	-2.1348^{***}
ϕ_{MON}	0.0890	1.0568	46.5032^{**}
ϕ_{NFP}	2.9315^{**}	2.2542^{**}	5.6728^{***}
ϕ_{IJC}	1.1424^{**}	0.6903^{*}	0.9722^{***}
ϕ_{RS}	—	1.6845^{*}	2.0923^{***}
ϕ_{MAN}	—	—	0.7369
ϕ_{NMAN}	—	—	1.5100^{**}

Note: Quasi-maximum likelihood estimates with Bollerslev-Wooldridge (1992) standard errors. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Figures

Figure 1: Daily differences in euro area interest rates

Evolution of daily changes of euro area interest rates in percentage terms over the period January 5, 1999 to December 30, 2005. Weekends and holidays are excluded from the data set, providing 1,804 usable observations. Figures A to E are EONIA swap rates corresponding to horizons of 2 weeks, 1 month, 3 months, 6 months and 1 year, respectively. Figures F to H are German bond yields corresponding to 3 years, 5 years and 10 years, respectively.

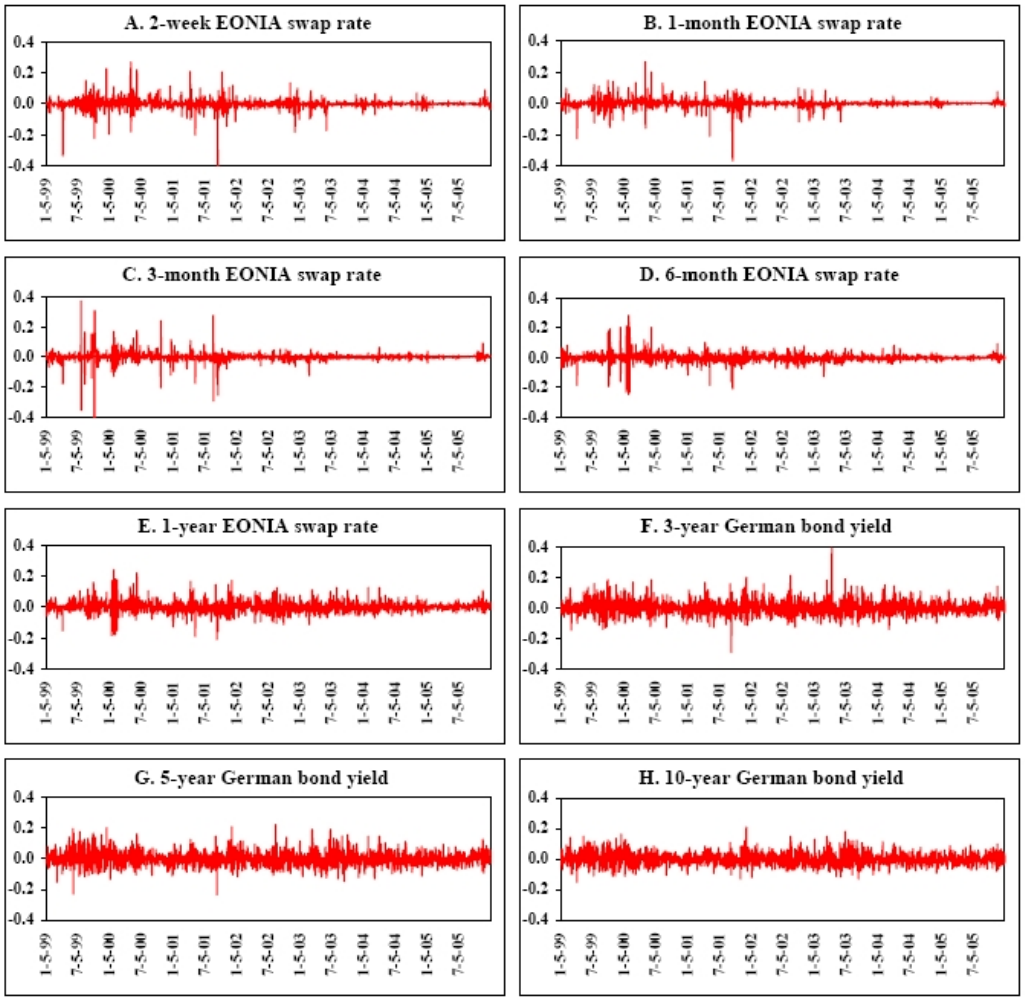


Figure 2: Jump probabilities per weekday and jump contributions to volatility

Panel A shows the probability of a jump per weekday of daily changes of euro area interest rates for different maturities, modelled as a GARCH-Poisson-Gaussian process with mean reversion and intensity defined in equation (6). Panel B exhibits the associated conditional jump variance contribution over the total conditional variance per weekday for this model. The parameter values in both figures are the estimations from Table 2.

