FINANCIAL INTERMEDIARIES' INSTABILITY AND EURO AREA MACROECONOMIC DYNAMICS

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ABSTRACT. Fitting a Markov-switching structural vector autoregression to euro area data, we show that, after taking into account heteroskedasticity, the differences in the behavior of the economy between tranquil and financial distress periods (e.g., Great Recession and sovereign debt crisis) reflect variations in the transmission mechanism. When and only when a period of financial distress occurs, disruptions in financial intermediation trigger adverse effects for the real economy and turn out to be the primary source of business cycle fluctuations. Finally, we provide strong evidence that ECB interventions in the financial sector had beneficial effects on the real economy during the sovereign debt crisis.

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I. Introduction

> "The special nature of financial systems [...] is that they can result in [...] powerful feedback and amplification mechanisms, which render their implications more severe and widespread. In the aggregate, they lead to the nonlinear adjustments that are so characteristic of financial instability. [...] Such adjustments may cause violent regime changes, pushing the system from a state of tranquility to a state of turmoil."
>
> —Jean-Claude Trichet[1]

It is widely recognized that disturbances to the financial intermediation sector, triggered by capital losses after the Lehman Brothers event and during the European sovereign debt crisis, have played a central role in the double-dip recession experienced by the euro area. Figure 1 plots the industrial production growth rate, along with the excess bond premium — an indicator of credit supply conditions — from October 1999 to June 2016. As can be seen, there is a close connection between sharp reductions in output and violent surging risk premia during crises.

These rare and episodic events, which are not often observed by nature, have led the macro-finance theorists to depart from log-linearized models (e.g., Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Bernanke, Gertler, and Gilchrist, 1999), which study the dynamics around a non-stochastic steady state, and to study global dynamics of the system, characterized by "normal" and "crisis" states. These states are determined by financial constraints in the intermediation sector, depending upon whether they bind or not. This new generation of theoretical models (e.g., He and Krishnamurthy, 2012, 2013; Brunnermeier and Sannikov, 2014; Adrian and Boyarchenko, 2012; Maggiori, 2012) is thus able to study explicitly nonlinear effects. Intuitively, while in normal times the good financial conditions of financial intermediaries can absorb losses induced by a negative shock, in times of crisis the financial sectors fragility creates grave and long lasting problems with firms financing conditions tightened, leading to substantial cuts in spending, employment and production.

Although it is widely accepted, from a theoretical perspective, that financial markets could act as an important nonlinear amplification mechanism, quantitative studies have been scant. The reason lies in the fact that most empirical models used by the profession rule out, by construction, the possibility of change in the economy.

This paper aims to fill part of this gap by modeling empirically the nonlinear link between financial intermediaries' health and the macroeconomy in a multivariate regime-switching framework. We first provide some statistical regularities and establish evidence that the connection of financial intermediaries' health to real economy is very unstable. While there

[1]See Trichet (2009).

exists a strong link between them in periods of financial distress, there is almost non-existent link in tranquil periods.

To better understand these features of the data, we confront a number of structural vector autoregressions (SVARs), with several possible patterns of time variation in equation coefficients and disturbance variances, to macroeconomic and financial data of the euro area. Following closely the methodology of Sims and Zha (2006), the first objective is to consider whether the euro area economy has been subject in periods of "turmoil" times to changes in the transmission of structural shocks so that macroeconomic variables are more sensitive to them or, rather, changes in the sizes of these shocks? The second objective is to understand how different is the importance of the financial sector as a source of business cycle fluctuations between turmoil and tranquility times.

Time variations in the multivariate time series model are allowed while we maintain weak identifying assumptions to isolate financial institutions behavior and its effects on economic activity. Identification is achieved by using the so-called excess bond premium constructed by De Santis (2016) for the euro area, an indicator that reflects the ability of financial institutions to provide funds. Following the methodology of Gilchrist and Zakrajšek (2012), the author construct this financial indicator by purging euro area corporate credit spreads — the difference in yields between various corporate bonds and government securities of matched maturities — from countercyclical movements in expected defaults. We postulate that innovations in excess bond premium represent financial disturbances, which we refer as *credit supply shocks*. These disturbances are orthogonal to the current state of the economy; that is to say, they affect output and prices, as well as monetary policy actions, with at least one period of lag.

