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Modeling the European Central Bank official rate: a stochastic approach

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Abstract

Following its main task of price stability in the euro area, the European Central Bank (ECB) increases or decreases interest rates in order to cool inflation or respectively to support economic growth. Monetary policy shows delayed effects on inflation and thus the ECB modifies interest rates on the basis of forecasts about the state of economy over the coming quarters. Aim of our contribution is to provide a stochastic model for the ECB official rate taking into account the expectations on the future state of economy. We propose a non homogeneous Poisson process to describe the intervention times of the ECB. In particular the jump process parameters depend on the evolution of the economic cycle as modeled by a MS-AR model. We show an application on suitably aggregated European data.

Keywords: ECB rates, Markov-switching, business cycle, non-homogeneous Poisson process.

JEL codes: C51, E32, E37, E50.

1. Introduction

The European Central Bank (ECB) is the central bank for Europe single currency, the euro. The ECB main task is to maintain the euro purchasing power and thus the price stability in the euro area. The euro area comprises the 17 European Union countries that have introduced the euro since 1999.

The ECB monetary policy operates by steering short-term interest rates, thereby influencing economic developments for the euro area over the medium term. Monetary policy decisions are taken by the ECB's Governing Council that meets every month to analyze and assess economic monetary developments and to decide the appropriate level of key interest rates, based on the ECB strategy. The Governing Council of the ECB sets the key interest rates for the euro area: the interest rate on the main refinancing operations (MRO), which provide the bulk of liquidity to the banking system; the rate on the deposit facility, which banks may use to make overnight deposits with the Eurosystem; the rate on the marginal lending facility, which offers overnight credit to banks from the Eurosystem.

Short-term interest rates set by central banks have a large impact on the pricing of financial assets and on the broader economy, which in turn affect prices of shares and corporate debt securities. Many authors focus their research on modeling the evolution of Central Banks official rates. One of the most popular approaches is the "Taylor rule" [19]. It describes the behavior of a central bank by means of a policy reaction function. The interest rate is the policy instrument, depending on both inflation and current output gap. The Taylor rule is based on the assumption that interest rate follows a linear, continuous process and such an assumption is not in line with its discrete changes. Indeed central banks announce interest rates changes during their regular meetings and define somewhat an upper limit on possible changes during a year; usually adjustment occur in a series of small steps (25 basis points). As a consequence the interventions can be well represented by applying discrete choice models. Among the others, for the ECB rates [6], [16] and [10], whereas [7] looks at Federal Reserve's reaction function.

In line with the discrete approach, in our work we refer to [3] where they present the techniques they employ to simulate the future behavior of interest rates. Observing that any rate (regardless of its maturity) has a strong correlation with the ECB rate, they develop an original approach to the generation of future term structure scenarios considering the fluctuations of each rate with respect to the ECB official rate. To this aim they assume that the interventions of the ECB can be represented as a stochastic jump process. Some features of this process are readily apparent by looking at the evolution of the ECB official rate since January 1999: there have been about three interventions per year until today, in each intervention the rate jumps by either 25 or 50 basis points. However they do not include in the model any variable linking the ECB official rate to the evolution of macroeconomic indicators.

While ECB reacts to many factors and staff assess literally hundreds of time series of data in preparing the background material for policy meetings, empirically it looks like only a few data series are needed to capture a central bank's policy decisions [10]. In particular the ECB interventions are due to: real economic activity expected growth; money growth which is an indicator of inflation pressure; exchange rate appreciation or depreciation which influence inflation directly through import prices and indirectly by affecting competitiveness of the euro area and the demand for euro area goods; finally, to current inflation.

Following its main task, ECB increases interest rates when the economy is in an expansion phase to cool inflation and, vice versa, decreases interest rates when the economy is in a recession phase to support economic growth. Monetary policy shows its effects on inflation some time later (one year and over). On the other hand the effects on output are immediate and temporary, being the monetary policy neutral in the long run. As a consequence, monetary policy must anticipate economic cycle to be effective. That is why ECB modifies interest rates on the basis of forecasts about the state of economy over the coming quarters.

In the present paper our aim is to improve the simple jump process proposed by [3] taking into account the macroeconomic indicators that impact on ECB interventions on interest rates. We are aware that ECB interventions respond to several macroeconomic indicators (real economic activity expected growth, money growth, exchange rate appreciation or depreciation, current inflation). Nevertheless as a first step of our research we focus on the link between the ECB rates and the expectations on the growth of real economic activity. We look at this macroeconomic variable basing on the evidence that the editorials by the ECB's Governing Council contain frequent statements about development in real economic activity presumably because it has an impact on the rate of inflation with a lag [10].

