Jumps in interest rates: To what extent do news surprises matter?*

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Abstract

The paper proposes a macro-jump model to study to what extent news surprises are responsible for jumps in euro area interest rates. We find that for very short rates the surprises in current monetary policy decisions of the European Central Bank (ECB) matter, while for rates with longer maturities expectations regarding future decisions play a crucial role. The ECB surprised markets mainly before November 8, 2001 when it held bimonthly meetings and its decisions were hard to anticipate. Mostly US macro variables affect the jump arrival process of individual interest rates. We also study the impacts of news surprises on yield curve factors, estimated by the Nelson-Siegel approach. The findings are consistent with those reported for individual rates. We compare the performance our macro-jump model with that of the autoregressive jump intensity model of Chan and Maheu (2002). Our analysis shows that the macro-jump model identifies the jumps more accurately.

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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.

In this paper we study the extent to which monetary policy and macroeconomic 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.

We propose a macro-jump model where the jump arrival process depends on the size of the unexpected component of a broad set of monetary policy and macro variables. We consider announcements both from the euro area and from the US, and not only aggregated euro area economic figures, but also national releases. The most important information in interest rate markets are central bank news, such as monetary decisions, statements, speeches, etc. We define two surprise measures for the ECB's decisions: one is based on surveys taken prior to decisions and the other relies on market interest rates. This way we are able to examine whether an unexpected decision itself induces sharp movements in interest rates or it is the content of the statement released after the decision that matters. We find that the first component is more relevant in very short rates, while for longer maturities changes in expectations regarding the future stance of monetary policy determine the likelihood of jumps.

Several approaches have been proposed to model financial time series with jumps. Das (2002) assumes a Poisson process for jump arrivals and estimates several specifications for the jump intensity, including a model in which it is a function of the activity of the Fed. Chan and Maheu (2002) propose a pure time-series model, the autoregressive conditional jump intensity (ARJI) model, in which the conditional jump arrival follows an endogenous autoregressive process. Moreover, they also develop a filter to infer ex post the jump distribution. They apply this model to the Dow Jones Industrial Average price index, and Maheu and McCurdy (2004) estimates the ARJI model for individual US stock returns. Parallel to our approach, Beber and Brandt (2006) develop a model where the jump intensity depends on dummy variables for announcement days, and the jump size mean is a function of surprises. Beber and Brandt (2009) uses the same model, but they study whether macroeconomic announcements have different impacts in economic expansions and recessions.

To compare our model to other approaches, we take the ARJI model, since it is a time series model without fundamentals. Therefore, estimating jump dynamics with the two methods allows us to analyse whether explaining the jump intensity with economic variables provides a better fit, comparing to a pure statistical approach. Regarding the fit of the models, the ARJI model seems to suffer from overestimating the jump frequency for variables whose time series are relatively smooth without big outliers because of the highly persistent jump arrival rate. However, our macro-jump model links jumps to announcement days on which big surprises occur without any autoregressive structure. Further support to our model is that our analysis also reveals that price adjustment is much faster after jump innovations than after normal innovations.

A strength of this paper is that we work with interest rates from the whole euro area term structure, thus we are able to estimate the impacts of news surprises not only on individual interest rates, but also on the yield curve. 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 (see Ang and Piazzesi, 2003; Hördahl et al., 2006; Wu, 2002), or vice versa (see Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1998). Only a few studies allow for a bidirectional linkage, see Kozicki and Tinsley (2001); Rudebusch and Wu (2008); Dewachter and Lyrio (2006) and Diebold et al. (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.

Methodologically, the work closest to ours is Diebold et al. (2006), since it also relies 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. Then they 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 study the three latent factors individually with our macro-jump model. 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 again 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 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.

The paper is structured as follows. Section 2 introduces the interest rate data and provides descriptive 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 macro-jump 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. Finally, Section 6 concludes with a summary of our findings.

[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 et al. (2010) and Bianchi et al. (2008), although the first is not based on the Nelson-Siegel framework.

2 Interest rate data and descriptive statistics

The interest rate data analysed here consist of daily observations in euro area interest rates of several maturities. Since the euro area is a currency area without a single common bond market, it is not obvious which instruments to choose to represent euro area interest rates. Hence, consistent with the ECB's earlier practice[2], our analysis is based on money market rates for maturities of up to one year and on the fixed side of interest rate swap contracts for maturities of one to ten years.

In particular, Euribor (EURo InterBank Offered Rate) is the benchmark rate of the euro money market that has emerged since 1999. It is sponsored by the European Banking Federation (EBF), which represents the interests of some 5000 European banks and by the Financial Markets Association (ACI). It is the rate at which euro interbank term deposits are offered by one prime bank to another prime bank and is published at 11.00am Central European Time (CET) for spot value. Due to the release time of the daily Euribor, and taking into account that the vast majority of macroeconomic announcements take place after this time, we shift back the Euribor data one day. That is, the Euribor of day t corresponds to day $t-1$ data releases.

The reason why the ECB used swap rates for its yield curve calculations is the fact that the swap curve has become the pre-eminent benchmark yield curve in the euro area, against which even some government bonds have often been referenced. Moreover, the euro area swap market is one of the largest and most liquid financial markets in the world, see BIS (2005). The rapid emergence of a single euro swap curve could be observed thanks to the fragmented nature of European government bond markets, thus market participants (and even some European governments) began to use interest rate swaps for hedging and speculating on interest rate movements. The benchmark status of the euro swap curve is also reflected by the fact that euro-denominated corporate bonds are usually quoted in terms of a spread over the swap curve.

Regarding the pricing of euro interest rate swaps, for long-term swaps, Euribor is the key reference rate for the floating rate leg. Moreover, unlike the convention for US dollar swaps, for euro swaps quotes are provided in terms of the yields that specify the fixed payments for the contracts rather than in terms of spreads over government bonds.

[2]Since 10 July 2007, the ECB releases yield curve estimates calculated from euro area government bonds on a daily basis. However, this change occurred after the end of our sample period, and furthermore, the ECB publishes yields computed by the Svensson method, while we demand "raw" yields and estimate the yield curve in another way.

Despite the benchmark status of euro swaps, their yields are still usually above the yields for the most liquid AAA-rated government bonds in a given maturity. This is not surprising as swap rates contain a premium for counterparty credit risk, which is often associated with the major dealers in the market. However, due to daily settlement and collateralisation this risk has reduced, leading to narrower and more stable swap spreads. A deterioration in the perceived creditworthiness of a government could result in a smaller spread too.

Our sample covers the period from February 18, 1999 (the first day for which swap yield data is available) through December 29, 2006. For Euribor, maturities of one to twelve months are considered in this paper, whereas for euro swap rates, maturities of two to ten years are taken. Thus for the yield curve analysis we use a cross-section of 21 yields. However, studying all maturities one by one would be cumbersome and counterproductive, so for the individual analysis four maturities are chosen: 1 month, 6 months, 2 years and 10 years. This choice aims both to represent different segments of the term structure and to reflect market participant's preferences. According to anecdotal evidence and discussions with market participants, these maturities are widely monitored by investors.

Weekends and holidays are excluded from the data set, providing 2014 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; 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, although long rates seem "more normal", a well-known empirical fact. Note that the skewness is negative for money market rates while it is positive for swap rates. Meanwhile, the kurtosis is considerably higher for short 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 1-month and 6-month interest rate differences are relatively smooth with extremely sharp jumps (mainly the 1-month rate), while the 2-year and 10-year swap 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 and preliminary analysis

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

3.1 The econometric model

The dynamics of daily changes in euro area interest rates, taking into account the empirical characteristics of Δr_t discussed in the previous section, is described as follows. Daily differences in interest rates are modelled as

$$\Delta r_t = \mu_t + \varepsilon_{1,t} + \varepsilon_{2,t}, \tag{1}$$

where

$$\begin{aligned} \mu_t &= \alpha_0 + \sum_{i=1}^{p} \alpha_i \Delta r_{t-i} && (2) \\ \varepsilon_{1,t} &= \sigma_t z_t && (3) \\ \varepsilon_{2,t} &= \sum_{k=1}^{n_t} J_{t,k} - \mu_J \lambda_t. && (4) \end{aligned}$$

The α_i coefficients stand for possible autoregressive terms. We determine the optimal number of lags both by studying the autocorrelation structure of the series and by using an information criterion, particularly, the Schwarz Information Criterion (SIC). Both point to 1 lag in the 1-month series, 2 lags in the 6-month series, and no lags in the daily differences of swap yields.

In equation (3), $\varepsilon_{1,t}$ indicates a zero-mean normal innovation, representing diffusive information flow, where z_t is an i.i.d. standard normal variable. Equation (4) defines the jump innovation term, representing the impact of abrupt information arrival. Note that the term $-\mu_J \lambda_t$ serves for adjusting the jump innovation to have conditionally zero mean. Moreover, J_t is the jump size which is assumed to be normally distributed with constant mean and variance denoted by μ_J and σ_J^2, respectively. We assume that z_t and J_t are independent. Moreover, n_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 n_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 et al. (2007) — with probability λ_t when there is a jump and hence, with probability $1-\lambda_t$ when no jump occurs. This means that on a given day either only one jump occurs or no jump occurs, which seems reasonable for data at the daily frequency.

3.1.1 Modelling the conditional variance

The diffusive component of the conditional variance of Δr_t, σ_t^2, is assumed to follow a GARCH (1,1) process, i.e.

$$\sigma_t^2 = \omega_0 + \omega_1 \varepsilon_{t-1}^2 + \omega_2 \sigma_{t-1}^2, \tag{5}$$

where $\varepsilon_{t-1} = \varepsilon_{1,t-1} + \varepsilon_{2,t-1}$ denotes the total innovation observed at time $t-1$.

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,

$$f\left(\Delta r_t \mid n_t = j, \Phi_{t-1}\right) = \frac{1}{\sqrt{2\pi\left(\sigma_t^2 + j\sigma_J^2\right)}} \exp\left[-\frac{\left(\Delta r_t - \mu_t + \mu_J \lambda_t - j\mu_J\right)^2}{2\left(\sigma_t^2 + j\sigma_J^2\right)}\right], \tag{6}$$

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

$$f\left(\Delta r_t \mid \Phi_{t-1}\right) = \left(1-\lambda_t\right) f\left(\Delta r_t \mid n_t = 0, \Phi_{t-1}\right) + \lambda_t f\left(\Delta r_t \mid n_t = 1, \Phi_{t-1}\right). \tag{7}$$

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.

The jump intensity can also be written as $\lambda_t = \mathbb{E}\left(n_t \mid \Phi_{t-1}\right)$, thus it can be interpreted as our *ex ante* assessment of the expected number of jumps over the interval $(t-1, t]$. It would also be

[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.

desirable to quantify the change in our conditional forecast as the information set is updated, i.e., the *ex post* assessment of the expected number of jumps. Fortunately, this can be easily done via Bayes' rule[4],

$$\mathbb{E}\left(n_t \mid \Phi_t\right) = \frac{f\left(\Delta r_t \mid n_t = 1, \Phi_{t-1}\right) \cdot \Pr\left(n_t = 1 \mid \Phi_{t-1}\right)}{f\left(\Delta r_t \mid \Phi_{t-1}\right)}. \tag{8}$$

The first term in the numerator is given in equation (6), the second term is simply λ_t, and the denominator is the value of the likelihood function at time t. The filter in equation (8) is very useful for inference purposes. Since we approximate the Poisson process with a Bernoulli distribution, and since for the latter the expected value coincides with the conditional probability, equation (8) directly provides us the ex post probability that a jump occurred on day t.

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

$$\begin{aligned} \mathbb{E}\left(\Delta r_t \mid \Phi_{t-1}\right) &= \mu_t \\ \mathbb{V}\text{ar}\left(\Delta r_t \mid \Phi_{t-1}\right) &= \sigma_t^2 + \lambda_t\left(\sigma_J^2 + \mu_J^2\right) \end{aligned} \tag{9}$$

The second term in the second equation, $\lambda_t\left(\sigma_J^2 + \mu_J^2\right)$, is the jump contribution to the conditional variance in (9). However, note that the first term, σ_t^2, besides the impacts of past diffusive innovations, also includes the effects of past jump innovations to returns, since $\varepsilon_{t-1} = \varepsilon_{1,t-1} + \varepsilon_{2,t-1}$.

Therefore, instead of assuming that jumps affect the conditional variance only through the time-varying jump probabilities, 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, ε_{t-1}^2, in the GARCH structure, and is captured by the parameter ω_1 in equation (5). As Maheu and McCurdy (2004) argue, this feedback can be important, since realised innovations may induce different trading strategies in the markets. Evidently, these activities generate further volatility clustering, besides clustering of jump arrivals.

The problem is that it is difficult to decompose the total feedback impact (ε_t) into normal ($\varepsilon_{1,t}$) and jump ($\varepsilon_{2,t}$) components. Maheu and McCurdy (2004) propose the use of a proxy for the jump contribution.[5] 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 (5) as

$$\sigma_t^2 = \omega_0 + g\left(\boldsymbol{\theta}, \Phi_{t-1}\right)\varepsilon_{t-1}^2 + \omega_2\sigma_{t-1}^2 \tag{10}$$

[4]See also Chan and Maheu (2002) and Maheu and McCurdy (2004).

