FINANCIAL INSTABILITY AND THE EURO AREA MACROECONOMIC DYNAMICS

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Abstract. How different have the role played by the financial sector during the double-dip recession been from historical patterns ? Using regime-switching models, I reach two main answers. First, the experience since the recession is the result of sporadic changes in the systematic and non-systematic behavior of financial system. More generally, changes in systematic part operate in 'financial distress' periods, where the adverse effects on output of a financial shock are more than twice as large and fast as those in 'normal' periods. Second, counterfactual analyses suggest that the changing systematic component accounted for up to 4 percentage points of output growth drops during the two severe recessions.

I. Introduction

The double-dip recession that has started in the first quarter of 2008 has been the greatest business cycle turning point in the history of euro area. What was surprising about the recession compared with historical patterns was its extreme severity. Real GDP fell by nearly 6.0 percent in the fourth quarter of 2009 and more than 4 million jobs were lost. The second most important way the double-dip recession marked a turning point in European history was in its precipitating causes: unprecedented financial instability driven primarily by the bursting of the U.S. housing bubble, and then preserved by sovereign risk tensions. These recent events raise the possibility of important changes in the role of financial sector as a source of business cycles fluctuations since the crash of Lehman Brothers.

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This paper examines the specific dimensions along which the role of financial sector during the two severe recessions have been different from historical patterns. More specifically, I consider two kinds of questions: Is the experience since the double-dip recession the result of changes in the predictable and systematic financial system's reaction to the changing state of the economy ? Have variations in the unpredictable and non-systematic behavior of financial system, i.e disturbances originating in financial sector, been important in explaining the recent business cycles fluctuations?[1]. To tackle these questions require a dynamic multivariate model in which equation coefficients and shock variances are time-varying. Therefore, I follow the methodology of Sims and Zha (2006) by estimating a number of structural vector autoregressions (SVARs), allowing several possible patterns of time variation in coefficients and disturbance variances, with euro area data since 1999. I then compare the fit of these models with Bayesian posterior odds ratios, and use the best-fitting model to answer the questions posed above.

I believe such a methodology is actually well suited for such a question. It allows to deal with the entire sample and let the data "decide" which regime has prevailed at which period. In other words, I do not assume that changes have happened once and will never happen again. I believe that certain regimes might be sporadically reoccurring, which seems to be more realistic with regard to the rarity of financial crises.

Time variations in the multivariate time series model are allowed while maintaining weak identifying assumptions to isolate the financial system behavior and its effects on economic activity. Identification is achieved by postulating that innovations in credit spread represent financial disturbances. More specifically, I employ the non-financial corporates bond credit spread constructed by Gilchrist and Mojon (2014)[2]. This time series is conceived as an indicator of financial distress that reflects the ability of both firms and financial intermediaries to borrow. I then refer a shock to the credit market that is orthogonal to the current state of the economy as a "financial shock", that is financial disturbances affect output and prices, as well as monetary policy actions, with at least one period of lag.

My results show changes in the non-systematic and systematic behavior of financial system over time. The best fitting model reveals that the importance of financial shocks relative to other structural shocks was dramatically higher in a *high-volatility* regime, which has

[1]In the language of autoregressions, the systematic and predictable behavior of financial sector refers to changes in the equation coefficients describing the behavior of financial sector. If the behavior of financial sector varies over time, then the way macroeconomic variables respond to shocks can be fundamentally altered. The non-systematic and unpredictable behavior term refer simply to disturbances originating in financial sector, that is financial shocks.

[2]Gilchrist and Mojon (2014) follows the same methodology as Gilchrist, Yankov, and Zakrajšek (2009) and Gilchrist and Zakrajšek (2012) to construct the euro area credit spread.

prevailed sporadically in the first and last part of the sample, covering thus the recession episode. Regarding systematic part of financial sector, there are changes, whose the times are independent of the times of changes in the non-systematic part, in financial sector equation coefficients between a *normal* and a *distress* regime. The latter implies that the effects of financial shocks on the aggregate activity are extraordinarily more rapid and pronounced than those implied by the former. Output falls immediately and reaches its minimum after about 10 months while the lowest effect, more than twice weaker, occurs only after 24 months in *normal* times. The *distress* regime has been in place through nearly all the years of the two recent recessions, and sporadically during the 2001-2003 period (the 9/11 terrorist attacks, Dot-com bubble and corporate scandals) as well. The remaining years emerge as *normal* periods, where disruptions in corporate bond markets are predominantly absent and the cost of credit access is relatively low.

I also find that a large portion of macroeconomic fluctuations in the euro area can be attributed to financial instability, both non-systematic and systematic part. When the economy is pushed into the *distress* regime, financial shocks are amplified and accounts for up to 40 percent of long-run output variability while their contributions are about four times lower under the *normal* regime. Counterfactual simulations suggest that the poor economic performances of the double-dip recession and 2001-2003 would have been mitigated by greater financial stability. When I run a counterfactual historical simulation by placing the *normal* regime throughout the period 2007-2012 (and suppressing financial shocks), the simulation shows that output growth rate would have been mitigated up to three (four) percentage points. Finally, the counterfactual simulation clearly indicates much higher output growth during the downturn in 2001-2003. For both sub-periods, the counterfactual exercises indicate that the role of the financial system on inflation was modest.

The results taken together are thus consistent with the financial amplification mechanisms that operate only during crises. The first and most-known mechanism, emphasized by Bernanke and Gertler (1989) and Kiyotaki and Moore (1997), is at work through balance sheets and asset prices. A deterioration in the borrowers' balance sheets reduce their ability to raise funds, lowering prices, further worsening balance sheets, and deepening the crisis. The second mechanism, called Knightian uncertainty, suggests a disengagement from markets when uncertainty about agents' investment projects is high, implying also amplification effects; see, for example, the theoretical work of Bloom (2009) and Caballero and Krishnamurthy (2012). A limitation of my analysis is however that I cannot discriminate between both mechanisms.

The paper proceeds as follows. Section II explain how my findings relate to literature. Section III gives some descriptive statistics in the relationships between finance and macroeconomy. Section IV presents the general methodology employed in this paper. In section V, I compare the fit of a number of Markov-switching SBVARs, select the best-fit model, and provide the posterior estimates of this model. In section VI, I discuss the economic implications of the best-fit model. In Section VII, I conduct several exercises to assess the robustness of the results. Section VIII suggests two particular interpretations of the results. Section IX concludes.

II. Relation to other studies

This paper is related to an increasing literature that examines the nature of changes in financial system behavior and its effects on the rest of the economy. Instead of discussing all papers in this area one by one, this section asks how my results stand apart from much of the existing empirical literature in the area.

Focusing on the euro area, Hristov, Hulsewig, and Wollmershauser (2011), Van Roye (2011), Peersman (2012), Mallick and Sousa (2013) and Gilchrist and Mojon (2014) employ the standard approach, i.e the 'constant-parameters' approach, to quantify the impact of financial and banking conditions on real activity[3]. In particular, all studies adopt linear SVARs to quantify the contribution of different types of bank lending shocks (especially lending demand and lending multiplier shocks) and financial shocks (unpredictable part of credit spreads or composite financial stress indexes) on a number of macroeconomic variables, including output.

Most papers find a significant and long-lasting decrease of output after a credit market shock. Based on the graphs in Gilchrist and Mojon (2014), output (industrial production) reaches its minimum after about eight months, and slowly increases thereafter. This is consistent with the results produced under the *normal* regime of my model. However, their methodology cannot capture the dynamic effects produced from the *distress* regime. In contrast to my framework, their linear VARs rule out, by construction, any time varying effects in systematic and non-systematic part of financial system. In turn, they cannot answer directly to the question that I posed previously.

[3]There is also a large literature for the U.S. economy. See among others, Bernanke (1983), Hakkio and Keeton (2009), Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010), Carlson, King, and Lewis (2011), Gilchrist and Zakrajšek (2011), Boivin, Giannoni, and Stevanovic (2012), Gilchrist and Zakrajšek (2012), Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2013). Cardarelli, Elekdag, and Lall (2011) focus on 17 advanced economies.

Gambetti and Musso (2012) extend the standard approach by allowing time-varying parameters in SVARs. They emphasize the importance of taking into account shifts in the generation of shocks originating from the banking system, especially in recent years. Loan supply shocks explain more than one half of the fall in real GDP growth during 2008-2009. Their findings result mainly from bigger financial shocks. They do not report large changes in the way macroeconomic variables react to shocks over time. Benati (2013) reaches the same conclusion. I do not.

As mentioned above, my specification considers a credit spread as financial variable. The two previous studies do not. Instead of considering financial variables, Gambetti and Musso (2012) employ banking variables with the amount of loans to the non-financial private sector, as well as a composite lending rate, which is derived as weighted averages of several interest rates charged on loans to private sector. Such a difference may explain why they do not find drastic change in equation coefficients. Benati (2013) rules out any banking or financial variables. Another explanation lies in the methodology itself. A model with smooth and drifting coefficients seems to be less suited for capturing rapid shifts in data's behavior as observed during the double-dip recession. Financial crises are well-known as hitting the economy instantaneously, which favor models with abrupt changes such as Markov-switching models.

In contrast, Holló, Kremer, and Duca (2012) document important changes in the transmission mechanism of financial distress over time for the period 1987:M1-2011:6. They construct a Composite Indicator of Systemic Stress (CISS) and employ a threshold regression SVAR to document macro-financial linkages in the euro area since January 1987. By Choleski-decomposing, they show that the euro area economy oscillates between a *low-stress* and a *high-stress* regime over time. In other words, all equation parameters, i.e equation coefficients and shock variances, are allowed to change across the two regimes, whereas I only find changes in the financial sector. Further, they report that a shock to CISS (ordered first) has only a significant real impact under the *high-stress* regime. My findings are partially consistent with theirs, because I find significant effects across both regimes. A potential explanation may lie in the fact that they omit to take into account heteroskedasticity properly. This omission can strongly affect the estimated equation coefficients, as highlighted in Sims (2001).

The specification in Davig and Hakkio (2010) and Hubrich and Tetlow (2012) is closest to my benchmark specification, though they focus on the United States. They trace the effects of financial stress index shocks on output by a Cholesky decomposition using Markov-switching SVARs. In particular, Hubrich and Tetlow (2012) find repeated fluctuations in all equation coefficients between a *normal* (called "low-stress coefficient" in their paper) and a *distress*

("high-stress coefficient") regime over time, as well as heteroskedasticity. Because their financial series has been constructed from several relevant information content on banking system, it is likely difficult to compare its macroeconomic effects with those produced from my financial variable, the corporate bond spread, which captures only shifts in the ability of borrowers to raise funds. However, it is interesting to observe that their counterfactual analysis suggests that consumption would have been much higher than history since 2007 if the economy would have been in the "low-stress coefficient" regime since 2007, implying an important role of changes in the agents' behavior in explaining the recent U.S. business cycles.

III. Some Descriptive Statistics

In this section, I illustrate the possibility of non-linearities in euro area historical data. A quick examination of the facts shows that the non-linear relationships between finance and macroeconomy is easily identifiable in the euro area data. Figure 1 plots the monthly average credit spread on bonds issued by non-financial firms constructed by Gilchrist and Mojon (2014) along with the real GDP growth rate in the euro area. The grey areas denotes CEPR recessions of the euro area. The monthly corporate bond spread has been developed by Gilchrist and Mojon (2014). It is constructed by using market price of bonds issued by euro area non-financial corporations. The difference between each security and the German Bund interest rate of similar duration represent the credit spread. The average is obtained by weighting each credit spread by their corresponding volumes.

The corporate bond spread exhibits three main peaks during the early 2000 and the post-Lehman bankruptcy, while it is relatively low and stable for the remaining years. The two last peaks prevailed when the euro area economy has been experiencing both dramatic financial and economic disturbances since the post-Lehman recession while the first peak is associated with the corporate bond market meltdown.

The coincidence of financial distresses (i.e significant rises in corporate bond spread) in timing with output downturn is striking. More specifically, the 2001-2003 and 2008-2012 episodes emerge as periods where the credit spread is negatively correlated with real GDP. This is consistent with the prediction of Bernanke and Gertler (1995): the higher is the borrowers net worths, the lower is the cost for raising externally funds, and inversely. The closer correlation between the corporate bond spread and the aggregate activity during periods of financial turmoil also reflects the forward-looking nature of asset prices in signaling future economic conditions.

These graphical descriptive statistics are confirmed by the properties of financial and economic cycles in Table 1. It reports the standard deviations (std) for the credit spread (spread)

and the GDP growth rate (gdp) as well as their correlations (corr) for several periods: 1999-2012; 1999-2007 and 2007-2012. Clearly the counter-cyclicality of credit spread is confirmed in this table. Interestingly, there is an asymmetry in the covariances across the pre- and post-Lehman bankruptcy. One can see from the table that this correlation becomes higher since the post Lehman bankruptcy. The macroeconomic and financial volatility also differed, with higher volatilities since the double-dip recession. Overall, these properties confirm the points made through the graphical examination.

However, it is well known that the positive correlation between credit spread and output growth cannot prove by itself that variation in credit spread causes variation in output growth[4]. The nature of the shocks remain non-identifiable. Besides, these simple descriptive statistics do not allow us to know whether the differences across periods are due to bigger structural shocks that feed through linear dynamics or/and changes in transmission mechanisms, i.e in the way macro variables respond to shocks.

The objective of next sections is (1) to pin down the disruptions in financial markets and their macroeconomic effects and (2) to identify the nature of the nonlinearity.

