Country shocks, monetary policy expectations and ECB decisions. A dynamic non-linear approach*

Maximo Camacho
University of Murcia
mcamacho@um.es

Danilo Leiva-Leon
Central Bank of Chile
dleiva@bcentral.cl

Gabriel Perez-Quiros
Bank of Spain, Airef and CEPR
gabriel.perez@bde.es

Abstract

Previous studies have shown that the effectiveness of monetary policy depends, to a large extent, on the market expectations of its future actions. This paper proposes an econometric framework to address the effect of the current state of the economy on monetary policy expectations. Specifically, we study the effect of contractionary (or expansionary) demand (or supply) shocks hitting the euro area countries on the expectations of the ECB's monetary policy in two stages. In the first stage, we construct indexes of real activity and inflation dynamics for each country, based on soft and hard indicators. In the second stage, we use those indexes to provide assessments on the type of aggregate shock hitting each country and assess its effect on monetary policy expectations at different horizons. Our results indicate that expectations are responsive to aggregate contractionary shocks, but not to expansionary shocks. Particularly, contractionary demand shocks have a negative effect on short term monetary policy expectations, while contractionary supply shocks have negative effect on medium and long term expectations. Moreover, shocks to different economies do not have significantly different effects on expectations, although some differences across countries arise.

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JEL Classification: E32, C22, E27

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1 Introduction

Since the seminal work of Taylor (1993), many papers have tried to relate the endogenous component of monetary policy with the different shocks that affect the economy. Several versions of the well-known Taylor rule, where decisions on interest rates are related to inflation developments and output gap, have been estimated in reduced form for different countries and sample periods. However, the use of these rules in general equilibrium models and the importance that the identification of the shocks has on the effects of monetary policy have changed the focus, from simply imposing identifying restrictions on impulse response functions to monetary shocks to carefully analyze the monetary equation.

Among many others, Leeper et al. (1996), Leeper and Zha (2003) and Sims and Zha (2006a,b), or very recently, Arias et al. (2015) estimate behavioral relations of monetary policy decisions in the context of an endogenous relation with the rest of the variables that describe the economic conditions. In particular, Leeper et al. (1996) show that most of the movements in monetary policy instruments are responses to the state of the economy, not random behavior of the monetary authorities. Leeper and Zha (2003) analyze the effect of modest policy interventions within frameworks where agents perceive that policy is composed of a regular response to the state of the economy and a random part. In a switching framework, Sims and Zha (2006b) show that most of the variation in policy variables reflects the systematic part of monetary policy in response to the changing state of the economy. Arias et al. (2015) find that, imposing sign and zero restrictions on the systematic component of monetary policy, there exist a contractionary effect of an exogenous increase in the fed funds rate.

In the case of the euro area, the attention has been focused on the transmission of monetary policy shocks, that obviously implies a proper specification of the monetary policy rule although some papers have concentrated on estimating carefully the policy rule. To quote a few, Thanassis and Elias (2011) use a threshold model to quantify the attitude of the ECB towards inflation expectations reductions; Dieppe et al (2004) conclude that forecast-based rules are more optimal than outcome-based policies; and Stracca (2007) shows that a "speed limit" monetary policy rule, which relates decisions to output gap changes (not to the level), performs well as a guideline for policy in the euro area.

Notably, all of these contributions consider the euro area as a whole. Therefore, these approaches are precluded from capturing the implications of the monetary policy rule for each of the euro-area members. A significant exception to these aggregate approaches is Benigno and Lopez-Salido (2006), who show the heterogeneity in the dynamics of inflation in each of the euro-area members. These authors find that maintaining an aggregate HICP targeting rule is still optimal, although it could imply significant welfare losses for some countries and welfare gains for others.

Our paper relates to Benigno and Lopez-Salido (2006) because we focus on the idiosyncratic dynamics of some euro-area members: Germany, France, Italy and Spain. However, we focus on determining which country-specific shocks (demand or supply) have more influence in the determination of the final decisions of the ECB. Following Aruoba and Diebold (2010), we identify the shocks by analyzing the interaction between activity and inflation cycles. Within this framework, we construct indexes of real activity and inflation dynamics for each country, based on soft and hard indicators. Then, we use those indexes to assess the effect of aggregate shocks on monetary policy expectations at different horizons. To identify the shocks and compute their impact on expectations we propose a multi-state regime-switching framework that assesses the relationship between observed variables (expectations) and latent variables (shocks).

In the empirical analysis, we find that monetary policy expectations are responsive to aggregate contractionary shocks, but not to expansionary shocks. In addition, we find that negative demand shocks affect short-term expectations of interest rates, but that negative supply shocks have medium and long-run impact. Finally, we find that these results are robust across countries in the case of demand shocks, while we find more heterogeneity in the case of supply shocks. Supply shocks are more related to expectation of future rates in this case of Germany, France and Italy than in the case of Spain.

The structure of the paper is as follows. Section 2 develops indexes of real activity and inflation dynamics for euro area countries. Section 3 assesses the state of the economy and the aggregate shocks. Section 4 studies the effect of aggregate shocks on monetary policy expectations. Section 5 concludes.

2 Real activity and inflation cycles

2.1 The model

The purpose of this section is to propose a method to construct indexes of real activity and inflation dynamics for the four main economies of the euro area (Germany, France, Italy and Spain) from hard and soft economic indicators. To handle real activity and inflation developments in a specific country, we estimate both indexes simultaneously from a unified framework, allowing for potential interdependence between the two concepts.

Following Leiva-Leon (2015), we use a set of N economic real activity and inflation indicators, y_{it}, which are collected in the vector y_t, to extract two common factors. The first factor, $f_{a,t}$, captures the evolution of the real activity while the second factor, $f_{b,t}$, captures the inflation dynamics. For each of the four countries, the factor structure would read as

$$y_{it} = \gamma_i^a f_{a,t} + \gamma_i^b f_{b,t} + e_{it}, \tag{1}$$

where γ_i^a and γ_i^b refer to the factor loadings and $i = 1, 2..., N$. The factors, $f_{a,t}$ and $f_{b,t}$, and the idiosyncratic terms, e_{it}, are assumed to evolve according to the following autoregressive dynamics

$$f_{r,t} = \sum_{h=1}^{k} b_{rh} f_{r,t-h} + \omega_t^r, \tag{2}$$

$$e_{it} = \sum_{h=1}^{m} \phi_{ih} e_{it-h} + \varepsilon_{it}, \tag{3}$$

where the errors, ω_t^r, are distributed as $N(0, \sigma_r^2)$, $r = a, b$, and ε_{it} are distributed as $N(0, \sigma_i^2)$, with $i = 1, ..., N$.[1] Finally, all the shocks, ε_{it} and ω_t^r, are assumed to be mutually uncorrelated in cross-section and time-series dimensions. Leiva-Leon (2015) show that this model can easily be stated in state-space form and can easily be estimated by means of a Kalman filter. In the empirical application, we set $r = m = 2$.

[1] To identify the factor model, the variances σ_a^2 and σ_b^2 assumed to be one.

The state-space specification of the model is the following. The measurement equation is

$$y_t = H\beta_t \tag{4}$$

and transition equation is

$$\beta_t = F\beta_{t-1} + \upsilon_t, \quad \upsilon_t \sim i.i.d.N\left(0, Q\right). \tag{5}$$

where $\beta_t = (f_{a,t}, f_{a,t-1}, f_{b,t}, f_{b,t-1}, e_{1,t}, e_{1,t-1}, ..., e_{N,t}, e_{N,t-1})'$, H contains the restrictions in (1). Fcontains the restrictions in (2) and (3) and Q is the variance covariance matrix of $(\omega_t^1, \omega_t^2, \varepsilon_{1,t}....\varepsilon_{N,t})'$, enlarged with 0s to take into accounts the identities in F.

We apply the Kalman filter to extract optimal the inference on the state vector β_t. For this purpose, we compute the prediction equations as

$$\begin{aligned}
\beta_{t|t-1} &= F\beta_{t-1|t-1}, &(6)\\
P_{t|t-1} &= FP_{t-1|t-1}F' + Q, &(7)\\
\eta_{t|t-1} &= y_t - H\beta_{t|t-1}, &(8)\\
f_{t|t-1} &= HP_{t|t-1}H' + R, &(9)
\end{aligned}$$

and the updating equations as

$$\begin{aligned}
\beta_{t|t} &= \beta_{t|t-1} + P_{t|t-1}H'\left[f_{t|t-1}\right]^{-1}\eta_{t|t-1}, &(10)\\
P_{t|t} &= \left(I - P_{t|t-1}H'\left[f_{t|t-1}\right]^{-1}H\right)P_{t|t-1}. &(11)
\end{aligned}$$

In this paper we consider that only two factors are required to describe the dynamics of all the economic indicators. Using only two factors goes in line with the literature of small scale models, where the common dynamics of a small set of economic variables can successfully be described with one dynamic factor, usually related to activity, as in Aruoba and Diebold (2010), Aruoba, Diebold and Scotti (2009) or Camacho and Martinez-Martin (2014), among many others. When the activity variables are complemented with price indicators, it makes sense to consider an additional factor, which is expected to capture the common inflation dynamics. Assuming more than two factors would create problems in the interpretation of the results and would difficult the identification assumptions.

2.2 Data

We estimate the factor model in equations (1)-(3) for each of the four main economies of the euro area. For each country, we select the same four monthly indicators of real activity and the same four indicators of inflation. For the case of real activity, we use three hard indicators, Industrial Production (IP), Retail Sales (SALES) and Registered Unemployment (UNEM). In addition, we use one soft indicator, Purchase Manager Index (PMI). The selection of the variables follows Stock and Watson (1991) since it is the more parsimonious representation mimicking the way in which national accounts are constructed: one time series from the supply side, one time series from the demand side, and one indicator of employment, that we substitute for unemployment since employment is not available at monthly frequency for all countries.[2] In addition, to capture expectations, we use one of the most popular expectation series available for all countries, the PMI index.

For the case of price indicators, we use two hard indicators, Consumer Price Index (CPI) and Producer Price Index (PPI), and two soft indicators, Selling Price Expectations (EXPE) and 12-months price trends (TREN). The last two indicators are based on surveys and computed by the European Commission. Again, the indicators cover the most representative series for both price developments and expectations. To avoid unit root problems, we take the first log differences to all the hard indicators and the first differences to all the soft indicators. To relate our results to the ECB's monetary policy, our sample period goes from January 1999 to April 2014. Since the specifications are linear small-scale dynamic factor models, we estimate the parameters by maximum likelihood.

2.3 Factors' dynamics

Since both factors are estimated simultaneously from the same set of real activity and inflation indicators, we impose an identification restriction on the loading factors of all countries. The restriction relies on the hypothesis of money neutrality, which postulates

[2] Unfortunately, we do not have income series for these countries.

that changes in the stock of money affect only nominal variables and do not affect real (inflation-adjusted) variables. Therefore, we do not allow the factor $f_{a,t}$ to be loaded by the most representative indicator of inflation, CPI. Consequently, we label $f_{a,t}$ as the real activity factor and $f_{b,t}$ as the inflation factor.

Prior to using the factors, we develop the following robustness check. First, we extract the real activity factor from a model that uses only the real activity indicators, $\tilde{f}_{a,t}$, and the inflation factor, $\tilde{f}_{b,t}$, from a model that uses only the inflation indicators. Second, we run OLS regressions to assess the explanatory power of the factors estimated from the separated models on the factors estimated from the unified model. Specifically, we regress $f_{a,t}$ on $\tilde{f}_{a,t}$, obtaining the standard goodness of fit measure $R^2_{a,a}$, and then we regress $f_{a,t}$ on $\tilde{f}_{b,t}$, obtaining a fitting measure of $R^2_{a,b}$. If the factor $f_{a,t}$ is properly identified, $R^2_{a,a}$ should be higher than $R^2_{a,b}$. The analogous procedure is performed for $f_{b,t}$, which would be properly identified when $R^2_{b,b} > R^2_{b,a}$. We ran this robustness check for the models of each country and we found that the factors were properly labeled in all the cases.[3]

For each country, the estimated factors of real activity and inflation are plotted in Figure 1. Some features deserve attention. First, there are strong time variations in the comovements across these variables. Using a five year window for all the countries, we find that the comovements vary between a maximum of +0.51 and a minimum of -0.60, with positive and negative numbers for all the countries. In addition, there are also changes in the leading and lagging behavior of the variables. For some periods, the highest cross correlation is the contemporaneous correlation, but sometimes the maximum is captured with up to six lags of leading between real activity and inflation. Second, real activity factors decrease during the euro area recession, especially for Italy and Germany. Third, the inflation factors decrease during the last part of the sample, especially for Italy and Spain. Fourth, the lack of recovery in Spain after the 2008-9 recession is remarkable, leading to a double dip recession.