[5]See also Beber and Brandt (2009) for an application.

with

$$g\left(\boldsymbol{\theta}, \Phi_{t-1}\right)=\exp \left[\omega_1+\omega_{1, J} \mathbb{E}\left(n_{t-1} \mid \Phi_{t-1}\right)+\omega_1^{-} I\left(\varepsilon_{t-1}\right)+\omega_{1, J}^{-} I\left(\varepsilon_{t-1}\right) \mathbb{E}\left(n_{t-1} \mid \Phi_{t-1}\right)\right], \quad (11)$$

where $I\left(\varepsilon_{t-1}\right)$ is an indicator variable equal to 1 when $\varepsilon_{t-1}<0$ and zero otherwise.

Because the function $g\left(\boldsymbol{\theta}, \Phi_{t-1}\right)$ needs to be positive for a well-specified GARCH process, it is defined in terms of an exponential function. This specification gives us much flexibility. It allows us to study asymmetric effects of positive and negative innovations (bad vs good news). Furthermore, it allows for different responses after jump innovations than after normal ones through the parameter $\omega_{1,J}$. Finally, the combination of these two characteristics is also possible. For instance, if for the last day news ε_{t-1} is positive and no jump occurs, the feedback coefficient to σ_t^2 becomes $g\left(\boldsymbol{\theta}, \Phi_{t-1}\right)=\exp\left(\omega_1\right)$; whereas for $\varepsilon_{t-1}>0$ with one jump occurring, $g\left(\boldsymbol{\theta}, \Phi_{t-1}\right)=\exp\left(\omega_1+\omega_{1,J}\right)$. On the other hand, if $\varepsilon_{t-1}<0$ and no jump occurs, then $g\left(\boldsymbol{\theta}, \Phi_{t-1}\right)=\exp\left(\omega_1+\omega_1^{-}\right)$; and finally, if $\varepsilon_{t-1}<0$ and one jump occurs, it follows that $g\left(\boldsymbol{\theta}, \Phi_{t-1}\right)=\exp\left(\omega_1+\omega_{1,J}+\omega_1^{-}+\omega_{1,J}^{-}\right)$.

Likelihood-ratio tests can be used to test (i) whether previously realised jumps affect significantly expected volatility ($\omega_{1,J}=\omega_{1,J}^{-}=0$); (ii) whether the feedback from jump innovations to expected volatility depends on the sign of return innovations ($\omega_{1,J}^{-}=0$); (iii) whether both normal and jump innovations affect expected volatility in an asymmetric way ($\omega_1^{-}=\omega_{1,J}^{-}=0$). The test results, not reported here, show that there is no statistical evidence for asymmetric impacts of return innovations on the conditional volatility of all interest rates. Of course, it does not mean that jumps do not affect expected volatility, but are rather symmetric with respect to the type of news. However, for money market rates we find that jump innovations have a different effect on conditional volatility than normal innovations. Hence, for the short rates we estimate equation (11) with the restriction $\omega_1^{-}=\omega_{1,J}^{-}=0$. On the other hand, for long-term rates the simple GARCH(1,1) specification seems sufficient to model time-varying volatility. These results reflect the conclusions from the visual inspection of Figure 1 and from our preliminary estimation results described in the next subsection that jumps play a great role in short rates' volatility.

3.1.2 Modelling the jump intensity

As regards modelling λ_t, we consider several different specifications, which are explained as follows. First, as the simplest case, we set $\lambda_t=\lambda$, i.e. equal to a constant value. Second, we estimate the autoregressive conditional jump intensity (ARJI) model of Chan and Maheu (2002). It is a pure time-series model where λ_t does not depend on fundamentals, but it evolves endogenously over time according to a simple ARMA process,

$$\lambda_t = \lambda_0 + \sum_{i=1}^{r} \rho_i \lambda_{t-i} + \sum_{i=1}^{s} \gamma_i \, \xi_{t-i}, \tag{12}$$

where ξ_{t-i} stands for the innovation to λ_{t-i}, computed as

$$\xi_{t-i} \equiv \mathbb{E}\left(n_{t-i} \mid \Phi_{t-i}\right) - \lambda_{t-i} = \mathbb{E}\left(n_{t-i} \mid \Phi_{t-i}\right) - \mathbb{E}\left(n_{t-i} \mid \Phi_{t-i-1}\right). \tag{13}$$

From equation (13) it is obvious that ξ_{t-i} can be seen as a change in our conditional forecast on n_{t-i} as the information set is updated. We estimate an ARJI(1,1) model as Chan and Maheu (2002) and Maheu and McCurdy (2004). The initial value for λ_t is set equal to its unconditional mean, $\lambda_0/\left(1-\rho\right)$. Note that a sufficient condition for positive jump intensity in all periods in the ARJI(1,1) model is $\lambda_0 > 0$, $\rho \geq \gamma$ and $\gamma \geq 0$.

Finally, we model the jump intensity as a function of monetary policy and macroeconomic surprises. The specification and the results are presented in Section 4. Of course, this specification is ad hoc because of the choice of the potential explanatory variables. However, the comparison of these three specifications may give us some insight which model provides better fit to describe empirically the evolution of the jump arrival process over time. A formal comparison of the log-likelihood values of the models for λ_t is not possible due to the different specifications and the unequal number of parameters. Instead, we compare the SIC values of the models, and we also rely on a graphical inspection of the estimated jump intensity and ex post jump probability series.

Note that the mean of the jump size distribution is supposed to be constant. Beber and Brandt (2006, 2009) allows for time-varying jump size means which are modelled as functions of news surprises. We also tried several specification for the jump size mean, but it did not result in a much better fit, and the individual parameter estimates were difficult to interpret. Thus we omit those results and we keep the jump size mean constant, but we recognise that this issue should be an important direction for future research.

3.2 Preliminary empirical results

Some simpler models, though not reported here[6], have been estimated first. These models are: (i) a simple model with constant Gaussian volatility; (ii) a simple GARCH (1,1) model; (iii) a simple jump model with constant Gaussian volatility and constant intensity parameter; and (iv) a GARCH-jump model with constant jump intensity. We also implement for all these models an

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

AR process for the conditional mean μ_t. Note that formal comparison of the models is not possible because the models are not nested due to the presence of nuisance parameter(s) in some specifications (λ in the models with jumps, and the GARCH parameters in the models with GARCH errors). Instead, we use SIC to compare models, although it is well known that it is not a formal hypothesis test. Nonetheless, substantial differences in SIC values may be indicative for model choice.

We may conclude the following results. First, the Gaussian-jump 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 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 decrease in the SIC values. GARCH models for money market rates turn out to be non-stationary, i.e. $\omega_1 + \omega_2 > 1$ in equation (5), 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. This also supports our finding that previously realised jumps play a substantial role in the daily variability of money market rates.

Some important results of the GARCH-jump model with constant jump intensity are presented in Table 2. It is clear from the table that the estimated jump intensities are highly significantly different from zero (except that for the 10-year rate, which is only barely significant), suggesting that jumps do matter in the daily variation of euro area interest rates. Although the estimated λ's are quite similar in magnitude (with the exception of that for the 2-year rate which is much smaller), this can be explained by the fact that we set λ to be constant, and other jump statistics exhibit considerably different pictures for rates of different maturities.

[Insert Table 2]

Table 2 also contains the total number of jumps over the sample period, which is the number of days on which the ex-post expected number of jumps, $\mathbb{E}(n_{t-1} \mid \Phi_{t-1})$, is bigger than 0.5.[7] The total number of jumps per year is computed as the number of jumps multiplied by 250 (the average number of trading days in one year), and divided by the number of days in the sample. Finally, the table also contains the average jump contribution to total volatility, which is the

[7] Of course, this is an ad hoc "rule", since there is no theory that would suggest the choice of 0.5. However, a probability bigger than 0.5 can be considered as high. The same rule is used by Beber and Brandt (2009).

average of the ratio of $\lambda_t\left(\sigma_J^2+\mu_J^2\right)$ to the total conditional variance, $\mathbb{V}\mathrm{ar}\left(\Delta r_t \mid \Phi_{t-1}\right)$, given in equation (9).

On average, around 20 jumps per year occurred in the rates of maturities lower than one year, while around 4 per year in swap rates. This is consistent with the visual inspection of Figure 1, although it may also reflect the fact that, due to their larger inherent volatility, jumps in long-term rates are more difficult to identify. The contribution of jumps to total volatility of interest rate differences decreases with maturity, but even for the 10-year maturity is around 20%. This finding is in line with that of Beber and Brandt (2009) for US bond returns, although our results for short rates indicate a much higher contribution of jumps to the total conditional variance. Summarising, it is evident even with constant jump intensity that jumps play a prominent role in the daily evolution of euro area interest rates.

Now we allow for a time-varying jump intensity and apply the ARJI model of Chan and Maheu (2002), defined in equation (12). The estimated coefficients are presented in Table 3. The estimated jump clustering parameter is very high for all rates, and the parameter γ, which measures the change in the conditional forecast of the number jumps as the information set is updated, is below 0.1 for money market rates, whereas is between 0.2 and 0.3 for swap yields. This means that the feedback effect of past shocks is very weak and most of the dynamics in the conditional jump intensity comes from the autoregressive part. As a consequence, the impact of a large realised jump can be long-lived and can systematically deviate the jump arrival process from its unconditional mean, even if it is a single event which induced a jump as, for instance, the September 11, 2001 terrorist attack. The unconditional jump intensities, $\lambda_0/\left(1-\rho\right)$, are higher than the estimated constant jump intensities in Table 2 (except for the 6-month rate), especially in case of the 10-year rate for which is twice as much.

[Insert Table 3]

Table 3 also contains some useful statistics, similarly to Table 2. Before interpreting those statistics, we introduce our macro-jump model, since it is more useful and provides a better insight into the implications of the two different models if we make comparisons between the two specifications, one being a time-series based jump filtering model, while the other being based on fundamentals to identify jumps. We present this comparative analysis in Section 4.5.

4 The role of announcements

The results presented in the previous section do not provide an insight into the factors that drive jumps. It is widely known that the most important motive for changes in financial prices is news arrival. Empirical evidence[8] suggests that the largest yield movements can be observed on days of monetary policy and macroeconomic announcements. To provide some preliminary insight into the importance of announcements, the fifth row of Table 2 shows the proportions of jumps occurred on days on which at least one announcement is released over all jumps. It is evident that around 80% of jumps, estimated by the constant intensity model, occurred on announcement days. This finding does not seem to depend on the maturity of the interest rate, indicating that news releases play an important role in every segment of the yield curve.

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. Moreover, it is reasonable to suggest that rather than an announcement itself, it is the surprise contained in an announcement that moves financial prices. Hence, instead of using dummies, we define a surprise component for each variable. The details are explained later in this section.

4.1 Macroeconomic surprises

A very 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. Moreover, long yields may react to macroeconomic announcements because of their implication for future monetary decisions.

We collected the most important macroeconomic announcements both from the euro area and from the US. In addition to the aggregated euro area variables, numbers from the three biggest euro area economies (Germany, France and Italy) and from the UK were also gathered. The variables taken are of several types: economic activity, employment, price, income and forward-looking. In total, 45 macro announcements are considered here. The variables are displayed in Table 4.

The surprise component, proposed by Balduzzi et al. (2001), is defined as

$$S_t^k = \frac{A_t^k - E_t^k}{\sigma_k} \tag{14}$$

[8] See Fleming and Remolona (1999); Balduzzi et al. (2001) and Johannes (2004), among others.

where A_t^k and E_t^k are the actual and expected values of variable k, respectively, and σ_k denotes the standard deviation of $A_t^k - E_t^k$. The median expectation values taken from surveys conducted by Bloomberg are used as expectations for the macro variables. Overall, if on day t an announcement occurs in variable k, S_t^k takes on the value given in equation (14), 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 Monetary policy surprises

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 have impacts on long-term yields through the expectation hypothesis. To see the importance of central banks' decisions in causing jumps in market rates, the last row of Table 2 shows the proportions of jumps occurred on days when either the ECB or the Fed (or both) held a monetary meeting over all jumps. Consistently with our expectations, jumps in money market rates are more likely to be induced by monetary policy decisions (especially made by the ECB) than those in long-term rates. The finding that only 15% of jumps in the 1-month rate occured on monetary meeting days vis-a-vis the higher value for the 6-month rate will be studied in more detail in Section 4.5.

Hence, we collected all monetary policy decisions of the ECB and the Fed over the sample period. For the ECB's monetary policy surprise the mean of analysts' expectations, collected by Reuters are taken for E_t^k in equation (14). Note that the 50 basis point cuts done by both central banks in September 17, 2001 are omitted as they occurred in non-scheduled meetings; thus, no market expectations are available. It is also noteworthy that the Fed publishes its decisions when the European markets are already closed (20.15 CET), thus the observations for the Fed's surprises are shifted to the following day.

As a surprise component for the Fed's decisions, we follow the methodology of Kuttner (2001)[9], and take the one-day change in the spot-month Fed funds futures rate on announcement days. Evidently, this measure is not standardised by the standard deviation of the surprises, since it is more natural to use it in its original form.