Our results show changes not only in the variances of structural disturbances over time, but also in *the predictable* and *systematic part* of the economy. By this, we mean changes in the transmission mechanism, i.e., the way aggregate macroeconomic variables respond to shocks. These changes in equation coefficients prevailed in periods of financial crisis; i.e., from 2008 to 2009, characterized by the Great Recession, and from 2010 to 2011, associated with the sovereign debt crisis. It follows that the transmission of credit supply shocks is strongly nonlinear over time; e.g., an adverse shock that causes a 25 basis points increase in the excess bond premium implies, in periods of financial distress, a decline in output and prices by 3 percent and 0.20 percent, respectively, but effects that are close to zero in tranquil periods. The contribution of these shocks to output variability becomes considerable in periods of financial distress (up to 75 percent of the long-run forecast error variance), while negligible for the remaining periods. Our counterfactual simulations suggest that these structural shocks were the primary source of the decline in output during crisis events. Furthermore, if changes in the estimated coefficients would not have occurred, the euro area economy would have never faced a double-dip recession.

Finally, we evaluate the role of ECB policies, involving government bond purchases, in mitigating these crises. To do so, we display counterfactual simulations of history with alternate time series of credit supply shocks. That is, conditional on available estimates of the effects of ECB interventions on long-term sovereign spread, we generate a new sequence of structural shocks that suppress the effects of the major announcements of unconventional monetary policy on sovereign spread. We show that, without the first announcements in 2010-2011, output would have been much lower by around four percentage points, while the measures announced in 2012 could not have prevented the decline in output.

Relation to other studies. This paper is related to an increasing literature that examines how disruptions in financial intermediation sector manifest themselves and what their effects are on the rest of the economy. Instead of discussing all of the papers in this area one by one, we ask how our results stand apart from much of the existing empirical literature in the area.

Focusing on the euro area, Hristov, Hulsewig, and Wollmershauser (2012), Peersman (2012), and Moccero, Darracq Pariès, and Maurin (2014) employ a "constant-parameters" approach to quantify the impact of credit supply conditions on real activity.[2] Most papers find a significant and long-lasting decrease of output after a credit market shock. Based on the graphs in Peersman (2012), output (industrial production) reaches its minimum after about fifteen months and slowly increases thereafter. A limit of the methodology employed in these papers is that linear VARs rule out, by construction, any time-varying in equation coefficients and shock variances and, therefore, cannot answer directly to the questions that we posed previously, especially the time-varying role of the financial sector as a source of business cycle fluctuations.

Gambetti and Musso (2017) extend the standard approach by allowing time-varying parameters in SVARs and show that the relative importance of loan supply shocks to the economy has dramatically increased between 2007 and 2009; they contributed to about one half of the fall in real GDP growth. The authors' findings primarily result from larger shocks and do not reveal any changes in the way macroeconomic variables react to those shocks. Conversely, we find a nonlinear transmission of these shocks to the economy over time.

[2]There is also a large literature for the U.S. economy. See, among others, Gilchrist and Zakrajšek (2011, 2012); Boivin, Giannoni, and Stevanovic (2012); and Caldara, Fuentes-Albero, Gilchrist, and Zakrajăek (2016).

A major difference relative to our paper lie within the fact that Gambetti and Musso (2017) — but also the three previous papers — employ a sign restriction approach to identify credit supply shocks. More specifically, they identify these shocks as a negative co-movement between the amount of loans and a composite lending rate. Conversely, we use the De Santis (2016) excess bond premium, an indicator that directly reflects the risk appetite in the corporate bond market and so credit supply conditions, to identify a credit supply shock. Therefore, our excess bond premium allows us to employ a simple Cholesky approach. The difference in the choice of variables, methodology[3] and identification may explain why Gambetti and Musso (2017) do not find drastic change in equation coefficients.