[3] To save space, these results are omitted. They are available upon request.

3 Assessing the state of the economy

3.1 The model

To account for the interactions between high and low real activity and inflation regimes, we rely on the framework proposed by Leiva-Leon (2014). Specifically, assume that the autocorrelation in the dynamics of the factors can be approximated by regime-switching mean Markov-switching specification. Accordingly, we consider the following tractable bivariate two-state Markov-switching model

$$\begin{bmatrix} f_{a,t} \\ f_{b,t} \end{bmatrix} = \begin{bmatrix} \mu_{a,0} + \mu_{a,1} S_{a,t} \\ \mu_{b,0} + \mu_{b,1} S_{b,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{a,t} \\ \varepsilon_{b,t} \end{bmatrix}, \tag{12}$$

where

$$\begin{bmatrix} \varepsilon_{a,t} \\ \varepsilon_{b,t} \end{bmatrix} \sim i.i.d.N \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{bmatrix} \right). \tag{13}$$

In this expression, the state variable $S_{k,t}$ indicates that the common factor f_{kt} is in regime 0 with a mean equal to $\mu_{k,0}$, when $S_{k,t} = 0$, and that f_{kt} is in regime 1 with a mean equal to $\mu_{k,0} + \mu_{k,1}$, when $S_{k,t} = 1$, for $k = a, b$. Moreover, we assume that $S_{a,t}$ and $S_{b,t}$ evolve as irreducible two-state Markov chains, whose transition probabilities are given by

$$\Pr(S_{k,t} = j | S_{k,t-1} = i) = p_{k,ij}, \tag{14}$$

for $i, j = 0, 1$ and $k = a, b, ab$.

Within this framework, we define three Markov processes to capture the dynamics of the unobserved state. The first Markov process, $S_{a,t}$, captures the dynamics of the economic activity. The second Markov process, $S_{b,t}$, captures the dynamics of inflation. In addition, we also define a Markov process $S_{ab,t}$ that captures the dynamics of the factors in the case they would evolve with perfect synchronization. To account for the interrelation between $f_{a,t}$ and $f_{b,t}$, we allow for time-varying interdependence between $S_{a,t}$

and $S_{b,t}$. Specifically, the joint probability of the model's regimes is given by

$$\Pr(S_{a,t} = j, S_{b,t} = j) = \Pr(V_t = 1)\Pr(S_{ab,t} = j) + (1 - \Pr(V_t = 1))\Pr(S_{a,t} = j)\Pr(S_{b,t} = j), \tag{15}$$

where

$$V_t = \begin{cases} 0 \text{ If } \; S_{a,t} \text{ and } S_{b,t} \text{ are unsynchronized} \\ 1 \text{ If } \; S_{a,t} \text{ and } S_{b,t} \text{ are synchronized} \end{cases}, \tag{16}$$

and the latent variable V_t also evolves according to an irreducible two-state Markov chain whose transition probabilities are given by

$$\Pr(V_t = j_v | V_{t-1} = i_v) = p_{ij,v}, \tag{17}$$

for $ij, v = 0, 1$. Interestingly, the joint dynamics of $S_{a,t}$ and $S_{b,t}$ are a weighted average between the extreme dependent and the extreme independent cases, where the weights assigned to each of them are endogenously determined by

$$\delta_t^{ab} = \Pr(V_t = 1). \tag{18}$$

Therefore, the term δ_t^{ab} can be interpreted as the time-varying degree of synchronization between $S_{a,t}$ and $S_{b,t}$. Since the likelihood function of this model is conditional on several states, the estimation of parameters obtained with the maximum likelihood approach could become cumbersome. Therefore, we rely on a Bayesian approach to estimate this model. This approach also allows us to provide a measure of uncertainty about the parameter estimates. The Gibbs sampler used in the estimation procedure, which is detailed in the Appendix, can be summarized by iterating the following four steps:

Step 1: Generate the latent variables $S_{a,t}$,$S_{b,t}$,$S_{ab,t}$ and V_t, conditional on the factors and the vector of parameters, denoted by θ.

Step 2: Generate the transition probabilities associated with each latent variable, $p_{00,a}$, $p_{11,a}$, $p_{00,b}$, $p_{11,b}$, $p_{00,ab}$, $p_{11,ab}$, $p_{00,v}$, $p_{11,v}$, conditional on $S_{a,t}$,$S_{a,t}$,$S_{ab,t}$ and V_t.

Step 3: Generate the means associated with the factors, $\mu_{a,0}$,$\mu_{a,1}$,$\mu_{b,0}$,$\mu_{b,1}$, conditional on σ_a^2, σ_b^2, σ_{ab}, $S_{a,t}$, $S_{b,t}$, $S_{ab,t}$, V_t and the factors.

Step 4: Generate the variance-covariance matrix, with elements σ_a^2, σ_b^2, σ_{ab}, conditional on $\mu_{a,0}$, $\mu_{a,1}$, $\mu_{b,0}$, $\mu_{b,1}$, $S_{a,t}$, $S_{b,t}$, $S_{ab,t}$, V_t and the factors.

Table 1 presents the estimated coefficients of the model for all countries. The table shows that real fluctuations are higher in Italy and Spain than in France and Germany, with lower growth rates in recession and higher growth rates in expansion, (see values of $\mu_{a,0}$ and $\mu_{a,1}$). However, prices oscillate more similarly across countries. Figure 2 plots the inference on real activity (left-hand-side graphs) and inflation (right-hand-side graphs) regimes for all the countries. The results indicate high deflationary pressures during 2008-2009 for all countries and since the early 2013 for France, Italy and Spain. Regarding real activity, the results indicate high probability of recession around 2000-2001 and 2007-2009 in all countries, and in 2011 (mainly) in Germany and Italy.

Figure2B -lower row- plots the inference on the time-varying synchronization by country. As can be seen, the synchronicity changes over time, reaching up to 0.6 for France or 0.55 for Italy or 0 in other periods. France presents the highest synchronization of the real and nominal cycle with an average of $\delta_t^{ab}$of 0.43, while Italy presents the lowest with 0.20. The changes in the synchronization over time will be the key to identify the nature of the shocks.

3.2 Aggregate demand and supply shocks

Aruoba and Diebold (2010) showed that prices and quantities are related over the business cycle, and that the nature of this relationship contains information about the sources of shocks. While adverse demand shocks lead to periods of business cycle downturns and low inflation, adverse supply shocks lead to reductions in economic activity along with inflationary pressures. Equivalently, expansionary demand shocks increase economic activity and prices, and expansionary supply shocks lead to periods of business cycle upturns and low inflation.

Accordingly, inferences on contractionary versus expansionary and demand versus supply shocks can be computed from expression (15) as follows:

$$
\begin{aligned}
\Pr(S_{a,t} &= 1, S_{b,t}=1) \rightarrow \text{ High real and high inflation} \rightarrow \text{ Expansionary Demand} \\
\Pr(S_{a,t} &= 1, S_{b,t}=0) \rightarrow \text{ High real and low inflation} \rightarrow \text{ Expansionary Supply} \\
\Pr(S_{a,t} &= 0, S_{b,t}=1) \rightarrow \text{ Low real and high inflation} \rightarrow \text{ Contractionary Supply} \\
\Pr(S_{a,t} &= 0, S_{b,t}=0) \rightarrow \text{ Low real and low inflation} \rightarrow \text{ Contractionary Demand}
\end{aligned}
$$

The results of the inferences on aggregate shocks for Germany, France, Italy and Spain are shown in Figures 3 to 6, respectively. For illustrative purposes, we include in these figures the changes in the ECB main refinancing operations, the minimum bid rate. Before analyzing the relation between the shocks and the ECB rates, it is interesting to analyze the role that the comovements have in explaining the evolution of the shocks.

Equation (15) basically states the total probability theorem applied to our specification. The probability of expansionary (or contractionary) demand (or supply) shocks is a weighted average of those shocks assuming perfect comovements times the probability of perfect comovement plus the probability of those shocks in the perfect independent case times the probability of independence. The question now is which kind of shocks would imply a higher level of comovements. To answer this question, we compute a weighted average of the synchronization measure according to the probability of each type of shock. In particular, we compute

$$
\delta_{i,j}^{ab} = \frac{\sum_{t=1}^{T} \delta_t^{ab} \Pr(S_{a,t}=i, S_{b,t}=j)}{1/T \sum_{t=1}^{T} \Pr(S_{a,t}=i, S_{b,t}=j)}. \tag{19}
$$

Using this expression, we find that expansionary supply shocks present up to 40% more of comovement in Germany. In Italy, the increase in comovement is associated with higher probability of expansionary demand shocks. For all the countries, the degree of comovement is lower in the presence of contractionary shocks. In addition, for all the countries, expansionary demand shocks are predominant for most of the sample period.

It is worth emphasizing that, specially for Germany, periods of high probabilities of expansionary supply shocks and contractionary demand shocks display a negative relation to the changes in the ECB's interest rate. In France and Italy, such negative relationship is even more evident, especially for contractionary demand shocks. In Spain, inferences on contractionary demand shocks and the ECB's interest rate seem negatively related only during the 2008 recession. This provides evidence that the ECB tends to react with expansionary monetary policy (interest rate falls) during episodes of low inflation regardless of whether they appear in high growth (expansionary supply) or in low growth (contractionary demand) periods. These reactions are compatible with the mandate of the Statute of the ECB (Article 2): "The primary objective of the european Central Bank is to maintain price stability within the eurozone".

The fact that inferences on contractionary demand and expansionary supply shocks are negatively correlated with the ECB monetary policy, indicates that the ECB reacts to the state of the main economies in the euro area. This is not new in the literature since this result a is standard feature of any new Keynesian model. Dees et al. (2010), just to quote a recent contribution, show impulse response functions of the interest rate associated to demand and supply shocks for different countries, including the euro area, with similar results. However, the current state of the economy leads not only to current monetary policies changes, but also a market assessment about future changes in monetary policy, in the short, medium or even long run. Markets understand the reaction function of the ECB and the relative importance of the different countries of the system and act accordingly. Markets also understand that the monetary policy transmission mechanism may take several periods of time to achieve the central bank's goals and markets understand that in the medium to long run the response of the ECB might be different than the one given in the short run and that price and real developments have different impact on interest rates.[4] Examining the way in which markets react to different types of shocks in different countries is the purpose of next section.

[4] A simple panel analysis shows that the price factor is always significant when analyzing spot rates development, while activity factor is not significant. The activity factor only become significant in the medium to long run analysis. This could explain some leading behavior of price developments over real developments. ECB reacts faster to price developments and it takes more time to react to real activity developments.

4 Aggregate shocks and monetary policy expectations

In this section, we assess the effect of aggregate contractionary-expansionary demand-supply shocks in the main euro area countries, on the ECB's monetary policy expectations at different horizons. In order to assess the relationship between aggregate shocks (based on the interaction of real activity and inflation regimes) and monetary policy expectations under a unified framework, we include a measure of expectations in the set of information. In particular, we use the first differences of the j-year nominal interest rate swaps, $\hat{r}_{j,t}$, which provides information about market's expectations of the ECB's monetary policy j years ahead. We use data of swaps that span from March 2000 until October 2014, and from 1 to 17 years ahead expectations, due to data availability constraints. Interest rate swaps are the best measure of monetary policy expectations because, given that there is no transaction in period "t", they are not contaminated by liquidity premium.[5]

We assume that market agents infer the current state of the economy with the available information and then construct expectations about future monetary policy actions. Accordingly, the unified model reads as follows

$$\begin{bmatrix} f_{a,t} \\ f_{b,t} \\ \hat{r}_{j,t} \end{bmatrix} = \begin{bmatrix} \mu_{a,0} + \mu_{a,1} S_{a,t} \\ \mu_{b,0} + \mu_{b,1} S_{b,t} \\ \mu_{j,1} S_{a,t} S_{b,t} + \mu_{j,2} S_{a,t}(1 - S_{b,t}) + \mu_{j,3}(1 - S_{a,t}) S_{b,t} + \mu_{j,4}(1 - S_{a,t})(1 - S_{b,t}) \end{bmatrix} + \begin{bmatrix} \varepsilon_{a,t} \\ \varepsilon_{b,t} \\ \varepsilon_{j,t} \end{bmatrix}. \tag{20}$$

The main difference with respect to the model described in epresion (12) is the inclusion of the equation for $\hat{r}_{j,t}$. The monetary policy shock is modelled as a function of a time-varying mean and an error term. This time-varying mean is assumed to depend on the type of shock hitting the economy, i.e., expansionary demand ($S_{a,t} = 1, S_{b,t} = 1$), expansionary supply ($S_{a,t} = 1, S_{b,t} = 0$), contractionary supply ($S_{a,t} = 0, S_{b,t} = 1$) and contractionary demand ($S_{a,t} = 0, S_{b,t} = 0$). Since the Gibbs sampler, described in the Appendix, generates draws of the latent variables, in every iteration the unobserved becomes "observed" and the shocks can be used as any other regressor. Therefore, this framework allows us to assess the relationship between observed continuous and unobserved discrete variables.