IV. The Methodology

IV.1. **Markov-switching Structural Bayesian VARs.** Following Hamilton (1989), Sims and Zha (2006) and Sims, Waggoner, and Zha (2008), I employ a class of Markov-switching Structural VAR model of the following form

$$y_t' A(s_t) = \sum_{i=1}^{\rho} y_{t-i}' A_i(s_t) + C(s_t) + \varepsilon_t' \Xi^{-1}(s_t), \qquad t = 1, \ldots, T, \tag{1}$$

where y_t is defined as $y_t \equiv [gdp_t, p_t, r_t, sp_t]'$, where gdp_t is the logarithm of the interpolated monthly real GDP[5]; p_t is the logarithm of the HICP; r_t is the EONIA policy rate[6]; and sp_t is the Gilchrist and Mojon (2014) credit spread. The details are presented in Appendix.

[4]A large literature predicts the existence of feedback effects from output growth to credit spread, making difficult the understanding of the causality between credit spread and output growth. See, among others, Bernanke and Gertler (1995).

[5]I employ the Chow and Lin (1971) procedure to interpolate monthly real GDP (gdp_t). The details are presented in Appendix. Conclusions are similar when the index of industrial production is used as output measure.

[6]The EONIA is used as policy variable (r_t). This series is controlled by the ECB through either the minimum bid rate of variable rate tenders or the rate applied to fixed rate tenders in its main refinancing operations (MRO). The latter, implemented during the financial crisis, implies that the EONIA was lower than the MRO after September 2008. The EONIA captures the implementation of some non-standard policy actions (fixed rate full allotment).

The overall sample period is 1999:M2 to 2012:M7. Based on the lag-length selection criteria, I set the lag order to $\rho = 4$.

I assume that ε_t follows the following distribution

$$E(\varepsilon_t) = \text{normal}(\varepsilon_t|0_4, I_4), \tag{2}$$

where 0_4 denotes an 4×1 vector of zeros, I_4 denotes the 4×4 identity matrix, and $\text{normal}(x|\mu, \Sigma)$ denotes the multivariate normal distribution of x with mean μ and variance Σ. Finally, T is the sample size, $A(s_t)$ is a four-dimensional invertible matrix under the regime s_t; $A_i(s_t)$ is a four-dimensional matrix that contains the coefficients at the lag i and the regime s_t; $C(s_t)$ contains the constant terms, and $\Xi(s_t)$ is a four-dimensional diagonal matrix.

For $1 \leq i, j \leq h$, the discrete and unobserved variable s_t is an exogenous first order Markov process with the transition matrix Q

$$Q = \begin{bmatrix} q_{1,1} & \cdots & q_{1,j} \\ \vdots & \ddots & \vdots \\ q_{i,1} & \cdots & q_{i,j} \end{bmatrix}, \tag{3}$$

where h is the total number of regimes, $q_{i,j} = Pr(s_t = i|s_{t-1} = j)$ denote the transition probabilities that s_t is equal to i given that s_{t-1} is equal to j, with $q_{i,j} \geq 0$ and $\sum_{j=1}^{h} q_{i,j} = 1$. For more than 2 regimes, the transition matrix Q is restricted to avoid over-parameterization. Following Sims (2001) and Sims, Waggoner, and Zha (2008), I allow symmetric jumping among states[7].

When implementing k independent Markov-switching processes, $s_t = (s_t^1, ...s_t^k)$, the transition matrix Q becomes

$$Q = Q^1 \otimes ... \otimes Q^k, \tag{4}$$

where Q^k is an $h^k \times h^k$ matrix.

Following Sims and Zha (1998), I exploit the idea of a Litterman's random-walk prior from a structural-form parameters. I also introduce dummy observations as a component of the

[7]These restrictions seem to fit macroeconomic data better. It follows that the restricted transition matrix becomes

$$Q = \begin{bmatrix} q_{1,1} & (1-q_{2,2})/2 & \cdots & 0 & 0 \\ 1-q_{1,1} & q_{2,2} & \ddots & \vdots & \vdots \\ 0 & (1-q_{2,2})/2 & \ddots & (1-q_{k-1,k-1})/2 & 0 \\ \vdots & \vdots & \ddots & 1-q_{k-1,k-1} & 1-q_{k,k} \\ 0 & 0 & \cdots & (1-q_{k-1,k-1})/2 & q_{k,k} \end{bmatrix}.$$

prior in order to favor unit roots and cointegration[8]. For more details, see Doan, Litterman, and Sims (1984) and Sims (1993). As demonstrated by Robertson and Tallman (1999), these priors reveal more facility in forecasting. The appendix provides the details techniques for the Sims and Zha (1998) prior.

Finally, the prior duration of each regime is about 10 months, meaning that the average probability of staying in the same regime is equal to 0.90. As shown in section VII, I have also used other prior durations and the main conclusions remain unchanged.

IV.2. **Identification.** Identified vector autoregressions decompose the time-series variation into mutually independent components. Identification turns out to be extremely important to isolate the effects of a particular shock - uncorrelated to other structural shocks - on the vector of endogenous variables y_t. Because I am studying the macroeconomic effects of shocks that affect the ability of firms to borrow, a particular attention is paid on this structural 'financial' shock. The issue of identification is well-known for macroeconomists, this is why I briefly summarize it. Suppose that the VAR process has no constant terms and there is only one regime ($s_t = 1$) such that $\Xi(s_t = 1) = I$. The idea is strictly the same for a time-varying VAR model. Using (1), the model can be re-written in a reduced-form VAR as follows

$$y_t' = x_t' B + \mu_t', \tag{5}$$

with

$$B = FA_0^{-1} \qquad \text{and} \qquad \mu_t' = \varepsilon_t' A_0^{-1}, \tag{6}$$

where $x_t' = \left[\begin{array}{ccc} y_{t-1}' & \cdots & y_{t-\rho}' \end{array} \right]$ and $F = \left[\begin{array}{ccc} A_1 & \cdots & A_\rho \end{array} \right]'$.

The variance-covariance matrix Σ of the reduced-form VAR is a symmetric and positive definite matrix. It defines in the following way

$$\mathrm{E}[\mu_t \mu_t'] = \Sigma = (A_0 A_0')^{-1} \tag{7}$$

If there is no identifying restrictions, equations (6) and (7) define a relationships between the structural and reduced-form parameters (B, Σ) which is not unique. One can find two parameters points (A_0, F) and $(\tilde{A}_0, \tilde{F})$ that are observationally equivalent if and only if they imply the same distribution of y_t, for $1 \leq t \leq T$. That is, they have the same reduced-form representation (B, Σ) if and only if there is a matrix orthonormal matrix P such that $A_0 = \tilde{A}_0 P$ and $F = \tilde{F} P$.

[8]Regarding the Sims and Zha (1998) prior, the hyperparameters are defined such that the marginal data density (MDD) of the constant-parameters VAR model is maximized[9]: $\mu_1 = 0.6$ (over- all tightness of the random walk prior), $\mu_2 = 0.15$ (relative tightness of the random walk prior on the lagged parameters), $\mu_3 = 1.0$ (relative tightness of the random walk prior on the constant term), $\mu_4 = 0.1$ (erratic sampling effects on lag coefficients), $\mu_5 = 1.0$ (belief about unit roots), $\mu_6 = 1.0$ (belief in cointegration relationships).

There is a long tradition in macroeconomics of applying a Cholesky decomposition to the matrix Σ implying exact linear restrictions on the elements of A_0. This results in an unique solution. This is called a "recursive identification". The recent work by Rubio-Ramirez, Waggoner, and Zha (2010) have shown that this class of identification implies that the SVAR model is exactly identified. Following this long tradition, I use the following recursive ordering: gdp_t, p_t, r_t and sp_t. It follows that the contemporaneous matrix A_0 is an upper triangular matrix. The main objective is to identify a "financial shock", i.e an orthogonalized shock to the credit market. The fact that credit spread sp_t comes to last allow to pin down disturbances that originate in the credit bond markets.

The paragraphs that follow explain and justify this identification scheme. Following previous work by Leeper, Sims, and Zha (1996), I impose that production sector (output and prices) do not respond contemporaneously to credit market sector (credit, policy rate and credit spread). In other words, the credit market sector has only lagged effects on both variables. The argument for this restriction is based on the idea that most of firms are subject to planning delays. There are also planning processes involved in changing the prices of labor and manufactured goods. The policy rate, EONIA, responds immediately to the private (or production) sector but it responds with a delay to credit spread. This hypothesis is based, in part, on the work by Christiano, Eichenbaum, and Evans (1999). Leeper, Sims, and Zha (1996) prefer imposing a delay in the response of private sector. Their hypothesis is motivated by the long process of any central bank to implement its monetary policy. Because it takes time for ECB's macroeconomic policy to consult, analyze the new informations from financial markets - although they are observable on a daily basis - and then make a decision, it is preferable to impose a lag on the effects of the credit spread on policy. My view is that both arguments are reasonable. The delayed nominal interest rate response to credit spread results from the facts that central banks do not pay much attention within month to banking system.

Finally, the VAR specification assumes that credit spread is ordered last, which implies that credit spread react contemporaneously to every endogenous variable. The justification is not surprising. The financial market-related variables are forward-looking variables which have a considerable predictive content for economic activity.

V. Empirical Results

In this section, I estimate and compare various types of models with the following specifications.

- The constant-parameters SVAR, denoted **constant**, does not allow change in any parameters over time. This is the standard model used in most empirical works.

- For each model denoted $\mathfrak{M}_{\#v}$, the variances of all structural disturbances follow the same #-regimes Markov-switching process s_t.
- The models denoted $\mathfrak{M}_{\beta Fc\#v}$ allows the equation coefficients from the financial system (F) and the variances of structural disturbances to follow respectively a β-regimes Markov-switching process s_t^c and a #-regimes Markov-switching process s_t^v. In other words, the transition matrix of variance and coefficients regimes are independent. The process governing the equation coefficients (i.e the last column of matrices $A(s_t^c)$, $F(s_t^c)$) reflects the systematic part of financial system.
- The models denoted $\mathfrak{M}_{\beta Pc\#v}$, $\mathfrak{M}_{\beta FPc\#v}$ and $\mathfrak{M}_{\beta c\#v}$ allows the equation coefficients respectively from the production sector (P), from simultaneously P and F, and from all sector of the economy (including monetary policy) to follow a β-regimes Markov-switching process, s_t^c. Shock variances follow an independent #-regimes Markov-switching process s_t^v.

A few items deserve discussion. First, the times of changes in variations in the unpredictable and non-systematic part of financial system (financial shocks) are dependent of the time of changes in non-financial shocks. This is a parsimonious way to evaluate the relative importance of financial shocks over time. Second, the equation coefficients ("systematic behavior") are allowed to vary across time only if heterosekdasticity is taken into account, i.e the model makes allowance for shock variances to vary independently to coefficients. Otherwise, bias in estimates can appeared. See Sims (2001). Third, some specifications allow the nature of non-financial private sector responses to shocks to have been conditional on financial behavior. In particular, the systematic behavior of financial sector might be incorporated in the behavior of non-financial private sectors, inducing additional changes in the transmission mechanism. It could be also true that monetary policy has been conditional on financial behavior, modifying potentially also the patterns of fluctuations. This is why I am also interested in the model that allows all equations to vary simultaneously.

The results shown below are based on 10 millions of draws with the Gibbs sampling procedure (see Appendix for details). I discarded the first $1,000,000$ draws as burn-in, then I kept every 100th draws. I choose the normalization rule by Waggoner and Zha (2003b) to determine the signs of columns (or equations) of the matrix A_0 and F. This turns out to be important to avoid bimodal distribution in in the contemporaneous impulse responses of variables to structural shocks.

V.1. **Model Fit.** The comparison of models is based on marginal data densities (MDD's) which is a measure of model fit. I employ three different methodologies to compute them. Each method allows to approximate the marginal likelihood of a non-Gaussian distribution:

Sims, Waggoner, and Zha (2008), Bridge method of Meng and Wong (1996) and the unpublished Muller (2004) method. There are several reasons for using nonstandard methods for computing MDD's. Because the likelihood can be close to zero in the interior points of the parameter space, the standard method for computing MDD's is not appropriate in the case of mixture models such as Markov-switching models. The low posterior density at the sample mean also justifies to center the weighting function to the posterior mode in Sims, Waggoner, and Zha (2008). Appendix provides the mathematical details for each method.

Table 2 reports the log-values of MDD's. Because it is not necessary to compute the MDD of the constant model with the alternatives methods - as well as the computation of MDD's for Markov-switching SVARs with the classical method[10] - I display "*" instead of any numbers. The symbol "**" indicates that the number behaves erratically due to the weighting function used in the Sims, Waggoner, and Zha (2008) method.

The constant-parameter model is clearly rejected. The best-fit model is $\mathfrak{M}_{2Fc2v}$, that is the model in which the equation coefficients from the financial equation (F) is allowed to change over time, independently to time variation in shock variances. The log-values of MDD's associated with this model remain far above the values of the MDD's shown, for each column, above or below. For example, the MDD computed with the Bridge method, which is considered as the most robust method, reports a difference of 12 in absolute value with the second highest marginal data density model, $\mathfrak{M}_{4v}$. All methods give very similar log-values making the above results very robust.

Among models with changes only in shock variances, the log-values of MDD's of the three and four regime variances models, that is respectively $\mathfrak{M}_{3v}$ and $\mathfrak{M}_{4v}$, are very close, meaning that one cannot discriminate between both of them. The difference is only of 3 for the Mueller and Bridge methods and 6 for the Sims, Waggoner, and Zha (2008) method.

Finally, the data does not favor models associated with changes in all equation coefficients. For example, the difference in log-value between $\mathfrak{M}_{2c2v}$ and the best-fit model are of order of 11 for Mueller method and of 14 for Bridge method, reflecting a strong evidence in favor of changes only in the behavior of financial system. The way of the production sector responds to shocks remains similar over time.