We propose a stochastic model for the ECB interventions able to link the reference rates to the predicted states of the economy, that is to the forecast probability of expansion of real economic activity. We choose to describe the economic cycle via a Markov switching Auto Regressive model (MS-AR model) proposed first in Hamilton's seminal article [12] and we consider two possible states of the economy: recession and expansion. The MS autoregressive model allows us to estimate the filtered probability of being in each of the states. To link the rates dynamics to this probabilities we propose an empirical classification of economic cycle phases basing on some features of ECB's behavior in steering interest rates such as the asymmetry in the number and timing of ECB interventions between the two economic regimes.

Then we model the rates dynamics through a jump process whose parameters depend on the predicted states of the economy estimated by the proposed classification. Indeed, a non homogeneous Poisson process is often appropriate for the modeling of a series of events (in our case the ECB interventions) that occur over time in a non-stationary fashion, since its intensity function may vary with time. We assume that this intensity varies according to the real economic cycle phases, being constant as long as the economy remains in the same state. The proposed methodology is empirically validated on the time series of ECB interventions.

The paper is organized as follows. Section 2 introduces the adopted methodology, by describing in details the Markov Switching model of the business cycle, the non-homogeneous Poisson model for the ECB rates and the empirical classification rule we adopted. Section 3 briefly presents the data, while Section 4 is devoted to the description and discussion of the results. Section 5 concludes.

2. The Model

Modeling the Business Cycle

As first suggested by [12], we model the business cycle as a Markov switching process. Hamilton's work gave rise to a considerable number of papers that also use Markov switching models to capture regime changes in a diverse set of macroeconomic and financial time series. Indeed, many economic time series occasionally exhibit dramatic breaks in their behavior, associated with events such as financial crises or abrupt changes in government policy. In particular, many authors have successfully used Hamilton's model to characterize and explain business-cycle fluctuations. These studies were primarily motivated by a belief that recessions and expansions are distinct phases or regimes that make economic fluctuations a fundamentally asymmetric phenomenon. Because such models, yet still very tractable, allow for nonlinear dynamics and sudden changes, so matching many stylized facts about the business cycle, this approach has become an important alternative to linear, autoregressive structures. The following brief description helps us to establish the notation.

The most general form of a Markov-switching autoregressive (MS-AR) process of order p is given by [13, cap. 22]

$$y_t = \mu(s_t) + A_1(s_t)y_{t-1} + \ldots + A_p(s_t)y_{t-p} + \varepsilon_{t.} \tag{1}$$

Here ε_t is a Gaussian error term conditioned on s_t:

$$\varepsilon_t | s_t \sim NID\big(0, \sigma(s_t)\big);$$

while the parameter vector shift function $\mu(s_t)$ and the autoregressive coefficients $A_1(s_t),\ldots A_p(s_t)$ describe the dependence of the time series y on the regime variable $s_t \in \{1,\ldots M\}$, which represents the probability of being in a particular state of the world. We assume that s_t follows an ergodic Markov chain, so that the transition probability matrix will be

$$p_{j,k} = Prob(s_t = j \,|s_{t-1} = k), \qquad j,k \in \{1, \ldots M\} \qquad (2)$$

with $\Sigma_k\, p_{j,k} = 1$ for $j \in \{1,\ldots M\}$. If the process is governed by regime $s_t = j$ at date t, then for $j = 1,\ldots M$ the conditional density of y_t is assumed to be given by

$$f(y_t|s_t = j, \Upsilon_{t-1}; \theta),$$

where $\theta = (\mu, A_1,\ldots A_p, \sigma)$ is the vector of parameters characterizing the conditional density and Υ_t is a vector containing all observations obtained through date t.

To estimate both the parameters vector θ and the transition probabilities $p_{j,k}$, Hamilton proposed a filtering algorithm to iterate through the observations while making and updating inferences about the probability of being in a given state.

The filtered probability can be understood as an optimal inference on the state variable at time t using only the information up to time t:

$$Prob(s_t = j \mid \Upsilon_t), \qquad j \in \{1, \ldots M\}.$$

From this probability we obtain the forecast probability

$$\mathcal{P}_t = Prob(s_{t+1} = j \mid \Upsilon_t) = \sum_{i=1}^{M} p_{i,j} Prob\,(s_t = i \mid \Upsilon_t), \qquad j \in \{1, \ldots M\}. \qquad (3)$$

In this study, we consider a two-state model *(M = 2)*, that is, we use observations of a single variable y_t to estimate and forecast the probability of being in one of the two given states, that we identify as Expansion and Recession.