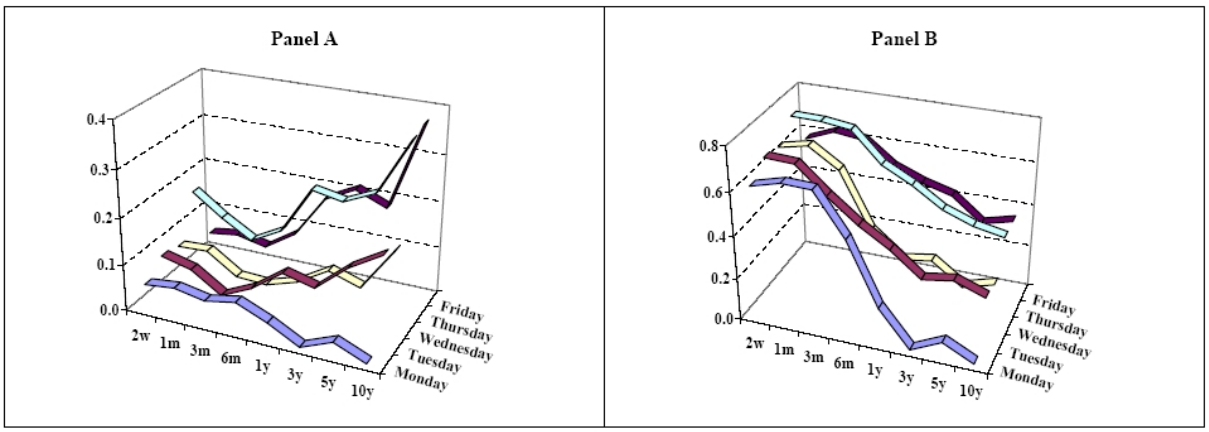


Figure 3: Volatility feedback coefficients for selected variables

Evolution of the feedback coefficient $g(\Phi_{t-1})$ defined in equation (13) across interest rates of different maturities for the following particular releases: the ECB's monetary policy release, the German ZEW business confidence index, the US non-farm payrolls, and the US initial jobless claims variables. In these figures, the label "No Jump (+)" represents the value of $g(\cdot)$ when there is no jump and past innovation is positive, i.e. $\varepsilon_{t-1} > 0$; "Jump (+)" if there is a jump and $\varepsilon_{t-1} > 0$; "No Jump (−)" if there is no jump and $\varepsilon_{t-1} < 0$ and "Jump (−)" if there is jump and $\varepsilon_{t-1} < 0$. The model is a GARCH-Poisson-Gaussian process with mean reversion with intensity parameter defined as $\lambda_t = \exp(u_t) / [1 + \exp(u_t)]$ where $u_t = \theta_0 + \theta_k \left|S_t^k\right|$ and S_t^k is the standardised announcement of release k, see equation (7).