It is desirable to use a similar surprise measure for the euro area as well for two reasons. First,

[9] This approach is standard in the literature and is followed by various authors, see Cochrane and Piazzesi (2002) and Bernanke and Kuttner (2007), among others.

we could easily compare the impacts of the surprises of the ECB and the Fed. Second, we could compare the effects of the two types of ECB surprises. One is based on expectations of analysts taken from surveys some days before the meetings (we call it the *survey measure*), while the other is based on market prices set by investors (we call it the *market measure*). It is important to emphasise the different nature of these two measures. The survey measure reflects analysts' expectations on the *current* decision only, which are gathered *prior* to the decision. On the other hand, the market measure provides information regarding the adjustment taken place in the given interest rate *after* the current decision. This adjustment occurs for two reasons. First, investors may have had different expectations on the current monetary decision, and after the decision is released, they adjust prices to a new level. Second, given that the market measure is defined as the daily difference in closing prices, it must reflect all new information across the trading day. The ECB announces its decision at 13.45 CET on a meeting day, and at 14.30 CET the president holds a press conference where he reads the introductory statement, a comprehensive summary of the Governing Council's assessment of economic developments shaping the monetary policy decision. Moreover, the introductory statement may also provide hints at the future stance of monetary policy, as it happens many times. Therefore, the market measure also reflects the change in market participants' expectations on the ECB's *future* decision within the maturity of the given interest rate.

Unlike the US, 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[10], 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 et al. (2003).

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.[11] Therefore we define the market-based monetary policy surprise as the daily difference in the 1-month Eonia swap rate on meeting days, and zero otherwise.

[10]Eonia (Euro OverNight Index Average) is an effective overnight rate computed as a weighted average of all overnight unsecured lending transactions in the interbank market, initiated within the euro area by the contributing panel banks. It is computed with the help of the ECB, and is the underlying rate of numerous derivatives transactions, such as swaps.

[11]Before November 2001 the ECB held bimonthly meetings, but afterwards it switched to monthly discussions.

4.3 Some descriptive results

Table 4 shows summary statistics for each surprise variable. The average surprise is generally small and statistically indistinguishable from zero.[12] The few cases where the average surprise is significantly different from zero can mostly be explained by the skewed surprise distribution, that is, where the number of negative surprises considerably differs from that of positive surprises. The distribution of negative and positive surprises in the sample also determines the sign of the average surprise in most cases. The number of zero surprises is informative because it indicates the extent to which the value of the macro variable was correctly predicted over the sample period. Many zero surprises are likely to suggest that the news content of the variable rarely surprises markets and induces jumps.[13]

[Insert Table 4]

It is reasonable to think that it is not the sign of the surprise that principally matters in inducing jumps, but rather its *size*. Hence, we report in column 3 of Table 4 the mean absolute surprise for each variable. The dispersion of mean absolute surprises is much smaller than that of mean surprises, and the average absolute surprise for our set of releases is about 0.7, i.e. less than one standard deviation. Therefore, it seems that the unexpected component of very different types of releases is of similar magnitude. This does not imply that jumps should also be approximately equally likely after the release of these announcements, though. This is mainly because investors put different weights on releases, and consider some as crucially important, while others as only marginally important.

As regards monetary policy surprises, the great relevance of transparency in modern central banking should suggest a high proportion of zero surprises. It has to be noted, however, that surprises constructed from market interest rates are less likely to be zeroes as they reflect all new information during the given trading day. Bearing this in mind, it is rather surprising that almost 40% of Fed surprises are zeroes, which may indicate that (i) the Fed's decisions were correctly priced by investors in around 40% of the cases over the sample period, suggesting a high degree of predictability of the Fed's monetary policy; (ii) Fed funds futures are good measures of monetary policy surprises and on announcement days mostly reflect changes in investors'

[12] Recall that, due to the standardisation in equation (14), the variance of surprises is unity, thus the standard error of the average surprise is given by $1/\sqrt{N}$, where N denotes the number of surprises in the sample, $\#\left(S_t^k\right)$.

[13] Of course, this does not mean that such a variable cannot cause sharp movements in financial prices, since a single non-zero surprise is sufficient to induce a jump.

expectations regarding the Fed's monetary stance.[14]

For the market-based surprise of the ECB a different pattern is observed, since around 90% of surprises differ from zero. This must be mainly because very short-term Eonia swap rates are also subject to liquidity issues, although not as much as cash Eonia rates. However, the average market-based surprise is essentially zero and the mean absolute surprise is also very small (around 2.5 basis points), and indeed is smaller than that of the Fed.

Concerning the survey-based ECB surprise, the range of its values is considerably broader than that of macro variables. However, its mean is statistically indistinguishable from zero, and its mean absolute surprise is substantially smaller than that of all macro variables. Moreover, more than half of the ECB's monetary decisions were perfectly predicted, resulting in zero surprises. This suggests a relatively high degree of predictability of the ECB's monetary policy.

The two types of ECB surprises are plotted in Figure 2. There are three conclusions to draw from the figure. First, the high dispersion of survey-based surprises can be explained by a low number of very big surprises (greater than 2 standard deviations in absolute value), shown in the left panel of Table 5. Each of these big surprises occurred on ECB meeting days, and all of them can be associated with unexpected ECB decisions where either the timing of the decision was unexpected, or its magnitude.

[Insert Figure 2]

Second, the signs of the two types of surprises are mostly the same (the correlation coefficient between the two surprise series is approximately 0.7), which may indicate that the two measures are consistent with each other. This is also supported by the fact that the days of the largest surprises of the two measures mostly coincide, see Table 5. Those few cases where they take opposite signs may be explained by the different information sets of the two surprises.

[Insert Table 5]

Finally, the biggest surprises occurred in the first half of the sample period, particularly, prior to November 8, 2001, when the ECB switched from bimonthly meetings to monthly discussions. The reason is that with two meetings a month the timings of the ECB's decisions were hard to anticipate, leading to bigger surprises. After November 8, 2001 the observed surprises of both types are much smaller in magnitude. This is also evident from Table 5, since all the

[14] The usefulness of Fed funds futures to measure monetary policy surprises is examined in more detail by Gürkaynak (2005) and Gürkaynak et al. (2005).

biggest surprises occurred before that date. Table 4 reports the descriptive statistics of the ECB surprises not only for the whole sample, but also for the two subsamples. It is clear from the table that both the mean absolute surprise and the range of surprises are much larger in the first subsample. The improved predictability of the ECB's decisions is reflected in the fact that, while before November 8, 2001 around 40% of the decisions were perfectly predicted, after that date almost two-thirds of the survey-based surprises were zeroes.[15]

4.4 Modelling jump intensity with surprises

The findings of the previous subsection support our prior intuition that it is not the sign of a surprise that matters in inducing jumps, but rather its magnitude. Further, the dominance of release days (particularly monetary meeting days) among days on which a jump occurs suggests that it is reasonable to model the jump intensity as a function of absolute surprises.

Therefore, now we assume that the intensity of the jump arrival process is not constant, but rather time-varying. In particular, our macro-jump model becomes

$$\lambda_t = \frac{\exp(u_t)}{1+\exp(u_t)}, \tag{15}$$

where

$$u_t = \lambda_0 + \sum_{i=1}^{\ell} \lambda_i \left| S_t^i \right|. \tag{16}$$

The exponential transformation guarantees that λ_t, being the probability of a jump, is between 0 and 1. Moreover, ℓ indicates the total number of monetary and macro surprises included into the specification of the jump intensity. Since our set of variables is broad, including all macro surprises at the same time would lead to cumbersome estimation. Instead, we follow the following estimation strategy: we estimate the model for each variable one by one, and we drop the variables that are insignificant in equation (16). Then we estimate the model with all significant surprises jointly. This way our model remains parsimonious and the pre-filtering of the variables helps us to better identify those announcements that drive jump arrivals in euro area interest rates.

[15] The issue of improved predictability of the ECB's decisions after November 8, 2001 is studied by ECB (2002). Also note that another reason for the many zero surprises in the second subsample 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.

4.5 Results

A mere presentation of the estimated coefficients would be counter-productive, thus instead we construct some statistics that help us the understanding and interpretation of the findings and provide a greater insight into the jump dynamics of euro area interest rates. Since monetary policy announcements are of crucial importance in determining market interest rates (mainly at the shortest maturities), we pay a special attention to the impacts of the ECB decisions and first study the extent to which the ECB's monetary policy decisions induced jumps in euro area interest rates over the sample period. The availability of two different measures of monetary policy surprise allows us to assess the relevance of these measures and compare their impact on daily interest rate movements. Then we turn to our broad set of surprise variables and determine the set of macro variables that are likely to produce sharp changes in euro are interest rates.

Since we estimate the ex ante jump probability, λ_t, via an exponential transformation, the mere values of the estimated parameters of equation (16) are not easy to interpret. However, it is easy to compute some useful statistics from the estimates. First, the constant term, λ_0, is related to the probability of a jump on a day without announcement (or with announcement but with zero surprise).[16] This probability, denoted by λ^0, is defined as $\lambda^0 \equiv \exp(\lambda_0) / [1 + \exp(\lambda_0)]$, and is of great interest, since it provides a "benchmark" jump probability for days without data release (or with zero surprise). On the other hand, λ_i, $(i = 1, \ldots, \ell)$, measures the sensitivity of jump intensity to variable i. Hence, a one standard deviation surprise in variable i implies a jump probability $\lambda^i \equiv \exp(\lambda_0 + \lambda_i) / [1 + \exp(\lambda_0 + \lambda_i)]$, everything else being equal.

Note that this last statistic is useful mostly if only one variable is included in equation (16), since in case of concurrent announcements (which occurs more than half of the days in the sample) the contribution of one variable to the jump intensity on a given day is affected by the contribution of other variable(s) too, and these concurrent announcements also affect the parameter estimates. Hence, we only compute this statistic if u_t depends on a single variable.

Some other measures regarding the jump frequency are also computed. In addition to the statistics shown in Table 2, we also report the number of jumps on announcement days over all announcement days, which tells us what proportion of the releases results in a jump. If this proportion is high it means that releases are likely to generate sharp movements in interest rates, instead of a smooth incorporation of the new information into prices. This suggests either that

[16]To be more precise, λ_0 controls for days on which no announcement (or with zero surprise) of the ℓ variables, considered in equation (16), occurs.

markets react very sensitively to any unexpected news of that variable or that new figures of the variable are hard to anticipate.

The following conclusions can be drawn when comparing the general fit of our macro-jump model to that of the ARJI model discussed in Section 3.2. First, the SIC values of the macro-jump model with only monetary variables are significantly lower than those of the ARJI specification for money market rates, see Tables 3 and 6, while for swap yields they are roughly equal. If we include all individually significant news surprises, for the 6-month rate the macro-jump model still yields lower SIC values, while for the other rates the ARJI specification performs better, especially for long-term rates, see Table 7. Hence, it seems that the model which explains jump arrivals with the ECB's unexpected decisions outperforms the time-series approach, while the addition of more explanatory variables leads to a penalisation reflected in the SIC values. Since the SIC is not a formal measure of goodness-of-fit, the comparison of its values only gives us some indications about model performance, rather than a formal decision rule which specification to choose. Since in the macro-jump model several news surprises yield significant impact on jump intensity, and the differences between the SIC values of the ARJI and the macro-jump models are not large and are likely to reflect penalisation for the higher number of parameters, we advocate using the macro-jump model. Another reason for choosing the macro/jump model is that it reflects a structural approach rather than a pure time-series approach, helping the understanding the factors underlying jumps in interest rates.

Second, the number of jumps identified by the ARJI model is similar to that implied by our macro-jump model for all rates, except for the 10-year rate for which the ARJI model identifies 344 jumps in the 10-year rate, comparing to the less than 60 implied by the macro-jump model. Of course, the estimated number of jumps is not a measure of model fit as the identification criteria of jumps are different in the two models, but it sheds some light on how the two models perform for series with different characteristics. The ARJI model assumes that jump intensity is determined endogenously by an autoregressive process, and a high persistence parameter implies that a high probability of a jump today tends to be followed by a high probability of a jump tomorrow. On the contrary, our macro-jump model assumes that jumps are more likely to occur when new, unexpected information appears in the markets. After the news is revealed, prices adjust quickly to their new level[17], and on the following day a jump is likely to occur only if another piece of new information is released. This much faster adjustment after jump innovations

[17]Studies using high-frequency data report very fast price adjustments, see Ederington and Lee (1993, 1995); Andersen et al. (2003, 2007) and Andersson et al. (2009), among many others.

is supported by our estimation results, since the estimates of the parameters of equation (11) show that $\omega_1 < 0$ and $\omega_{1,J} < 0$ for both money market rates[18], implying that the feedback effect after jump innovations is smaller than after normal innovations. In our case the value of $g(\cdot)$ after normal innovations is about 7–8 times bigger than after jump innovations. This lack of persistence in jump innovations can be another reason in favour of our specification, mainly for short rates.

4.5.1 Effects of the ECB's monetary surprises

Table 6 summarises the estimation results of the macro-jump model in which only the ECB's monetary policy surprises are assumed to affect the jump intensity of euro area interest rates. Three models are estimated for each rate: one with the survey-based measure (column (1)), another one with the market-based measure (column (2)), and a third one with both measures jointly (column (3)). The purpose of this last specification is to study which type of ECB surprise is more relevant in inducing jumps in interest rates. As the survey-based measure is backward-looking, while the market-based measure is forward-looking, we expect that the latter will dominate, blurring the impact of the survey-based measure.