In next sections, I will report the results of the best-fit model.

V.2. **Posterior distribution.** In this section, I present some key results produced from the $\mathfrak{M}_{2Fc2v}$ model. Figure 3 shows the probabilities of a specific regime for each process (s_t^{c} and s_t^{v}) over time produced by the $\mathfrak{M}_{2Fc2v}$ model. The probabilities are smoothed in the sense

[10] I employ the Chib (1995) procedure to approximate the MDD of the constant structural VAR.

of Kim (1994), i.e full sample information is used in getting the regime probabilities at each date.

Regarding the process in which equation coefficients from the financial system (systematic part) are allowed to change, s_t^c, shown in the left panel, it is apparent that the regime 1, ($s_t = 1$), was dominant during the beginning of the euro area with 9/11 attacks, Dot-com bubble and corporate scandals. This regime has been also in place during the financial crisis originated by subprime mortgages as well as the European debt crisis. I label this regime as the *distress* regime. All of these sub-periods, captured by this regime, contain the same similarities. This regime prevails in periods in which bond spread, displayed in the background of each panel, rises and is relatively high, except for the 9/11 period. Regime 1 has prevailed for the remaining years of the sample, characterizing by non-distress episodes, with no particular obstacle for access to credit and a large volume of transactions. This is the *normal* regime.

There are substantial differences in the contemporaneous coefficient matrix across the two regimes. Tables 5a and 5b report respectively the contemporaneous coefficient matrix, $A(s_t)$, respectively for the *distress* regime and *normal* regime. Each column represents an equation of the system and gives the name of the sectors in which shocks originate: Production sector (Prod y/p), monetary policy (Policy R) and financial sector (Financial F). Looking at the last column of Tables, the contemporaneous coefficients on output and prices, as well as those on nominal interest rate, are much larger in the *distress* regime. Put differently, financial markets become much more sensitive to any movements in economy activity in periods of high stress associated with high uncertainty. This result seems to characterize well the 2007-2009 recession as well as the sovereign debt crisis, experienced in the euro area, namely a powerful feedback mechanism to asset prices. The decline in sales, spending and income deteriorate balance sheets, through decreases in asset values. The 68 percent error bands associated with the contemporaneous coefficient on output in the fourth column, $[1.06; 81.32]$, lie within the same regime (i.e positive region) of the median (41.84). This is not the case under the *normal* regime, $[-7.88; 34.79]$.

Regarding the process governing the structural disturbance variances, s_t^v ,the model clearly captures two distinct regimes of volatility: a low and a high volatility regime. The estimates for the relative shock standard deviations differ substantially across regimes, as shown in Table 4. The combination of the regime of *distress* with the *high-volatility* regime implies the larger volatilities for all structural shocks. Keeping this *high-volatility* regime and pushing the economy into the regime of *normal* decreases dramatically their variances. This is specially true for credit spread. The right panel of Figure 3 displays the (smoothed) probabilities of the *high-volatility* regime. Thera are repeated fluctuations between the two regimes.

While maintaining near one from 1999 to the late 2003, the probability of the high-volatility regime rapidly falls in the early 2004 and remains close to zero until the dramatic financial turbulences in the United States. Indeed, this regime covers most of the period since the late 2007, with a break between the two recessions. Interestingly, the model attributes differences in the behavior of the euro area economy between the pre and the post 2010 as variation in the transmission mechanisms of a given shock on the economy, rather than variations in the sources of economic fluctuations.

Although reported in Table 3, the following estimated transition matrices (at the posterior median) summarize the two Markov-switching processes

$$Q^{\mathrm{c}} = \begin{bmatrix} \underset{[0.7816;0.9355]}{0.8419} & \underset{[0.0272;0.0700]}{0.0489} \\ \underset{[0.0645;0.2184]}{0.1579} & \underset{[0.9300;0.9728]}{0.9510} \end{bmatrix} \quad \text{and} \quad Q^{\mathrm{v}} = \begin{bmatrix} \underset{[0.8264;0.9449]}{0.8785} & \underset{[0.0444;0.1155]}{0.0857} \\ \underset{[0.0551;0.1736]}{0.1213} & \underset{[0.8845;0.9556]}{0.9142} \end{bmatrix}$$

where Q^{c} denotes the transition matrix governing the financial equation coefficients and Q^{v} the transition matrix for the structural disturbances. The 68% probability interval is indicated in brackets. Clearly, the regime of *distress* ($q^{\mathrm{c}}_{11} = 0.8419$) is much less persistent (an average duration of 6 months) than the *normal* regime ($q^{\mathrm{c}}_{22} = 0.9510$) which covers most of the sample with an average duration over 20 months. Regarding the process governing the variance shocks, s^v_t, the persistence of the *high-volatility* regime, ($q^{\mathrm{v}}_{11} = 0.8785$), is much lower than the *low-volatility* regime, with $q^{\mathrm{v}}_{22} = 0.9142$. For both regimes, the average duration is respectively about 8 and 11 months. The tight interval probabilities reinforce the estimated median values.

VI. The Contribution of Financial System to Fluctuations

Using the best-fit model, I consider the specific dimensions (non-systematic and systematic behavior) along which financial system have been an important source of business cycles fluctuations. First, I present the time-series of financial shocks. Second, the role of these shocks in driving the macroeconomic fluctuations is examined through variance decompositions. I then present the impulse responses of variables to financial shocks identified with a recursive identification. Then I provide evidence supporting the key role played by financial shocks over the business cycles through historical decomposition. Finally, to establish the contribution of financial markets to the double-dip recession and the downturn in 2001-2003, I display counterfactual simulations to investigate the effects of changes of the systematic part of financial markets on the rest of the economy.

VI.1. **Time-series of financial disturbances.** Before describing the relative importance of financial shocks to macroeconomic variability, I provide an empirical interpretation of

the evolution of the disturbances over time. Figure 4 displays the time series of the financial shock. The horizontal line reports the median while the grey areas report the 68% probability interval. To shed light the results, I report the unnormalized structural shocks $\varepsilon_t'\Xi^{-1}(s_t)$.

As it can be seen, the financial shocks capture the dramatic financial market disruptions since 2008, with an accumulation of adverse financial shocks and a dramatic positive shock in the mid-recession. These shocks also occur intensively before and during both recessions. In particular, there are positive shocks a few months before CEPR recessions dates but these are not the biggest of the historical positive financial shocks. Actually, the biggest shocks prevailed during the first CEPR recession, with the biggest shock occurred when Lehman Brothers collapsed. Before that period, these shocks have been almost non-existent except for the period of 2001-2003 where the euro area economy experienced a series of adverse financial shocks related to the strong instability in the financial sector. Overall, this pattern is in line with the time series of credit spread.

VI.2. **Variance decompositions.** Figure 5 reports variance decompositions for output, prices, policy rate and credit spread across regimes. More specifically, each column correspond to a specific regime with the following notation: Dr$[s_t^c = 1]$ Distress regime, Nr$[s_t^c = 2]$ Normal regime, Hv$[s_t^v = 1]$ High-volatility, Lv$[s_t^v = 2]$ Low-volatility. In each panel, the black line represents the median value of share of financial shocks to the volatility of each variable while the grey areas represents the 68% probability interval. The contribution is represented at different horizons: 6th, 12th, 24th and 36th months.

Under the *normal* regime (third and fourth column), financial shocks represent a small but noticeable part of the volatility of output and prices at any horizons. It explains about 15% of the output variance while it does not really have any contribution on prices. It turns out that financial shocks are unimportant in explaining price movements under periods corresponding to low financial market disruptions. In contrast, the contribution of such shocks to the long-run nominal interest rate volatility is about 40 percent. Note that the relative importance of these shocks do not change across the two regimes of volatility.

The most important contribution of the financial sector to explaining business cycles occurs under the *distress/high-volatility* regimes. As it can be seen in the first column, their contribution increases and accounts for more than 40% of the variance of output at any horizons, although it explains only 10% of the variance of prices to far off horizons $h = 36$. When pushing the economy into the *low-volatility* regime and keeping the *distress* regime in place, financial shocks also contributed to output variability substantially. A larger part of nominal interest rate variations is now attributed to financial shocks.

Overall, these findings suggest the importance of financial shocks in explaining the variability of macroeconomic variables differ across regimes. Although small in a low-financial stress environments, a larger portion of the variance of output is explained by financial shocks - more than 40% of long-run output variations - in periods of financial distress. Historical decompositions, discussed further, provide some additional evidence of the non-linear relationships between the macroeconomy and the financial sector.

VI.3. **Regime-dependent dynamic effects of financial shocks.** As a way to illustrate the difference in dynamics across the two regimes, I examine the response of the rest of the economy to a disturbance in the financial equation ("one-time financial shock"). Figures 6 reports the impulse responses of endogenous variables across the two regimes. Each panel displays the deviation in percent for the series entered in log-levels (output and prices) whereas it displays the deviation in percent point for the other variables (policy rate and credit spread). The thin black line represents the median and the shaded areas are the 68% error bands under the *normal* regime. The thick black line represents the median under the *distress* regime.

After a positive innovation in credit spread, the output falls slowly, reaches its minimum, then it begins to recover in a steady manner. However, across the two regimes the responses are dramatically different in timing and magnitude. The negative response is much stronger and more persistent under the regime of *distress*. Under this regime, the output falls immediately and reaches its minimum - that is -0.5 percent - after about 10 months, whereas under the *normal* regime output declines slowly to reach its lowest effect - that is -0.2 percent - only after 24 months. Then the output of the economy begins to rapidly recover in a steady manner. For the *normal* regime, the precision of estimates can be evaluated by the constructed 68% error bands. In each panel, error bands lie within the same region as the estimates at the median. This suggests that the dynamic is well preserved and that the pattern of each variable is robust. The fact that the median response under the *distress* regime does not lie within the 68 percent probability intervals of the response under the *normal* regime reinforces the findings.

For both regimes, the response of inflation is also negative but much more persistent and modest than output response, which is in line with the fact that the United States and in the euro area experienced a slow and modest decline in inflation during the global financial crisis[11]. The magnitude becomes, however, slightly larger under the *distress* regime.

[11]Del Negro, Giannoni, and Schorfheide (2013) uses a New-Keynesian model and explain the behavior of inflation during the Great Recession by a low frequency of price changes.

The monetary authority responds by lowering the policy rate, EONIA, in order to mitigate the negative impact of the financial shock on real economy, with a larger response under the *distress* regime.

Overall, these findings confirm the extraordinarily rapid transmission of financial shocks to real economy during the recent crises, as many commentators had suggested, as well as during the episode of financial disruptions in 2001-2003.

VI.4. **Historical decompositions.** Historical decompositions allow to decompose the data into components attributed to each structural shock. This turns out to be an interesting exercise for quantifying the importance of financial factors over time. Figure 7 reports the contribution of financial shocks within sample. The solid black lines report the deviation of actual series from baseline, together with the estimated contribution of financial shocks. Baseline is measured by the median unconditional forecast of series, i.e in the absence of any shock. The contribution of financial shocks to each variable - displayed in the thin black line - is calculated as the difference between the forecast of the series conditional on the estimated series of shocks and the unconditional forecast. The grey shaded areas reports the 68 percent probability interval.

The estimates of the best-fit model suggest larger responses of output to financial shocks since the second half of 2008. Financial shocks was even below the output deviation in the 2011-2012 period. This suggests that other sources have contributed to compensate these adverse financial shocks. Further research might investigate these sources. Before that period, there is a small, but notable, explanatory role of financial shocks in output movements. As can be seen, financial shocks contributed to output increase during the great moderation, the 2003-2007 period.

Surprisingly, financial shocks were not very crucial to explain deviations of prices from baseline within the sample. Further, during the second recession in the late 2011, error bands are so large that one cannot quantify the impact of financial shocks on prices. This contrasts with their contribution to the decline of the nominal interest rate during the post-Lehman bankruptcy. Finally, the co-movement between the forecast errors of credit spread and the contribution of financial shocks to this series is striking. In particular, financial shocks appear largely responsible of the two big peaks in the late 2009 and 2011, as well as in the late 2001.

VI.5. **Counterfactual analysis.** One of the most interesting asset to employ a regime-switching framework is to quantify what would have happened if regime switches had not occurred at particular historic dates. This is a natural exercise to provide the quantitative

implications of changes in the systematic and predictable behavior of financial system to fluctuations.

The procedure is straightforward. Given the actual data, a set of draws is generated from the posterior distribution using the Gibbs sampling procedure mentioned in Appendix. For each draw, I recover the sequence of structural disturbance variances of the model. I then simulate history (i.e a set of new series) with those time series of shocks, but replace equation coefficients of the *distress* regime with those of the *normal* regime. As a result, the counterfactual simulations report what would have been happened if the *distress* regime had not occurred. This is what I do in this section by focusing on periods in which the *distress* regime has been in place, i.e the 2001-2003 episodes and the double-dip recession starting in 2008.

VI.5.1. *Replaying the 2001-2003 episode.* As a first exercise, I replay the 2001-2003 episode by placing the equation coefficients of the *normal* regime throughout this period. I obtain the results shown in Figure 8. Each panel reports the actual data (thick line) and the median counterfactual paths (thin line) for output (left panel) and inflation (right panel). The grey areas denotes CEPR recessions of the euro area. The differences between actual and counterfactual output growth paths is remarkably large. The *normal* regime would have kept both output growth much higher by around 2 percentage points at its peak. Inflation would have been noticeably, but not drastically, higher.

I repeat now the same exercise but, in addition to place the *normal* regime through the sub-samples, suppress the financial shocks. That is I set the disturbances in the financial sector equation to zero. For the period 2001-2003, I obtain the results shown in Figure 9. Compared to Figure 8, the fact of suppressing shocks to the financial sector do not change the counterfactual path of output growth and inflation. The history of output growth is thus mainly attributed to non-financial sources that feed through nonlinear dynamics. Changes in the behavior of financial system, rather financial sources, explains the financial instability and the output decline in that period.