[5] Some examples of using interest rate swaps to measure monetary policy expectations can be found in Gurkaynak et al (2007) or Sack (2002) among may others.

Our main focus regarding the unified model is assessing how responsive are expectations of the ECB's monetary policy to aggregate shocks hitting the economies of Germany, France, Italy and Spain. Therefore, the parameters of interest are $\mu_{j,1}$, $\mu_{j,2}$, $\mu_{j,3}$ and $\mu_{j,4}$ for $j = 1, ..., 17$, since they measure the responses in monetary policy expectations to aggregate shocks of each country. The estimation of model (20) follows the lines suggested to estimate model (12).[6]

The parameters estimated along with their fan charts are plotted in Figures 7 to 10. The figures represent the estimated coefficients $\mu_{j,1}$, $\mu_{j,2}$, $\mu_{j,3}$ and $\mu_{j,4}$ for $j = 1, ..., 17$, representing the estimated values of each coefficient for every horizon of the swap rates. For example, the first estimated value $\mu_{1,1}$represents the swap response at year 1 of an expansionary demand shock, $\mu_{1,2}$ is the swap response at year 1 of an expansionary supply shock and so on.

Overall, the figures show that the ECB's monetary policy expectations react negatively to contractionary shocks. Contractionary demand shocks affect monetary policy expectations at short horizons, while contractionary supply shocks affect medium to long-term expectations. In addition, the effect on monetary policy expectations of expansionary shocks is not significant.

The results for Germany are plotted in Figure 7. The figure shows that both contractionary supply and demand shocks have a significantly negative effect on monetary policy expectations. Specifically, contractionary supply shocks affect medium and long term expectations, while contractionary demand shocks affect short term expectations. The figure also shows that expansionary supply shocks and demand shocks have no effect on expectations of interest rates. For the case of France, Figure 8 indicates that only contractionary demand shocks have a negative effect on short, medium, and long term monetary policy expectations. Moreover, the figure shows that contractionary supply shocks lead to a slightly negative effect on the expectations of the ECB's monetary policy. Figure 9 reveals that, as in the case of Germany, contractionary supply shocks in Italy affect medium and long term monetary policy expectations, while contractionary demand shocks only affect

[6] To avoid imposing judgement, we choose totally uninformative priors for $\mu_{j,i}$, i.e., $\mu_{j,i} = 0$ for $i = 1, ..., 4$ and $j = 1, ..., 17$.

short term expectations. As in the other countries, in this case, expansionary shocks have no significant effect on the ECB's monetary policy expectations. Finally, Figure 10 shows that only contractionary demand shocks in Spain have significant negative effect on short and medium term monetary policy expectations.

The differences in the significance of the long and short term effects could be explained as follows. When contractionary supply shocks hit the economy, the high inflation may be a bulwark against an immediate action by the ECB in decreasing the interest rate, and thus the market expects only an ECB action in the medium- to long-term. By contrast, when both real activity and inflation experience a downturn, i.e. a contractionary demand, the market may expect a soon reaction by the ECB in cutting rates to stimulate the economy and to keep inflation close to the target.

In sum, we find that the market assessment to the response to a monetary policy shock depends on the nature of the shock. If markets read monetary policy correctly, they believe that the monetary policy reaction function is more aggressive to negative demand shocks than to any other type of shocks. This reaction is immediate and significant for all countries, and of similar magnitude. In the case of negative supply shocks, this effect varies across countries (it is not significant in the case of Spain) and is more related to the long run than to short run expectations. The effect of expansionary demand and supply shock is more diffuse across countries and across time delays.

5 Conclusions

This paper addresses the effect of the current state of the economy on monetary policy expectations. In particular, we study the effect of contractionary (or expansionary) demand (or supply) shocks hitting the euro area countries on the expectations of the ECB's monetary policy. The results indicate that expectations are responsive to aggregate contractionary shocks, but not to expansionary shocks. Contractionary demand shocks have a negative effect on short term monetary policy expectations, while contractionary supply shocks have negative effect on medium and long term expectations. We also find that, for the case of demand shocks, these results are robust across countries. However, this is not the case for supply shocks, for which markets seem to discount more the German, French or Italian shocks than the shocks for Spain.

6 Appendix: Bayesian parameter estimation

The approach to estimate θ will be relied on a bivariate extended version of the multi-move Gibbs-sampling procedure implemented by Kim and Nelson (1998) for Bayesian estimation of univariate Markov-switching models. In this setting both the parameters of the model θ and the Markov-switching variables $\tilde{S}_{k,T} = \{S_{k,t}\}_1^T$ for $k = a, b$, $\tilde{S}_{ab,T} = \{S_{ab,t}\}_1^T$ and $\tilde{V}_T = \{V_t\}_1^T$ are treated as random variables given the data in $\tilde{y}_T = \{f_{a,t}, f_{b,t}\}_1^T$. The purpose of this Markov chain Monte Carlo simulation method is to approximate the joint and marginal distributions of these random variables by sampling from conditional distributions.

6.1 Priors

For the mean and variance parameters in vector θ, the Independent Normal-Wishart prior distribution is used

$$p(\mu, \Sigma^{-1}) = p(\mu)p(\Sigma^{-1}), \tag{21}$$

where

$$\begin{aligned} \mu &\sim N(\underline{\mu}, \underline{V}_\mu) \\ \Sigma^{-1} &\sim W(\underline{S}^{-1}, \underline{\upsilon}), \end{aligned}$$

and the associated hyperparameters are given by $\underline{\mu} = (\alpha_0^a, \alpha_1^a - \alpha_0^a, \alpha_0^b, \alpha_1^b - \alpha_0^b)'$, $\underline{V}_\mu = I/10$, $\underline{S}^{-1} = I$, $\underline{\upsilon} = 0$. Due to the business cycle heterogeneity across euro area countries we adjust the mean hyperparameters for each factor to the magnitude of the corresponding fluctuation. Specifically, α_0^a is the sample average among all the negative growth rates of f_t^a, while α_1^a is the sample average among all the positive growth rates of f_t^a. The same procedure is followed to obtain α_0^b and α_1^b. In this way provide an estimation in a more "data-driven" way. It is important to mention that when the Gibbs sampler is applied to estimate the trivariate unified model in Section 4, all the hyperparameters of the coefficients associated to the aggregate shocks, $\mu_{j,1}$, $\mu_{j,2}$, $\mu_{j,3}$, $\mu_{j,4}$, are equal to zero, meaning that we follow noninformative priors to provide an estimation robust to judgement.

For the transition probabilities, Beta distributions are used as conjugate priors

$$p_{00,\iota} \sim Be(u_{11,\iota}, u_{10,\iota}),\ p_{11,\iota} \sim Be(u_{00,\iota}, u_{01,\iota}), \text{ for } \iota = a, b, ab, v, \tag{22}$$

where the hyperparameters are given by $u_{\iota,01} = 2$, $u_{\iota,00} = 8$, $u_{\iota,10} = 1$ and $u_{\iota,11} = 9$, for $\iota = a, b, ab, v$. For each pairwise model, 6,000 iterations were performed, discarding the first 1,000.

6.2 Drawing $\tilde{S}_{a,T}$,$\tilde{S}_{b,T}$,$\tilde{S}_T$ and $\tilde{V}_T$ given θ and $\tilde{y}_T$

Inferences on the dynamics of the state variables, $\tilde{S}_{a,T}$, $\tilde{S}_{b,T}$, $\tilde{S}_T$ and $\tilde{V}_T$, can be done following the results in Kim and Nelson (1998) by first computing draws from the conditional distributions

$$g(\tilde{S}_{k,T}|\theta, \tilde{y}_T) = g(S_{k,T}|\tilde{y}_T)\prod_{t=1}^{T} g(S_{k,t}|S_{k,t+1}, \tilde{y}_t), \text{ for } k = a, b \tag{23}$$

$$g(\tilde{S}_{ab,T}|\theta, \tilde{y}_T) = g(S_{ab,T}|\tilde{y}_T)\prod_{t=1}^{T} g(S_{ab,t}|S_{ab,t+1}, \tilde{y}_t) \tag{24}$$

$$g(\tilde{V}_T|\theta, \tilde{y}_T) = g(V_T|\tilde{y}_T)\prod_{t=1}^{T} g(V_t|V_{t+1}, \tilde{y}_t). \tag{25}$$

In order to obtain the two terms in the right hand side of Equation (23)-(24) the following two steps can be employed:

Step 1: The first term can be obtained by running the filtering algorithm to compute $g(\tilde{S}_{k,t}|\tilde{y}_t)$ for $k = a, b$, $g(\tilde{S}_{ab,t}|\tilde{y}_t)$ and $g(\tilde{V}_{k,t}|\tilde{y}_t)$ for $t = 1, 2, \ldots, T$, saving them and taking the elements for which $t = T$.

Step 2: The product in the second term can be obtained for $t = T-1, T-2, \ldots, 1$, by following the result:

$$\begin{aligned} g(S_{ab,t}|\tilde{y}_t, S_{ab,t+1}) &= \frac{g(S_{ab,t}, S_{ab,t+1}|\tilde{y}_t)}{g(S_{ab,t+1}|\tilde{y}_t)} \\ &\propto g(S_{ab,t+1}|S_{ab,t})g(S_{ab,t}|\tilde{y}_t), \end{aligned} \tag{26}$$

where $g(S_{ab,t+1}|S_{ab,t})$ corresponds to the transition probabilities of $S_{ab,t}$ and $g(S_{ab,t}|\tilde{y}_t)$

were saved in Step 1.

Then, it is possible to compute

$$\Pr[S_{ab,t} = 1 | S_{ab,t+1}, \tilde{y}_t] = \frac{g(S_{ab,t+1} | S_{ab,t} = 1) g(S_{ab,t} = 1 | \tilde{y}_t)}{\sum_{j=0}^{1} g(S_{ab,t+1} | S_{ab,t} = j) g(S_{ab,t} = j | \tilde{y}_t)}, \tag{27}$$

and generate a random number from a $U[0,1]$. If that number is less than or equal to $\Pr[S_{ab,t} = 1 | S_{ab,t+1}, \tilde{y}_t]$, then $S_{ab,t} = 1$, otherwise $S_{ab,t} = 0$. The same procedure applies for $S_{a,t}$, $S_{b,t}$ and V_t.

6.3 Drawing $p_{00,a}$,$p_{11,a}$,$p_{00,b}$,$p_{11,b}$, $p_{00,ab}$,$p_{11,ab}$,$p_{00,v}$,$p_{11,v}$ given $\tilde{S}_{a,T}$,$\tilde{S}_{a,T}$,$\tilde{S}_{ab,T}$ and $\tilde{V}_T$

Conditional on $\tilde{S}_{k,T}$ for $k = a, b$, $\tilde{S}_{ab,T}$ and $\tilde{V}_T$, the transition probabilities are independent on the data set and the model's parameters. Hence, focusing on the case of $\tilde{S}_{ab,T}$, the likelihood function of $p_{00,ab}$, $p_{11,ab}$ is given by:

$$L(p_{00,ab}, p_{11,ab} | \tilde{S}_{ab,T}) = p_{00,ab}^{n_{00,ab}} (1 - p_{00,ab}^{n_{01,ab}}) p_{11,ab}^{n_{11,ab}} (1 - p_{11,ab}^{n_{10,ab}}), \tag{28}$$

where $n_{ij,ab}$ refers to the transitions from state i to j, accounted for in $\tilde{S}_{ab,T}$.