The results of the table support our hypothesis. The survey-based measure significantly affects the jump intensity of rates up to 2 years, but when the market-based measure is also included, it becomes insignificant, with the exception of the 1-month rate. This is not surprising because the market-based measure incorporates not only the investors' ex ante expectations regarding the current decision, but also ex post information, such as the introductory statement released by the ECB shortly after the announcement of the decision and the press conference held by the president. Both may contain hints at the future stance of monetary policy, which is captured by the market-based measure but not by the survey-based measure. This is reflected in the estimated coefficients of the two measures, shown in Table 6. For the maturities from 6 months through 10 years the increment in the log-likelihood value of the model with both measures comparing to that with only the market-based measure is negligible. Moreover, whereas the estimated coefficient of the market-based measure does not change much when it is the only explanatory variable and when it is estimated jointly with the survey-based measure, that of the survey-based measure drops substantially when the market-based measure is also included in the

[18] Recall that for long-term yields we did not find evidence on either different effects of normal and jump innovations or asymmetric impacts, while money market rates seem to be characterised by different impacts of normal and jump innovations.

model.

[Insert Table 6]

The only exception is the 1-month rate for which the model with the survey-based measure yields a considerably larger likelihood value than the model with the market-based measure, and it remains highly significant in the joint model. Moreover, unlike for the other rates, in the joint model the coefficient estimates for both measures decrease considerably comparing to the individual models, but both keep their significance. These findings suggest that the jump intensity of the 1-month rate on ECB meeting days can be split up into two components: one related to the current decision only and another related to expectations regarding future decisions. The sizes of these components depend on the particular monetary decision. Assume, for instance, that market participants expect a, say, 50 basis-point cut in the policy rate, but the ECB only cuts 25 basis points, and it hints at a further 25 basis-point cut in its next monetary meeting. In such a case both components are relevant, since the survey-based measure reflects the surprise caused by the current decision, while the market-based measure, which has a maturity of one month, incorporates the additional information given by the ECB. Without any hint about future decisions, the first component will dominate while the second may reflect minor changes in investors' expectations regarding the near future. Because the ECB's main objective is to maintain price stability over the medium term, short-lived shocks are only taken into account in its decisions if they affect this objective. As a consequence, expectations of future policy rate changes have an impact rather on medium and long-term interest rates. This can explain our finding that for very short rates the survey-based surprise is more important than the market-based surprise.

The estimated coefficients of the two measures are not directly comparable, since the survey-based measure is standardised, while the market-based measure is not. However, the statistic λ^i, which provides the probability of a jump when a one standard deviation surprise occurs in variable i, can help us compare the impacts of them. Since the market-based measure is not standardised, we multiply λ_i by its sample standard deviation (around 4.6 basis points) when computing the λ^i statistic. Table 6 shows that a one standard deviation monetary policy surprise leads to a very high probability of a jump in money market rates. The estimated jump probabilities are quite similar across the two measures for all rates but the 1-month rate, for which a one standard deviation surprise in the survey-based measure induces an almost sure jump, while in the market-based measure leads to a jump probability of 0.63. This big difference between the jump intensities supports our explanation above, namely that at such a short maturity it is the current decision that matters and new information regarding the future stance of monetary policy generate sharp movements only if a change occurs within the maturity of the 1-month rate.

The table also shows that about every fifth jump in the 1-month, 2-year and 10-year rates occur on ECB meeting days, while for the 6-month rate the proportion is almost 0.4. These numbers are considerably larger than those in the last row of Table 2, indicating again that, by making the jump intensity depend on monetary policy surprises, more, possibly smaller, jumps can also be identified. Due to the different total number of jumps in each rate, however, the absolute numbers exhibit a heterogeneous pattern according to which money market rates, not surprisingly, dominate. The fact that the 6-month rate is more exposed to jumps on ECB meeting days than the 1-month rate may support our rationale above that changes in expectations regarding future decisions are the main sources of sharp movements in market interest rates of not very short maturities rather than surprises in current decisions.

According to the last row of both panels of Table 6, about one-third of ECB meeting days are characterised by a jump in the 1-month rate; this ratio goes up to almost one half for the 6-month rate, while for swap yields it remains below 10%. This points 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, 2002; Poole et al., 2002). However, as we explain in Section 4.3, this can be related to the period prior to November 8, 2001 when the ECB held bimonthly meetings and the exact timing of its decisions were hard to anticipate. Our results show that this is indeed the case: the proportions of jumps on ECB meeting days before November 8, 2001 are 62%, 58%, 83% and 73% for the four rates, respectively. That is, after switching to monthly monetary discussions, the ECB has rarely surprised markets with its decisions.

4.5.2 Results for macroeconomic surprises

Now we consider the model that jointly estimates all monetary and macroeconomic surprise variables which have been significant individually in equation (16). Since for the maturities from 6 months up to 10 years the survey-based ECB surprise measure becomes insignificant when it is jointly estimated with the market-based measure, we omit it from the estimation for these maturities. The key estimation results are presented in Table 7.

The following findings can be derived from the table. First, the coefficients of the ECB surprise variables are very close to those in Table 6. This means that, even if there are concurrent announcements on monetary meeting days, the ECB's interest rate decisions are the main drivers of jumps in interest rates on those days. For example, the US initial jobless claims figures are released at the weekly frequency and almost always on a Thursday[19], which is also the typical ECB meeting day[20]. While the initial jobless claims surprise variable is significant individually, when it is included jointly with the monetary policy surprise variable, it becomes insignificant, and even negative for the 10-year rate, suggesting that its individual significance reflected the impact of unexpected monetary decisions rather than that of its own content.

[Insert Table 7]

Second, the Fed's surprise component is insignificant for money market rates, but is highly significant for long-term yields, reaching its maximum at the 2-year maturity. Its estimated coefficient cannot be compared to those of other macro variables, since it is not standardised, but using its sample standard deviation it is easy to convert the coefficients to implied probabilities. A one standard deviation surprise in the Fed's decision (around 5 basis points) induces a jump probability of 0.43 in the 2-year rate (everything else being equal), and 0.06 in the 10-year rate. The same probabilities for the ECB's market-based measure are 0.07 and 0.03, respectively. Hence, euro area longer term yields seem to be more likely to jump due to surprises in the Fed's decisions than to unexpected ECB decisions. This can be explained by the Fed's different objective function from the ECB's. While the ECB has a single main objective, price stability, the Fed aims, besides stable prices, maximum employment and moderate long-term interest rates. As a consequence, an unexpected Fed decision will be more likely to be reflected in bond prices in the US, and, because of the strong market linkages, in the euro area too. On the other hand, the ECB only indirectly affects medium and long-term rates through changes in investors' expectations.

Third, the set of relevant macroeconomic variables is quite heterogeneous both across and within maturities. Within maturities there are both real economy variables (such as production and employment), prices, income variables and forward-looking variables. Across maturities there are variables that only affect one interest rate (euro area industrial production, euro area

[19] Of the 405 initial jobless claims releases 392 occurred on a Thursday.

[20] Of the 128 monetary policy releases 121 occurred on a Thursday, and 116 of those are also characterised by an initial jobless claims release.

business climate, US GDP advance, US durable goods orders and US consumer credit) and others that have impacts on several rates. The only variable that appears in the model of all interest rates is the French business confidence index, although it becomes insignificant for money market rates when it is estimated jointly with other news surprises. Among euro area price variables, only PPI seems important, probably because it is always released before consumer prices, so is an early indicator of inflation. Real economy variables affect mostly longer term yields, and their effect is the strongest for the 10-year rate.

Fourth, US announcements matter. This is in line with previous findings (see Andersson et al., 2009), and some possible reasons behind this result are the leading role of the US in the world economy, the strict and predictable announcement schedule of US economic figures, and possible leakings prior to the official announcement time for some euro area variables.[21]

Regarding jump statistics, the inclusion of several monetary and macro surprises in the jump intensity does not involve a considerable increase in the number of jumps. Unlike the ARJI model, the estimated jump frequencies in Table 7 are not much higher than those obtained by either the constant jump intensity model or the model with only monetary policy surprises. This may suggest that the ARJI model overestimates the number of jumps due to its autoregressive structure (mainly for long rates for which jump innovations are more difficult to distinguish from normal innovations because of the bigger inherent volatility), while our macro-jump model is able to identify jumps more precisely by associating jumps with public information releases. As a further support to this, the table shows that the most jumps occur on announcement days: the ratio is almost 60% for the 1-month rate, and it increases over 90% for the 10-year rate. The ARJI model implies about 80% for all rates, but part of it may come from the autoregressive structure of jump arrivals, since the ARJI model is not able to directly link the probability of jumps to news release days. The high proportion of jumps on announcement days does not mean, however, that announcement days in general are characterised by jumps, since, as the last row of Table 7 shows, on overall less than one-fifth of release days occurs a jump, and this number drops to around 5% for long-term yields.

The probability of a jump on a day without news release (or with release(s), but with zero surprise), captured by λ^0, is low for all rates, and in particular for the 10-year rate it becomes insignificant. This suggests that news surprises constitute a big proportion of sources of jumps, and the remaining factors are almost negligible.

[21]For example, Andersson et al. (2009) provides compelling evidence that new German unemployment figures are systematically leaked before release for political reasons.

5 Modelling the term structure

So far we have estimated models with jumps 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 21 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 and Siegel (1987) model, modified by Diebold and Li (2006).[22] Three time-varying 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.

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 in months, by using the following three-factor model:

$$r_t(\tau) = \beta_{1t}F_{1t} + \beta_{2t}F_{2t} + \beta_{3t}F_{3t}, \tag{17}$$

with

$$\begin{aligned} F_{1t} &= 1 \\ F_{2t} &= \frac{1 - e^{-\eta_t \tau}}{\eta_t \tau} \\ F_{3t} &= \frac{1 - e^{-\eta_t \tau}}{\eta_t \tau} - e^{-\eta_t \tau} \end{aligned} \tag{18}$$

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}, 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

[22] 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, but rather in find a good fit for the observed data. In Christensen et al. (2007), it is reconciled the Nelson-Siegel model with the absence of arbitrage. Coroneo et al. (2008) studies whether the original Nelson-Siegel model is arbitrage-free in the statistical sense and they cannot reject the hypothesis that the loading structures of the Nelson-Siegel and a no-arbitrage model are equal.

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, a widely used empirical measure of the slope of the term structure. 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 $2r_t\,(\text{2-year}) - r_t\,(\text{3-year}) - r_t\,(\text{10-year})$.[23]

We estimate the latent factors, β_{jt} $(j = 1, 2, 3)$, by fixing η_t at a pre-specified value[24], by ordinary least squares for each day t. That is, a total of 2014 estimates are obtained, denoted by $\hat{\beta}_{jt}$. Figure 3 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: 0.93 (level), 0.98 (slope) and 0.99 (curvature), pointing to a very accurate fit. 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 3]

5.2 Modelling issues

The literature does not provide a "benchmark" model for studying empirically the effects of macroeconomic variables 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 filtering techniques. However, in the previous sections we have seen that there is overwhelming evidence of jumps in individual interest rates, thus it is reasonable to think that yield curve factors, being estimated from cross sections of individual rates and being very highly correlated with linear functions of observed rates, are also exposed to jumps.

Descriptive statistics of the latent factors (not shown here) exhibit non-normality, although

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

[24] 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 0.06. This value for η_t was kept fixed while we estimated again equation (17) by ordinary least squares, and obtained the daily $\hat{\beta}_{jt}$ 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.

the excess kurtosis values are lower than those for the four individual interest rates in Table 1. Moreover, analysis of serial correlation shows 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 inherit the dynamic properties of individual rates which are clearly conditionally heteroskedastic, but most papers so far have only considered the constant volatility case.

Preliminary estimations, similar to those described in Section 3.2, show that the constant-intensity GARCH-jump model outperforms both simple GARCH and simple jump models in terms of SIC values for all factors, even though λ does not result statistically significant for $\Delta\hat{\beta}_{2t}$. Therefore, in addition to the constant jump intensity model, we estimate for the $\Delta\hat{\beta}_{jt}$ series two other specifications: the ARJI(1,1) model and the macro-jump model. The main advantage of our macro-jump model over the model of Diebold et al. (2006) is that, instead of the somewhat arbitrarily chosen macro variables, we use a broad set of monetary and macro variables and let the data tell which variables drive the jump dynamics.

That is, jump intensity is modelled as in equations (15)–(16). For $\Delta\hat{\beta}_{1t}$, we have found no statistical evidence for the hypotheses that normal and jump innovations affect differently future expected volatility and that positive and negative innovations (either normal or jump) have asymmetric effects on expected volatility. Hence, a simple GARCH(1,1) seems adequate for the modelling of σ_t^2 for this variable. On the other hand, for $\Delta\hat{\beta}_{2t}$ and $\Delta\hat{\beta}_{3t}$ the likelihood-ratio tests indicate that normal and jump innovations impact on expected volatility in a different but symmetric way. That is, for these variables σ_t^2 is modelled as $\sigma_t^2 = \omega_0 + g\left(\boldsymbol{\theta}, \Phi_{t-1}\right)\varepsilon_{t-1}^2 + \omega_2\sigma_t^2$, where $g\left(\boldsymbol{\theta}, \Phi_{t-1}\right) = \exp\left[\omega_1 + \omega_{1,J}\mathbb{E}\left(n_{t-1} \mid \Phi_{t-1}\right)\right]$. Preliminary data analysis also suggests to include two autoregressive terms in the conditional mean of $\Delta\hat{\beta}_{1t}$, and one lag for the other two factors.