From a methodological standpoint, the use of MS-SBVARs to capture differences in macroeconomic fundamentals between periods of tranquility and financial distress is similar to Hubrich and Tetlow (2015) and Lhuissier and Tripier (2016), for the United States, and Hartmann, Hubrich, Kremer, and Tetlow (2015), for the euro area. Our focus, relative to the latter, is however clearly different. First, we focus on credit supply shocks, instead of shocks to the overall financial sector, which do not allow them to provide a structural interpretation of shocks. Second, we run several counterfactual exercises to assess the effects of ECB unconventional monetary policies on aggregate activity. Third, we fully characterize the uncertainty about our results by generating draws from the posterior distributions of functions of parameters (such as impulse responses, historical counterfactuals, etc...).

This paper proceeds as follows. To illustrate the possibility of nonlinearity between financial intermediation and macroeconomy, Section II provides some insight into how different the time series properties of output and risk premia are between distress and non-distress periods. Section III presents the general methodology employed in this paper. Section IV compares the fit of a number of Markov-switching SVARs, selects the best-fit model, and provides the posterior estimates of this model. Section V discusses the economic implications of the best-fit model. Section VI conducts several exercises to assess the robustness of the results. Section VII evaluate the macroeconomic effects of ECB actions involving government bond purchases. Section VIII concludes.

II. Some Descriptive Statistics

In this section, we illustrate the possibility of non-linearities in the euro area historical data. To do so, we compute covariances of the output growth rate and the level of the

[3]Indeed, another explanation lies in the methodology itself — a model with smooth and drifting coefficients as in Gambetti and Musso (2017) seems to be less suited for capturing rapid shifts in the behavior of the data as observed during the double-dip recession. Financial crises are well-known for hitting the economy instantaneously, which favors those models with abrupt changes like the Markov-switching models.

excess bond premium using monthly data from October 1999 to June 2016. The industrial production growth rate is obtained by the first log difference in the industrial production index.

The excess bond premium is drawn from De Santis (2016). To construct it, the author proceeds in several steps along the line of Gilchrist and Zakrajšek (2012). First, he constructs a corporate bond spread by using the market price of bonds issued by euro area corporations. The difference between each security and the overnight index swap (OIS) of similar duration represents the credit spread. The average is obtained by weighting each credit spread by their corresponding volumes. Second, he breaks up the variation of the spread into two components: a component that is predictable from fluctuations in expected defaults, and an unexpected component — the excess bond premium — that represents risk premium that lenders charge for bearing default risk. The excess bond premium reflects the financial health of financial intermediaries. To prove it, De Santis (2016) reports a remarkable connection between the excess bond premium and the changes in bank lending obtained from the euro area bank lending survey. Figure 1 plots this indicator (solid red line) and the output growth (dotted blue line) along with the CEPR recession dates of the euro area (in yellow areas).

Table 1 presents covariances conditional on their location in the "distress" (Panel A) or in the "non-distress" (Panel B) period. For our benchmark classification, we define distress periods as the highest one-third of realizations of the excess bond premium and we require that the distress or non-distress periods minimally cover two monthly periods. We classify three distress periods: January 2008-October 2012, June 2013-July 2013, January 2016-February 2016. Clearly, the two first distress periods are associated with the recent global financial crisis and the sovereign debt crisis, which typically followed in several European countries, while the last one corresponds to short-lived periods of financial distress. Therefore, the distress periods prevail sporadically not only during CEPR recession dates, but also at later times.

Looking across the first column in Table 1, there is an asymmetry in the covariances across the distress and non-distress periods. The macroeconomic and financial volatilities differed, with obviously higher volatilities in the distress period than in the non-distress period. While in a non-distress period, the relation between the excess bond premium and industrial production is almost non-existent, the distress period sees a close connection between both series.

These results are robust to alternative classifications of the distress periods. Column (2) defines the distress periods as the highest one-fifth of realizations of the excess bond premium. Column (3) considers the CEPR recession dates as distress periods. Column (4) considers the Bryan and Boschan (1971) procedure on the logarithm of the monthly industrial production to determine the periods of recessions and to consider them as the distress periods.[4] This procedure has been also proposed by Harding and Pagan (2002) for quarterly observations. The latter procedure allows us to identify three distress periods: January 2001-November 2001, May 2008-April 2009, September 2011-November 2012.