Combining the prior distribution in Equation (22) with the likelihood, the posterior distribution is given by

$$p(p_{00,ab}, p_{11,ab} | \tilde{S}_T) \propto p_{00,ab}^{u_{00,ab}+n_{00,ab}-1} (1-p_{00,ab})^{u_{01,ab}+n_{01,ab}-1} p_{11,ab}^{u_{11,ab}+n_{11,ab}-1} (1-p_{11,ab})^{u_{10,ab}+n_{10,ab}-1} \tag{29}$$

which indicates that draws of the transition probabilities will be taken from

$$p_{00,ab} | \tilde{S}_{ab,T} \sim Be(u_{00,ab}+n_{00,ab}, u_{01,ab}+n_{01,ab}), \;\; p_{11,ab} | \tilde{S}_{ab,T} \sim Be(u_{11,ab}+n_{11,ab}, u_{10,ab}+n_{10,ab}). \tag{30}$$

The same procedure applies for the cases of $\tilde{S}_{k,T}$ for $k = a, b$ and $\tilde{V}_T$.

6.4 Drawing $\mu_{a,0}$,$\mu_{a,1}$,$\mu_{b,0}$,$\mu_{b,1}$ given σ_a^2,σ_b^2,σ_{ab},$\tilde{S}_{a,T}$,$\tilde{S}_{b,T}$,$\tilde{S}_{ab,T}$,$\tilde{V}_T$ and $\tilde{y}_T$

The model in Equation (12) can be compactly expressed as

$$\begin{aligned}
\begin{bmatrix} y_{a,t} \\ y_{b,t} \end{bmatrix} &= \begin{bmatrix} 1 & S_{a,t} & 0 & 0 \\ 0 & 0 & 1 & S_{b,t} \end{bmatrix} \begin{bmatrix} \mu_{a,0} \\ \mu_{a,1} \\ \mu_{b,0} \\ \mu_{b,1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{a,t} \\ \varepsilon_{b,t} \end{bmatrix}, \quad \begin{bmatrix} \varepsilon_{a,t} \\ \varepsilon_{b,t} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{bmatrix} \right) \\
y_t &= \bar{S}_t \mu + \xi_t, \quad \xi_t \sim N(\mathbf{0}, \Sigma), \qquad (31)
\end{aligned}$$

stacking as:

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_T \end{bmatrix}, \quad \bar{S} = \begin{bmatrix} \bar{S}_1 \\ \bar{S}_2 \\ \vdots \\ \bar{S}_T \end{bmatrix}, \text{ and } \xi = \begin{bmatrix} \xi_1 \\ \xi_2 \\ \vdots \\ \xi_T \end{bmatrix},$$

the model in Equation (31) remains written as a normal linear regression model with an error covariance matrix of a particular form:

$$y = S\mu + \xi, \quad \xi \sim N(\mathbf{0}, I \otimes \Sigma) \qquad (32)$$

Conditional on the covariance matrix parameters, state variables and the data, by using the corresponding likelihood function, the conditional posterior distribution $p(\mu|\tilde{S}_{a,T}, \tilde{S}_{b,T}, \tilde{S}_{ab,T}, \tilde{V}_T, \Sigma^{-1}, \tilde{y}_T)$ takes the form

$$\mu|\tilde{S}_{a,T}, \tilde{S}_{b,T}, \tilde{S}_{ab,T}, \tilde{V}_T, \Sigma^{-1}, \tilde{y}_T \sim N(\overline{\mu}, \overline{V}_\mu), \qquad (33)$$

where

$$\begin{aligned}
\overline{V}_\mu &= \left(\underline{V}_\mu^{-1} + \sum_{t=1}^{T} \bar{S}_t' \Sigma^{-1} \bar{S}_t \right)^{-1} \\
\overline{\mu} &= \overline{V}_\mu \left(\underline{V}_\mu^{-1} \underline{\mu} + \sum_{t=1}^{T} \bar{S}_t' \Sigma^{-1} y_t \right).
\end{aligned}$$

After drawing $\mu = (\mu_{a,0}, \mu_{a,1}, \mu_{b,0}, \mu_{b,1})'$ from the above multivariate distribution, if the generated value of $\mu_{a,1}$ or $\mu_{b,1}$ is less than or equal to 0, that draw is discarded, otherwise it is saved, this is in order to ensure that $\mu_{a,1} > 0$ and $\mu_{b,1} > 0$.

6.5 Drawing σ_a^2,σ_b^2,σ_{ab} given $\mu_{a,0}$,$\mu_{a,1}$,$\mu_{b,0}$,$\mu_{b,1}$,$\tilde{S}_{a,T}$,$\tilde{S}_{b,T}$,$\tilde{S}_{ab,T}$,$\tilde{V}_T$ and $\tilde{y}_T$

Conditional on the mean parameters, state variables and the data, by using the corresponding likelihood function, the conditional posterior distribution

$$p(\Sigma^{-1}|\tilde{S}_{a,T}, \tilde{S}_{b,T}, \tilde{S}_{ab,T}, \tilde{V}_T, \mu, \tilde{y}_T),$$

takes the form

$$\Sigma^{-1}|\tilde{S}_{a,T}, \tilde{S}_{b,T}, \tilde{S}_{ab,T}, \tilde{V}_T, \mu, \tilde{y}_T \sim W(\overline{S}^{-1}, \overline{v}), \tag{34}$$

where

$$\begin{aligned} \overline{v} &= T + \underline{v} \\ \overline{S} &= \underline{S} + \sum_{t=1}^{T} \left(y_t - \bar{S}_t\mu\right)\left(y_t - \bar{S}_t\mu\right)', \end{aligned}$$

after Σ^{-1} is generated the elements is Σ are recovered.

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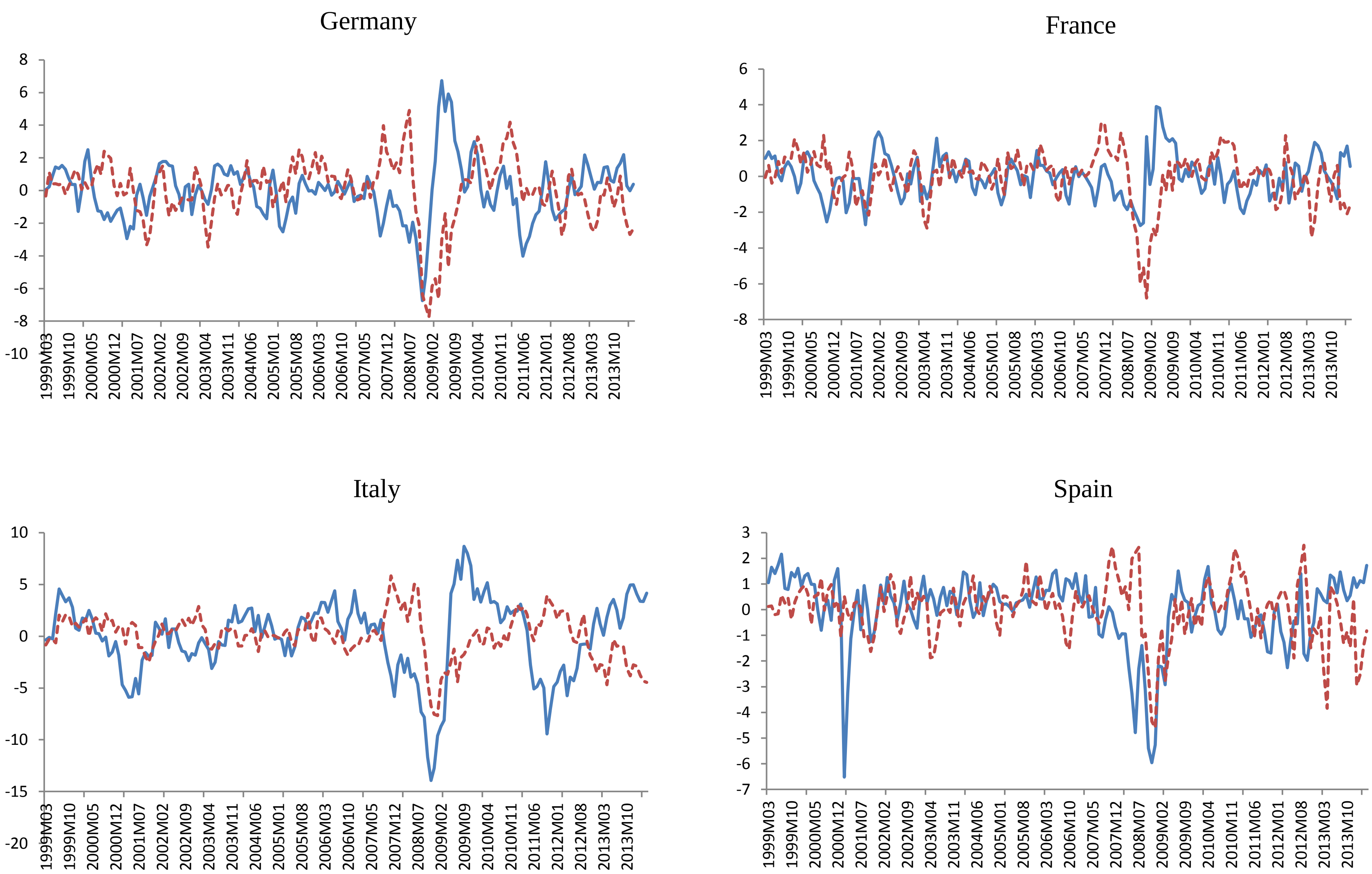
Table 1. Parameter estimates coefficients of equation (12)

	Germany	France	Italy	Spain
$\mu_{a,0}$	-2,56	-1,50	-5,12	-3,37
	(0,55)	(0,39)	(0,39)	(0,26)
$\mu_{a,1}$	2,89	1,65	6,62	3,66
	(0,46)	(0,39)	(0,40)	(0,26)
$\mu_{b,0}$	-3,74	-2,93	-3,03	-2,19
	(0,54)	(0,37)	(0,31)	(0,31)
$\mu_{b,1}$	4,10	3,25	3,81	2,40
	(0,50)	(0,35)	(0,31)	(0,30)
$p_{a,11}$	0,98	0,97	0,97	0,98
	(0,02)	(0,02)	(0,01)	(0,01)
$p_{a,00}$	0,84	0,79	0,91	0,84
	(0,08)	(0,09)	(0,04)	(0,08)
$p_{b,11}$	0,98	0,97	0,98	0,97
	(0,01)	(0,02)	(0,01)	(0,01)
$p_{b,00}$	0,83	0,79	0,91	0,80
	(0,08)	(0,08)	(0,05)	(0,09)
$p_{ab,11}$	0,99	0,98	0,98	0,98
	(0,01)	(0,01)	(0,01)	(0,01)
$p_{ab,00}$	0,81	0,78	0,85	0,80
	(0,09)	(0,09)	(0,07)	(0,09)
$p_{v,11}$	0,84	0,86	0,87	0,82
	(0,10)	(0,10)	(0,09)	(0,11)
$p_{v,00}$	0,92	0,88	0,96	0,90
	(0,08)	(0,10)	(0,03)	(0,07)
σ_a^2	2,28	1,15	5,90	0,89
	(0,33)	(0,16)	(0,65)	(0,10)
σ_b^2	2,26	1,09	2,31	0,82
	(0,30)	(0,14)	(0,26)	(0,10)
σ_{ab}	-0,25	-0,05	0,91	0,07
	(0,46)	(0,13)	(0,36)	(0,07)