5.3 Estimation results

The estimated constant jump intensities are 0.35, 0.13 and 0.06 for the level, slope and curvature factors, respectively.[25] The value for $\Delta\hat{\beta}_{1t}$ is quite large and suggests that the level of the euro area yield curve is very likely to jump. The constant jump intensity model implies that ex post 209 jumps occurred in $\Delta\hat{\beta}_{1t}$ over the sample period, and almost 80% of them occurred on announcement days. For the slope and curvature components, the number of realised jumps are

[25]The estimation results of the constant jump intensity model are not presented here to save space, but are available upon request.

56 and 53, respectively.

Panel A of Figures 4–6 plots the estimated yield curve factors. As the scale of the three graphs is the same, it is easy to notice that while the time series of $\Delta\hat{\beta}_{1t}$ is very smooth, $\Delta\hat{\beta}_{3t}$ exhibits by far the largest volatility with some big outliers. $\Delta\hat{\beta}_{2t}$ lies somewhere in between the two, showing relatively small variability with some occasional bigger movements. Hence, the large λ obtained for the level factor must reflect many small jumps rather than rare big jumps. As a consequence, we may expect from our previous results that the ARJI model will identify a large number of jumps for the level and slope factors, while the macro-jump model will imply less jumps, but also a better link between specific monetary and macroeconomic factors and jumps in yield curve factors.

[Insert Table 8]

The ARJI model, as for individual rates, exhibits a very high degree of persistence for the arrival of jump innovations and a relatively weak feedback from already realised jumps, see Table 8, suggesting that the model is likely to overestimate the number of jumps. An exception may be the curvature for which ρ takes a moderate value, and the feedback effect from previously realised jumps is much stronger than for the other factors. The table clearly shows that the ARJI model identifies 508 jumps in the level factor and 420 in the slope, indicating that about one-fifth—one-fourth of observations are affected by jump innovations. These numbers seem very high, and they probably reflect that both the level and slope series are very smooth with small overall volatility, thus it is not easy empirically disentangle jump innovations from normal shocks.

The key estimation results of the macro-jump are presented in Table 9. Similarly to Table 7, only those surprise variables are included in the model which have been significant individually. It is evident from the table that the set of variables that drive the jump arrival process of yield curve factors is very similar to the one observed for individual interest rates. This is not surprising, of course, since the latent factors are estimated from cross sections of individual rates. The SIC values are smaller than those of the ARJI model, providing a non-formal proof for the better fit of the macro-jump model.

Monetary policy surprises are not relevant in explaining jumps in the level of the term structure, which is not surprising given that monetary policy can only affect directly the very short end of the yield curve, while its impacts via changing investors' expectations on longer-term yields are rather indirect. Hence, monetary policy surprises are more likely to have an effect on the slope of the term structure. This is exactly the case, as Table 9 shows, since both the

ECB's market-based surprise and the Fed's surprise are significant in the slope factor. Given our findings about the impact of the Fed's surprise on individual rates, it is reasonable to think that the Fed's unexpected decisions are likely to affect the slope by inducing jumps in long rates rather than in short rates. The opposite must hold for the ECB's market-based surprise which has an impact mainly on the short end of the term structure. The survey-based measure is significant only individually, but it becomes insignificant when estimating jointly with the market-based measure. Hence, expectations regarding future decisions matter more in the slope than surprises in current decisions.

Regarding the curvature, all the three monetary policy surprises are likely to generate jumps in the curvature of the yield curve. Now the survey-based measure seems very relevant, probably because an unexpected decision is able to change the shape of the whole term structure. The estimated coefficient of the survey-based measure is much higher than those of macroeconomic news surprises, emphasising the role of monetary policy in determining the shape of the yield curve. In addition to surprises in the current decision, ECB statements and hints also seem important as the very high coefficient estimate shows.

[Insert Table 9]

Concerning the impacts of the macro variables, US releases matter again, and the non-farm payrolls announcement seems to be the most important among them. This variable, released with the US employment report, is considered as the "king of announcements" by many researchers and market participants, and its new figures are always very widely monitored by markets. Our results show that this announcement is likely to generate jumps across the whole term structure, although it affects mostly the curvature and the slope, that is, the medium and long-term factors. The other variable which also affects all three latent factors is the US ISM manufacturing business confidence index, although it becomes insignificant in the level. There are only two significant euro area variables: industrial production that has an effect on the slope (short-term factor) and the business climate index which affects the curvature (medium-term factor). Comparing the coefficients in Table 9 to those in Table 7 it is evident that news surprises have a stronger impact on the jump arrival process of yield curve factors than on individual rates. This may be because an unexpected economic figure is likely to affect more than one individual interest rate, so increasing the probability of inducing a jump in a segment of the term structure.

The induced number of jumps for the level factor are even higher than that of the ARJI model, reflecting the difficulty to identify jumps in such a smooth series. A further evidence for this is the very high value of λ^0 (about 0.3), which suggests that in additions to the three macroeconomic variables, much remain to explain the jump arrival process. Concerning the slope, the number of jumps is much lower than that of the ARJI specification, probably because of the better identification of jumps in the series. Recall from Panel A of Figure 5 that the time series of $\Delta\hat{\beta}_{2t}$ is also very smooth with a low number of sharp movements. On the contrary, for the curvature factor the macro-jump model identifies as twice as many jumps than the ARJI model. This may be explained by the much smaller persistence parameter and the much larger feedback parameter for this factor, shown in Table 8, which leads to a lower number of jumps. However, if we associate the likelihood of jumps with the surprise component of announcements, we are able to detect more jumps.

Similarly to the case of individual rates, the ARJI model implies that around 80% of jumps in all factors occurred on announcement days. However, the macro-jump model exhibits a bigger heterogeneity and shows that jumps in the curvature factor are most frequently occur on announcement days, while this ratio is only about two-thirds for the slope factor. The last row of Table 9 shows that the proportion of announcement days with jumps is not very high (except for the level, which can be explained by the above reasons), although larger than for individual rates in general.

[Insert Figures 4–6]

Figures 4–6 plot the time series of the three factors, the contribution of jumps to total volatility, as well as the ex ante and ex post measurements of jump intensity, both for the ARJI and for the macro-jump model. It is clear from the graphs that jumps contribute substantially to conditional volatility, especially in case of the slope factor for which some huge jumps contributions can be observed. These are all related to unexpected monetary policy decisions of the ECB, providing other evidence that monetary policy affects considerably the slope of the yield curve. Regarding the graphs of λ_t and $\mathbb{E}\left(n_t \mid \Phi_t\right)$, the difference between the two specifications of jump intensity is obvious from the graphs. For the level and the slope the persistence parameter is very high, implying that the jump intensity can systematically deviate from its unconditional mean, and this is what we can observe. For the curvature this persistence is smaller and the feedback from past jumps is bigger, which is reflected in less but sometimes very big deviations from the unconditional mean. As regards the macro-jump model, the estimated ex ante and ex post probabilities are usually small with high peaks on days when big surprises occur.

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. A simple GARCH-jump 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 some possible factors and shows some simple applications for the short rate in the US, but does not provide a general approach to identify the factors underlying jumps in interest rates. We propose a macro-jump model which assumes that the jump arrival process depends on the magnitude of news surprises of monetary policy and macroeconomic variables. We have extended this 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.

For comparison, we have also estimated a pure time series model to describe jump intensity, the ARJI model. Our results show that for series with larger inherent volatility and jumps of smaller magnitude, the ARJI model identifies a large number of jumps because of its autoregressive structure. On the other hand, our macro-jump model follows a more structural approach and associates the likelihood of jumps with the size of the unexpected content of releases. This way we gain more insight into the economic factors underlying jumps in interest rates, and we can possibly better identify jumps.

The most relevant variables appear to be the ECB's monetary policy surprise, and further analysis revealed that survey-based surprises only affect very short-term rates, but for longer maturities the expectations' regarding future decisions dominate, which is reflected by the big relevance of the market-based measure. Regarding the macro variables, US releases matter, and the set of relevant variables is quite heterogeneous both within and across maturities.

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. After studying the statistical properties of these factors, we employ our macro-jump 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. The ARJI model seems to overestimate the jump frequency, while the macro-jump model provides similar results to those for individual rates. The ECB's unexpected monetary policy decisions affect both the slope and the shape of the term structure, while the set of macroeconomic variables is very close to that found for individual rates. The most important macro variable turns out to be the US non-farm payrolls release, which is a very widely monitored indicator, and considered as the "king of announcements".

Possible future directions for research include the modelling the mean (and possibly the variance) of the jump size distribution in a time-varying fashion. Another interesting direction can be the analysis of the impacts of jumps on higher moments, such as skewness and kurtosis. This would help us understand better how the return distribution changes after a jump, and it can be of great importance for risk management.

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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 February 18, 1999 through December 29, 2006. Weekends and holidays are excluded from the data set, providing 2014 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 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 40th order for the squared first differences of daily interest rates. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	EURIBOR		Euro swap rates	
	1-month	6-month	2-year	10-year
PANEL A: Interest rate level (r_t)				
Mean	3.028	3.130	3.532	4.716
Median	2.844	3.049	3.408	4.556
Max	5.046	5.202	5.591	6.157
Min	2.016	1.923	2.014	3.178
Std	0.901	0.911	0.920	0.794
VC	0.298	0.291	0.261	0.168
ADF	0.232	0.502	0.216	-0.272
PANEL B: Interest rate difference (Δr_t)				
Mean	3×10^{-4}	4×10^{-4}	5×10^{-4}	-1×10^{-4}
Median	0.000	0.000	-0.001	-0.001
Max	0.432	0.177	0.332	0.187
Min	-0.418	-0.266	-0.372	-0.147
Std	0.025	0.021	0.044	0.042
Skew	-1.545	-1.098	0.109	0.397
Kurt	119.349	29.587	9.613	4.282
LB	147.667***	83.462***	212.985***	535.008***
ADF	-38.888***	-25.754***	-43.916***	-45.833***

Table 2: GARCH-Poisson-Gaussian process with constant jump intensity

Daily data of euro area interest rates for the period February 18, 1999 to December 29, 2006. The table contains the key results for the GARCH-Poisson-Gaussian model with constant jump intensity parameter. The model is defined as $\Delta r_t = \mu_t + \varepsilon_{1,t} + \varepsilon_{2,t}$, where $\mu_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \Delta r_{t-i}$, $\varepsilon_{1,t} = \sigma_t z_t$, $\varepsilon_{2,t} = \sum_{k=1}^{n_t} J_{t,k} - \mu_J \lambda$, $z_t \sim \mathcal{N}(0,1)$, $J_t \sim \mathcal{N}\left(\mu_J, \sigma_J^2\right)$, and n_t is a Poisson process, approximated by a Bernoulli distribution with probability of a jump equal to λ. σ_t follows a GARCH(1,1) process, $\sigma_t^2 = \omega_0 + \omega_1 \varepsilon_{t-1}^2 + \omega_2 \sigma_{t-1}^2$, where $\varepsilon_{t-1} = \varepsilon_{1,t-1} + \varepsilon_{2,t-1}$. It is assumed that z_t, J_t and n_t are independent. We use one lag in the 1-month series, two lags in the 6-month series, and no lags in the daily differences of swap yields. The # of jumps is the number of days on which the ex-post expected number of jumps, $\mathbb{E}\left(n_{t-1} \mid \Phi_{t-1}\right)$, is bigger than 0.5. The # of jumps per year is computed as the # of jumps multiplied by 250 (the average number of trading days in one year), and divided by the number of days in the sample. The average jump contribution to total volatility is the average ratio of $\lambda\left(\sigma_J^2 + \mu_J^2\right)$ to the total conditional variance, $\mathbb{V}\mathrm{ar}\left(\Delta r_t \mid \Phi_{t-1}\right)$. The # of jumps on announcement days over all jumps is the ratio of the number of jumps that occurred on a day with at least one release to the total number of jumps. The # of jumps on monetary meeting days over all jumps is the ratio of the number of jumps that occurred on a day on which either the ECB or the Fed (or both) held a monetary meeting to the total number of jumps.

	EURIBOR		Euro swap rates	
	1-month	6-month	2-year	10-year
λ	0.1042 (0.0084)	0.1170 (0.0137)	0.0398 (0.0135)	0.1113 (0.0692)
log-L	7103.90	5664.04	3590.11	3639.79
SIC	−14146.96	−11259.61	−7126.97	−7226.33
# of jumps	172	126	26	41
# of jumps per year	21.37	15.66	3.23	5.09
Average jump contribution to total volatility	0.8697	0.6499	0.2657	0.2070
# of jumps on announcement days over all jumps	0.8108	0.8777	0.7692	0.7805
# of jumps on monetary meeting days over all jumps	0.1459	0.2518	0.1154	0.0732

Table 3: Estimation results of the ARJI(1,1) model for individual interest rates

The table contains the key estimates of the ARJI(1,1) model for individual euro area interest rates. The model assumptions and the statistics are the same as the ones presented in Table 2, but now λ_t is modelled as $\lambda_t = \lambda_0 + \rho\lambda_{t-1} + \gamma\xi_{t-1}$, where $\xi_{t-1} \equiv \mathbb{E}(n_{t-1} \mid \Phi_{t-1}) - \lambda_{t-1}$.