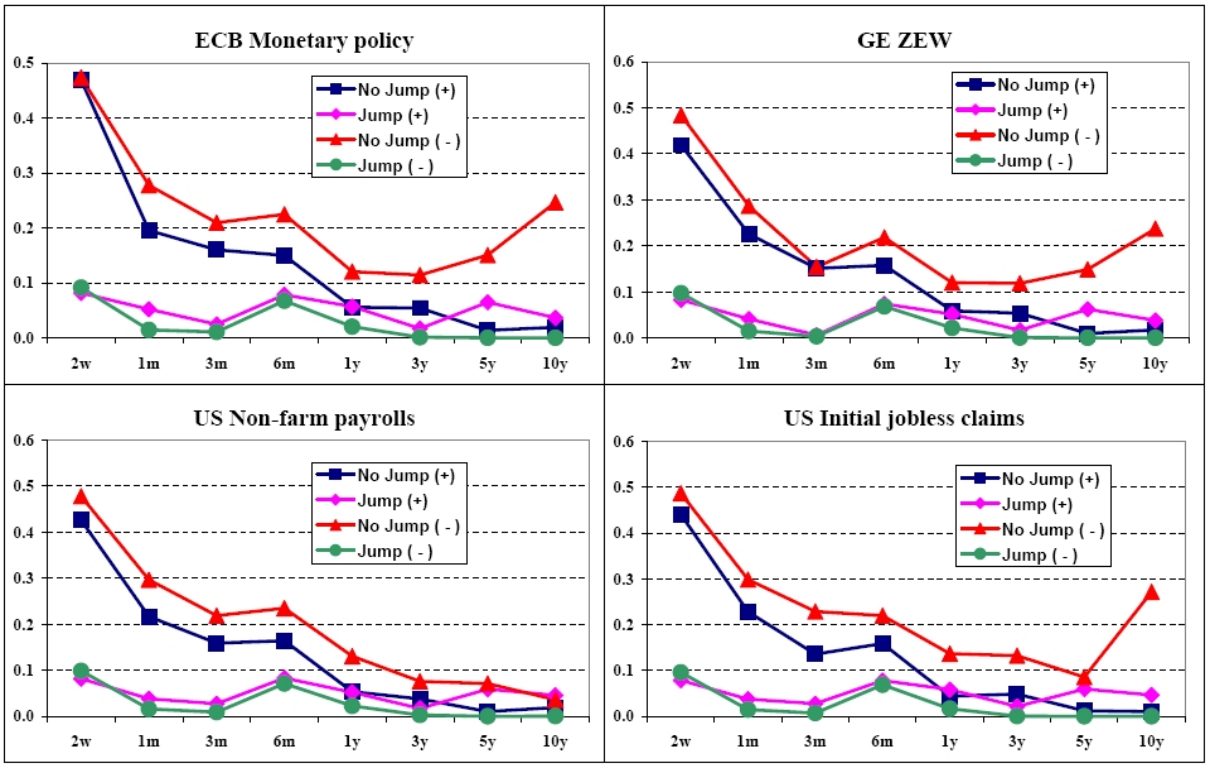


Figure 4: Model versus data-based level, slope and curvature

Evolution of the daily model-based level, slope and curvature (measured as $\hat{\beta}_{1t}$, $-\hat{\beta}_{2t}$ and $0.3\hat{\beta}_{3t}$, respectively) against the daily data-based level, slope and curvature (measured the level as the 10-year yield, the slope as the difference between the 10-year and 3-month rates, and the curvature as twice the 2-year yield minus the sum of the 3-month and 10-year rates.