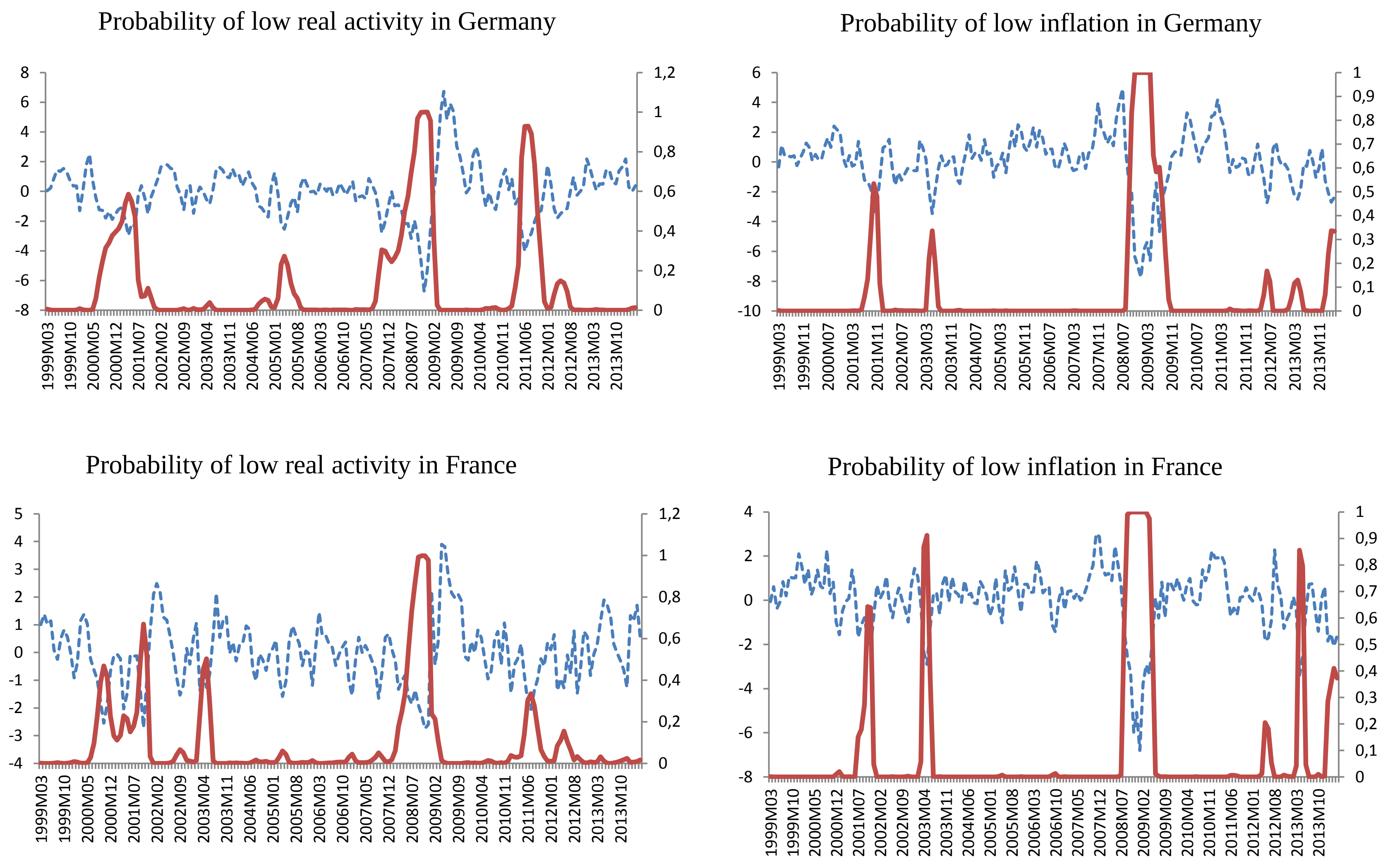
Notes.Parameter estimates for the coefficients of the two means, of each factor, transition probabilities of the MS models and variance covariance matrices. Factor "a" relates to real activity while factor "b" relates to inflation developments. Standard errors are in parenthesis.

Figure 1. Real Activity and Inflation Indexes



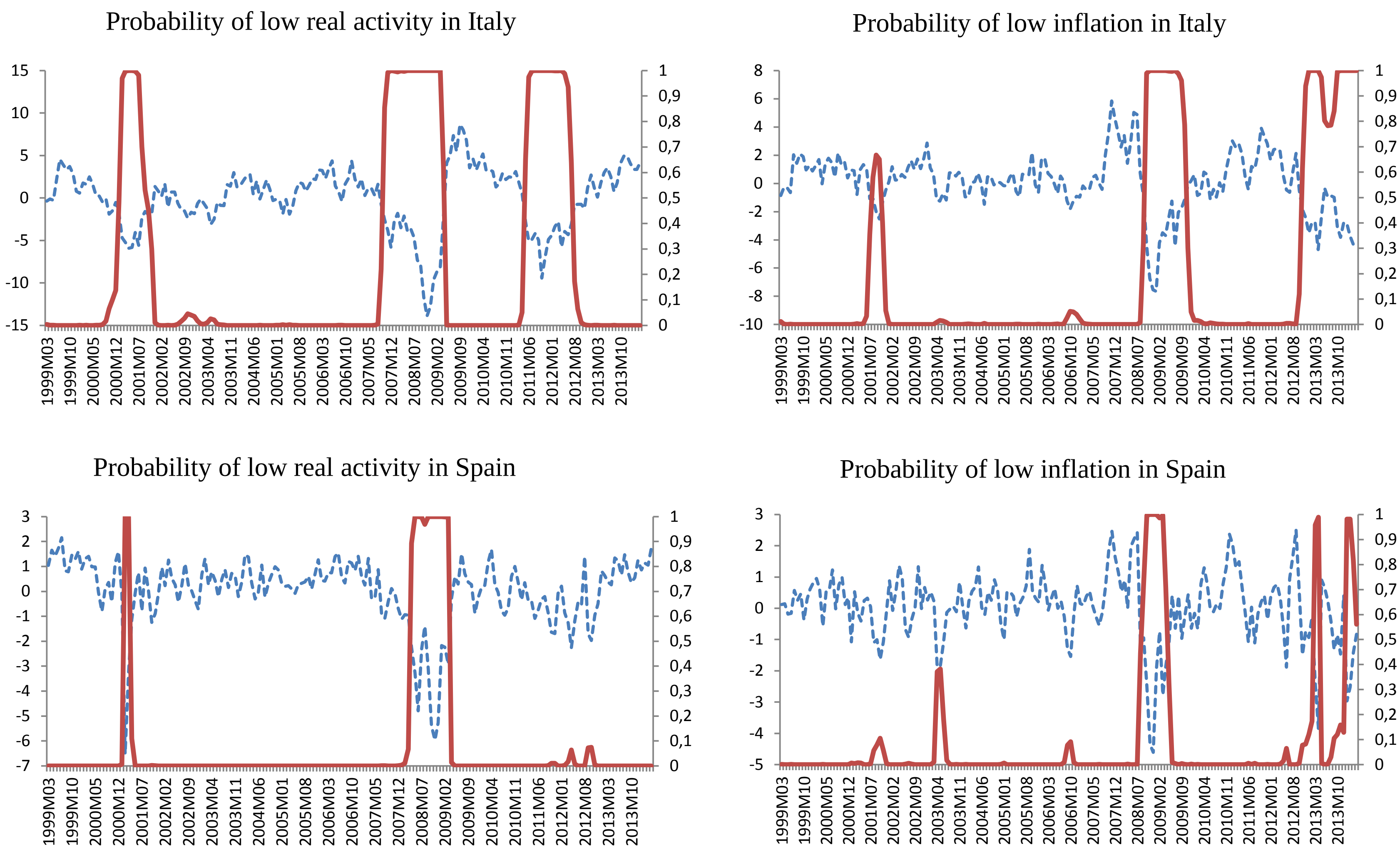
Notes. The figure plots the real activity index (blue solid line) and the inflation index (red dashed line) for each country.

Figure 2. Regime inferences of Real Activity and Inflation



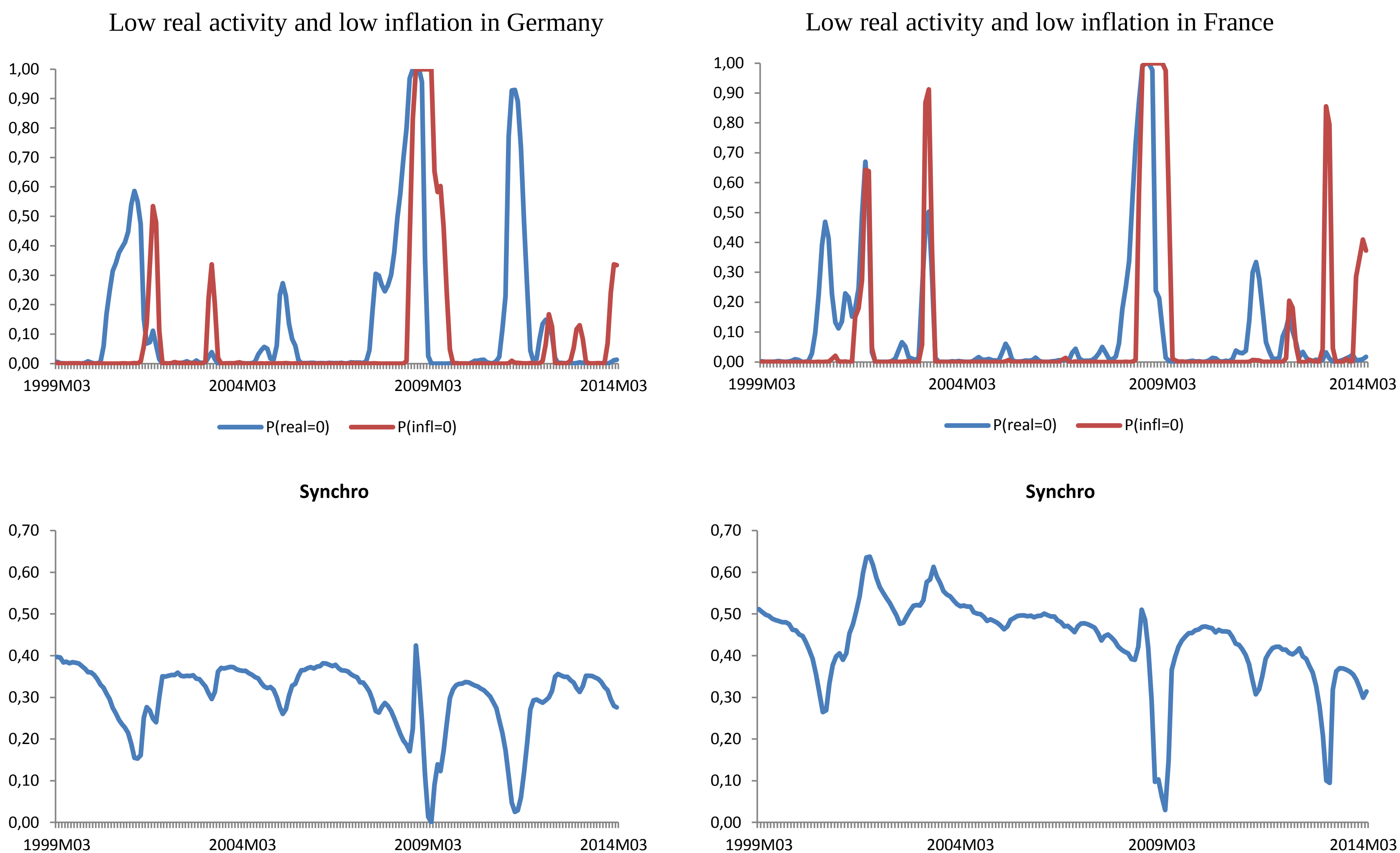
Notes. Each chart plots the probability of low mean (solid red line) and the corresponding index (dashed blue line).

Figure 2. Regime inferences of Real Activity and Inflation (cont.)