	EURIBOR		Euro swap rates	
	1-month	6-month	2-year	10-year
λ_0	0.0011 (0.0007)	0.0052 (0.0023)	0.0072 (0.0033)	0.0027 (0.0017)
ρ	0.9917 (0.0054)	0.9516 (0.0189)	0.8583 (0.0591)	0.9890 (0.0062)
γ	0.0444 (0.0122)	0.0951 (0.0287)	0.2747 (0.1047)	0.2004 (0.0787)
μ_J	0.0010 (0.0006)	0.0003 (0.0021)	0.0360 (0.0137)	0.0153 (0.0061)
σ_J	0.0649 (0.0032)	0.0470 (0.0030)	0.0969 (0.0116)	0.0509 (0.0040)
log-L	7133.28	5677.77	3598.17	3646.02
SIC	−14190.49	−11271.86	−7127.87	−7223.58
# of jumps	202	145	35	344
# of jumps on announcement days over all jumps	0.8317	0.8414	0.8000	0.7645
# of jumps on announcement days over all announcement days	0.1077	0.0782	0.0179	0.1685

Table 4: Descriptive statistics of announcements

	Mean	Abs. mean	Min.	Max.	$\#\left(S_t^k\right)$	$\#\left(S_t^k<0\right)$	$\#\left(S_t^k>0\right)$	$\#\left(S_t^k=0\right)$
				Monetary policy				
Fed surprise*	−0.0068	0.0289	−0.2300	0.1500	63	19	19	25
ECB surprise (market)*								
whole sample	0.0018	0.0258	−0.2250	0.2000	128	52	62	14
before 08/11/2001	−0.0017	0.0359	−0.2250	0.2000	66	26	31	5
after 08/11/2001	0.0054	0.0150	−0.0900	0.0875	62	26	31	5
ECB surprise (survey)								
whole sample	0.0830	0.4361	−5.4785	3.8868	128	26	35	67
before 08/11/2001	0.1686	0.6706	−5.4785	3.8868	66	16	23	27
after 08/11/2001	−0.0081	0.1865	−1.6288	0.9966	62	10	12	40
				Euro area aggregated				
Industrial production	−0.1052	0.7862	−3.0562	1.7191	69	36	30	3
Retail sales	−0.0473	0.7917	−2.6116	1.6898	52	24	26	2
Unemployment	−0.3114	0.5989	−2.7309	2.7309	57	16	5	36
PPI	−0.1239	0.6196	−2.7758	2.7758	56	14	9	33
Harmonised CPI	−0.0244	0.6111	−1.4912	2.9823	61	13	11	37
M3	0.3360	0.8498	−1.7639	2.7718	51	18	29	4
Manufacturing PMI	0.0021	0.8065	−2.5474	2.5474	76	30	32	14
Business climate	0.0543	0.5279	−1.4604	1.6183	48	23	25	0
Consumer confidence	0.0980	0.7166	−1.7396	3.0444	63	18	20	25
				Euro area national				
Industrial production (GE)	−0.2366	0.7830	−2.4975	1.7839	76	42	32	2
ZEW (GE)	−0.1526	0.8137	−2.5913	2.4713	58	32	26	0
IFO (GE)	0.2848	0.8932	−2.1985	2.7847	53	21	30	2

Continued on next page

Table 4: Descriptive statistics of announcements

	Mean	Abs. mean	Min.	Max.	$\#(S_t^k)$	$\#(S_t^k<0)$	$\#(S_t^k>0)$	$\#(S_t^k=0)$
Business confidence (FR)	−0.1648	0.7199	−2.9078	1.4539	55	20	19	16
CPI (IT)	−0.1763	0.4681	−4.3403	1.2401	51	14	18	19
Retail price index (UK)	0.0387	0.7501	−2.1112	2.1112	91	34	32	25
Nationwide house price index (UK)	0.3693	0.8617	−1.1489	3.2825	32	11	18	3
Business confidence (BE)	−0.0498	0.7928	−2.7734	2.9071	51	27	23	1
					US			
Industrial production	−0.1113	0.8382	−3.1376	2.4403	94	48	36	10
GDP preliminary	0.3957	0.8705	−2.1104	2.1104	32	10	19	3
GDP advanced	−0.1420	0.8834	−2.0783	1.7116	31	20	11	0
GDP final	0.0131	0.7449	−2.0908	2.0908	32	12	13	7
Factory orders	0.0686	0.7991	−3.3111	3.3111	94	35	54	5
Durable goods orders	0.0117	0.7652	−2.8384	3.7384	95	45	48	2
Business inventories	0.1610	0.8350	−3.7425	2.8069	93	30	46	17
Retail sales	0.0685	0.7997	−2.6251	3.3411	94	43	43	8
Non-farm payrolls	−0.3579	0.7795	−3.2448	1.9183	94	59	35	0
Initial jobless claims	0.0126	0.7657	−3.9906	4.4964	406	197	199	10
PPI	0.0109	0.7104	−2.4767	3.0959	95	44	40	11
CPI	−0.0849	0.7980	−2.3939	2.3939	94	34	30	30
GDP deflator	−0.0056	0.7070	−3.4514	1.8983	31	14	16	1
Building permits	0.2212	0.8494	−1.5091	2.7005	53	24	29	0
Housing starts	0.1716	0.8575	−2.7520	2.7846	95	41	54	0
Capacity utilisation	−0.0418	0.7732	−2.5914	2.2675	93	45	39	9
Consumer credit	0.0526	0.8548	−2.7850	2.8608	94	48	45	1
Consumer spending	0.0952	0.7446	−2.5242	2.5242	88	38	45	5

Continued on next page

Table 4: Descriptive statistics of announcements

	Mean	Abs. mean	Min.	Max.	$\#(S_t^k)$	$\#(S_t^k<0)$	$\#(S_t^k>0)$	$\#(S_t^k=0)$
Existing home sales	0.2957	0.8535	−3.2187	3.7394	93	32	58	3
New home sales	0.2151	0.8140	−2.3657	3.4773	94	38	56	0
Personal income	0.1147	0.6536	−1.8559	6.4956	93	31	39	23
Trade balance	−0.1112	0.8336	−3.5485	2.7824	95	50	42	3
University of Michigan consumer sentiment index	−0.1176	0.8215	−2.5165	2.3385	91	51	40	0
ISM manufacturing business confidence	−0.0028	0.8021	−2.3713	3.7335	89	50	37	2
ISM non-manufacturing business confidence	0.1664	0.8282	−1.9903	2.4656	93	39	53	1
Chicago PMI	0.1245	0.8447	−2.8305	2.2788	94	42	52	0
Consumer confidence	0.0400	0.7903	−2.7600	2.5901	94	44	50	0
Philadelphia Fed index	−0.0880	0.7800	−3.4841	1.8953	95	49	46	0

* Not standardised surprises.

Table 5: The biggest monetary policy surprises of the ECB

The table presents the biggest monetary policy surprises of the ECB, both survey and market-based. A survey-based surprise is considered as big if its absolute value exceeds 2 standard deviations, whereas a big market-based surprise is defined as one with an absolute value greater than 10 basis points.

	Survey-based		Market-based	
Date	Surprise	Note	Surprise	Note
April 8, 1999	−5.48	50bp cut	−0.23	50bp cut
July 15, 1999	—	—	−0.13	No specific event
November 4, 1999	2.78	50bp raise	—	—
February 3, 2000	2.35	25bp raise	—	—
April 27, 2000	2.81	25bp raise	—	—
June 8, 2000	3.89	50bp raise	0.20	50bp raise
October 5, 2000	2.78	25bp raise	—	—
April 11, 2001	2.82	Expected cut that did not occur	0.14	Shortfall of bids in the main refinancing operations conducted on April 10, 2001*
May 10, 2001	−3.55	25bp cut	−0.21	25bp cut
October 11, 2001	2.25	Expected cut that did not occur	—	—

* See ECB (2001) for more detail.

Table 6: The impacts of monetary policy surprises on individual interest rates

The table presents the key results of the macro-jump model with time-varying jump intensity parameter for individual euro area interest rates. The model is the same as the one presented in the notes of Table 2, but now the jump intensity is defined as $\lambda_t = \exp(u_t) / [1 + \exp(u_t)]$, where $u_t = \lambda_0 + \sum_{i=1}^{\ell} \lambda_i \left|S_t^i\right|$. σ_t follows a GARCH(1,1) process, $\sigma_t^2 = \omega_0 + \omega_1 \varepsilon_{t-1}^2 + \omega_2 \sigma_{t-1}^2$ for the 2-year and 10-year rates, while for the 1-month and 6-month rates, σ_t is defined as $\sigma_t^2 = \omega_0 + g(\boldsymbol{\theta}, \Phi_{t-1}) \varepsilon_{t-1}^2 + \omega_2 \sigma_{t-1}^2$, where $g(\boldsymbol{\theta}, \Phi_{t-1}) = \exp\left[\omega_1 + \omega_{1,J} \mathbb{E}(n_{t-1} \mid \Phi_{t-1})\right]$. The statistics in the table are: $\lambda^0 \equiv \exp(\lambda_0) / [1 + \exp(\lambda_0)]$ and $\lambda^i \equiv \exp(\lambda_0 + \lambda_i) / [1 + \exp(\lambda_0 + \lambda_i)]$.

	1-month (1)	1-month (2)	1-month (3)	6-month (1)	6-month (2)	6-month (3)
ECB survey	7.0502 (1.6695)	—	4.9581 (1.4834)	10.5544 (4.3456)	—	−0.0224 (0.7442)
ECB market	—	61.3941 (12.5548)	31.8304 (11.5807)	—	119.2703 (31.4300)	119.7050 (34.6786)
λ^0	0.0972 (0.0087)	0.0917 (0.0085)	0.0942 (0.0087)	0.1087 (0.0132)	0.0988 (0.0125)	0.0987 (0.0125)
λ^i	0.9920 (0.0132)	0.6335 (0.1348)	—	0.9998 (0.0009)	0.9646 (0.0491)	—
μ_J	0.0004 (0.0006)	0.0004 (0.0006)	0.0005 (0.0006)	−0.0027 (0.0018)	−0.0029 (0.0019)	−0.0029 (0.0019)
σ_J	0.0689 (0.0037)	0.0704 (0.0040)	0.0691 (0.0037)	0.0445 (0.0029)	0.0450 (0.0030)	0.0450 (0.0030)
log-L	7142.28	7137.23	7146.49	5685.31	5700.00	5700.00
SIC	−14216.11	−14206.00	−14216.91	−11294.57	−11323.93	−11316.32
# of jumps	187	177	187	157	154	154
# of jumps on ECB meeting days over all jumps	0.2139	0.2034	0.2246	0.3822	0.3831	0.3831
# of jumps on ECB meeting days over all ECB meeting days	0.3150	0.2835	0.3307	0.4724	0.4646	0.4646

	2-year (1)	2-year (2)	2-year (3)	10-year (1)	10-year (2)	10-year (3)
ECB survey	1.1389 (0.4259)	—	−0.3112 (0.7677)	0.7942 (1.0045)	—	0.0156 (1.1511)
ECB market	—	27.2632 (8.9078)	31.5076 (13.4487)	—	24.7661 (13.3143)	27.5746 (19.3550)
λ^0	0.0348 (0.0127)	0.0306 (0.0105)	0.0297 (0.0104)	0.1189 (0.0722)	0.1071 (0.0627)	0.1071 (0.0628)
λ^i	0.1012 (0.0515)	0.1001 (0.0441)	—	0.2299 (0.2325)	0.2738 (0.1625)	—
μ_J	0.0367 (0.0185)	0.0413 (0.0200)	0.0435 (0.0213)	0.0210 (0.0111)	0.0222 (0.0114)	0.0222 (0.0114)
σ_J	0.1064 (0.0164)	0.1119 (0.0165)	0.1131 (0.0170)	0.0478 (0.0083)	0.0491 (0.0081)	0.0491 (0.0081)
log-L	3595.71	3597.40	3597.48	3640.49	3641.34	3641.34
SIC	−7130.57	−7133.95	−7126.5	−7220.12	−7221.83	−7214.22
# of jumps	28	27	27	50	48	48
# of jumps on ECB meeting days over all jumps	0.2143	0.2222	0.2222	0.1600	0.2292	0.2292
# of jumps on ECB meeting days over all ECB meeting days	0.0472	0.0472	0.0472	0.0630	0.0866	0.0866

Table 7: The joint impacts of news surprises on individual interest rates

The table contains the key estimates of the macro-jump model with time-varying jump intensity parameter for individual euro area interest rates. The model assumptions and the statistics are the same as the ones presented in Table 6.