These alternative classifications confirm the asymmetry in the covariances between the distress and non-distress periods. Interestingly, given that all classifications define the two recent crises as being almost only the distress periods, one can say that the recent financial disruptions contribute, in large part, to the asymmetry in covariances.

It is important to note that 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 and/or to changes in transmission mechanisms; i.e., in the way that macro variables respond to shocks. The objective of the next sections is: 1) To identify the nature of the nonlinearity; and 2) To investigate the role of the financial intermediation in financial crises and in standard business-cycle fluctuations.

III. The Methodology

III.1. **Markov-switching Structural Bayesian VARs.** Following Hamilton (1989), Sims and Zha (2006), and Sims, Waggoner, and Zha (2008), we employ a class of Markov-switching structural VAR models of the following form:

$$y_t' A_0(s_t) = \sum_{i=1}^{\rho} y_{t-i}' A_i(s_t) + C(s_t) + \varepsilon_t' \Xi^{-1}(s_t), \qquad t = 1, \ldots, T, \tag{1}$$

where y_t is defined as $y_t \equiv [ip_t, p_t, r_t, ebp_t]'$; ip_t is the logarithm of the monthly industrial production index; p_t is the logarithm of the Harmonized Index of Consumer Prices (HICP); r_t is the Euro OverNight Index Average (EONIA), i.e., the policy rate[5]; and ebp_t is the De Santis (2016) excess bond premium. The two latter series are end-of-month data, which turn out to be crucial for imposing credible identifying assumptions on the structure. Figure 2 shows the time series for each series. Data sources are presented in Appendix A.

[4]Following Bryan and Boschan (1971), we impose that a phase must last at least six months, a complete cycle must have a minimum duration of fifteen months, and a local minimum relative to the five months on either side of the series.

[5]The EONIA is used as a 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 October 1999 to June 2016. Based on the lag-length selection criteria, we set the lag order to $\rho = 4$.

We assume that ε_t follows the following distribution:

$$p(\varepsilon_t|Y_{t-1}) = \text{normal}(\varepsilon_t|0_n, I_n), \tag{2}$$

where n is the number of endogenous variables, 0_n denotes an $n \times 1$ vector of zeros, I_n denotes the $n \times n$ 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; $A_0(s_t)$ is an n-dimensional invertible matrix under the regime s_t; $A_i(s_t)$ is an n-dimensional matrix that contains the coefficients at the lag i and the regime s_t; $C(s_t)$ contains the constant terms; $\Xi(s_t)$ is an n-dimensional diagonal matrix; and $Y'_{t-1} = \left[y'_1 \ldots y'_{t-1}\right]$.

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; and $q_{i,j} = \Pr(s_t = i|s_{t-1} = j)$ 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 two regimes, the transition matrix Q is restricted to avoid over-parameterization. That is, we follow Sims (2001) and Sims, Waggoner, and Zha (2008) by allowing symmetric jumping among states[6].

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.

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

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

This restricted transition matrix implies that when we are in regime j, we can only move to regime $j-1$, j, or $j+1$. Note also that the probability of switching to regime $j-1$ or $j+1$ is symmetric and independent of j.

Following Sims and Zha (1998), we exploit the idea of a Litterman's random-walk prior to structural-form parameters. We also introduce dummy observations as a component of the prior in order to favor unit roots and cointegration.[7] For more details, see Doan, Litterman, and Sims (1984) and Sims (1993). Appendix B provides the details techniques for the evaluation of the posterior density under the prior of Sims and Zha (1998).

Finally, the prior duration of each regime is about twenty five months, meaning that the average probability of staying in the same regime is equal to 0.96. As shown in Section VI, we have also used other prior durations and the main conclusions remain unchanged.

III.2. **Identification.** Identified vector autoregressions decompose the time series variation into mutually independent components. Identification turns out to be extremely important in isolating the effects of a particular shock — uncorrelated to other structural shocks — on the vector of endogenous variables y_t. Since we are studying the macroeconomic effects of shocks that affect the ability of financial intermediaries to lend, particular attention is paid on this structural credit supply shock. As the issue of identification is well-known for macroeconomists, we 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 rewritten in a reduced-form VAR as follows:

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

with

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

where $x_t' = \begin{bmatrix} y_{t-1}' & \cdots & y_{t-\rho}' \end{bmatrix}$ and $F = \begin{bmatrix} A_1 & \cdots & A_\rho \end{bmatrix}'$.