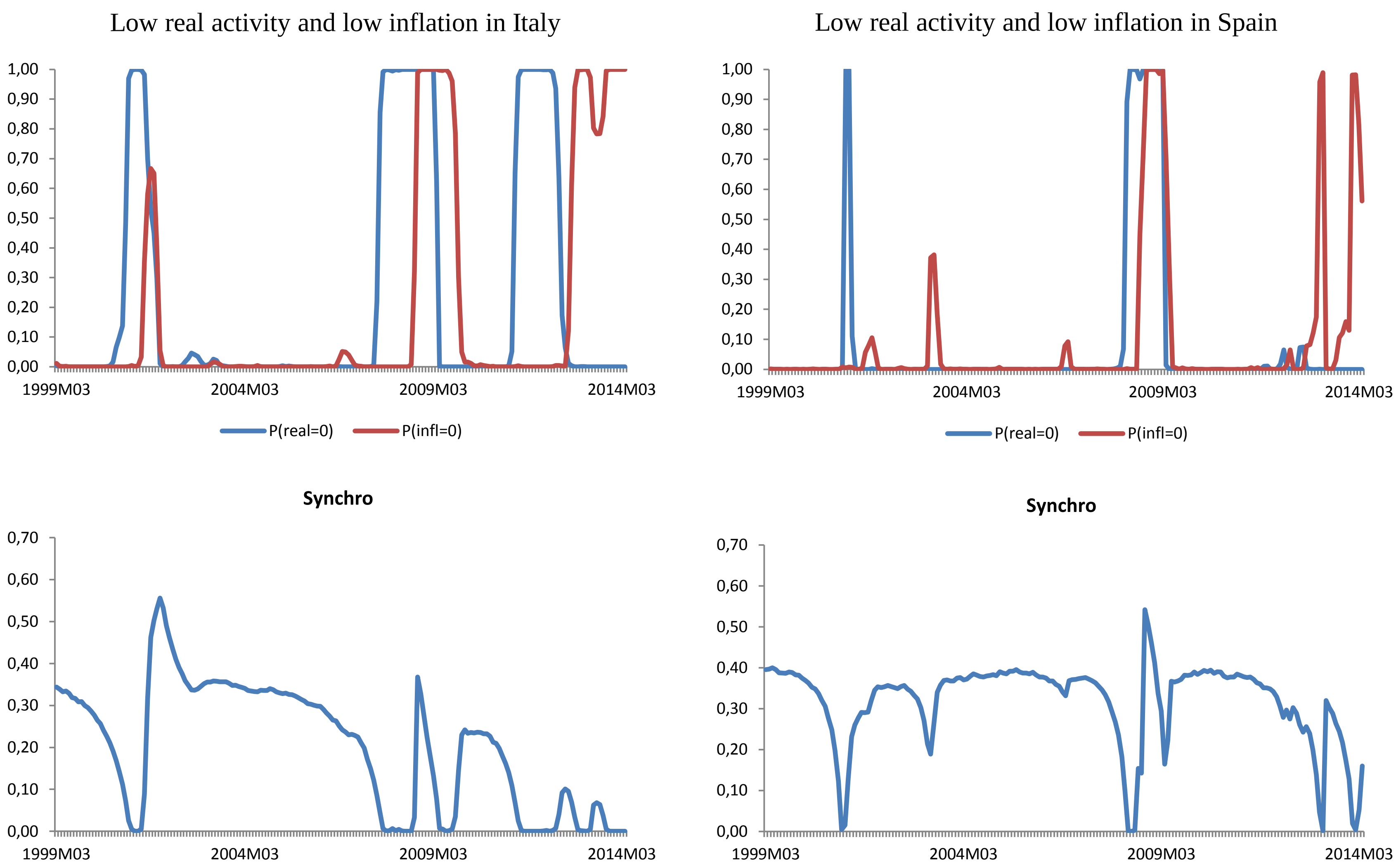
Notes. Each chart plots the probability of low mean (solid red line) and the corresponding index (dashed blue line).

Figure 2B. Regime inferences of Real Activity and Inflation



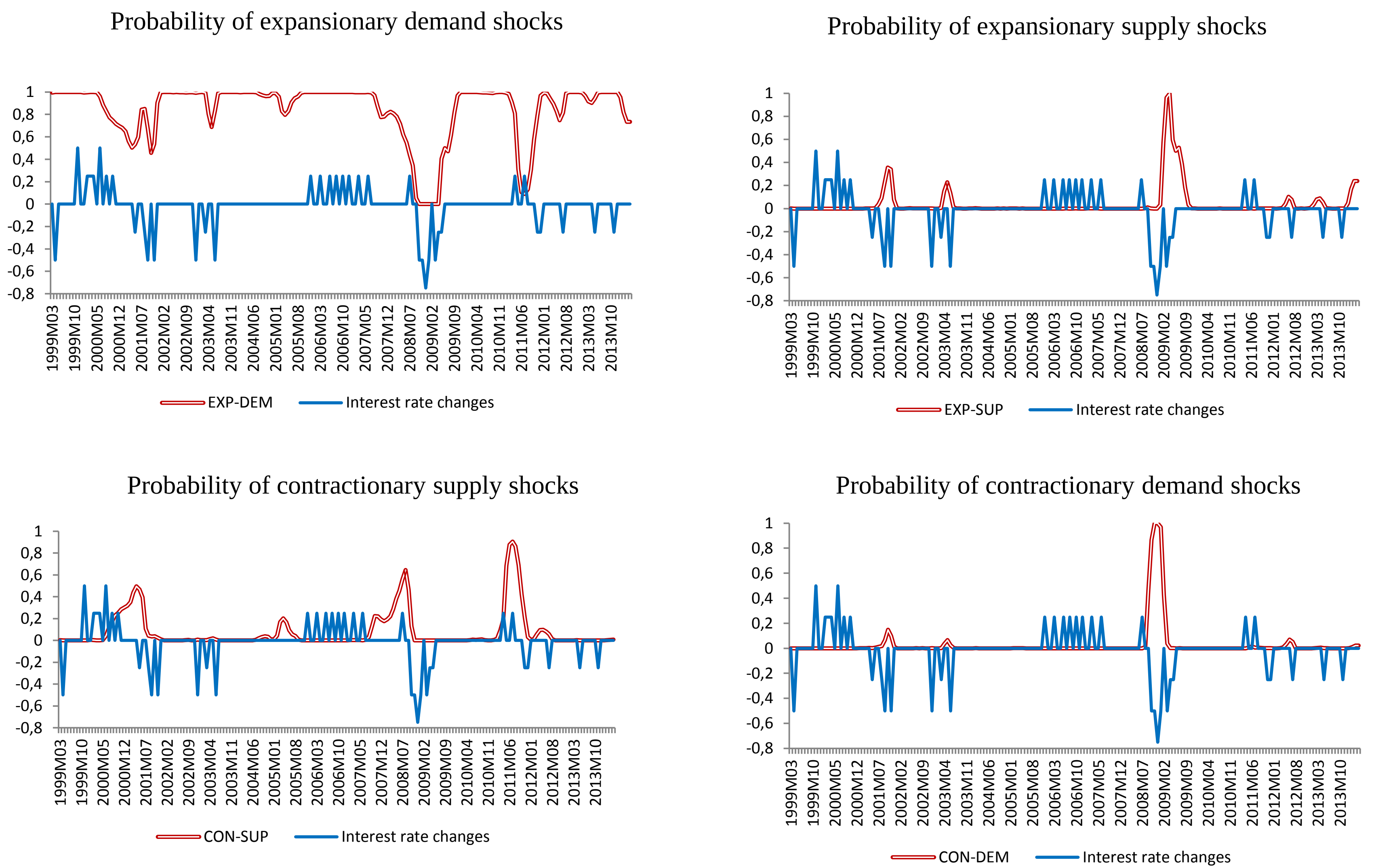
Notes. Top charts plots the probabilities of low real activity and of low inflation. Bottom charts shows their synchronization.

Figure 2B. Regime inferences of Real Activity and Inflation (Cont)



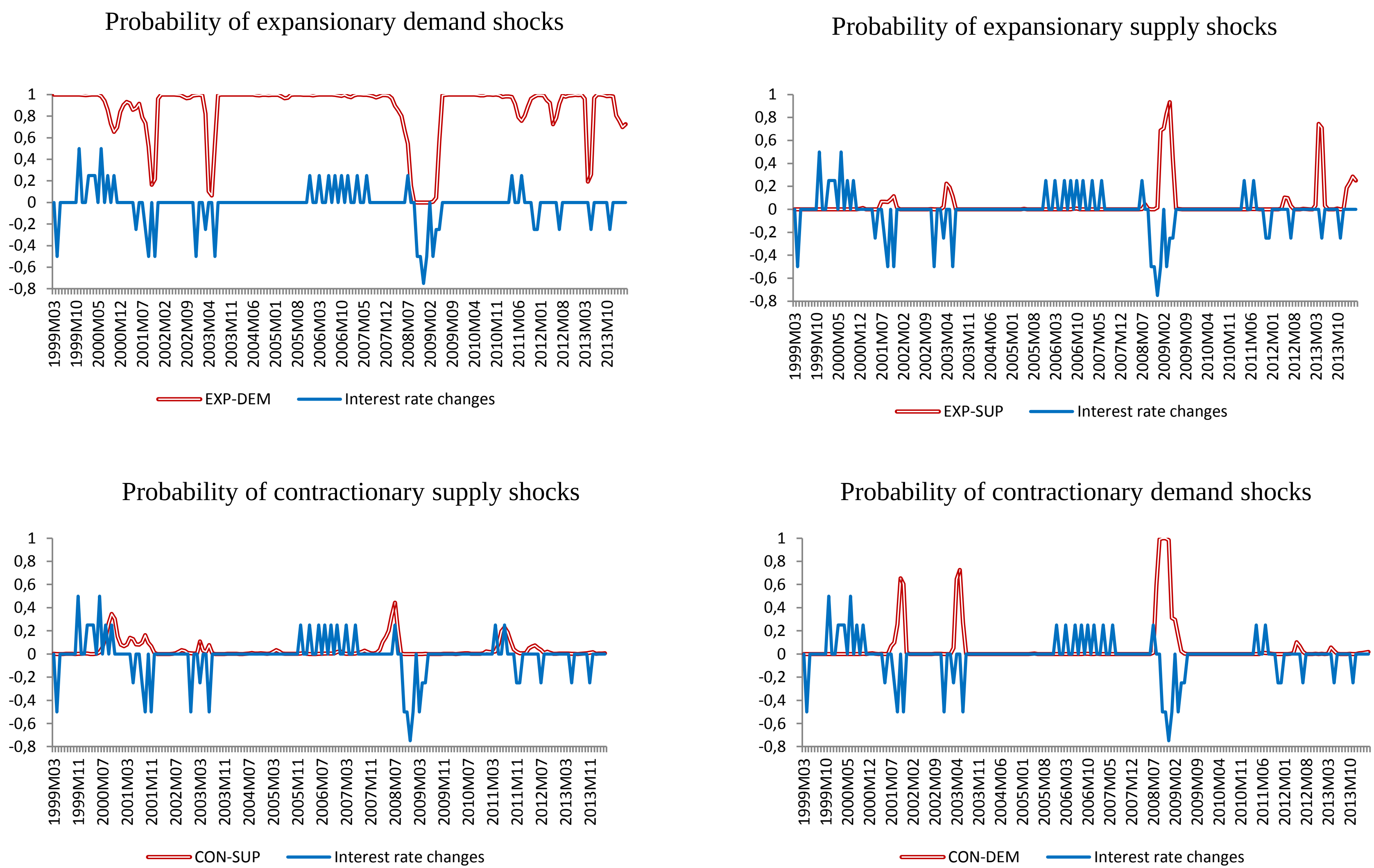
Notes. Top charts plots the probabilities of low real activity and of low inflation. Bottom charts shows their synchronization.

Figure 3. Regime inferences on aggregate shocks in Germany



Notes. Each chart plots the probability of aggregate shocks (double red line) and the main refinancing operations: minimum bid rate in first differenced (solid blue line).

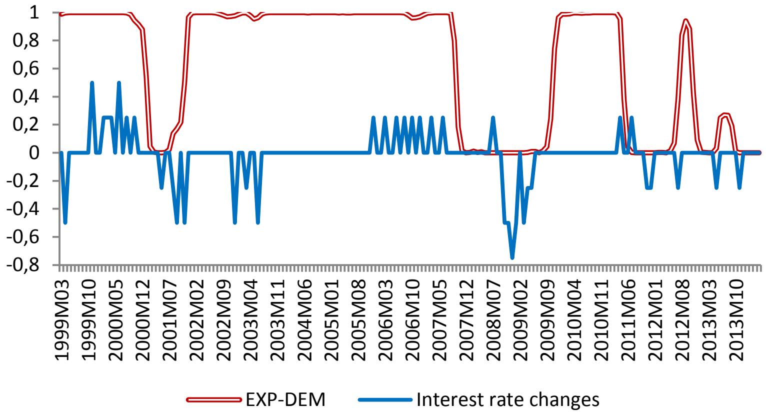
Figure 4. Regime inferences on aggregate shocks in France



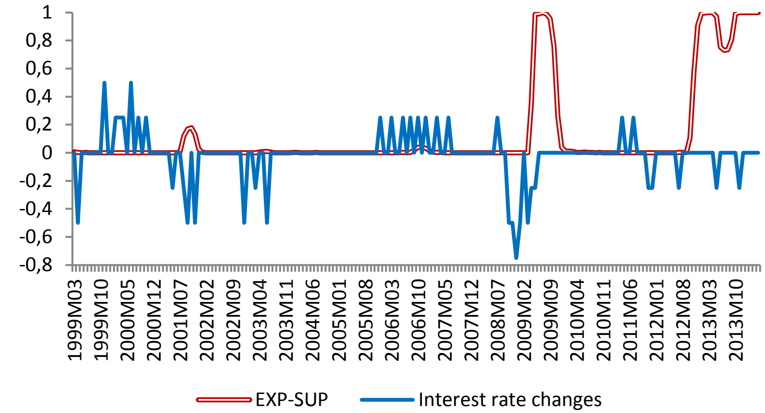
Notes. Each chart plots the probability of aggregate shocks (double red line) and the main refinancing operations: minimum bid rate in first differenced (solid blue line).