VI.5.2. *Replaying the double-dip recession.* With the *normal* regime in place throughout this 2007-2012 episode instead, I obtain the counterfactual simulation in Figure 10. On the left panel, the decline of output growth would have been mitigated by up to 3 percentage points if the behavior of agents would not have changed during the high-financial stress environment. Overall, the model reproduces the large fall in output growth during the first recession (grey areas), implying that these events are better explained by larger structural shocks than a change in the behavior of the financial system. The right panel reports the counterfactual path of inflation rate. Similarly, the simulation reproduced history closely, although inflation

would have not reached negative rates in the mid-2009. The counterfactual simulation that implies modest higher aggregate activity means that the changing behavior of the economy (i.e private sector and policy) in turmoil times cannot explain entirely the two unprecedented financial crises.

Figure 11 report the results for the period 2007-2012. The simulation also reproduces the history of inflation very closely, with the falls during the two CEPR recessions, reported in grey areas. Non-financial sources are therefore behind the inflation variability. Finally, the simulation shows that output growth would have been mitigated up to 4 percentage points in the fourth quarter of 2009. This simulation keeps output much higher than the actual path, but does not prevent the entire collapse, meaning that the fall of output is also attributed to non-financial sources.

Overall, results like this imply that financial amplification mechanisms operate in financial distress episodes. They confirm the point that I have already made, namely an important nonlinearity in the behavior of financial system.

VII. Robustness Analysis

In order to assess the robustness of results, I study a number of other relevant models. First, I examine how the main results change if the prior duration of each regime is lower than 10 months. Second, I slightly modify the identification scheme by letting the policy rate ordered last. Third, only changes in the equation coefficients are allowed to vary across time. Fourth, I employ the Sims and Zha (2006) specification to restrict time variation in equation coefficients in matrix $F(s_t)$. All of these exercises reinforces the findings in the previous sections. Although the results of this section are not reported, they are available upon request.

VII.1. **Prior duration.** In section VI, I have shown the large persistence of each regime over time. This may be due to the belief that average duration of each regime is about 10 months. Here I explore several other prior durations to see if this delivers to completely different outcomes. The belief that the average duration of each regime is about (1) 3 months; (2) 6 months. Clearly, the changes in prior duration does not affect the main conclusions. For both beliefs (1) and (2), the data are still in favor of change in the behavior of financial system as long as heteroskedasticity is properly taking into account, i.e the model $\mathfrak{M}_{2Fc2v}$. The economic implications, not shown, of the best-fit model are strictly the same as those reported in previous sections.

VII.2. **Policy ordered last.** The identification scheme employed in the paper assume a recursive economic structure by imposing that the policy variable appear before the financial

sector variable in the recursive ordering. In this section, I relax this assumption and assume that the policy rate can immediately respond to movements originated in the financial markets. Thus, the recursive ordering becomes gdp_t, p_t, sp_t and r_t.

I still use the MDDs as measure of fit. Clearly, the best-fit model is still $\mathfrak{M}_{2Fc2v}$. Economic implications produced from this model remain unchanged.

VII.3. **Change only in coefficients.** An interesting exercise is to allow only equation coefficients to vary across time. Although Sims (2001) considers U.S. data to point out the importance of taking into account heteroskedasticity when allowing coefficients to vary, the euro area macroeconomic data might prefer only variations in the dynamics of the effects of a particular shock instead of independent drifts between coefficients and shock variances. Actually, shock variances may drift to compensate the absence of changes in equation coefficients. However, the estimated MDD's for the models in which coefficients switch between 2 and 4 regimes remain far below the levels of the MDDs in Table 2, reinforcing the finding of Sims (2001).

VII.4. **Sims and Zha (2006) specification.** In order to avoid overparameterization, Sims and Zha (2006) prevent an excessive number of parameters to change across regimes. First, they rewrite $F(s_t)$ as

$$\underset{m\times n}{F(s_t)} = \underset{m\times n}{D(s_t)} + \underset{m\times n}{\bar{S}}\,\underset{n\times n}{A(s_t)}, \tag{8}$$

where $\bar{S} = \begin{bmatrix} \mathbf{I}_n \\ \mathbf{0}_{n\times(m-n)} \end{bmatrix}'$. Second, they propose to decompose the lagged matrix $D(s_t)$ into two components, $g_{(i,j,l)}$ as constant across regimes and $\delta_{(i,j,s_t)}$ varying with constraints, as follows

$$D(s_t)_{(i,j,l)} = g_{(i,j,l)}\delta_{(i,j,s_t)}, \tag{9}$$

with $F(s_t)_{(i,j,l)}$ denotes the i^{th} variable, j^{th} equation, and l for the l^{th} lag in matrix $F(s_t)$. This indicates that the coefficients at the first lag can change across regimes, while the coefficients at other lags are proportional ($\delta_{(i,j,s_t)}$) those at the first lag, for a given regime.

By confronting such a specification that imposes time-varying restrictions with the one that imposes no restriction, it is clear that all models with Sims and Zha (2006)'s specification are dominated in fit by the model that allows changes in coefficients of the financial sector that are stochastically independent to changes in shock variances, $\mathfrak{M}_{2Fc2v}$. However, the log-value MDD of its restricted version remains above the log-value MDD's of unrestricted model. Using this restricted model, the main conclusions of the paper remain unchanged.

VIII. Interpretation

Results like those reported above are consistent with the financial amplification mechanisms that operate during financial distress episodes. Two main mechanisms exist. The first one is based on the seminal works of Bernanke and Gertler (1989) and Kiyotaki and Moore (1997). In particular, the mechanism operates when the agents' borrowing constraint is binding. When constraints are binding, any negative shock to their balance sheets causes them to reduce their capital demand, lowering asset prices, further deteriorating balance sheets and amplifying the shock. When constraints are slack, the same size negative shock causes only a small decline in spending and production. Since recently Mendoza and Smith (2006), Mendoza (2010), Brunnermeier and Sannikov (2013), He and Krishnamurthy (2012) and He and Krishnamurthy (2013) have considered this mechanism by studying the full dynamics of the model with occasionally binding constraints. In short, these new macro-finance models generate amplification effects that occur only during states where constraints bind due to the financial sector's fragility.

The second mechanism implies investors' Knightian uncertainty. As argued by Knight (1921), investors' behavior tend to modify during periods of high-uncertainty. A shock that triggers an increase in uncertainty about their investments cause them to pull back new projects. Investors prefer waiting to accumulate more information about its economic prospects prior to undertake a new investment. Thus, a negative shock would be amplified in high-uncertainty episodes. Among others, McDonald and Siegel (1986), Bloom (2009) and Caballero and Krishnamurthy (2012) provide theoretical foundations of such a mechanism.

Overall, my findings corroborate with this theoretical literature that shows changes in the systematic part of financial system, potentially leading to financial amplification effects.

IX. Conclusion

How different have the role played by the financial sector during the double-dip recession been from historical patterns ? To answer this question, this paper confronts a number of structural Bayesian vector autoregressions with several possible patterns of time variation in coefficients and disturbance variances. Using marginal data densities, I compare the fit of a number of identified Bayesian vector autoregressions models with changes in the stochastic volatilities of all structural shocks and/or in the coefficients. These regime switches follow a Markov-switching process along the line of Hamilton (1989) and Sims and Zha (2006). I refer a shock to the credit market that is orthogonal to the current state of the economy as a "financial shock". These shocks directly affect the ability of agents to borrow. Using the best-fit model, I reach the following conclusions.

- There is evidence of time variation in the behavior of financial sector. The relative importance of financial shocks ("non-systematic part") becomes higher in episodes of financial distress (such as the recession episode but also the downturn in 2001-2003), and the predictable response of financial system to the state of the economy ("systematic part") also differed.
- The systematic part oscillates between a *normal* and a *distress* regime. In the latter, when credit spread increases, output falls immediately and reaches its minimum after about 10 months. In the former, the lowest effect occurs only after 24 months and is more than twice weaker.
- Changes in the systematic component between these two regimes explain a substantial part of the fluctuations in output during the downturn in 2001-2003 and the double-dip recession starting in 2008 (up to 4 percentage points of output growth drops).
- As a result, I strongly recommend to treat modeling of the financial system and their effects as nonlinear. Brunnermeier and Sannikov (2013), He and Krishnamurthy (2013), Bloom (2009) and Caballero and Krishnamurthy (2012) are, among others, attempts to this direction.

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Appendix A. Data

All data are monthly from January 1999 to July 2012. Data comes from ECB - Statistical Data warehouse, except for the credit spread which was generously given by Benoit Mojon. Figure 2 shows the time series for each series.

- gdp_t: output is real interpolated GDP. The Chow and Lin (1971) procedure is used to interpolate the real quarterly GDP (ESA.Q.I6.Y.0000.B1QG00.1000 .TTTT.L.U.A). The monthly indicator variables are industrial production (STS.M.I6.Y.PROD. NS0010 .4.000), passenger car registrations (STS.M.I6.Y. CREG.PC0000.3.ABS) and total turnover index (STS.M.I6.Y.TOVT.2C0000. 4.000).
- p_t: prices is a consumer price index HICP (ICP.M.U2.N.000000.4.INX). The series has been deseasonnalized with the *Eviews* procedure.
- r_t: EONIA is used as policy rate (FM.M.U2.EUR.4F.MM.EONIA.HSTA).
- sp_t: the average of credit spreads on bonds issued by non-financial corporations from Gilchrist and Mojon (2014). This is a measure of credit tightening in the euro area.

Appendix B. Markov-switching Structural Bayesian VAR model

This section provides a detailed description of Bayesian inference employed in this paper. More specifically, I follow closely Sims, Waggoner, and Zha (2008).

B.1. **The posterior.** Before describing the posterior distribution, I introduce the following notation: θ and q are vectors of parameters where θ contains all parameters of the model (except those of the transition matrix) and $q = (q_{i,j}) \in \mathbb{R}^{h^2}$; $Y_t = (y_1, \ldots, y_t) \in (\mathbb{R}^n)^t$ are observed data with n the number of endogenous variables; and $S_t = (s_0, \ldots, s_t) \in H^{t+1}$ with $H \in \{1, \ldots, h\}$.

The log-likelihood function, $p(Y_T|\theta, q)$, is combined with the prior density functions, $p(\theta, q)$, to obtain the posterior density $p(\theta, q|Y_T) = p(\theta, q)p(Y_T|\theta, q)$.

B.1.1. *The likelihood.* Following Hamilton (1989), Sims and Zha (2006) and Sims, Waggoner, and Zha (2008), I employ a class of Markov-switching Structural VAR models of the following form

$$y_t' A(s_t) = x_t' F(s_t) + \varepsilon_t' \Xi^{-1}(s_t), \tag{10}$$

with $x_t' = \begin{bmatrix} y_{t-1}' & \cdots & y_{t-\rho}' & 1 \end{bmatrix}$ and $F(s_t) = \begin{bmatrix} A_1(s_t) & \cdots & A_\rho(s_t) & C(s_t) \end{bmatrix}'$.

Let $a_j(k)$ be the jth column of $A(k)$, $f_j(k)$ be the jth column of $F(k)$, $\xi_j(k)$ be the jth diagonal element of $\Xi(k)$. The conditional likelihood function is as follows

$$p(y_t|s_t, Y_{t-1}) = |A(s_t)| \prod_{j=1}^{n} |\xi_j(s_t)| \exp\left(-\frac{\xi^2(s_t)}{2} \left(y_t' a_j(s_t) - x_t' f_j(s_t) \right)^2 \right), \tag{11}$$

To simplify the Gibbs-sampling procedure described in next section, it is preferable to rewrite the condition likelihood function with respect to free parameters from matrix $A(s_t)$ and $F(s_t)$

$$|A(s_t)| \prod_{j=1}^{n} |\xi_j(s_t)| \exp\left(-\frac{\xi^2(s_t)}{2} \left((y_t' + x_t' W_j) U_j b_j(s_t) - x_t' V_j g_j(s_t) \right)^2 \right), \tag{12}$$

where $a_j(s_t) = U_j b_j(k)$ and $f_j(s_t) = V_j g_j - W_j U_j b_j(k)$ is a result from the linear restrictions $R_j \begin{bmatrix} a_j & f_j \end{bmatrix}' = 0$ and U_j and V_j are matrix with orthonormal columns and W_j is a matrix. See Waggoner and Zha (2003a) for further details.