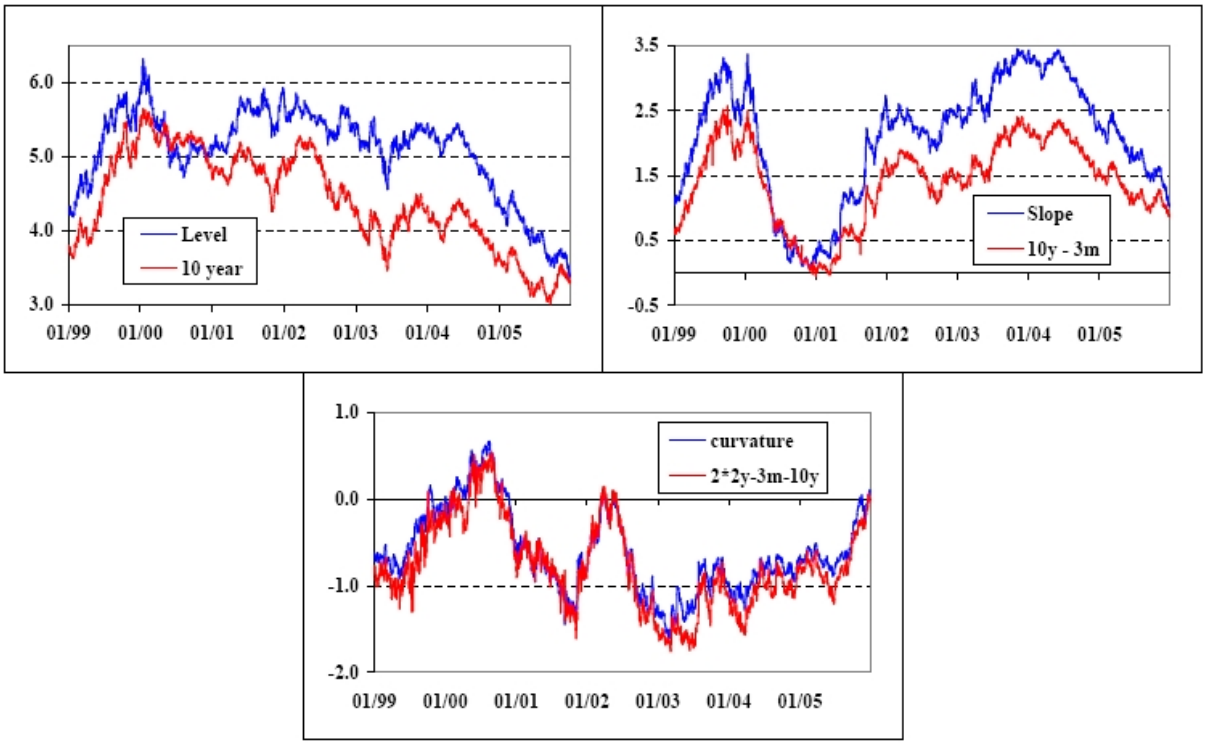


Figure 5: Simulated probabilities for the three latent dynamic factors of the yield curve

The probabilities are obtained as median values from simulations for absolute standardised surprises, $|S_t^k|$, for different releases (a total of $10,000$ random values per release) and using the parameter estimates of Table 6. The parameters of the triangular distribution are the sample minimum, maximum and mode of each $|S_t^k|$. "MON" stands for the ECB's monetary policy surprise, "NFP" denotes US non-farm payroll, "IJC" is US initial jobless claims, "RS" is US retails sales, "MAN" is US ISM manufacturing confidence index, and "NMAN" is US ISM non-manufacturing confidence index.