The variance–covariance matrix Σ of the reduced-form VAR is a symmetric and positive definite matrix as follows

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

If there are no identifying restrictions, equations (6) and (7) define a relationship between the structural and reduced-form parameters (B, Σ), which is not unique. One can find two parameter points, (A_0, F) and $(\hat{A}_0, \hat{F})$, 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

[7]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. A grid-search approach is employed to maximize the marginal data density. We obtain the following values: $\mu_1 = 0.70$ (overall tightness of the random walk prior); $\mu_2 = 0.30$ (relative tightness of the random walk prior on the lagged parameters); $\mu_3 = 0.1$ (relative tightness of the random walk prior on the constant term); $\mu_4 = 1.0$ (erratic sampling effects on lag coefficients); $\mu_5 = 2.0$ (belief about unit roots); and $\mu_6 = 2.0$ (belief in cointegration relationships).

representation (B, Σ) if, and only if, there is a orthonormal matrix P, such that $A_0 = \hat{A}_0 P$ and $F = \hat{F} P$.

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 a unique solution called the "recursive identification". Following this tradition, the contemporaneous matrix A_0 is an upper triangular matrix with the following recursive ordering: ip_t, p_t, r_t, and ebp_t.

The paragraphs that follow explain and justify our identification scheme. Following previous work by Leeper, Sims, and Zha (1996), we propose that the production sector (output and prices) does not respond contemporaneously to the credit market sector; namely, the policy rate and the excess bond premium. 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 firms are subject to planning delays. There are also planning processes involved in changing the prices of labor and manufactured goods.

Given that EONIA is an end-of-month policy rate, we think it is reasonable to impose that the monetary authority responds immediately to the private (i.e., production) sector.[8] Although ECB does not know current values of industrial production and consumer prices, it has an approximate knowledge of its actual information set. Thus ECB can react to these macroeconomic conditions, which are approximately observed, at the end of the month.

Given that the excess bond premium is also an end-of-month data, we impose the restriction that ECB does not respond immediately to the excess bond premium within month. We justify this hypothesis by the fact that it takes time for ECB's macroeconomic policy to consult, analyze the new informations from financial markets and then make a decision. Thus it would be unlikely that the monetary authority, by setting its nominal interest rate at the end of the month, reacts immediately to movements in the (end-of-month value) excess bond premium.

In our robustness section (i.e., section VI), we propose alternative identification schemes, including one in which ECB does not respond immediately to the private sector. This hypothesis is drawn from Leeper, Sims, and Zha (1996). We will show that our main conclusions remain unchanged.

Finally, the VAR specification assumes that the excess bond premium is ordered last, which implies that it reacts 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.

[8]Christiano, Eichenbaum, and Evans (1999) also propose an immediate response of the monetary authority to macroeconomic variables.

IV. Empirical Results

In this section, we estimate and compare various types of models with the following specifications:

- $\mathfrak{M}_{\text{constant}}$: Each equation (coefficients and variances) is time-invariant.
- $\mathfrak{M}_{\#\text{v}}$: The variances of all structural disturbances follow the same #-regimes Markov process.
- $\mathfrak{M}_{\#_1\text{c}\#_2\text{v}}$: Each equation allows the coefficients to change under one $\#_1$-regimes Markov process; disturbance variances follow another independent $\#_2$-regimes Markov process.
- $\mathfrak{M}_{\#_1\text{Fc}\#_2\text{v}}$: The financial sector equation (i.e., the fourth equation) allows its coefficients to change under one $\#_1$-regimes Markov process and the variances of all structural disturbances follow another independent Markov process with $\#_2$-regimes.
- $\mathfrak{M}_{\#_1\text{Pc}\#_2\text{v}}$: The production sector equations (i.e., the first and second equations) allow its coefficients to change under one $\#_1$-regimes Markov process and the variances of all structural disturbances follow another independent Markov process with $\#_2$-regimes.