The log likelihood function is given by

$$p(Y_T|\theta, q) = \sum_{t}^{T} \ln \left\{ \sum_{s_t=1}^{h} p(y_t|s_t, Y_{t-1}) \Pr\left[s_t | Y_{t-1} \right] \right\}, \tag{13}$$

where

$$\Pr\left[s_t = i|Y_{t-1}\right] = \sum_{j=1}^{h} \Pr\left[s_t = i, s_{t-1} = j|Y_{t-1}\right] \tag{14}$$

$$= \sum_{j=1}^{h} \Pr\left[s_t = i|s_{t-1} = j\right] \Pr\left[s_{t-1} = j|Y_{t-1}\right], \tag{15}$$

The probability terms are updated as follows

$$\Pr\left[s_t = j|Y_t\right] = \Pr\left[s_t = j|Y_{t-1}, y_t\right] = \frac{p(s_t = j, y_t|Y_{t-1})}{p(y_t|Y_{t-1})} \tag{16}$$

$$= \frac{p(y_t|s_t = j, Y_{t-1})\Pr[s_t = j|Y_{t-1}]}{\sum_{j=1}^{h} p(y_t|s_t = j, Y_{t-1})\Pr[s_t = j|Y_{t-1}]}. \tag{17}$$

B.1.2. *The prior.* Following Sims and Zha (1998), I exploit the idea of a Litterman's random-walk prior from a structural-form parameters. Dummy observations are introduced as a component of the prior. The n first dummy observation are the "sums of coefficients" by Doan, Litterman, and Sims (1984) and the last dummy observation is a "dummy initial observation" by Sims (1993). Using the linear restrictions, the overall prior, $p(\theta, q)$, is given in the following way

$$p(b_j(k)) = \text{normal}(b_j(k)|0, \bar{\Sigma}_{b_j}), \tag{18}$$

$$p(g_j(k)) = \text{normal}(g_j(k)|0, \bar{\Sigma}_{g_j}), \tag{19}$$

$$p(\xi_j^2(k)) = \text{gamma}(\xi_j^2(k)|\bar{\alpha}_j, \bar{\beta}_j), \tag{20}$$

$$p(q_j) = \text{dirichlet}(q_{i,j}|\alpha_{1,j}, \ldots, \alpha_{k,j}), \tag{21}$$

where $\bar{\Sigma}_{b_j}$, $\bar{\Sigma}_{\psi_j}$, $\bar{\Sigma}_{\delta_j}$, denotes the prior covariance matrices, $\bar{\alpha}_j$ and $\bar{\beta}_j$ are are set to one, allowing to the standard deviations of shocks to have large values for some regimes. The Gamma distribution is defined as follows

$$\text{gamma}(x|\alpha, \beta) = \frac{1}{\Gamma(\alpha)}\beta^{\alpha}x^{\alpha-1}e^{-\beta x}, \tag{22}$$

Regarding the transition matrix, Q, suppose that $q_j = [q_{1,j}, \ldots, q_{h,j}]'$. The prior denoted $p(q_j)$, follows a Dirichlet form as follows

$$p(q_j) = \left(\frac{\Gamma\left(\sum_{i\in H}\alpha_{i,j}\right)}{\prod_{i\in H}\Gamma(\alpha_{i,j})}\right) \times \prod_{i\in H}(q_{i,j})^{\alpha_{i,j}-1}, \tag{23}$$

where Γ denotes the standard gamma function.

B.2. **Gibbs-sampling.** Following Kim and Nelson (1999) and Sims, Waggoner, and Zha (2008), a Markov chain Monte Carlo (MCMC) simulation method is employed to approximate the joint posterior density $p(\theta, q, S_T|Y_T)$. The advantage of VARs is that conditional distributions $p(S_T|Y_T, \theta, q)$, $p(q|Y_T, S_T, \theta)$ and $p(\theta|Y_T, q, S_T)$ can be obtained in order to exploit the idea of Gibbs-sampling and sample alternatively from these conditional posterior distributions.

B.2.1. $p(\theta|Y_T, q, S_T)$. To simulate draws of $\theta \in \{b_j(k), g_j(k), \xi_j^2\}$ from $p(\theta|Y_T, S_t, q)$, one can start to sample from the conditional posterior

$$p(b_j(k)|y_t, S_t, b_i(k)) = \exp\left(-\frac{1}{2}b_j'(k)\bar{\Sigma}_{b_j}^{-1}b_j(k)\right) \times \prod_{t\in\{t:s_t=k\}}\left[|A(k)|\exp\left(-\frac{\xi^2(s_t)}{2}(y_t'a_j(k) - x_t'f_j(k))^2\right)\right] \tag{24}$$

using the metropolis-Hastings algorithm. Then, a multivariate normal distribution is employed to draw $g_j(k)$

$$p(g_j(k)|y_t, S_t) = \text{normal}(g_j(k)|\tilde{\mu}_{g_j(k)}, \tilde{\Sigma}_{g_j(k)}). \tag{25}$$

The computational details of the posterior mean vectors and covariance matrices are given in Sims, Waggoner, and Zha (2008).

Disturbance variances ξ_j^2 are simulated from a gamma distribution

$$p(\xi_j^2(k)|y_t, S_t) = \text{gamma}(\xi_j^2(k)|\tilde{\alpha}_j(k), \tilde{\beta}_j(k)), \tag{26}$$

where $\tilde{\alpha}_j(k) = \bar{\alpha}_j + \frac{T_{2,k}}{2}$ and

$$\tilde{\beta}_j(k) = \bar{\beta}_j + \frac{1}{2}\sum_{t\in\{t:s_{2t}=k\}}(y_t'a_j(s_t) - x_t'f_j(s_t))^2, \tag{27}$$

with $T_{2,k}$ is the number of elements in $\{t : s_{2t} = k\}$.

B.2.2. $p(S_T|Y_T, \theta, q)$. A multi-move Gibbs-Sampling is employed to simulate $S_t, t = 1, 2, ..., T$. First, draw s_t according to

$$p(s_t|y_t, S_t) = \sum_{s_{t+1}\in H} p(s_t|Y_T, \theta, q, s_{t+1})p(s_{t+1}|Y_T, \theta, q), \tag{28}$$

where

$$p(s_t|Y_t, \theta, q, s_{t+1}) = \frac{q_{s_{t+1},s_t}p(s_t|Y_t, \theta, q)}{p(s_{t+1}|Y_t, \theta, q)}. \tag{29}$$

Then, to generate s_t, one can use a uniform distribution between 0 and 1. If the generated number is less than or equal to the calculated value of $p(s_t|y_t, S_t)$, we set $s_t = 1$. Otherwise, s_t is set equal to 0.

B.2.3. $p(q|Y_T, S_T, \theta)$. The conditional posterior distribution of q_j is as follows

$$p(q_j|Y_t, S_t) = \prod_{i=1}^{h} (q_{i,j})^{n_{i,j}+\beta_{i,j}-1}, \tag{30}$$

where $n_{i,j}$ is the number of transitions from $s_{t-1} = j$ to $s_t = i$.

Appendix C. Marginal Data Densities

The marginal data density is defined as

$$p(Y_T) = \int p(Y_T|\theta)p(\theta)d\theta, \tag{31}$$

where $p(Y_T|\theta)$ is the likelihood function and $p(\theta)$ the priors. One usually employ the modified harmonic mean (MHM) of Gelfand and Dey (1994) to compute the marginal data density. The approximation of (31) is then

$$p(Y_T)^{-1} = \int \frac{h(\theta)}{p(Y_T|\theta)p(\theta)} p(\theta|Y_T)d\theta, \tag{32}$$

where $h(\theta)$ is any probability density called a *weighting* function. Denote

$$m(\theta) = \frac{h(\theta)}{p(Y_T|\theta)p(\theta)}. \tag{33}$$

The Monte Carlo (MC) integration allows to evaluate the integral on the right hand side (32)

$$p(Y_T)^{-1} = \frac{1}{N} \sum_{i=1}^{N} m(\theta^{(i)}), \tag{34}$$

where $\theta^{(i)}$ is the i^{th} draw of θ from the posterior distribution represented by $p(\theta|Y_T)$. Geweke (1999) proposes a Gaussian function for $h(.)$ constructed from the posterior simulator. This is adequate for constant-parameters models in which the posterior turns out to be quite Gaussian. However, in the case of Markov-switching models, the posterior is highly multi-modal and it contains zeros in the interior points of the parameter space. Sims, Waggoner, and Zha (2008) proposes a truncated non-Gaussian weighting function for $h(.)$ to remedy the problem. In particular, they use a truncated elliptical distribution centered at the posterior mode.

The second method employed in this paper is the so-called "Bridge sampling" method of Meng and Wong (1996). This is a generalization of the importance sampling method. Meng and Wong (1996)'s technique combines the MCMC draws from the posterior probability density function (pdf) with the draws from the weighting function (or importance density)

through a bridge function $\alpha(.)$ that re-weights both functions. Their method is based on the following result

$$p(Y_T) = \frac{\mathrm{E}_q(\alpha(\theta)p^*(\theta))}{\mathrm{E}_p(\alpha(\theta)h(\theta))}, \tag{35}$$

where $\alpha(\theta)$ is an arbitrary function; $p^*(\theta)$ the posterior kernel such that $p^*(\theta|Y_t) = p(Y_T|\theta)p(\theta)$.

It follows that the estimator $\hat{p}(Y_T)$ is called the general bridge sampling estimator

$$\hat{p}(Y_T) = \frac{\frac{1}{N_p}\sum_{j=1}^{N_p}\alpha(\theta^j)p^*(\theta^{(j)})}{\frac{1}{N_h}\sum_{i=1}^{N_p}\alpha(\theta^i)h(\theta^{(i)})}, \tag{36}$$

where N_h is the number of draws from the weighting density and N_p is the number of draws from the posterior distribution.

Once all draws from the importance density $h(\theta)$ and MCMC draws from the posterior density $p(\theta|Y_T)$ have been made, one can easily calculate $\hat{p}(Y_T)$. Meng and Wong (1996) proposes the following bridge function

$$\alpha(\theta) \propto \frac{1}{N_h h(\theta) + N_p p(\theta|Y_T)}. \tag{37}$$

The third method employed in this paper is the unpublished method of Ulrich Müeller. Like Bridge sampling, he proposes to combine the draws from the weighting pdf and the posterior pdf. He proposes also a particular weighting function $h(.)$ for computing the marginal data density. Because Liu, Waggoner, and Zha (2011) provides a review of this method, I briefly summarize it. Let $p(\theta|Y_t)$ the posterior probability density function (pdf); $p^*(\theta)$ the posterior kernel such that $p^*(\theta|Y_t) = p(Y_T|\theta)p(\theta)$. It follows that $p(\theta|Y_T) = c^*p^*(\theta|Y_T)$, where $c^* = p(Y_T)^{-1}$. Müeller constructs the following function $f(c)$

$$f(c) = \mathrm{E}_h\left[\mathbb{1}\left\{\frac{cp^*(\theta)}{h(\theta)} < 1\right\}\left(\frac{1 - cp^*(\theta)}{h(\theta)}\right)\right] - \mathrm{E}_p\left[\mathbb{1}\left\{\frac{h(\theta)}{cp^*(\theta)} < 1\right\}\left(\frac{h(\theta)}{1 - cp^*(\theta)}\right)\right],$$

where $\mathbb{1}\{x\}$ is an indicator function that returns to 1 if x is true and 0 if false. Given the properties of this function[12], one can use a bisection method to find an estimate c^* where $f(c^*) = 0$.

[12]The function f has the following properties

(1) $f(c)$ is monotonically decreasing in c

(2) $f(0) = 1$ and $f(\infty) = -1$

Using the Monte Carlo (MC) Methods, one can approximate the function value $f(c)$ as follows

$$\begin{aligned}\hat{f}(c) =& \frac{1}{N_h}\sum_{j=1}^{N_h}\left[\mathbb{1}\left\{\frac{cp^*(\theta^{(j)})}{h(\theta^{(j)})}<1\right\}\left(\frac{1-cp^*(\theta^{(j)})}{h(\theta^{(j)})}\right)\right] \\ & -\frac{1}{N_p}\sum_{j=1}^{N_p}\left[\mathbb{1}\left\{\frac{h(\theta^{(j)})}{cp^*(\theta^{(j)})}<1\right\}\left(\frac{h(\theta^{(j)})}{1-cp^*(\theta^{(j)})}\right)\right], \end{aligned} \tag{38}$$

where $\theta^{(i)}$ is the i^{th} draw of θ from the posterior distribution; $\theta^{(j)}$ is the j^{th} draw of θ from the weighting density. The draws from the posterior distribution are realizable through Markov Chain Monte Carlo (MCMC) methods.

After generating draws from the posterior pdf and the weighting function, the estimate of $c^* = p(Y_T)^{-1}$ such that $\hat{f}(c^*) = 0$ can be found by using a bisection method.

Appendix D. Tables

Table 1. Property statistics

period	std(spread)	std(gdp)	corr(spread,gdp)
2000-2012	0.7206	2.1600	-0.6558
2000-2007	0.4675	1.1591	-0.4785
2007-2012	0.8013	2.6801	-0.6166

Table 2. Measures of fit. Four different methods to approximate the marginal likelihood are employed: Chib (1995), Mueller, Meng and Wong (1996)'s bridge sampling, and Sims, Waggoner and Zha (2008).

	Marginal Data Densities			
Model	Chib	Mueller	Bridge	SWZ
$\mathfrak{constant}$	3006.60	*	*	*
$\mathfrak{M}_{2v}$	*	3048.41	3048.81	3052.85
$\mathfrak{M}_{3v}$	*	3063.34	3063.17	3063.75
$\mathfrak{M}_{4v}$	*	3068.13	3064.91	**
$\mathfrak{M}_{5v}$	*	3063.31	3054.77	**
$\mathfrak{M}_{2c2v}$	*	3064.85	3061.63	3073.52
$\mathfrak{M}_{2c3v}$	*	3066.21	3062.99	**
$\mathfrak{M}_{2Fc2v}$	*	3075.93	3076.83	3077.55
$\mathfrak{M}_{2Fc3v}$	*	3027.75	3024.33	**
$\mathfrak{M}_{2Pc2v}$	*	3052.12	3052.76	3058.76
$\mathfrak{M}_{2PFc2v}$	*	3063.47	3063.80	3065.11

TABLE 3. Transition matrices from the model $\mathfrak{M}_{2Fc2v}$, process s_t^c on the left, and process s_t^v on the right, , computed from the posterior median. The 68% probability interval is indicated in brackets.

0.8419 [0.7816;0.9355]	0.0489 [0.0272;0.0700]	0.8785 [0.8264;0.9449]	0.0857 [0.0444;0.1155]
0.1579 [0.0645;0.2184]	0.9510 [0.9300;0.9728]	0.1213 [0.0551;0.1736]	0.9142 [0.8845;0.9556]

TABLE 4. Relative shock standard deviations across regimes for $\mathfrak{M}_{2Fc2v}$ model, computed from the posterior mode. The 68% probability interval is indicated in brackets.