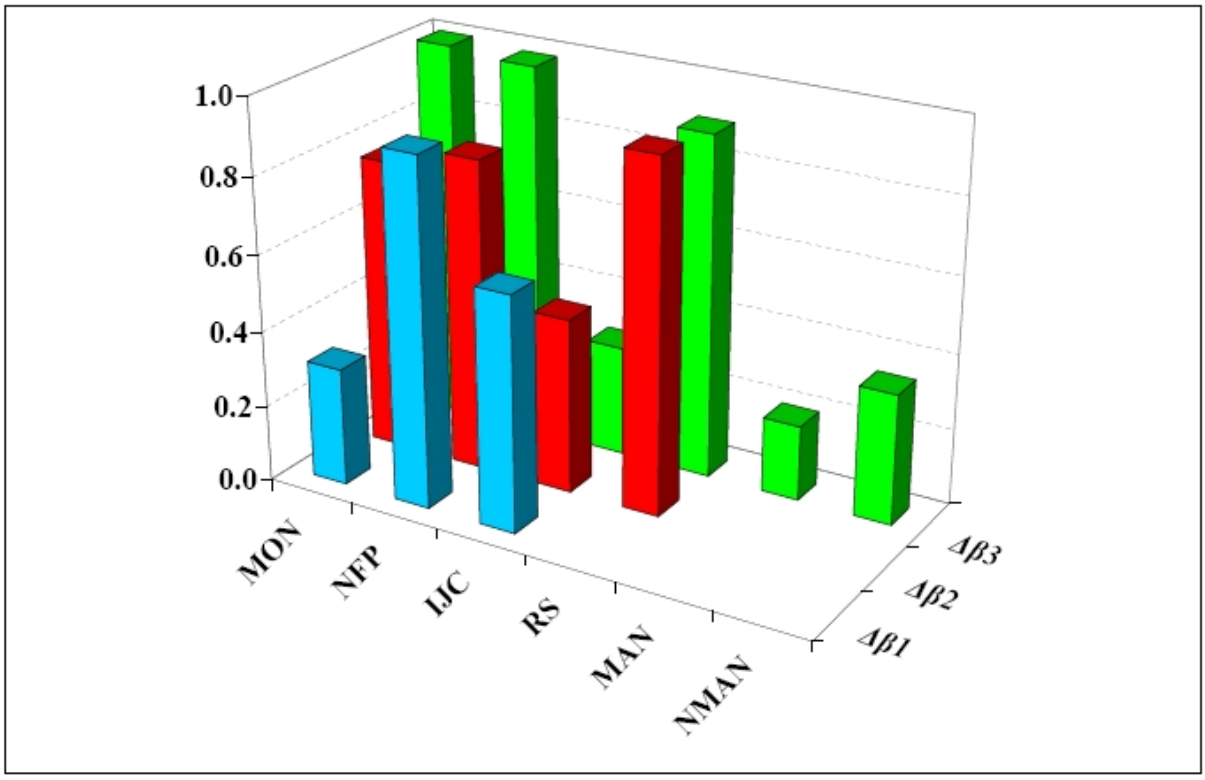
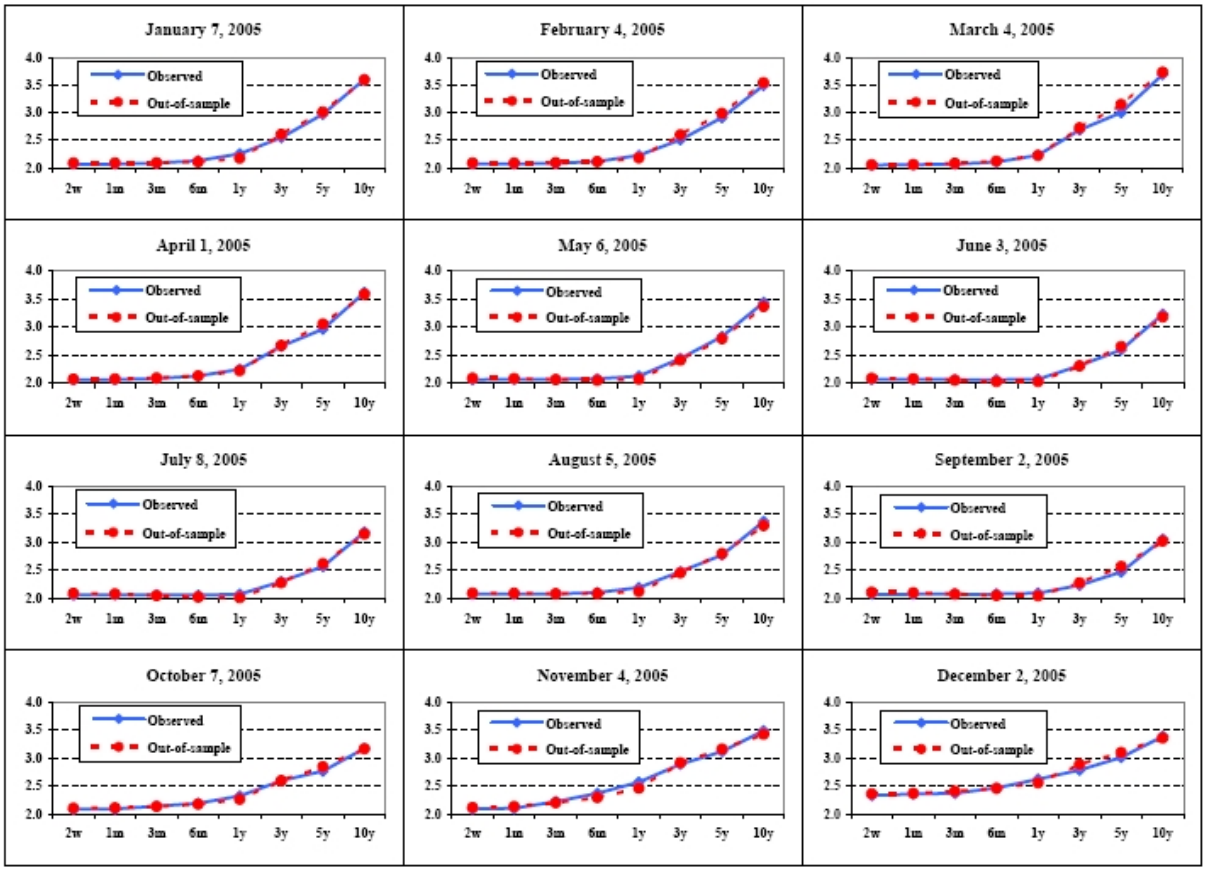