A few items deserve discussion. First, when allowing changes in shock variances, the times of these changes are synchronized. These time-variation restrictions allow us to keep our model parsimonious. Second, the equation coefficients ("systematic behavior") are allowed to vary across time only if heterosekdasticity is taken into account; i.e., the model makes allowances for shock variances to vary independently of coefficients. Otherwise, bias in estimates can appear.[9] Third, some specifications include only a subset of the equation coefficients to vary over time. It might be possible, for various reasons, that only some sectors of the economy change, while others remain unchanged over time. In particular, we have looked at models in which the behavior within the production sector (output and prices) and the financial sector (excess bond premium) changes independently, while monetary policy remains invariant over time.[10]

The results shown in this paper are based on 5 million draws with the Gibbs sampling procedure (see Appendix B for details). We discard the first $500,000$ draws as burn-in, then keep every 100th draw. As normalization rule, we simply impose that the diagonal of matrices

[9]Sims (2001) and more recently, Lhuissier and Zabelina (2015) show how important it is to control heteroskedasticity when estimating equation coefficients of the model.

[10]Of course, ECB has dramatically changed its conduct of implementing monetary policy by implementing new unconventional measures during the two recent recessions. These policies are, however, not fully captured by the measure of monetary policy used in our models. Furthermore, we have also looked at a model in which only systematic monetary policy is allowed to change (while taking into account heteroskedasticity), but this model is largely outperformed by other specifications.

$A_0(s_t)$ is always positive. This turns out to be important to avoid bimodal distribution in the contemporaneous impulse responses of variables to structural shocks.

We use the Dynare software operating within MATLAB to estimate and simulate our MS-SBVARs.[11]

IV.1. **Model Fit.** The comparison of models is based on marginal data density (also called marginal likelihood), which is a measure of model fit. We employ the Sims, Waggoner, and Zha (2008) method to compute the marginal data density (MDD) for each model, except for the $\mathfrak{M}_{\text{constant}}$ model, for which we employ the Chib (1995) procedure. The authors demonstrate that their method, contrary to standard modified harmonic means (MHM) method, overcomes problems that are specific to non-Gaussian models — such as Markov-switching models — namely, that the posterior distribution can be multi-modal, very low at the sample mean and contains zeros in the interior points of the parameter space. Appendix C provides the mathematical details for this method.

Table 2 reports the log-value of MDD for each model. The constant-parameter model, $\mathfrak{M}_{\text{constant}}$, is clearly rejected. The best-fit model is $\mathfrak{M}_{\text{2c2v}}$; that is, the model in which the times of changes in equation coefficients from the entire system are stochastically independent of the times of changes in shock variances. The log-value of the MDD associated with this model remains far above the values of the other MDDs mentioned in this paper. The difference between $\mathfrak{M}_{\text{2c2v}}$ and the second highest marginal data density model, $\mathfrak{M}_{\text{3v}}$, is of the order of 11 in absolute value. This is a noticeable difference that dramatically supports changes not only in all disturbance shocks, but also in the systematic component of the system.

The data does not favor models associated with changes only in equation coefficients from a specific sector of the economy. When only equation coefficients from the financial sector is allowed to change — as in $\mathfrak{M}_{\text{2Fc2v}}$ — the MDD is remarkably lower than the best-fit model (the difference is of the order of 11) and close to the second highest marginal data density model. Also, the way the production sector responds to shocks remains similar over time. Indeed, the value of log MDD for $\mathfrak{M}_{\text{2Pc2v}}$ is far below most of the other models.

The estimated MDD for the $\mathfrak{M}_{\text{4v}}$ and $\mathfrak{M}_{\text{2c3v}}$ models seems to be erratic, meaning that there are some redundant states. In particular, the addition of a new regime of volatility

[11]The Dynare development team has created a simple and intuitive interface to the C/C++ codes developed in Sims and Zha (2006) and Sims, Waggoner, and Zha (2008). The following link `http://www.stephanelhuissier.eu/PublicCodes_L17.zip` provides all files and data to replicate the main results of the paper using Dynare/MATLAB. The replicating files propose how to retrieve the Dynare output — the mode and the draws from the Gibbs sampling procedure — to obtain the posterior distribution of impulse responses, historical decompositions, and counterfactuals. We believe that these programs are very relevant for anyone interested in inference of multivariate Markov-switching models.

is clearly rejected by the data. We thus prefer displaying "***" for this case rather than a specific number. See Sims and Zha (2006) for details.