	Private y	Private p	Policy R	Financial sp
$s_t^c = 1$	1.0000 [1.0000;1.0000]	1.0000 [1.0000;1.0000]	1.0000 [1.0000;1.0000]	1.0000 [1.0000;1.0000]
$s_t^c = 2$	0.7472 [0.5317;0.9185]	0.2660 [0.2028;0.3270]	0.1691 [0.1167;0.1967]	0.3356 [0.2327;0.4096]

TABLE 5A. Contemporaneous coefficient matrix, $A(s_t = 1)$, for *distress* regime in $\mathfrak{M}_{2Fc2v}$ model, computed from the posterior median. The 68% probability interval is indicated in brackets.

Prod. y	Prod. p	Policy R	Financial F
266.86 [243.21;294.29]	10.98 [−4.67;25.89]	−29.35 [−43.42;−17.05]	41.84 [1.06;81.32]
0.00 [0.00;0.00]	493.10 [449.36;539.77]	−11.98 [−49.51;28.61]	116.29 [−32.02;232.15]
0.00 [0.00;0.00]	0.00 [0.00;0.00]	555.07 [497.05;593.31]	189.34 [16.59;284.48]
0.00 [0.00;0.00]	0.00 [0.00;0.00]	0.00 [0.00;0.00]	247.97 [205.78;286.25]

TABLE 5B. Contemporaneous coefficient matrix, $A(s_t = 2)$, for *normal* regime in $\mathfrak{M}_{2Fc2v}$ model, computed from the posterior median. The 68% probability interval is indicated in brackets.

Prod. y	Prod. p	Policy R	Financial F
266.86 [243.21;294.29]	10.98 [−4.67;25.89]	−29.35 [−43.42;−17.05]	17.31 [−7.88;34.79]
0.00 [0.00;0.00]	493.10 [449.36;539.77]	−11.98 [−49.51;28.61]	−23.43 [−80.64;22.98]
0.00 [0.00;0.00]	0.00 [0.00;0.00]	555.07 [497.05;593.31]	−59.85 [−129.44;21.86]
0.00 [0.00;0.00]	0.00 [0.00;0.00]	0.00 [0.00;0.00]	862.27 [763.83;961.78]

Appendix E. Figures

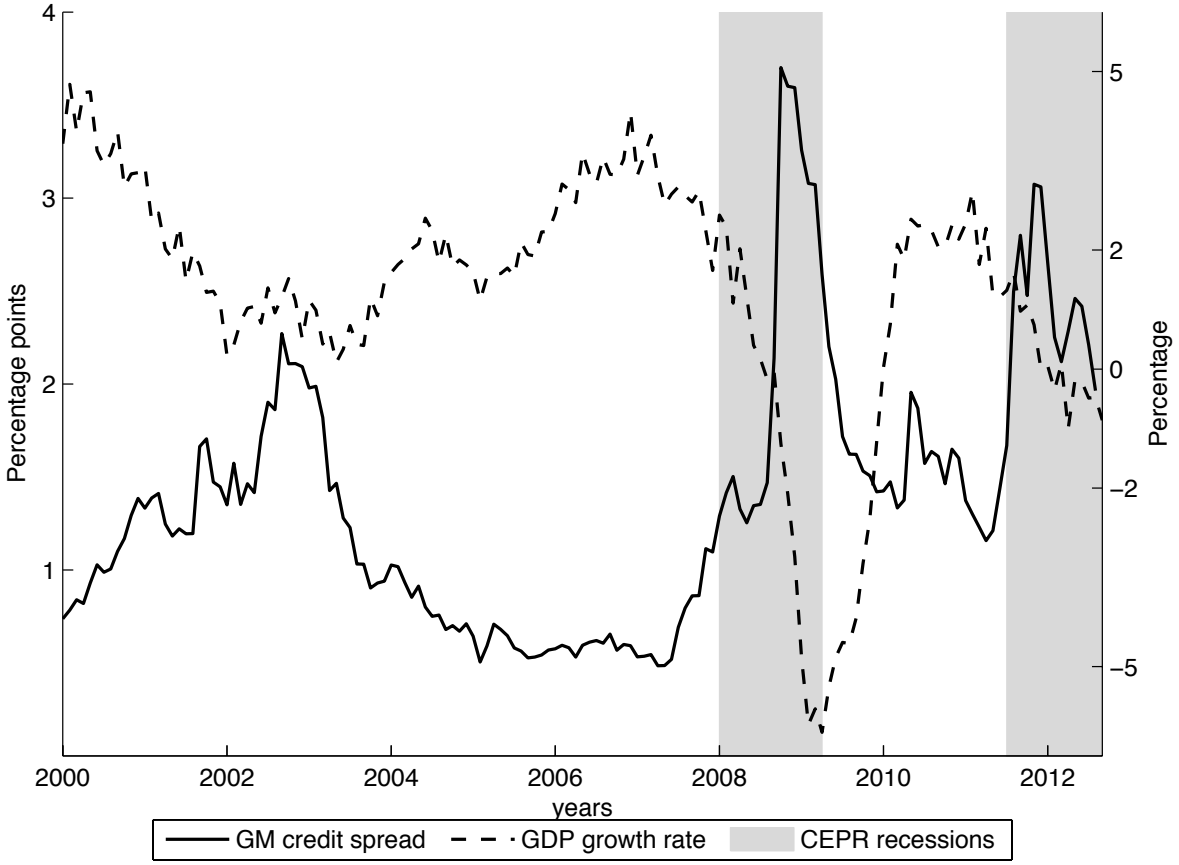

Figure 1. Sample period: January 2000 - July 2012. The real GDP growth rate (dotted line) is labeled on the right. The Gichrist-Mojon (GM) corporate bond spread (solid line) is labeled on the left. The grey areas denotes CEPR recessions of the euro area.

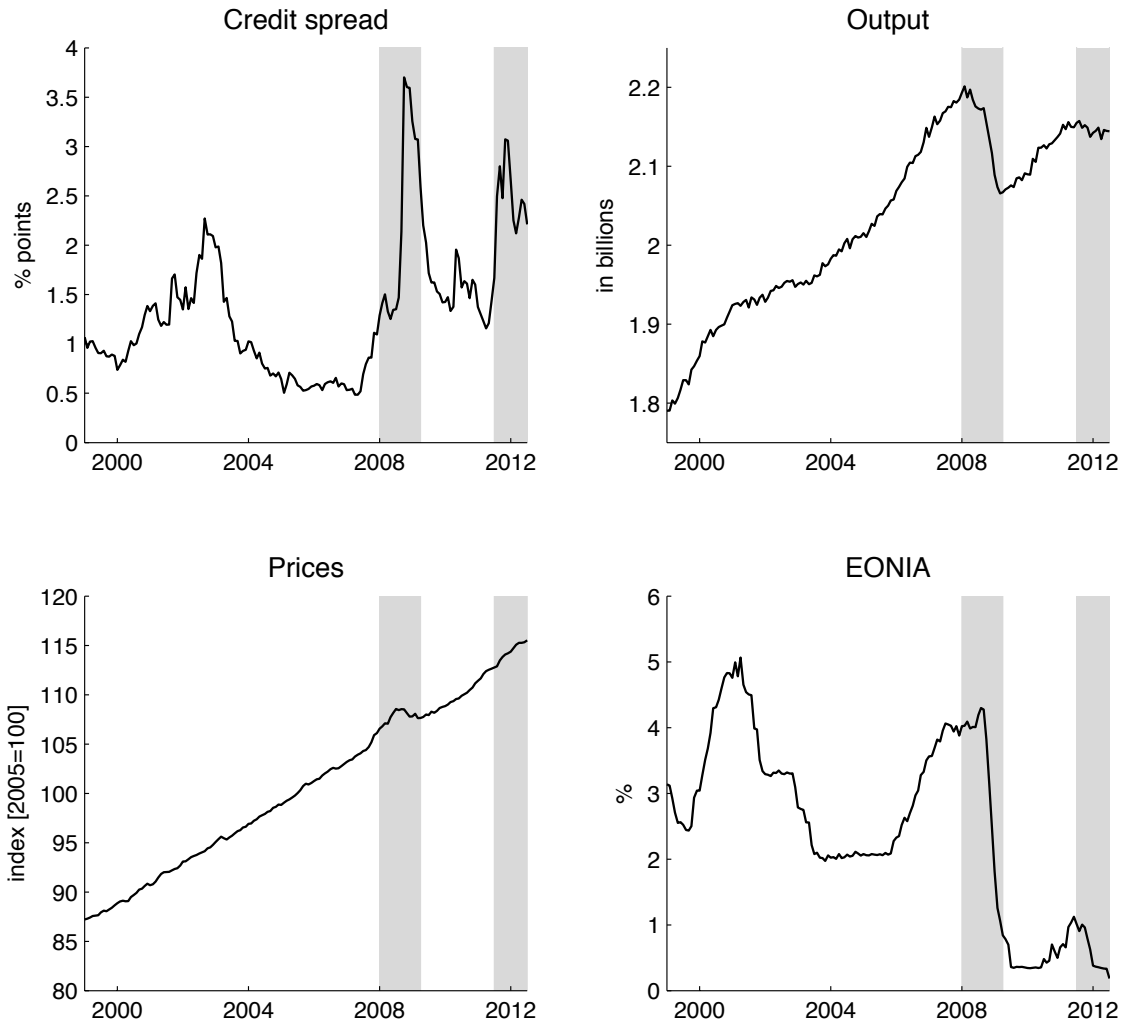

FIGURE 2. Sample period: January 1999 - July 2012. The solid lines depicts the five series: Non-financial corporates credit spread, output, prices and EONIA. These series have been transformed before estimating each model. All the variables, except the EONIA and the credit spread, enter as log-levels. The grey areas denotes CEPR recessions of the euro area.

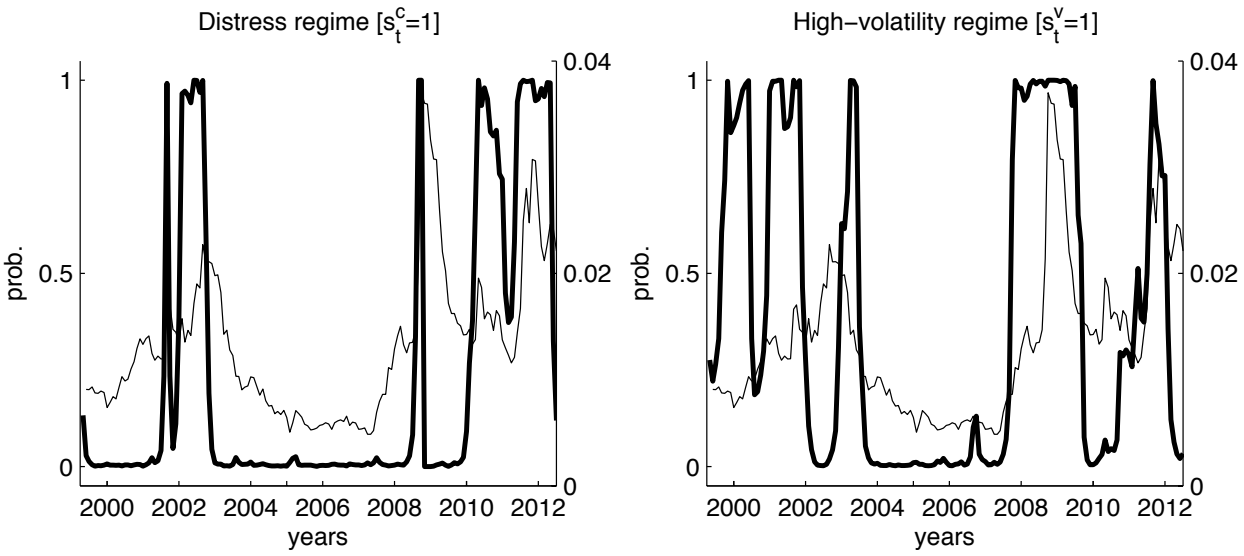

FIGURE 3. Sample period: January 1999 - July 2012. Smoothed probabilities (in solid line and labeled on the left) of the *distress* regime (left panel) and of the *high-volatility* regime (right panel) produced from the model, $\mathfrak{M}_{2Fc2v}$, in which the coefficients of financial sector equation and variances of structural disturbances evolves independently according to two-states Markov-switching processes, respectively s_t^c and s_t^v. The credit spread (thin line) is labeled on the right.