<u>Classification of business cycle phases</u>

The MS autoregressive model described in the previous Section allows us to estimate the filtered probability of being in each of the states.

To link the rates dynamics to this probability we must take into account some additional features such as the asymmetry in the number and timing of ECB interventions between the two economic regimes.

Then we build an empirical classification rule basing on the following three assumptions:

- ECB ``upward'' interventions are limited to stable and certain expansion phases, as identified by a forecast probability of expansion above a fixed threshold α_E and very slightly oscillating;
- on the contrary, ``downward'' interventions are often realized not only when a certain recession is expected (forecast probability of expansion below a second fixed threshold α_R), but also in uncertain (oscillating) situations, while leaving an expansion phase;

- moreover, when leaving a recession phase, the ECB tends to wait. In this case, counterbalancing interventions are delayed until a certain expansion state is reached.

Thus, the empirical rule we propose relies on the evaluation of the forecast probability of expansion $P_t(E)$ as defined by (3) identifying the ECB intentions at time t as

- counterbalancing expansion when $P_t(E) > \alpha_E$;
- counterbalancing recession when $P_t(E) < \alpha_R$ or $\alpha_R < P_t(E) < \alpha_E$ while leaving an expansion period;
- waiting when $\alpha_R < P_t(E) < \alpha_E$ while leaving a recession period.

Application of this rule leads us to partitioning the considered time interval in non-overlapping subintervals, each of them classified as an expansion, recession or uncertainty period. Clearly, isolated single points are reclassified to agree with their neighbors classification. Results of the application of our classification rule to the probability estimated by a two states MS model using business cycle indicators data will be shown in Section 4.

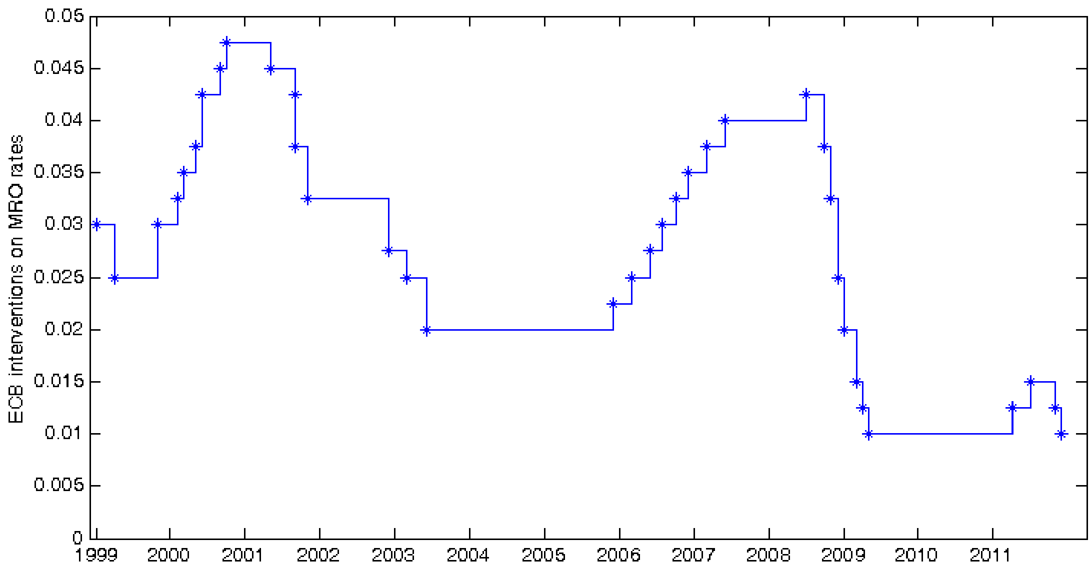

FIGURE 1: Historical value of the MRO rates as fixed by ECB; stars represent ECB interventions.

Modeling the ECB official rate

By considering the empirical evidence of the historical observed rate (as shown in Figure 1) we note that the ECB official rate time series starts in January 1999, thus it is much shorter than any available business cycle indicators data series, and there have been about three interventions per year until today; moreover, in each intervention the rate jumps by either 25 or 50 basis points. These starting observations suggest that the ECB rate dynamics should be defined, following the approach proposed by [3], by a jump model:

$$ECB_t = ECB_0 + \sum_{h=1}^{N_t} a_h b_h \tag{4}$$

where N_t represents the total number of interventions up to time t, while $a_h \in \{0, 0.25, 0.50\}$ and $b_h \in \{-1, +1\}$ are the width and the direction of the intervention h, respectively. In particular, we assume that the number of ECB interventions is a counting process that can be modeled as a non homogeneous Poisson process: its intensity function $\lambda(t)$ may vary with time and the cumulative intensity function $\Lambda(t) = \int_0^t \lambda(\tau) d\tau$ gives the expected number of events by time t.