These results are robust to alternative values of the parameter that define the proportion of draws from the posterior distribution used in the approximation. Although not reported, these estimated MDDs confirm that the $\mathfrak{M}_{\mathrm{2c2v}}$ model is the one that best fits the euro area data. In the next sections, we will report the economic implications of this best-fit model.

IV.2. **Posterior distribution.** In this section, we present some key results produced from the $\mathfrak{M}_{\mathrm{2c2v}}$ model. Figure 3 shows the probabilities of a specific regime for each Markov-switching process over time produced by the $\mathfrak{M}_{\mathrm{2c2v}}$ model. For clarity, we refer s_t^{c} as the process governing equation coefficients, and s_t^{v} as the process dictating shock variances. The probabilities are smoothed in the sense of Kim (1994); i.e., full sample information is used in getting the regime probabilities at each date.

When looking at the process in which equation coefficients from the system (systematic part) are allowed to change (see s_t^{c} shown in the right panel), it is apparent that the regime 2, ($s_t^{\mathrm{c}} = 2$), was dominant during the two periods of financial distress, namely the Great Recession in 2008-2009 and the European sovereign debt crisis in 2010-2012. For obvious reasons, we label this regime as "high-stress coefficients regime", also called the "distress regime" in a concise way. All of the above-mentioned sub-periods, captured by this regime, contain the same similarities. That regime prevailed in periods in which excess bond premium rose and was relatively high. The regime 1 has prevailed for the remaining years of the sample, characterized by episodes of non-distress, in which there are no particular obstacles for access to credit and a large volume of transactions. This is the "low-stress coefficients regime" or the "tranquility regime" to make it more concise.

There are substantial differences in the contemporaneous coefficient matrix across the two regimes. Tables 3 and 4 report the contemporaneous coefficient matrix, $A_0(s_t^{\mathrm{c}})$, for the tranquil and the distress regime, respectively. Each column represents an equation of the system and gives the name of the sectors in which shocks originate: the production sector (Prod ip/p), monetary policy (Policy R), and the financial intermediary sector (Financial F). When looking at the last column in both tables, we see that the contemporaneous coefficients on output and prices, as well as those on the nominal interest rate, are much larger in the distress regime. Put differently, financial intermediaries become much more sensitive to any movements in economy activity in periods of high stress.

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", as shown in Tables 5 and 6. Each table reports the relative shock variances across the two volatility regimes once the diagonal of $A_0(s_t^{\mathrm{c}})$ is normalized to a vector of ones. For each table (i.e., for each $A_0(s_t^{\mathrm{c}})$ normalized), the estimated shock variances in the first regime are substantially smaller than those in the second regime. The left panel of Figure 3 displays the (smoothed) probabilities of the high-volatility regime. There are repeated fluctuations between the two regimes. While nearing 1 during the early 2000s, the probability of the high-volatility regime rapidly falls in late 2003 and remains close to zero until the dramatic U.S. financial turbulences in 2008. Indeed, the high-volatility regime covers largely the Great Recession of 2008-2009, then it was never in place again. This last finding corroborates with Lhuissier (forthcoming) who, instead of using a class of MS-SBVAR models, estimates a richly parameterized DSGE model of the euro area economy with regime changes in shock variances over time. The author also associates the Great Recession to a high-volatility regime.

Interestingly, the recent financial disruptions that occurred in the early 2010, associated with the European debt crisis, result from a change in the transmission mechanism — through the systematic part of the system — of a given shock on the economy, rather than variations in the size of shocks.