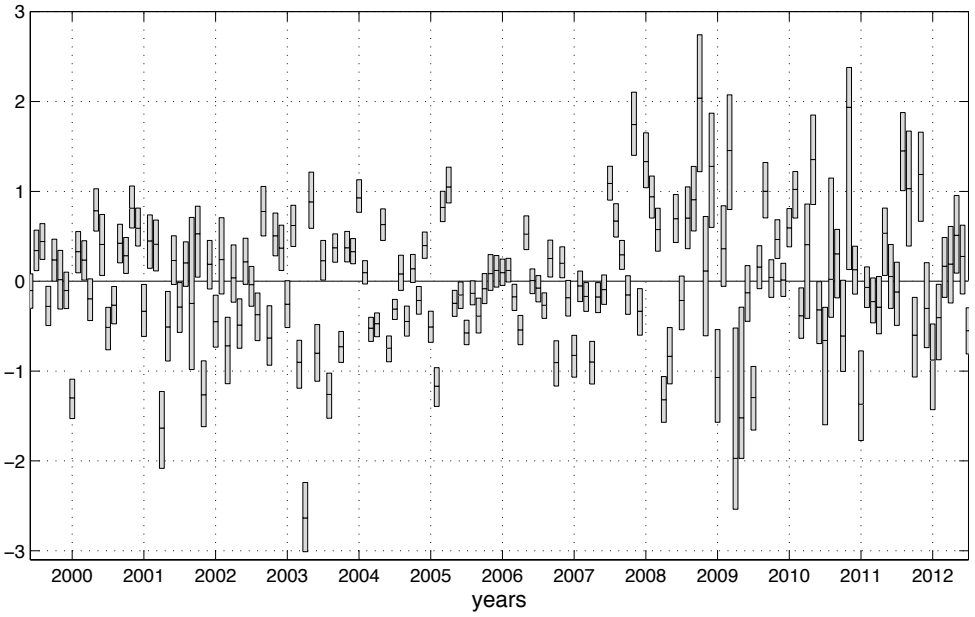

FIGURE 4. Sample period: January 1999 - July 2012. Time-series of financial shocks produced from $\mathfrak{M}_{2Fc2v}$ model. A positive bar means an adverse financial shock. The black horizontal line represents the median and the grey areas denotes the 68% probability interval.

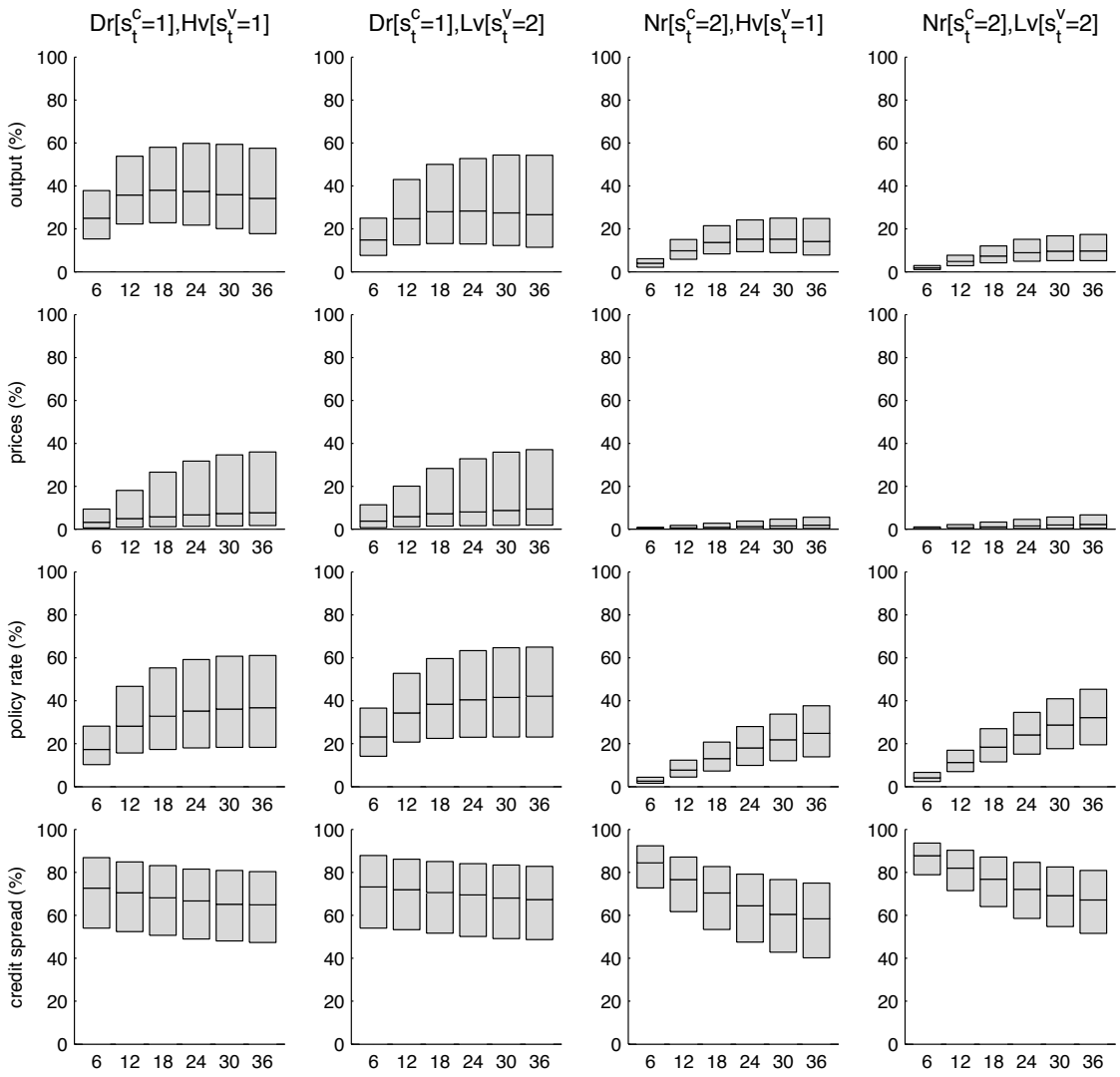

FIGURE 5. Variance decomposition of endogenous variables at various horizons $h = \{6, 12, 18, 24, 30, 36\}$ across regimes. The black horizontal line represents the median contribution (in percentage) of financial shocks to the volatility of each of endogenous variable. The grey bar represents the 68% probability interval. I use the following notation: Dr$[s_t^c = 1]$ Distress regime, Nr$[s_t^c = 2]$ Normal regime, Hv$[s_t^v = 1]$ High-volatility, Lv$[s_t^v = 2]$ Low-volatility.

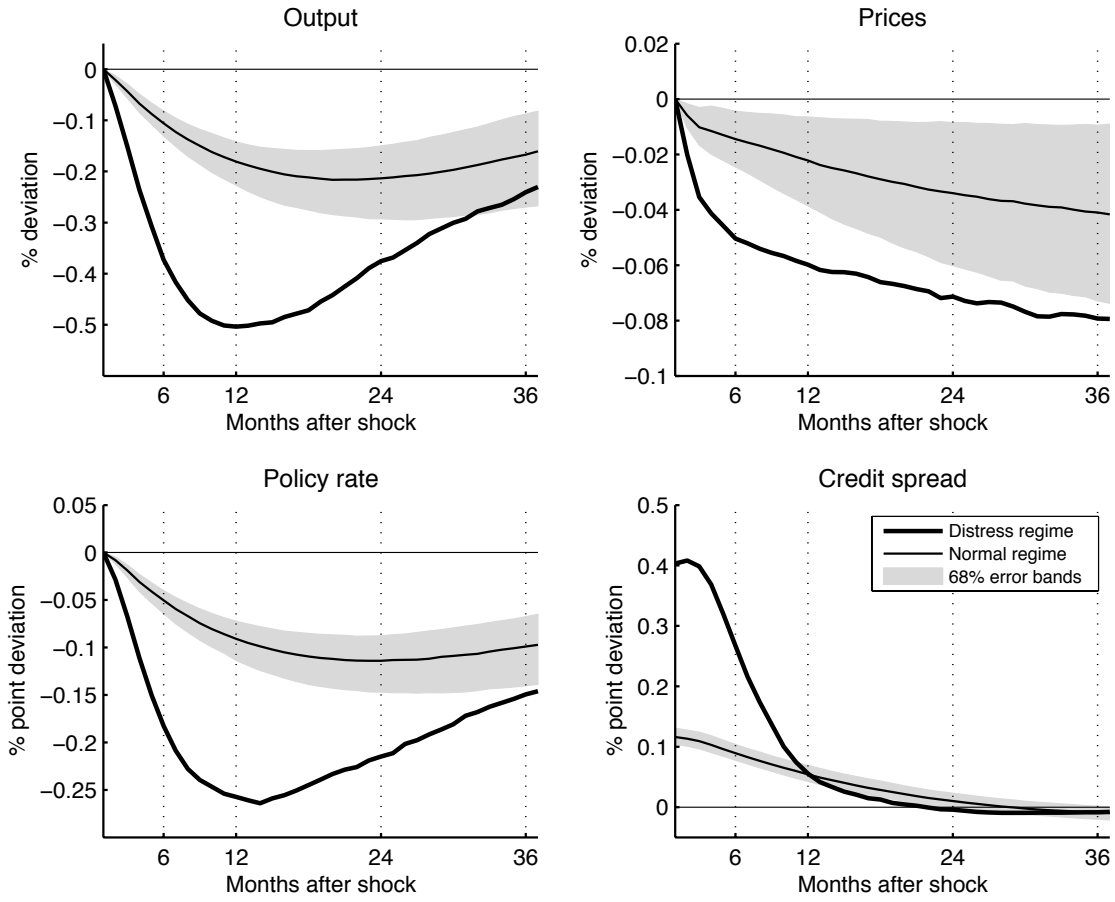

FIGURE 6. Impulse responses of endogenous variables to a financial shock across the two regimes for the $\mathfrak{M}_{2Fc2v}$ model, that is two independent Markov-switching processes: (1) two-states process governing the coefficients of the financial sector equation; (2) two-states process governing variance shocks. The black (solid and thin) line represents the median and the grey areas are the 68% probability interval.

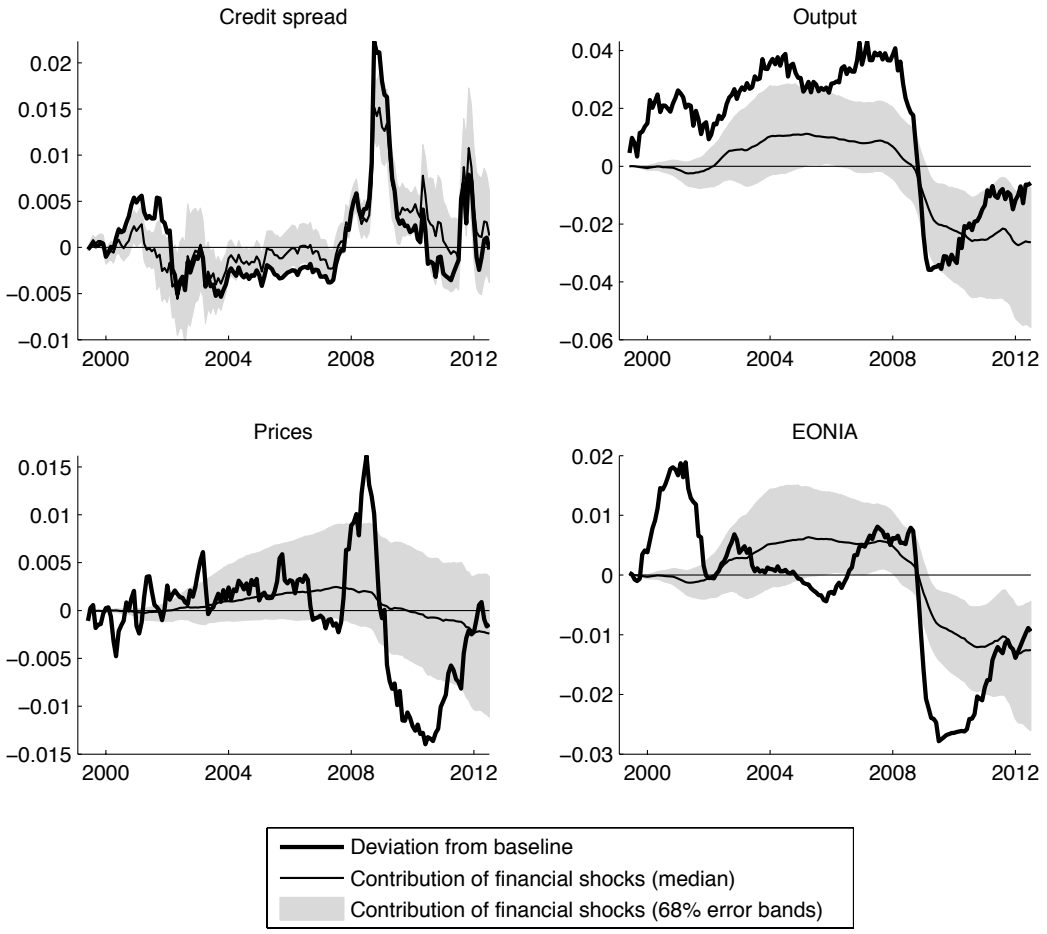

FIGURE 7. Sample period: January 1999 - July 2012. Historical decomposition of endogenous variables. The tick line represents the deviation of actual series from baseline - measured by the median unconditional forecast of series, i.e in the absence of any shock. The thin line represents the contribution of financial shocks. The grey areas represent the 68% error bands.