Figure 5. Regime inferences on aggregate shocks in Italy

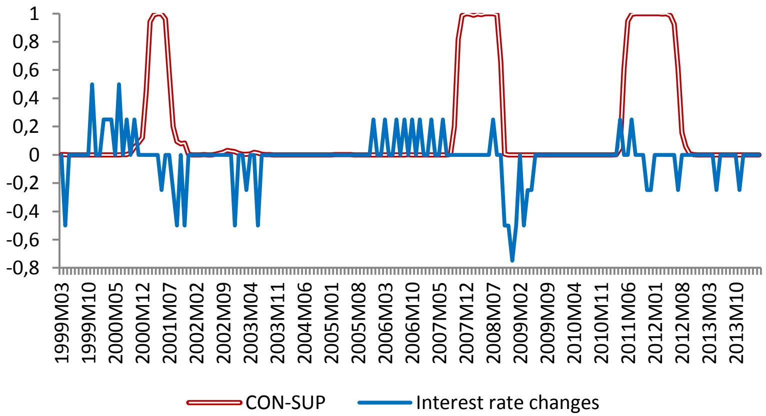
Probability of expansionary demand shocks



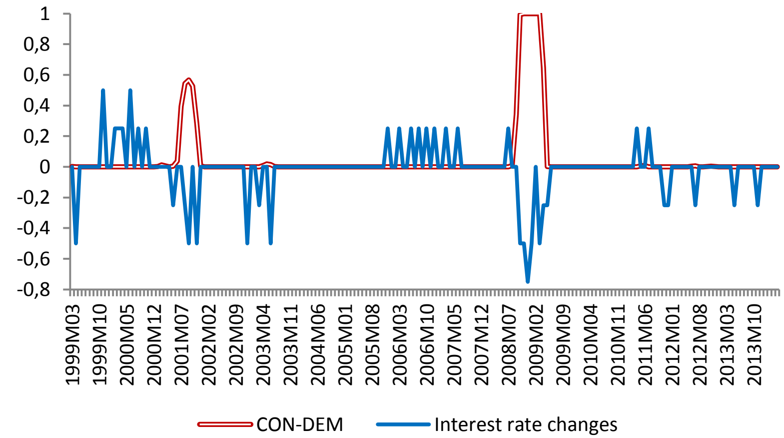
Probability of expansionary supply shocks



Probability of contractionary supply shocks



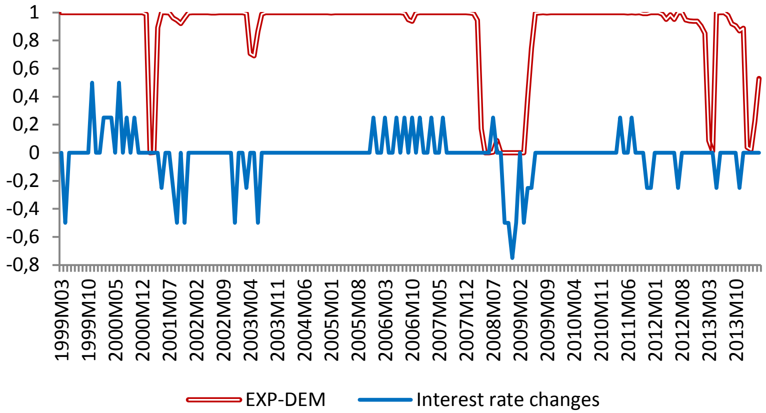
Probability of contractionary demand shocks



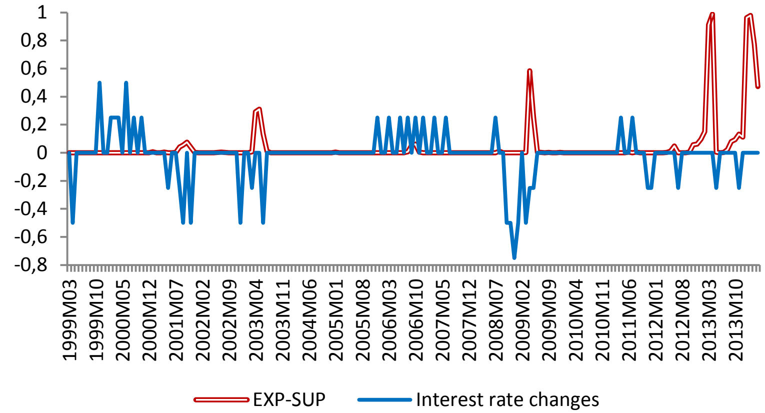
Notes. Each chart plots the probability of aggregate shocks (double red line) and the main refinancing operations: minimum bid rate in first differenced (solid blue line).

Figure 6. Regime inferences on aggregate shocks in Spain

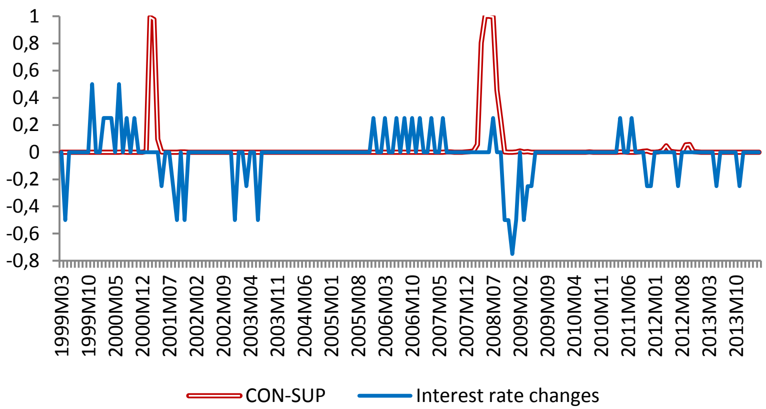
Probability of expansionary demand shocks



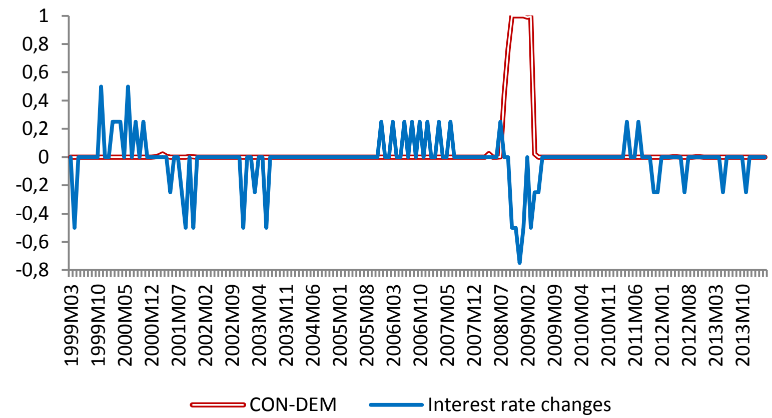
Probability of expansionary supply shocks