	EURIBOR		Euro swap rates	
	1-month	6-month	2-year	10-year
Fed market	9.2038 (7.7489)	12.3433 (7.9843)	65.5510 (20.5310)	37.0388 (10.9533)
ECB survey	5.3013 (1.5460)	—	—	—
ECB market	33.3060 (12.5126)	110.9277 (31.7796)	26.7280 (6.5516)	25.4914 (7.4196)
Industrial production (EA)	0.6559 (0.3444)	—	—	—
Business climate (EA)	—	—	2.4710 (0.8344)	—
PPI (EA)	0.8069 (0.3593)	—	0.6493 (0.9007)	0.8870 (0.5219)
Business confidence (FR)	0.3849 (0.3756)	0.7236 (0.4440)	1.1984 (0.5688)	1.9663 (0.7750)
GDP advance (US)	—	—	—	3.3542 (0.6833)
GDP final (US)	—	—	−0.7989 (1.7471)	2.2656 (0.5275)
Durable goods orders (US)	0.9017 (0.2711)	—	—	—
Non-farm payrolls (US)	—	0.7861 (0.4819)	1.2846 (0.4544)	1.5791 (0.3746)
Initial jobless claims (US)	—	0.3553 (0.2323)	—	−1.6048 (0.9119)
CPI (US)	0.4568 (0.2768)	0.7770 (0.3333)	—	0.1113 (0.0692)
Housing starts (US)	0.7483 (0.2695)	—	—	—
Consumer credit (US)	—	—	—	2.0677 (0.5277)
Consumer spending (US)	—	—	1.4371 (0.3758)	−0.9398 (0.9355)
ISM manufacturing business confidence (US)	—	0.5489 (0.3547)	—	5.3646 (1.4437)
Consumer confidence (US)	0.5446 (0.2933)	0.4744 (0.4081)	—	—
λ^0	0.0799 (0.0080)	0.0836 (0.0123)	0.0219 (0.0078)	0.0088 (0.0094)
μ_J	0.0002 (0.0006)	−0.0021 (0.0020)	0.0553 (0.0199)	0.0904 (0.0445)
σ_J	0.0683 (0.0036)	0.0443 (0.0030)	0.1089 (0.0142)	0.0453 (0.0223)
log-L	7163.30	5709.40	3611.86	3673.18
SIC	−14189.67	−11289.49	−7109.61	−7194.21
# of jumps	195	160	37	59
# of jumps on announcement days over all jumps	0.5692	0.6875	0.6757	0.9153
# of jumps on announcement days over all announcement days	0.1820	0.1365	0.0509	0.0640

Table 8: Estimation results of the ARJI(1,1) model for yield curve factors

The table contains the key estimates of the ARJI(1,1) model for yield curve factors computed from euro area interest rates. The yield curve fitting model is the Nelson-Siegel model, defined as $r_t(\tau) = \beta_{1t}F_{1t} + \beta_{2t}F_{2t} + \beta_{3t}F_{3t}$, where $F_{1t} = 1$, $F_{2t} = \left(1 - e^{-\eta_t\tau}\right) / (\eta_t\tau)$ and $F_{3t} = \left(1 - e^{-\eta_t\tau}\right) / (\eta_t\tau) - e^{-\eta_t\tau}$. The equation of r_t is estimated by OLS for each day by setting $\eta_t = 0.06$, the median value of a first-stage NLS estimation. Then we apply the ARJI(1,1) model with time-varying jump intensity parameter for the estimated yield curve factors. The model's basic assumptions are the same as those presented in the notes of Table 5. σ_t follows a GARCH(1,1) process, $\sigma_t^2 = \omega_0 + \omega_1\varepsilon_{t-1}^2 + \omega_2\sigma_{t-1}^2$ for $\Delta\hat{\beta}_{1t}$, while for $\Delta\hat{\beta}_{2t}$ and $\Delta\hat{\beta}_{3t}$, σ_t is defined as $\sigma_t^2 = \omega_0 + g(\boldsymbol{\theta}, \Phi_{t-1})\,\varepsilon_{t-1}^2 + \omega_2\sigma_{t-1}^2$, where $g(\boldsymbol{\theta}, \Phi_{t-1}) = \exp\left[\omega_1 + \omega_{1,J}\mathbb{E}\left(n_{t-1} \mid \Phi_{t-1}\right)\right]$. We include one autoregressive term in the equation of $\Delta\hat{\beta}_{2t}$ and $\Delta\hat{\beta}_{3t}$, and two lags in the equation of $\Delta\hat{\beta}_{1t}$. The additional statistics are defined as before.

	$\Delta\hat{\beta}_{1t}$	$\Delta\hat{\beta}_{2t}$	$\Delta\hat{\beta}_{3t}$
λ_0	0.0263 (0.0205)	0.0015 (0.0010)	0.0288 (0.0155)
ρ	0.9372 (0.0459)	0.9950 (0.0031)	0.6104 (0.1569)
γ	0.2318 (0.1579)	0.1351 (0.0421)	0.6056 (0.3135)
μ_J	0.0086 (0.0052)	−0.0239 (0.0064)	0.0247 (0.0234)
σ_J	0.0464 (0.0043)	0.0778 (0.0048)	0.2339 (0.0263)
log-L	3188.62	2843.31	1747.22
SIC	−6301.19	−5610.55	−3418.37
# of jumps	508	420	76
# of jumps on announcement days over all jumps	0.7933	0.7857	0.8421
# of jumps on announcement days over all announcement days	0.2583	0.2115	0.0410

Table 9: The joint impacts of news surprises on yield curve factors

The table contains the key estimates of the macro-jump model with time-varying jump intensity parameter for yield curve factors computed from euro area interest rates. The yield curve fitting model is the Nelson-Siegel model, defined as $r_t(\tau) = \beta_{1t}F_{1t} + \beta_{2t}F_{2t} + \beta_{3t}F_{3t}$, where $F_{1t} = 1$, $F_{2t} = \left(1 - e^{-\eta_t \tau}\right) / (\eta_t \tau)$ and $F_{3t} = \left(1 - e^{-\eta_t \tau}\right) / (\eta_t \tau) - e^{-\eta_t \tau}$. The equation of r_t is estimated by OLS for each day by setting $\eta_t = 0.06$, the median value of a first-stage NLS estimation. Then we apply the macro-jump model with time-varying jump intensity parameter for the estimated yield curve factors. The model's basic assumptions are presented in the notes of Table 6. σ_t follows a GARCH(1,1) process, $\sigma_t^2 = \omega_0 + \omega_1 \varepsilon_{t-1}^2 + \omega_2 \sigma_{t-1}^2$ for $\Delta\hat{\beta}_{1t}$, while for $\Delta\hat{\beta}_{2t}$ and $\Delta\hat{\beta}_{3t}$, σ_t is defined as $\sigma_t^2 = \omega_0 + g(\boldsymbol{\theta}, \Phi_{t-1})\varepsilon_{t-1}^2 + \omega_2 \sigma_{t-1}^2$, where $g(\boldsymbol{\theta}, \Phi_{t-1}) = \exp\left[\omega_1 + \omega_{1,J}\mathbb{E}(n_{t-1} \mid \Phi_{t-1})\right]$. We include one autoregressive term in the equation of $\Delta\hat{\beta}_{2t}$ and $\Delta\hat{\beta}_{3t}$, and two lags in the equation of $\Delta\hat{\beta}_{1t}$. The additional statistics are defined as before.

	$\Delta\hat{\beta}_{1t}$	$\Delta\hat{\beta}_{2t}$	$\Delta\hat{\beta}_{3t}$
Fed market	—	97.1984 (47.7249)	29.7434 (17.9646)
ECB survey	—	—	9.9084 (5.1467)
ECB market	—	44.9076 (19.8498)	75.5944 (34.6176)
Industrial production (EA)	—	1.4378 (0.7163)	—
Business climate (EA)	—	—	3.3992 (2.1191)
Non-farm payrolls (US)	1.9982 (0.9733)	2.3684 (0.7570)	3.0909 (0.8635)
Initial jobless claims (US)	2.8965 (1.5148)	—	−0.0366 (0.5585)
CPI (US)	—	1.0077 (0.5494)	—
Consumer spending (US)	—	—	0.6766 (0.5350)
ISM manufacturing business confidence (US)	2.1594 (1.4364)	2.2250 (0.6450)	1.4339 (0.6097)
λ^0	0.3085 (0.0736)	0.0783 (0.0318)	0.0602 (0.0166)
μ_J	0.0085 (0.0053)	−0.0348 (0.0132)	−0.0070 (0.0205)
σ_J	0.0451 (0.0034)	0.0825 (0.0079)	0.1873 (0.0157)
log-L	3199.82	2860.19	1758.39
SIC	−6315.97	−5613.88	−3395.06
# of jumps	529	70	149
# of jumps on announcement days over all jumps	0.7618	0.6571	0.8456
# of jumps on announcement days over all announcement days	0.7108	0.0941	0.1909

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 February 18, 1999 to December 29, 2006. Weekends and holidays are excluded from the data set, providing 2014 usable observations.

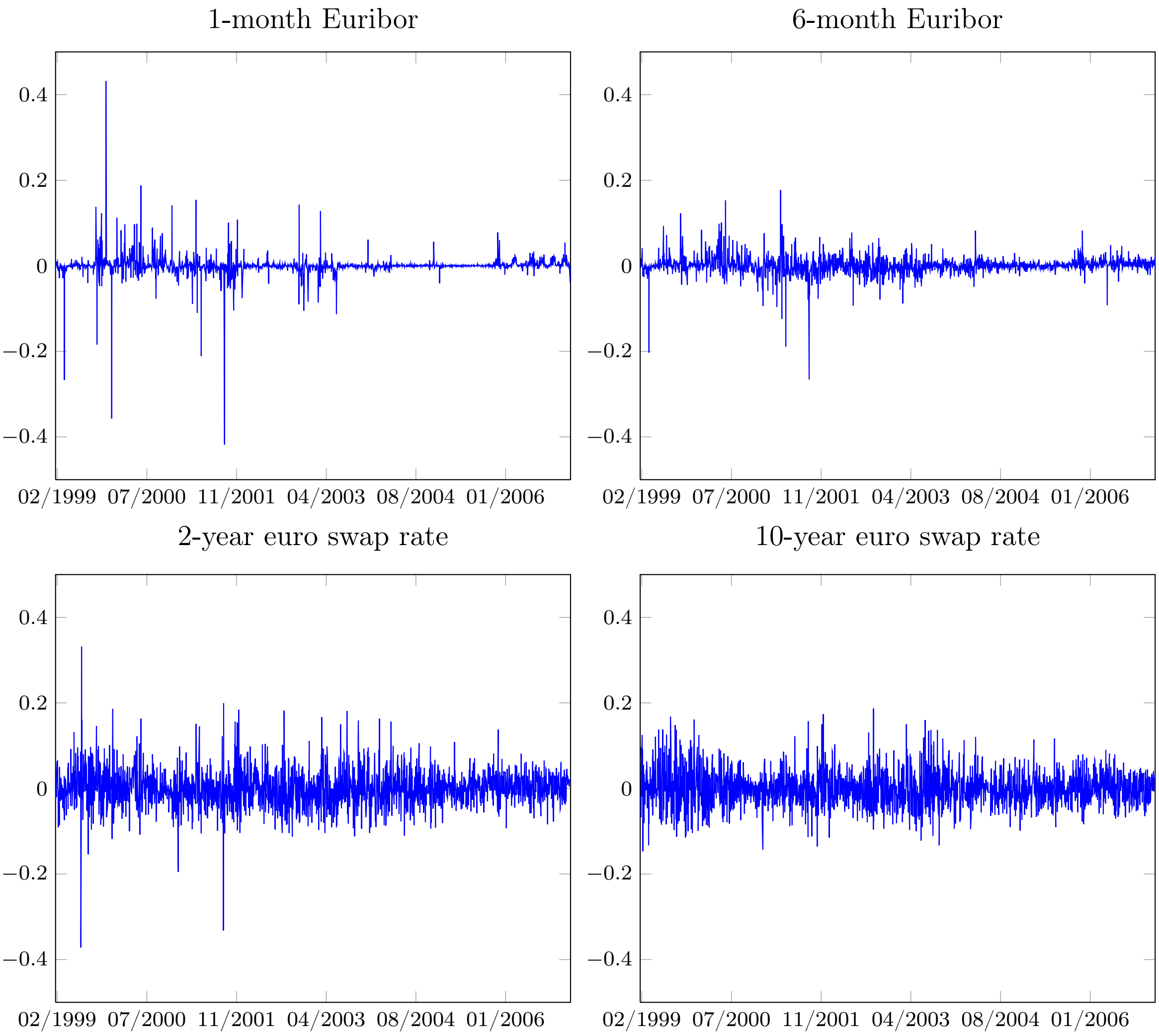

Figure 2: Survey and market-based monetary policy surprises of the ECB

The survey-based measure is defined as the difference between the ECB's actual decision and the mean of analysts' expectation regarding the actual decision, collected by Reuters, divided by the standard deviation of this difference on days when the ECB held a monetary meeting, and zero otherwise. The market-based measure is the daily difference in the 1-month Eonia swap rate on meeting days and zero otherwise. The left scale stands for the survey-based measure, while the right scale stands for the market-based measure. The sample period is from February 18, 1999 through December 29, 2006.