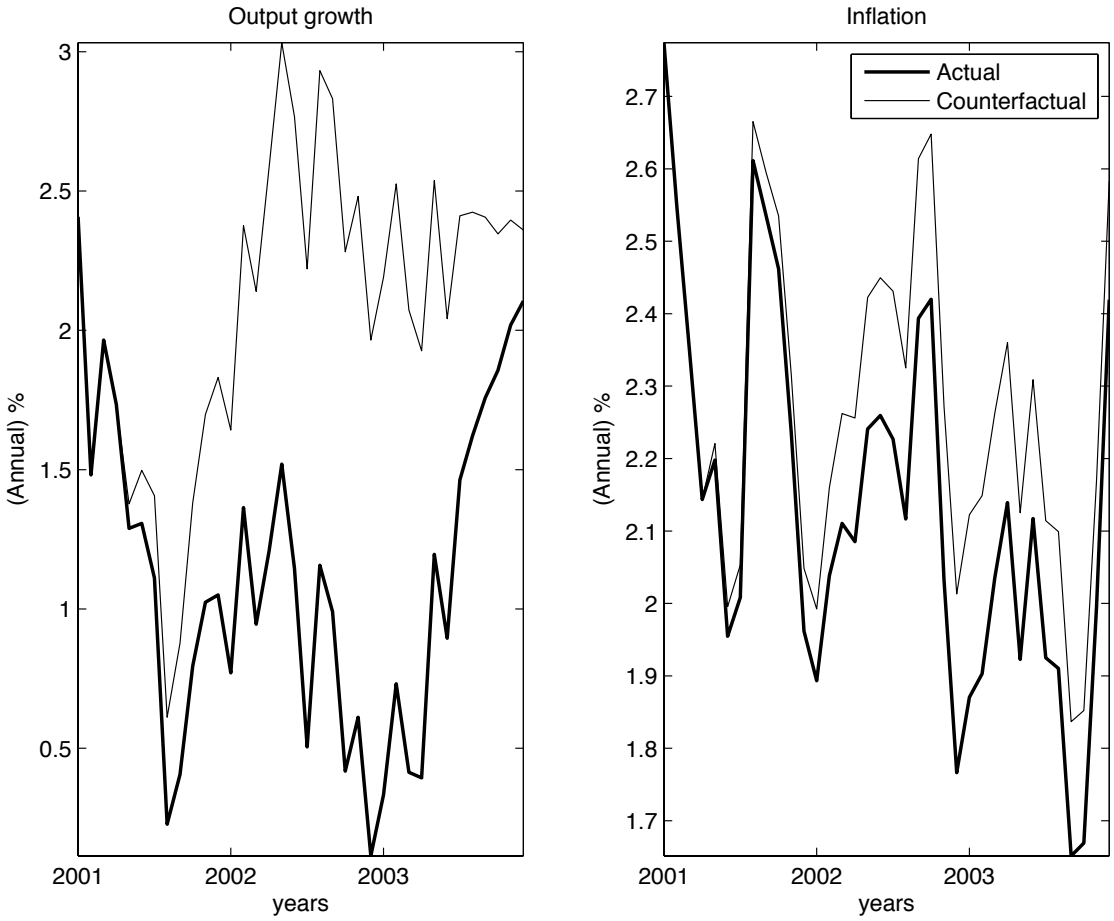

FIGURE 8. Sample period: January 2001-December 2003. Fixed *normal* regime throughout. Counterfactual paths produced from $\mathfrak{M}_{2Fc2v}$ model, that is two independent Markov-switching processes: (1) two-states process governing the coefficients of financial sector equation; (2) two-states process governing all variance shocks. Each graph shows the actual path (thick line) and the (median) counterfactual path (thin line).

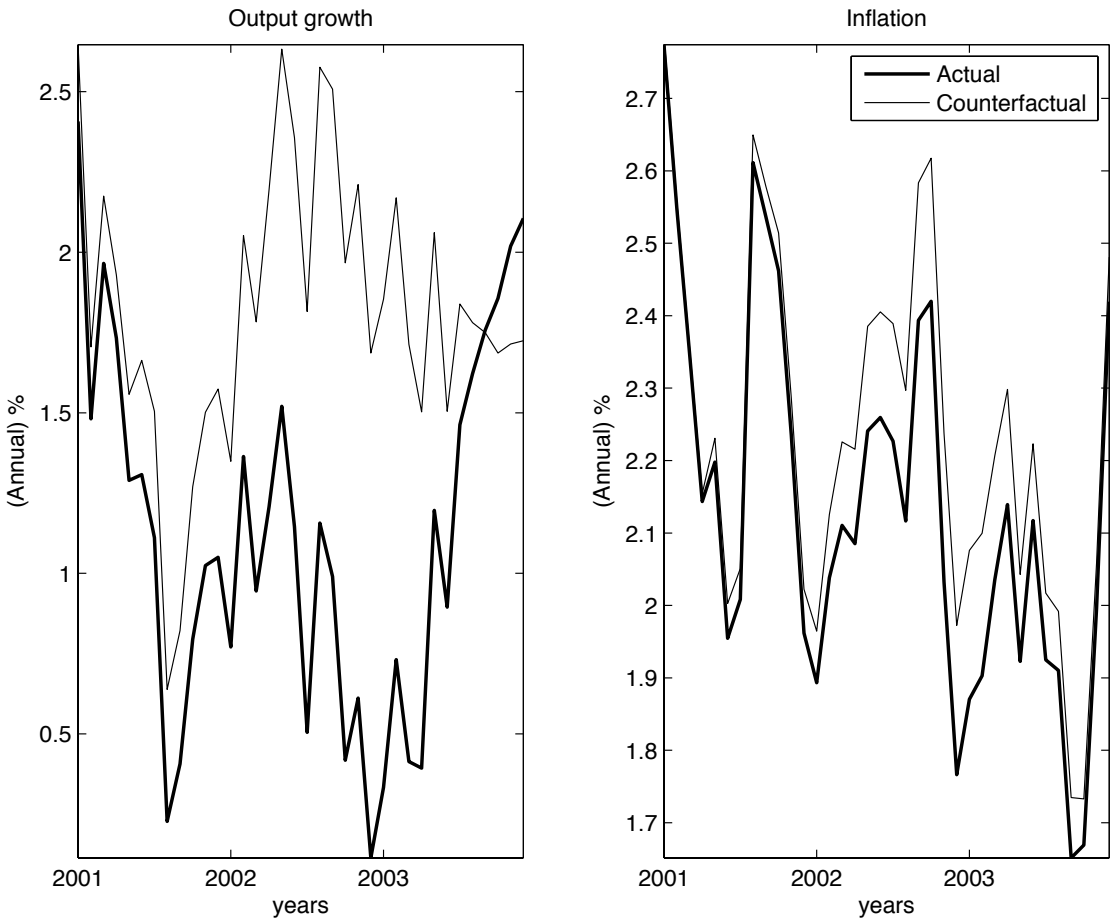

FIGURE 9. Sample period: January 2007-December 2003. Fixed *normal* regime throughout and suppressing financial shocks. Counterfactual paths produced from $\mathfrak{M}_{2Fc2v}$ model, that is two independent Markov-switching processes: (1) two-states process governing the coefficients of financial sector equation; (2) two-states process governing all variance shocks. Each graph shows the actual path (thick line) and the (median) counterfactual path (thin line).

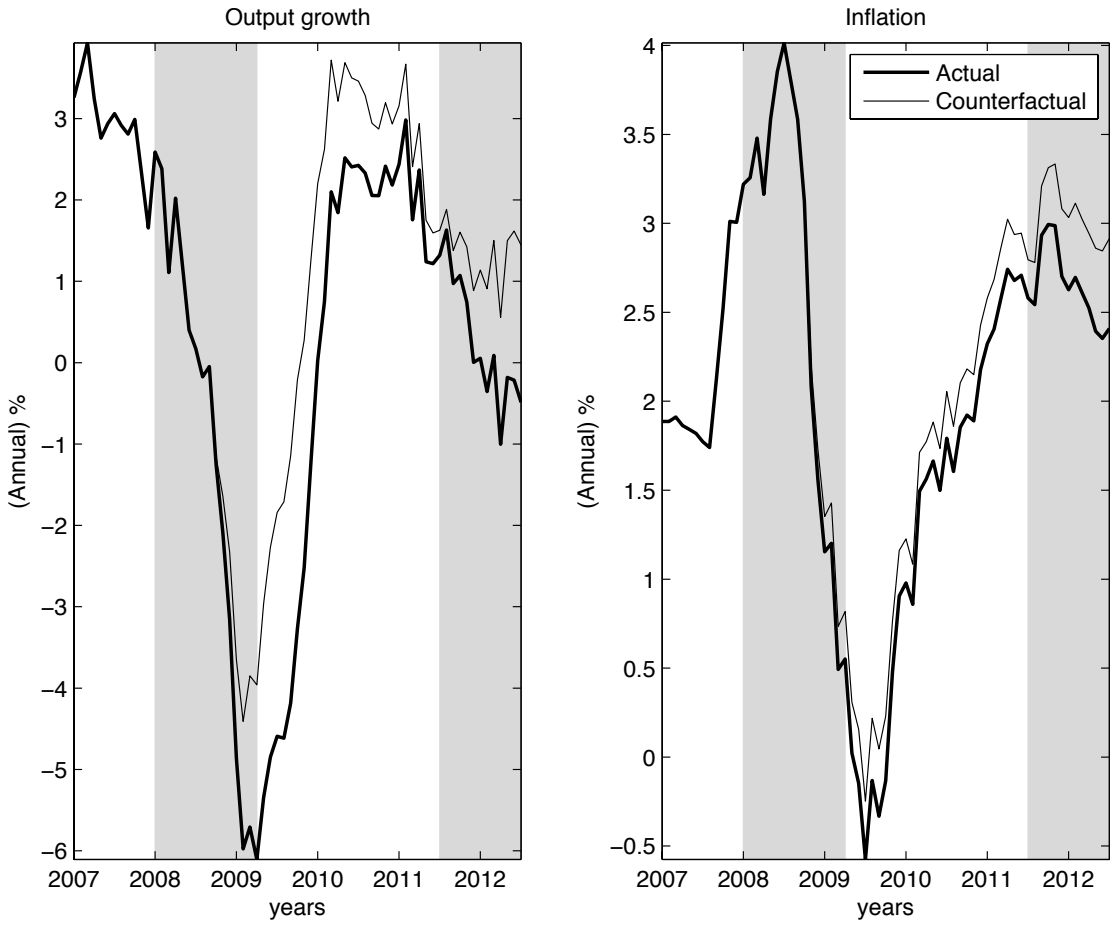

FIGURE 10. Sample period: January 2007-July 2012. Fixed *normal* regime throughout. Counterfactual paths produced from $\mathfrak{M}_{2Fc2v}$ model, that is two independent Markov-switching processes: (1) two-states process governing the coefficients of financial sector equation; (2) two-states process governing all variance shocks. Each graph shows the actual path (thick line) and the (median) counterfactual path (thin line). The grey areas denotes CEPR recessions of the euro area.

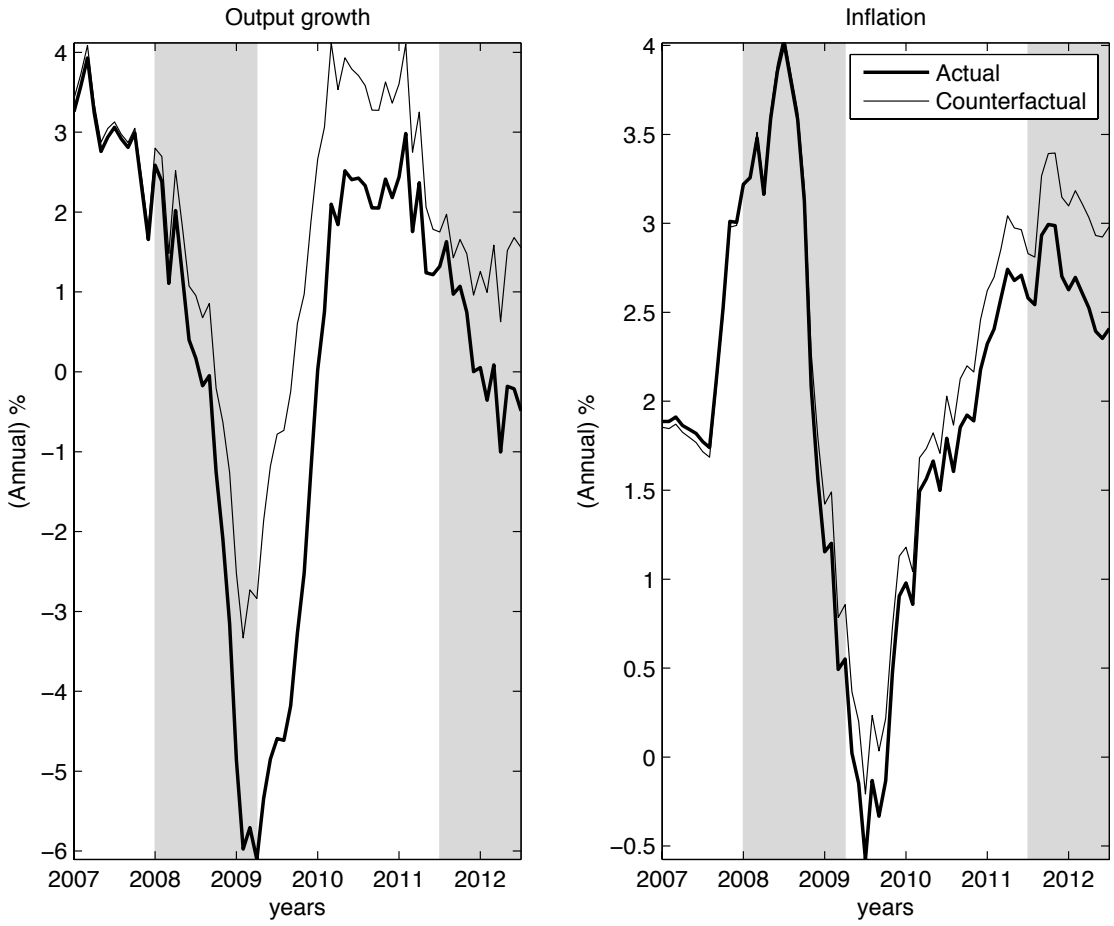

FIGURE 11. Sample period: January 2007-July 2012. Fixed *normal* regime throughout and suppressing financial shocks. Counterfactual paths produced from $\mathfrak{M}_{2Fc2v}$ model, that is two independent Markov-switching processes: (1) two-states process governing the coefficients of financial sector equation; (2) two-states process governing all variance shocks. Each graph shows the actual path (thick line) and the (median) counterfactual path (thin line). The grey areas denotes CEPR recessions of the euro area.