Probability of contractionary supply shocks

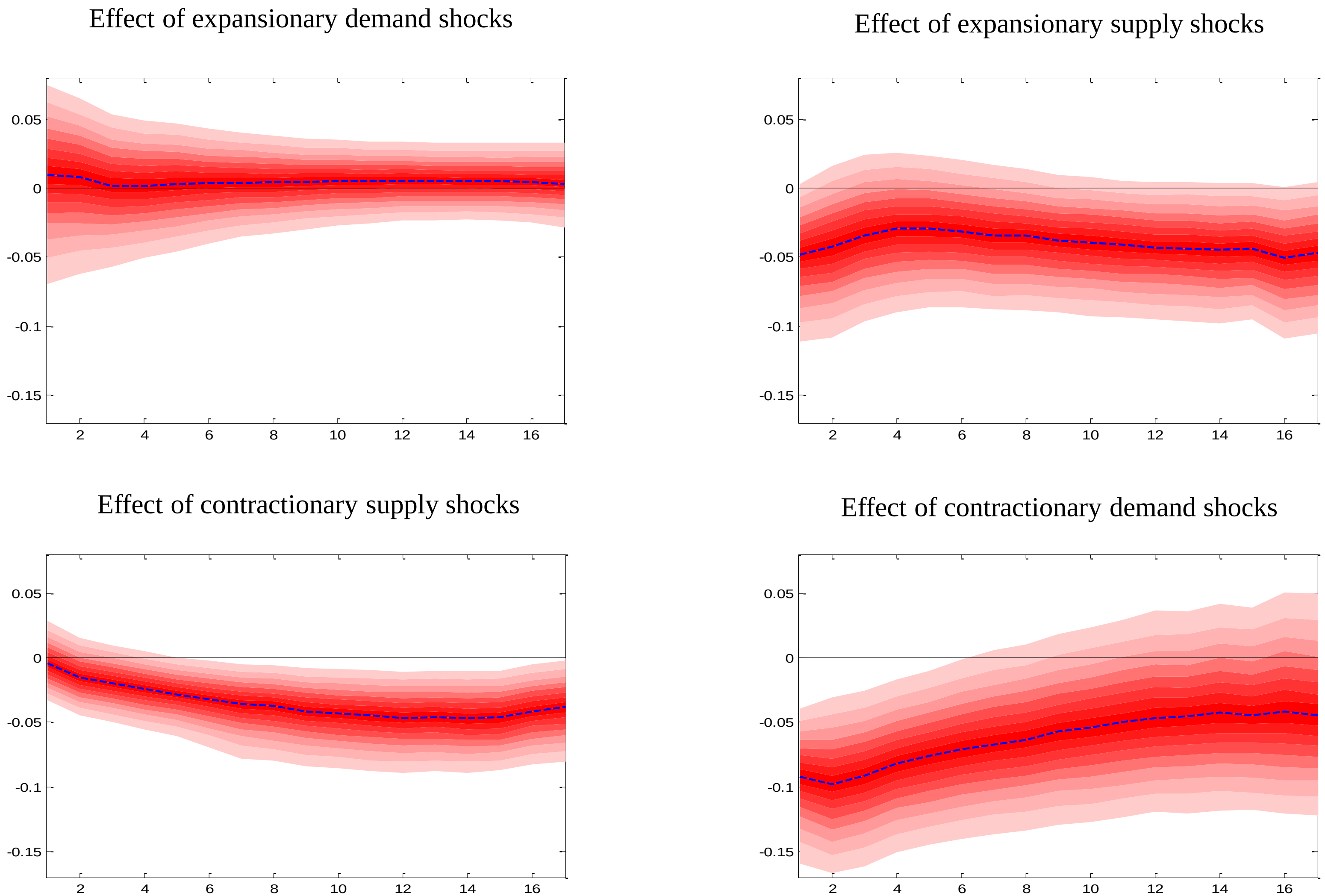


Probability of contractionary demand shocks



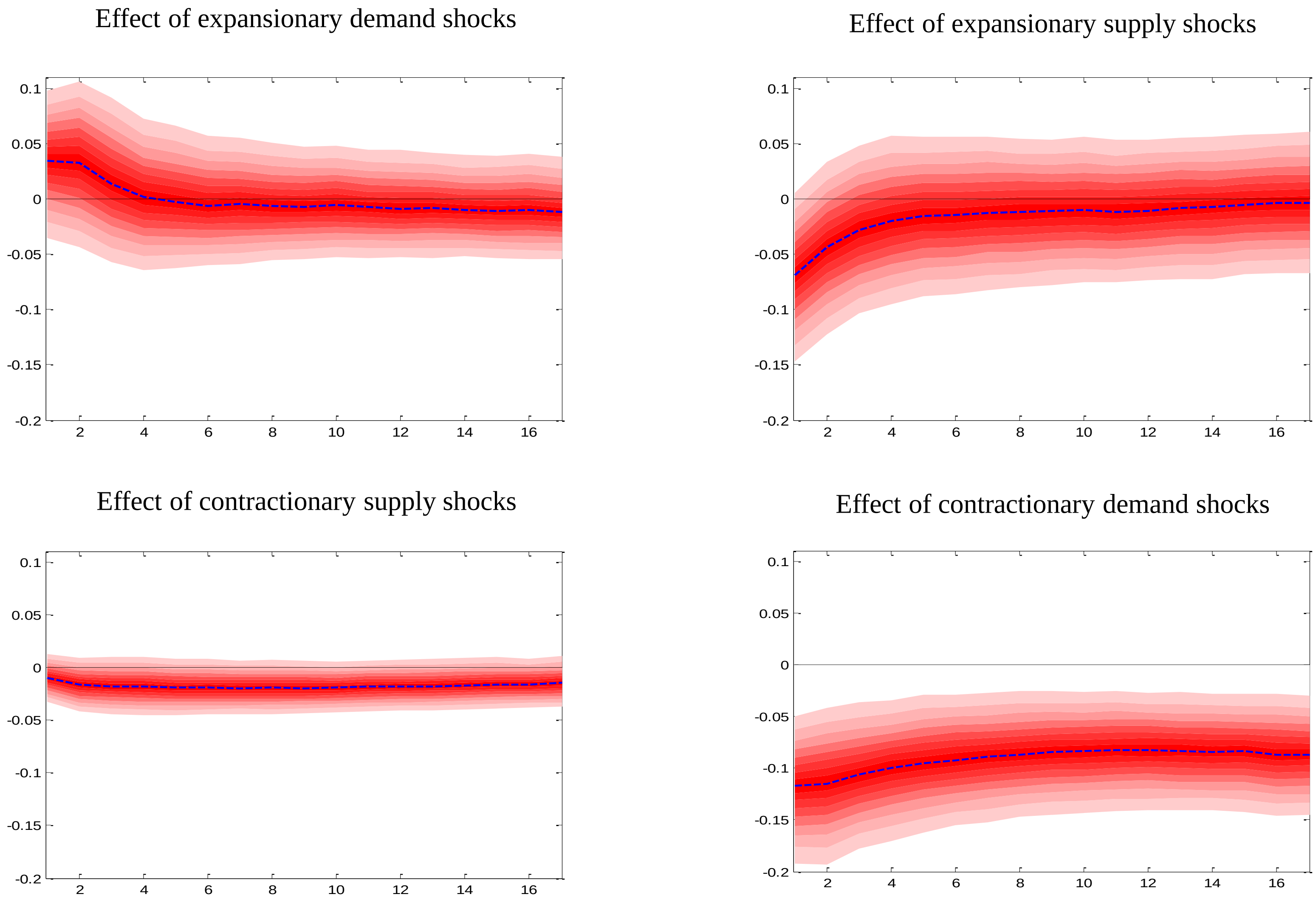
Notes. Each chart plots the probability of aggregate shocks (double red line) and the main refinancing operations: minimum bid rate in first differenced (solid blue line).

Figure 7. Effects of aggregate shocks in Germany on monetary policy expectations



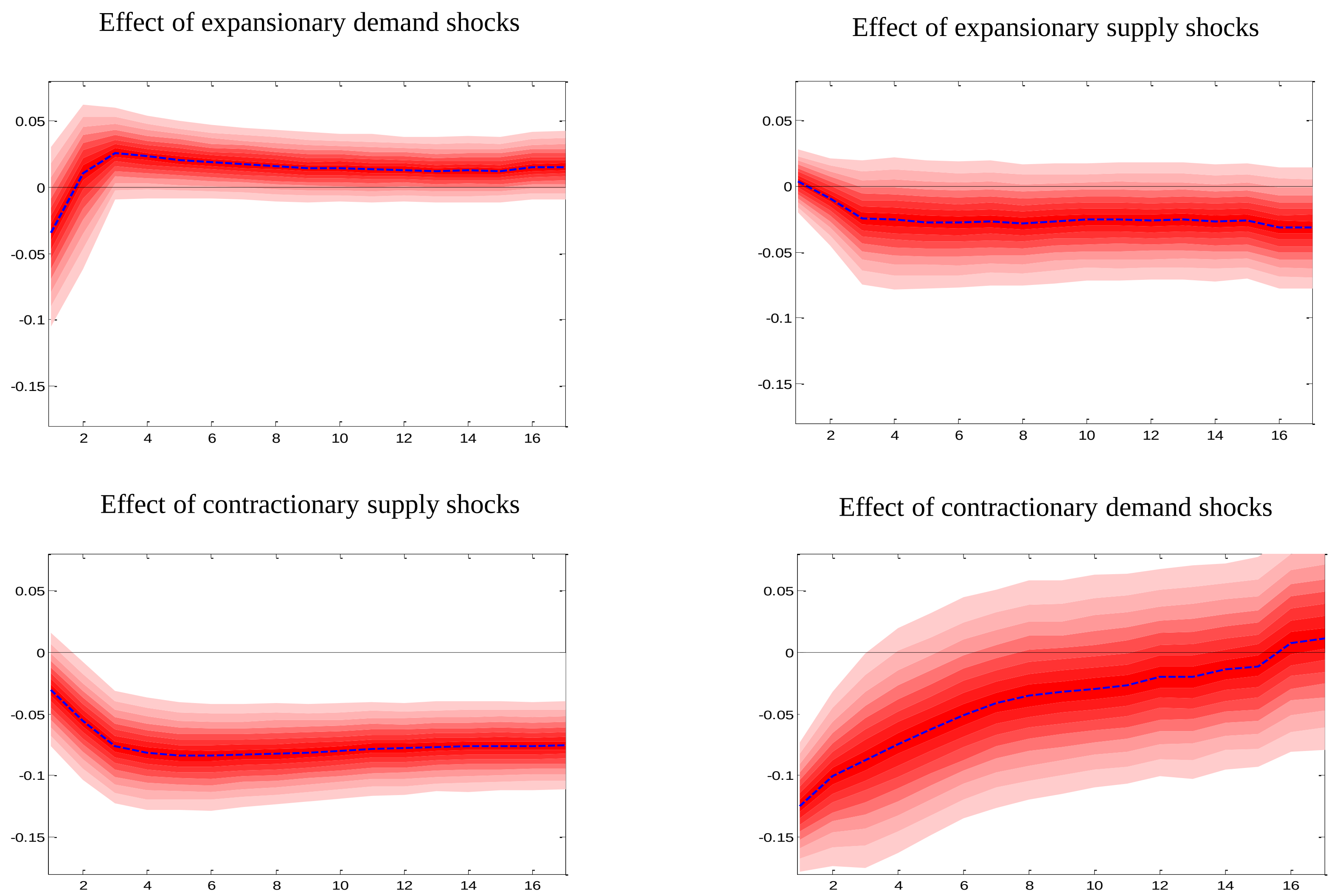
Notes. In each chart the vertical axis represents the effect of a specific aggregate shock on monetary policy expectations at different horizons (blue dashed line). Horizontal axis represents the horizon of expectations in years. The red bands (fan chart) represent up to the 0.90 quantile of the corresponding estimate's distribution, as a measure of uncertainty.

Figure 8. Effects of aggregate shocks in France on monetary policy expectations



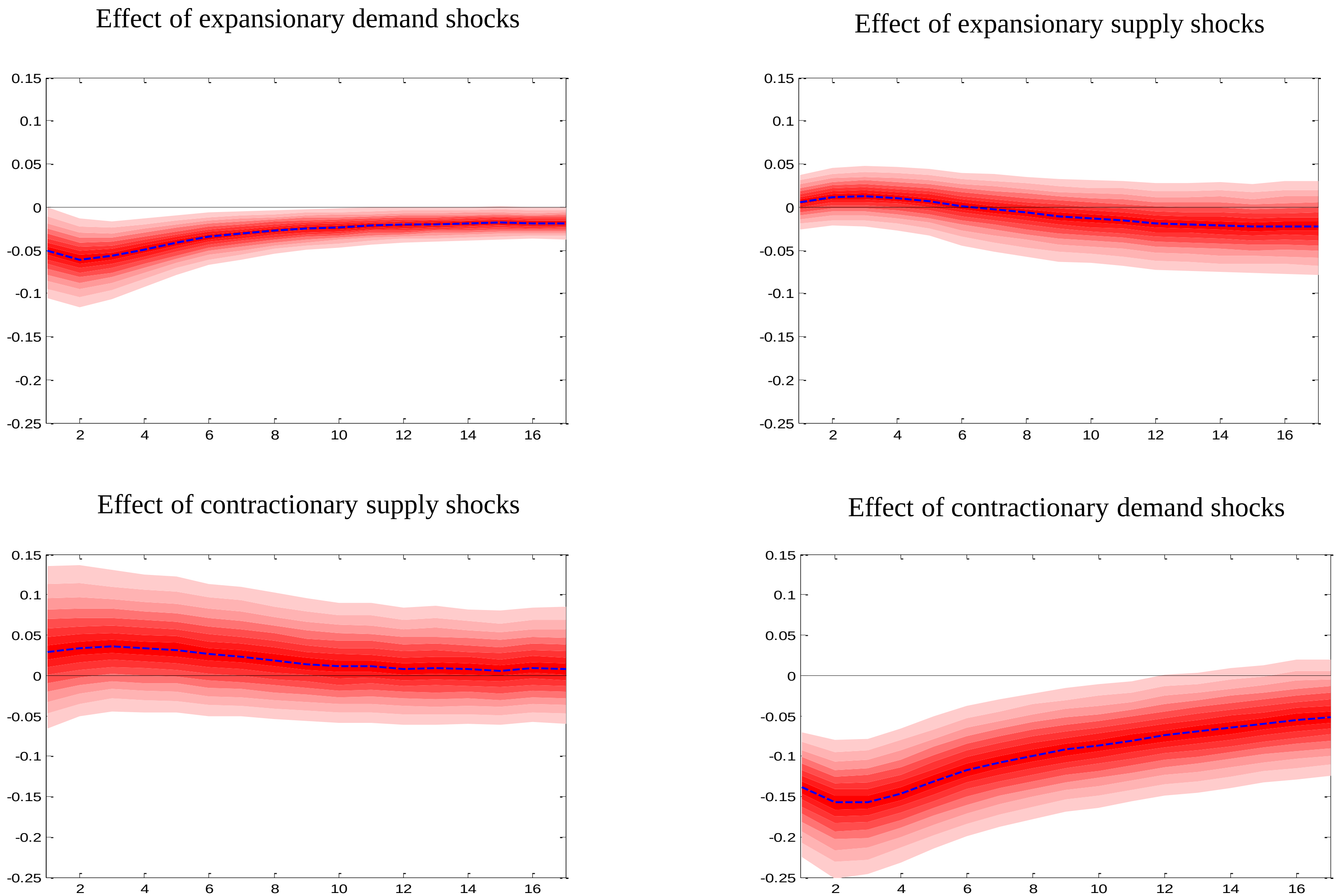
Notes. In each chart the vertical axis represents the effect of a specific aggregate shock on monetary policy expectations at different horizons (blue dashed line). Horizontal axis represents the horizon of expectations in years. The red bands (fan chart) represent up to the 0.90 quantile of the corresponding estimate's distribution, as a measure of uncertainty.

Figure 9. Effects of aggregate shocks in Italy on monetary policy expectations



Notes. In each chart the vertical axis represents the effect of a specific aggregate shock on monetary policy expectations at different horizons (blue dashed line). Horizontal axis represents the horizon of expectations in years. The red bands (fan chart) represent up to the 0.90 quantile of the corresponding estimate's distribution, as a measure of uncertainty.

Figure 10. Effects of aggregate shocks in Spain on monetary policy expectations



Notes. In each chart the vertical axis represents the effect of a specific aggregate shock on monetary policy expectations at different horizons (blue dashed line). Horizontal axis represents the horizon of expectations in years. The red bands (fan chart) represent up to the 0.90 quantile of the corresponding estimate's distribution, as a measure of uncertainty.