Moreover, we aim at improving the simple jump model in [3] by linking the intensity function λ to the predicted state of the economy. To this purpose, after having partitioned the entire time interval in m subintervals $I_1, \ldots, I_m$, each of them classified as described in the previous Subsection, we allow $\lambda(t)$ to be piecewise constant on each subinterval. Thus, its Maximum Likelihood estimator is the average number of events that occurred on the interval I_j, normalized to the length of that interval

$$\hat{\lambda}(t) = \frac{n_j}{|I_j|} \qquad t \in I_j. \tag{5}$$

As a consequence, if no events are observed on an interval, then the intensity function estimate is zero on that interval.

In a similar way, to assign a value for the parameter b_h in (4), we look at the time t_h of the intervention and set $b_h = +1$ in expansion subintervals, while $b_h = -1$ in recession subintervals.

Finally, to reduce the model parameters we fix a_h=0.25; this choice is not restrictive, provided that any ECB intervention modifying rates of 50 basis points (0.50) is accordingly counted as a multiple intervention.

3. The data

Business cycles are usually measured by considering the growth rate of real gross domestic product (GDP). However GDP data are published with a lag of several quarters and are typically revised several times, occasionally by large amounts.

The Directorate General for Economic and Financial Affairs (DG ECFIN) conducts regular harmonised surveys for different sectors of the economies in the European Union (EU) and in the applicant countries. They are addressed to representatives of the industry (manufacturing), the services, retail trade and construction sectors, as well as to consumers. These surveys allow comparisons among different countries' business cycles and have become an indispensable tool for monitoring the evolution of the EU and the euro area economies, as well as monitoring developments in the applicant countries. Survey measures are typically available with very short lags and never updated. Moreover it is well known that editorials in the ECB's *Monthly Bulletin* frequently comment on business and consumer confidence and survey measures of expected output growth.

For these reasons in the following we model the business cycle by means of a survey measure as a proxy of the real GDP. Among the several proposed survey indicators (see [18] for a review and, more recently, [9, 4, 5]), we choose the Economic Sentiment Indicator(ESI) that pertains to the euro area and is based on a large survey of firms and consumers. It has a number of features that make it suitable for our analysis: it is strongly correlated with data on the real state of economy, it is available monthly instead of quarterly as is the case for real GDP, it is available much faster than the GDP data and move in advance of the output gap picking up business cycle turning points more rapidly than real GDP does. Furthermore, according to several authors [11, 5], this indicator is much more significant in the regressions than output gaps that are traditionally used to capture the state of the economy.

ESI is a composite indicator made up of five sectorial confidence indicators with different weights: Industrial confidence indicator, Services confidence indicator, Consumer confidence indicator, Construction confidence indicator, Retail trade confidence indicator. Confidence indicators are arithmetic means of seasonally adjusted balances of answers to a selection of questions closely related to the reference variable they are supposed to track. Surveys are defined within the Joint Harmonised EU Programme of Business and Consumer Surveys. The ESI is calculated as an index with mean value 100 and standard deviation of 10 over a fixed standardized sample period. Long time series of the ESI and confidence indicators are available at the Survey database in the DG ECFIN website
`http://ec.europa.eu/economy_finance/db_indicators/surveys/index_en.htm.`

Figure 2, where GDP growth rate and ESI rate are simultaneously plotted at monthly frequency, confirms not only the strong agreement between the two data series, and so the ability of ESI in capturing the state of the business cycle, but also the fact that ESI moves in advance, picking up business cycle turning points more rapidly than GDP growth rate.