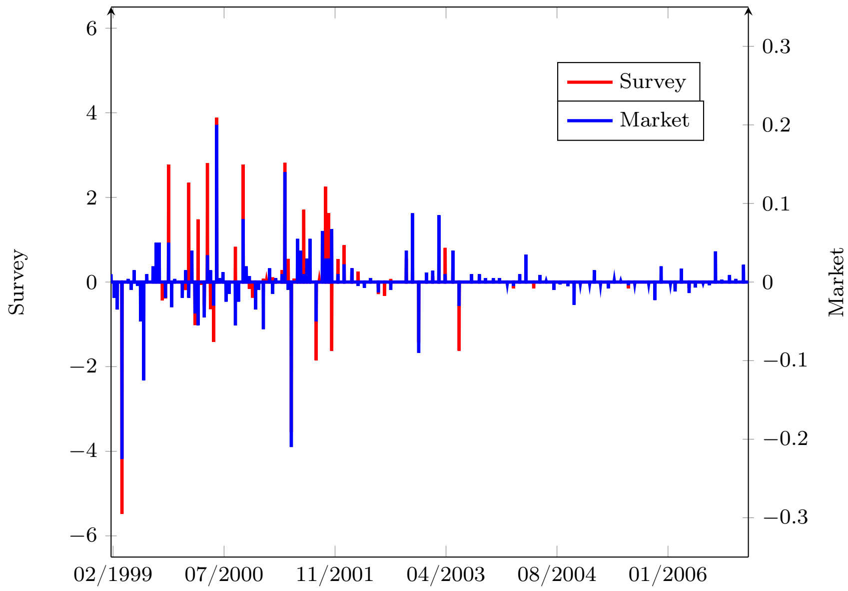

Figure 3: Model vs data-based level, slope and curvature

Evolution of daily model-based level, slope and curvature (measured as $\hat{\beta}_{1t}$, $-\hat{\beta}_{2t}$ and $0.3\,\hat{\beta}_{3t}$, respectively) against the 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. The sample period is from February 18, 1999 through December 29, 2006.

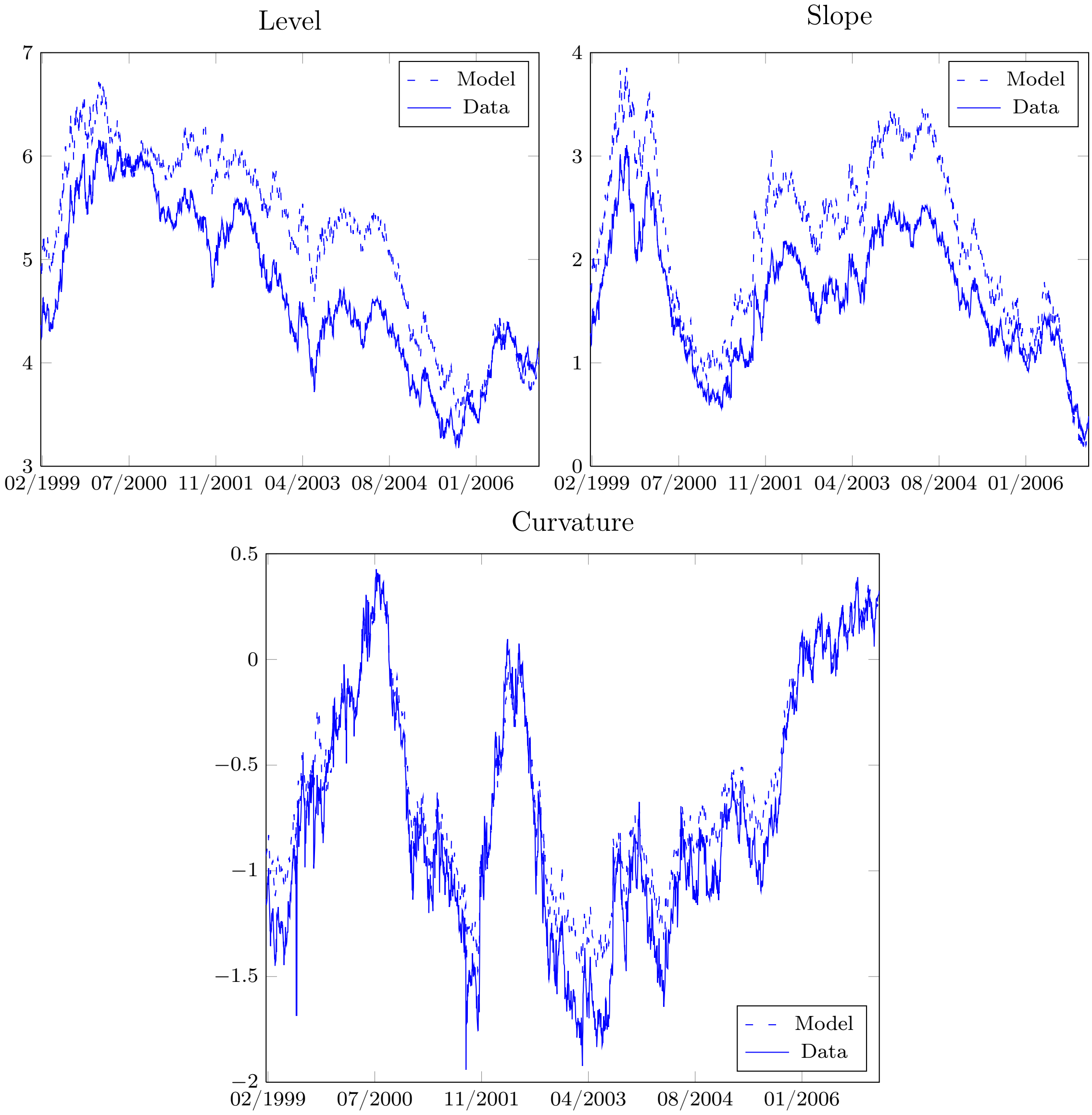

Figure 4: Time series of $\Delta\hat{\beta}_{1t}$

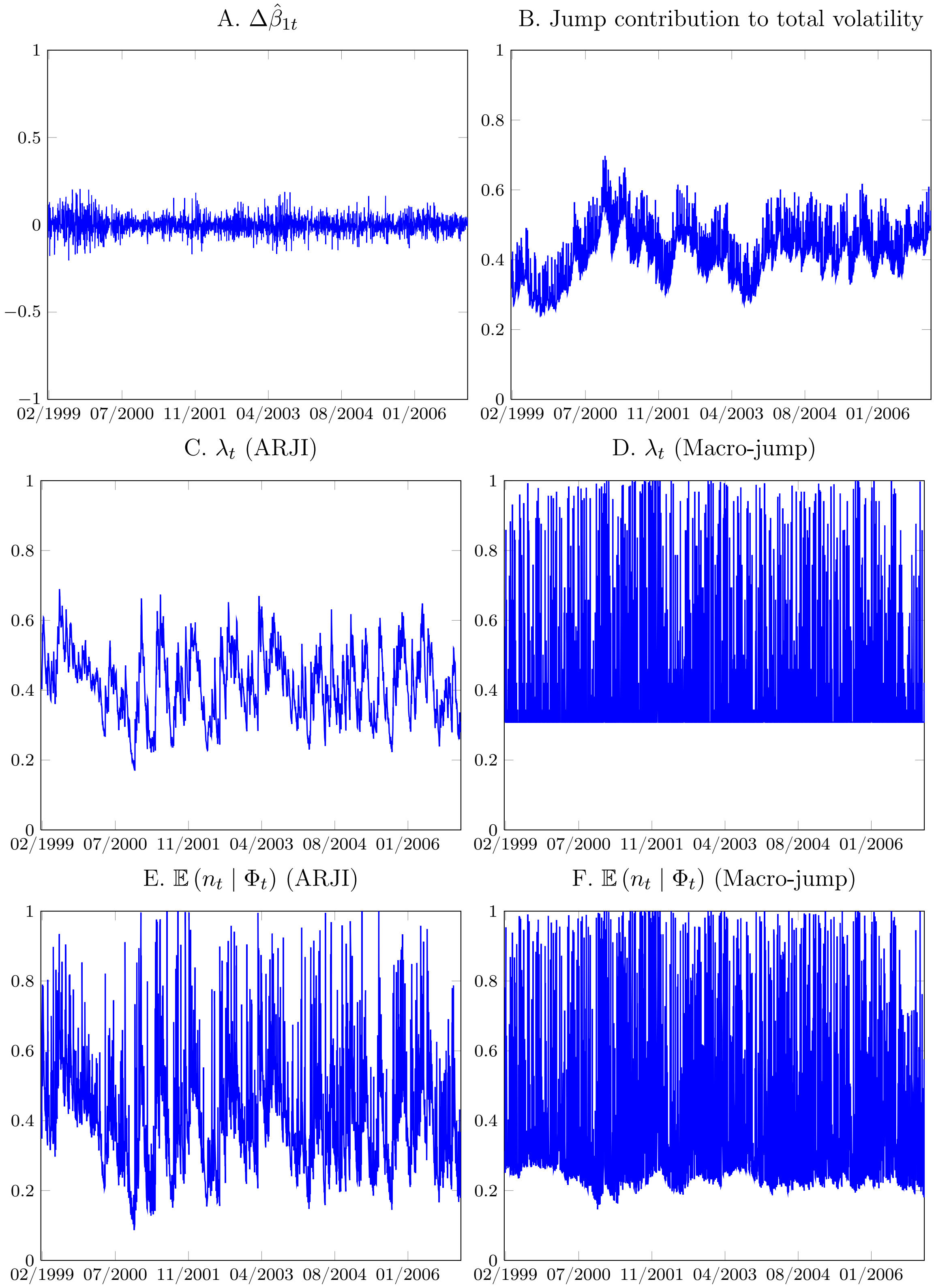

Figure 5: Time series of $\Delta\hat{\beta}_{2t}$

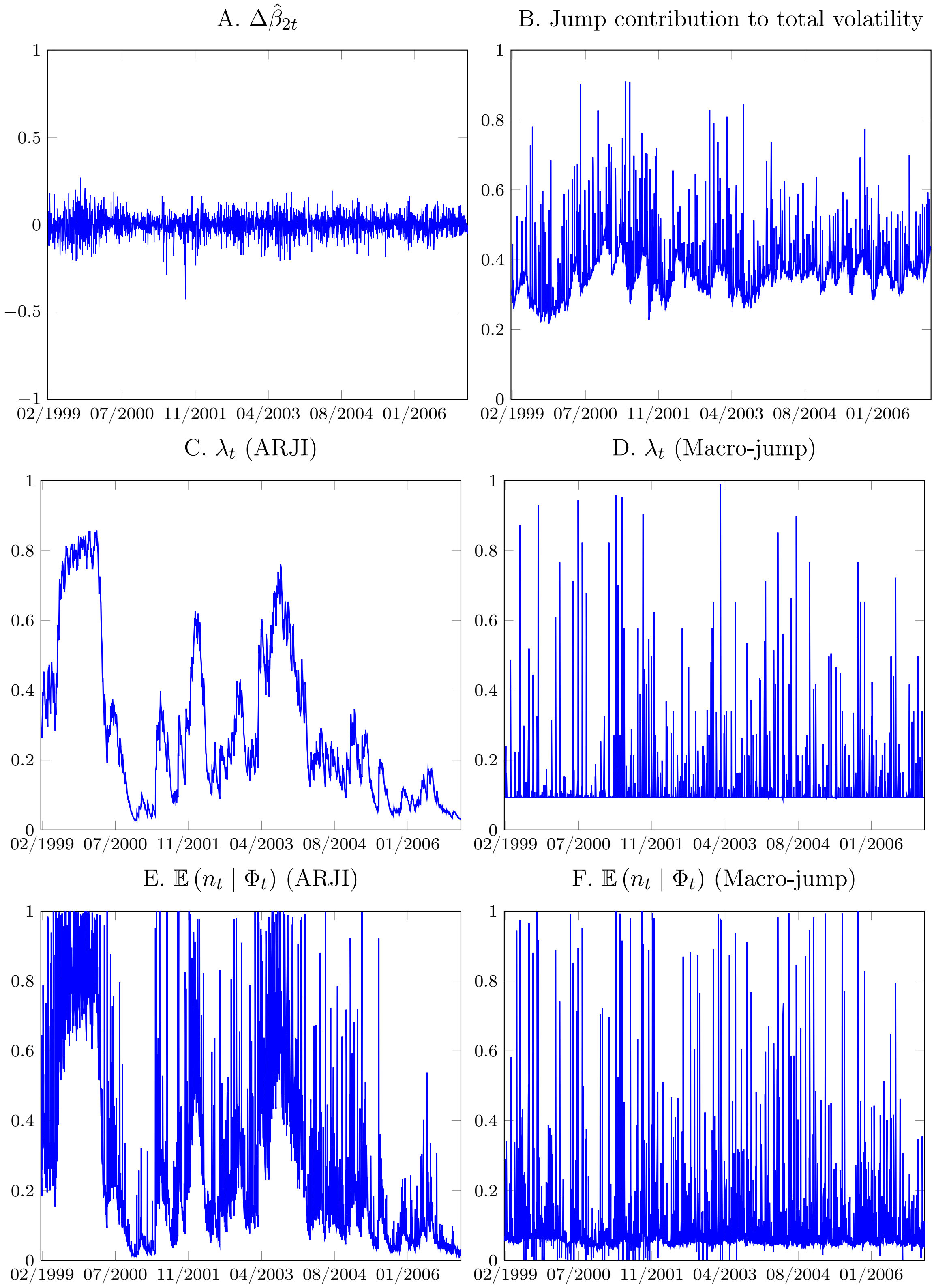

Figure 6: Time series of $\Delta\hat{\beta}_{3t}$