Figure 6: Forecasting yield curves for non-farm payrolls announcement days

The figure depicts both predicted and observed yield curves on announcement days of US non-farm payrolls in 2005. Forecasts are based on the model $\hat{r}_{t+1|t}(\tau) = \hat{\beta}_{1,t+1|t} + \hat{\beta}_{2,t+1|t}\left(\frac{1-e^{-\eta\tau}}{\eta\tau}\right) + \hat{\beta}_{3,t+1|t}\left(\frac{1-e^{-\eta\tau}}{\eta\tau} - e^{-\eta\tau}\right)$, where $\hat{\beta}_{j,t+1|t} = \hat{\beta}_{j,t} + \hat{\alpha}_0 + \hat{\mu}_J\hat{\lambda}_t$, with $\hat{\alpha}_0$ and $\hat{\mu}_J$ being obtained by estimating our GARCH-Poisson-Gaussian model for the latent factors. $\hat{\lambda}_t$ is given by $\hat{\lambda}_t = \exp(\hat{u}_t) / [1 + \exp(\hat{u}_t)]$, where $\hat{u}_t$ is defined as $\hat{u}_t = \hat{\phi}_0 + \hat{\phi}_{\text{NFP}} \left|S_t^{\text{NFP}}\right|$, and S_t^{NFP} is the standardised surprise for the non-farm payroll release. The historical mean of this surprise is taken for forecasting.



Appendix

Tables

Table A1: The weekly distribution of US, euro area and national macroeconomic releases

	Monday	Tuesday	Wednesday	Thursday	Friday	*Positive*	*Negative*	*Total*
ECB monetary policy decisions	0	0	7	105	0	*35*	*23*	*112*
US activity and employment								
Non-farm payroll	0	0	0	1	83	*33*	*51*	*84*
Industrial production	4	21	17	9	33	*32*	*41*	*84*
Factory orders	3	19	19	28	15	*31*	*47*	*84*
Durable goods orders	0	13	32	25	14	*43*	*39*	*84*
Business inventories	17	7	18	16	25	*40*	*27*	*83*
Retail sales	2	21	12	28	21	*36*	*39*	*84*
GDP advance	0	0	4	9	15	*12*	*16*	*28*
GDP preliminary	0	3	6	9	10	*17*	*8*	*28*
GDP final	0	1	7	12	8	*13*	*10*	*28*
Initial jobless claims	0	1	13	348	0	*173*	*180*	*362*
US forward-looking								
University of Michigan consumer sentiment	0	2	0	3	74	*35*	*44*	*79*
ISM manufacturing confidence	30	15	8	13	11	*34*	*42*	*77*
ISM non-manufacturing confidence	11	12	33	15	12	*46*	*36*	*83*
Chicago PMI	10	11	14	15	34	*46*	*38*	*84*
Consumer confidence	0	81	1	1	1	*43*	*41*	*84*
Philadelphia Fed index	0	0	0	84	0	*42*	*42*	*84*
US prices								
Producer price index	0	9	6	24	45	*35*	*38*	*84*
Consumer price index	0	20	27	13	24	*28*	*31*	*84*
Euro area activity and employment								
Industrial production	7	18	10	11	11	*26*	*29*	*57*
Unemployment	1	32	10	7	6	*5*	*16*	*56*
Retail sales	7	11	16	7	10	*26*	*23*	*51*
Euro area forward looking								
Business climate	6	6	8	5	13	*16*	*21*	*38*
Consumer confidence	7	12	7	8	17	*15*	*16*	*51*
PMI	23	10	8	10	14	*26*	*26*	*65*
Euro area prices								
Producer price index	9	16	12	9	9	*9*	*14*	*55*
Flash HICP	6	9	7	6	20	*13*	*12*	*48*
HICP	8	9	21	10	12	*11*	*13*	*60*
M3	7	9	7	17	11	*29*	*18*	*51*
National activity and employment								
Industrial production (GE)	15	16	12	17	20	*42*	*35*	*80*
Unemployment (GE)	0	30	20	26	3	*41*	*38*	*79*
Industrial production (FR)	6	18	16	14	26	*30*	*48*	*80*
Unemployment (FR)	0	12	12	19	40	*30*	*51*	*83*
GDP (FR)	0	3	4	7	14	*6*	*11*	*28*
Industrial production (IT)	11	7	5	3	9	*8*	*24*	*35*
GDP (IT)	1	7	4	8	7	*12*	*12*	*27*
National forward-looking								
ZEW (GE)	0	45	0	0	0	*24*	*21*	*45*
IFO (GE)	15	25	16	18	9	*41*	*40*	*83*
Business confidence (FR)	1	10	13	23	7	*19*	*20*	*54*
Business confidence (IT)	2	18	19	20	6	*27*	*32*	*65*
National prices								
Consumer price index (GE)	13	17	12	16	21	*31*	*27*	*79*
Consumer price index (FR)	2	24	13	9	26	*30*	*20*	*74*
Consumer price index (IT)	5	7	11	9	18	*18*	*14*	*50*