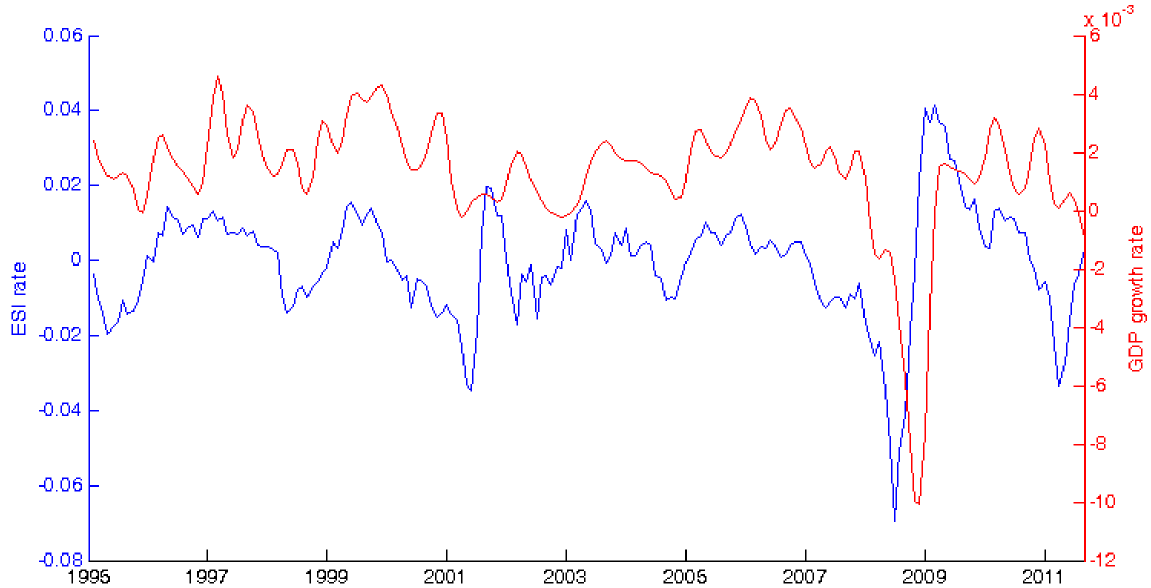

FIGURE 2: ESI rate (blue) and GDP growth rate (red) data starting from January 1995. Monthly GDP data are obtained by linear interpolation of quarterly data.

4. Results

The data used here are a third order moving average of the monthly ESI rates from 1985:1 to 2012:2 as drawn from the EUROSTAT database. We estimated the transition matrix p_{ij} and the parameters σ, A_{11}, ... A_{1p}, A_{21}, ... A_{2p} of the MS-AR model (1) in the case of two regimes with order p ranging from 1 to 3 by means of a Matlab package [17]; we outline that for such data $\mu_1 = \mu_2 = 0$. The estimation results are reported in Table 1, where Regime 1 corresponds to growth, while

Regime 2 represents recessions. It is evident from these results that all of the models for the considered orders gave us exactly the same transition matrix and just slightly different values of the parameters. Even though they are essentially equivalent in estimating the forecast probability, nevertheless we choose the model with the highest Likelihood value (p = 3).

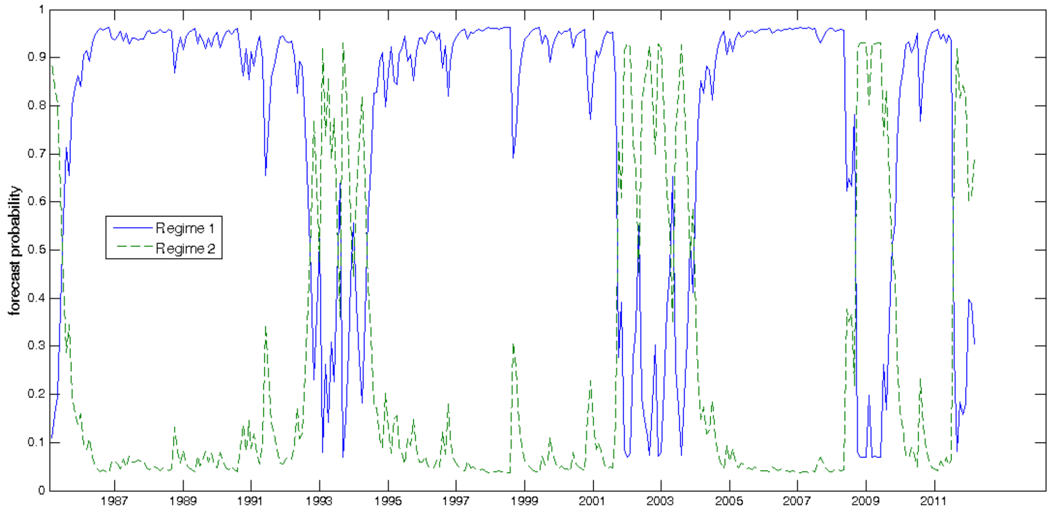

FIGURE 3: Forecasted probability of being in Regime 1 and 2 as estimated by the MS-AR model with three lags in the period 1985:3 to 2012:3.

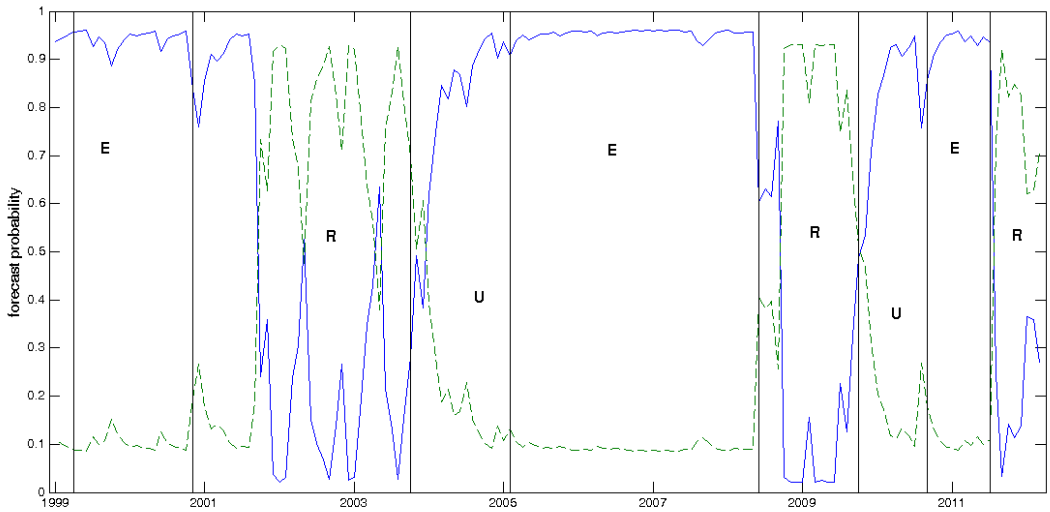

FIGURE 4: Forecasted probability of being in Regime 1 and 2 as estimated by the MS-AR model with three lags in the period 1999:1 to 2012:3; vertical lines mark the Expansion (E), Recession (R) and Uncertainty (U) subintervals as identified by the proposed classification rule.

The time paths of the forecasted probability (3) are depicted in Figure 3 for the entire time period from 1985 to 2012; the following Figure 4 presents the same probability from January 1999, when ECB started its activity in fixing rates, along with the results of the classification rule proposed in Section 2. Then, Figure 4 helps us to clarify the rationale for our classification rule: stable periods of expansion (marked with an E label) can be easily recognized in the plot; moreover, we labeled with an R not only the intervals where the forecast probability is below the recession threshold α_R, but also the intervals where this probability is below the certain expansion threshold α_E and moving towards a certain recession; finally, we denoted as uncertain (U label) the intervals following a recession, when a stable expansion phase is not yet reached. As long as the choice of the parameters α_R, α_E is concerned, basing on these considerations we adopted for the former the ``natural'' value 0.5, while for the latter we choose the expected value of the probability considering only the values above the recession threshold α_R, obtaining $\alpha_E = 0.9$.

To check the robustness of this choice we repeated the classification while allowing the parameter α_E to vary in the range 0.85 - 0.95. For each repetition, to evaluate the success of our classification we considered the series of ECB interventions and counted the matches between increasing (resp. decreasing) rates interventions and the corresponding classification of that month as belonging to an expansion (resp. recession) interval. Clearly, the lowest value of the parameter ($\alpha_E = 0.85$) leads to a minor sensitivity to the detection of uncertainty periods, so that the classification error increases in these intervals. On the other hand, the highest value ($\alpha_E = 0.95$) excessively penalizes the expansion periods, leading to a minor expected number of interventions. Table 3 summarizes the classification results for any chosen α_E, while Figure 5 shows the classification corresponding to $\alpha_E = 0.9$, $\alpha_R = 0.5$. In the same Figure we also report the real ECB rates to visually confirm the good classification results. Indeed, for this choice of the parameters there is only one real ECB intervention (July 2008) which is misclassified since it increases the rates while classified as belonging to a recession interval.

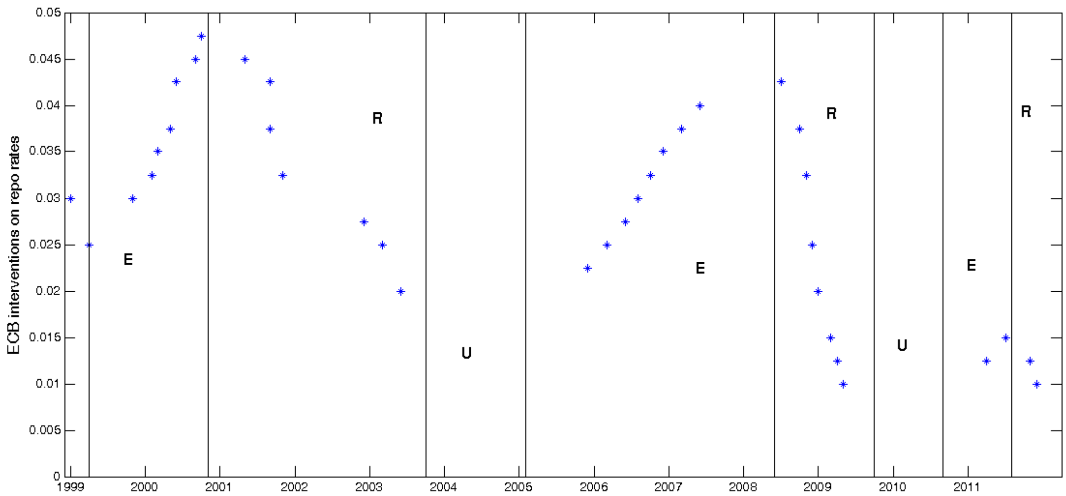

FIGURE 5: Classification results for the considered time period (1999 to 2012) compared with ECB decisions. Stars represent time of the real ECB interventions and corresponding value of the rates. Vertical lines mark the Expansion (E), Recession (R) and Uncertainty (U) subintervals as identified by the proposed classification rule.

Classification results are detailed in Table 2, which also reports the rates variation in each time interval and the estimated intensity function for the Poisson process modeling the ECB rates. Indeed, in each of the intervals we estimated the intensity function λ of the Poisson process as given by Eq. 5.

Finally we validate our model for the ECB rates by simulating their dynamics with the estimated intensity functions over the entire period 1999--2011. Specifically, for each time point *t* we estimate the intensity function according to Eq. 5 in the subinterval ending at *t-1* and generate the corresponding value of the rate for time *t*. In Figure 6 we show the average rates dynamics over 5000 simulations along with an estimate of the confidence interval corresponding to the 10th and 90th percentiles. Red stars represent the real ECB interventions. Such a short period simulation confirms the good agreement between the average trend of the simulated Poisson process and the real ECB rates dynamics.

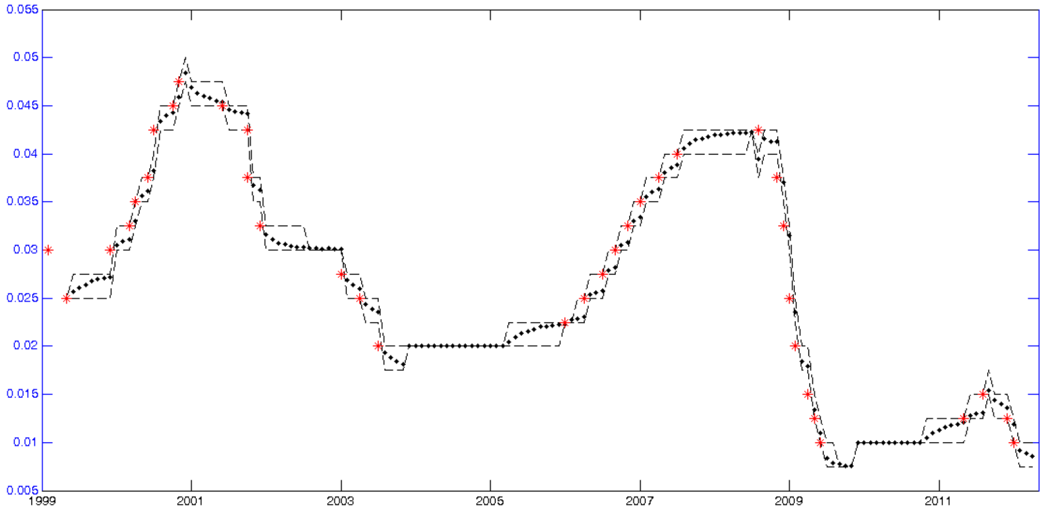

FIGURE 6: Short term simulation results for the considered time period (1999 to 2012) compared with ECB decisions. Red stars represent time of the real ECB interventions and corresponding value of the rates. The dotted line represents the average value of the ECB rates over 5000 simulations, while the dashed lines represent the 10th and 90th percentiles.

5. Conclusion

In the present paper we propose a stochastic model for the ECB interventions able to link the reference rates to the states of the economy. Basing on the empirical evidence that a jump process is suitable to describe ECB interventions, we aim at improving the simple jump model in [3] by linking the intensity function to the predicted state of the economy. The first step is to model the economic cycle. We choose a two-state MS-AR model and develop an empirical classification algorithm of the business cycle phases, basing on the ECB's interventions since 1999. The empirical rule relies on the evaluation of the forecast probability of expansion as estimated by the two-state MS model and on the comparison of this probability with a fixed threshold. Application of the classification rule leads us to partitioning the considered time interval in non-overlapping subintervals. Referring to ECB interventions each interval is than classified as an expansion, recession or uncertainty period. We define the rates dynamics through a stochastic jump process whose parameters depend on the predicted states of the economy as defined by our classification rule. The overall proposed methodology is empirically validated on the series of the ECB interventions. Our work shows that an MS model (using ESI as the only explanatory variable) and a classification rule relying on such a model is completely coherent with the ECB choices in fixing the interest rates, allowing us to model the time series of ECB interventions.

We are aware that ECB interventions respond not only to real economic activity expected growth but also to other macroeconomic indicators of the business cycle evolution. Indeed future investigation related to our work should consider other recently proposed survey indicators of the economic variables [4, 9] and generalize our univariate model by considering the joint effect of several relevant indicators of the Business Cycle, hence modeling the business cycle via a multivariate model (MS-VAR). Another proper improvement of our contribution should be the extension of the ECB rate jump model to a full doubly stochastic Poisson process where the intensity is assumed to be a generic function of time. Finally, providing that many contributions in the economic literature [2, 8] give theoretical and empirical evidence that the term structure of interest rates is a leading indicator of the business cycle, we intend to explore the use of our model to link the economic cycle to the term structure of interest rates via official ECB rate.

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		$p = 1$			$p = 2$			$p = 3$		
<u>Regime 1</u>	A_{11}	0.89	(0.03)	[0.00]	1.01	(0.07)	[0.00]	1.01	(0.07)	[0.00]
	A_{12}				-0.13	(0.07)	[0.05]	-0.10	(0.09)	[0.32]
	A_{13}							-0.04	(0.06)	[0.54]
	$\sigma*10^{-4}$	0.2	(0.0)	[0.00]	0.2	(0.0)	[0.00]	0.2	(0.0)	[0.00]
Expected duration (months)			50.1			48.2			47.5	
<u>Regime 2</u>	A_{21}	0.92	(0.05)	[0.00]	1.32	(0.09)	[0.00]	1.21	(0.11)	[0.00]
	A_{22}				-0.46	(0.11)	[0.00]	-0.13	(0.21)	[0.55]
	A_{23}							-0.26	(0.15)	[0.08]
	$\sigma*10^{-4}$	1.0	(0.2)	[0.00]	0.8	(0.2)	[0.00]	0.7	(0.2)	[0.00]
Expected duration (months)			14.8			14.8			14.5	
LogLikelihood			1244.22			1254.96			1257.59	
	p_{11}	0.98	(0.06)	[0.00]	0.98	(0.06)	[0.00]	0.98	(0.06)	[0.00]
	p_{12}	0.07	(0.05)	[0.18]	0.07	(0.05)	[0.20]	0.07	(0.05)	[0.20]
	p_{21}	0.02	(0.02)	[0.22]	0.02	(0.02)	[0.23]	0.02	(0.02)	[0.25]
	p_{22}	0.93	(0.11)	[0.00]	0.93	(0.11)	[0.00]	0.93	(0.11)	[0.00]

Table 1: Estimation results for the MS-AR models with 1,2,3 lags. For each coefficient, standard values are reported in parenthesis, ( ) and p-values in brackets,[ ].

Time interval	Estimated Regime	ECB rates variation	Estimated Intensity
1999:4 to 2000:10	Expansion	+2.25	0.47
2000:11 to 2003:9	Recession	-2.75	0.31
2003:10 to 2005:1	Uncertainty	--	--
2005:2 to 2008:5	Expansion	+2.25	0.23
2008:6 to 2009:9	Recession	-3.25	0.81
2009:10 to 2010:8	Uncertainty	--	--
2010:9 to 2011:6	Expansion	+0.5	0.22
2011:7 to 2012:3	Recession	-0.5	0.25

Table 2: Results of the classification rule for α_R = 0:5, α_E = 0:9; for each time interval the estimated intensity of the Poisson process is also reported in the last column

α_E	T error (%)	S error (%)	M error (%)
0.85	15.2	15.2	--
0.90	2.2	2.2	--
0.95	10.8	6.5	4.3

Table 3: Sensitivity of the classification rule to the threshold for the probability of a certain expansion α_E: classification error for different values of the parameter, measured as the percentage of ECB interventions falling in a misclassified time interval. The second column gives the total error (T), while the third and fourth columns refer to wrong direction of the intervention error (S) and missed intervention error (M), respectively.