The following estimated transition matrices (at the posterior median) summarize the two Markov-switching processes:

$$Q^{\mathrm{c}} = \begin{bmatrix} \underset{[0.9513;0.9839]}{0.9694} & \underset{[0.0537;0.1428]}{0.0927} \\ \underset{[0.0161;0.0487]}{0.0306} & \underset{[0.8572;0.9463]}{0.9073} \end{bmatrix}, \qquad \text{and} \qquad Q^{\mathrm{v}} = \begin{bmatrix} \underset{[0.9093;0.9674]}{0.9409} & \underset{[0.0254;0.0771]}{0.0461} \\ \underset{[0.0326;0.0907]}{0.0591} & \underset{[0.8710;0.9533]}{0.9238} \end{bmatrix},$$

where Q^{c} denotes the transition matrix governing equation coefficients and Q^{v} the transition matrix governing the structural disturbances. The 68% probability intervals are indicated in brackets. Clearly, the regime of distress ($q_{22}^{\mathrm{c}} = 0.9073$) is much less persistent (an average duration of 11 months) than the tranquility regime ($q_{11}^{\mathrm{c}} = 0.9694$) which covers most of the sample with an average duration over 34 months. Regarding the process governing the variance shocks, s_t^{v}, the persistence of the high-volatility regime, ($q_{22}^{\mathrm{v}} = 0.9238$), is lower than the low-volatility regime, with $q_{11}^{\mathrm{v}} = 0.9413$. The average duration of the low- and high-volatility regime is about 17 and 13 months, respectively. Once again, the tight interval probabilities reinforce the estimated median values.

In summary, once taking into account heteroskedasticity, we find that periods of financial distress produce changes in the way macroeconomic variables respond to shocks. The objective of the next section is then to investigate how these responses change across regimes.

V. Economic Implications

Using the best-fit model, we examine the role of disruptions to the financial intermediation sector as a source of business cycle fluctuations. First, we present the time series of credit supply shocks. We then present the impulse responses of variables to credit supply shocks identified with our recursive identification. In addition, we assess the quantitative importance of these shocks across regimes. Finally, to establish the contribution of financial intermediaries to the double-dip recession, we display counterfactual historical simulations to investigate the role of credit supply shocks and changes in the transmission mechanism in shaping macroeconomic fluctuations.

V.1. **Time-series of credit supply disturbances.** Before describing the relative importance of credit supply shocks to macroeconomic fluctuations, we provide an empirical interpretation of the evolution of these disturbances over time. Figure 4 displays the time series of the credit supply shock from February 2000 to June 2016. The red star reports the median, while the blue bars report the 68 percent probability interval. A positive bar means an adverse credit supply shock.

As can be seen, credit supply shocks capture the dramatic financial market disruptions since the end of 2007, with an accumulation of adverse credit supply shocks (positive bars). These shocks also occur intensively before and during both recessions, displayed in yellow areas.

In particular, there are positive shocks a few months before the CEPR recession dates but these are not the largest of the historical positive credit supply shocks. Actually, the biggest shocks prevailed during the first CEPR recession, with the largest shock occurring when Lehman Brothers collapsed in September 2008. The second recession was also associated with large shocks, whose the size is remarkably similar to those produced during the first recession. Before both recessions, these shocks have been also existent, although relatively modest, except for the early 2000s, where the euro area economy experienced a series of positive and adverse credit supply shocks whose their sizes are relatively "larger" than those usually produced. Overall, this pattern is in line with the time series of the excess bond premium.

V.2. **Regime-dependent dynamic effects of credit supply shocks.** As a way to illustrate possible differences in dynamics across the two regimes in the systematic behavior of the economy (i.e., equation coefficients), we examine the response of the rest of the economy to a disturbance in the financial equation ("one-time credit supply shock"). Figure 5 reports the impulse responses of endogenous variables across the two regimes. More specifically, the panels of the first column display the impulse responses under the tranquil regime, the panels of the second column display the impulse responses under the distress regime, and the panels of the third column reports the differences between the impulse responses in both regimes. The two first rows of each column report the deviation in percent for the series entered in log-levels (output and prices, respectively), whereas the panels of the two last rows display the deviation in percent points for other variables (policy rate and excess bond premium, respectively). For each panel, the median is reported in dotted blue line and the 68% error bands in solid lines. For comparability across regimes, the credit supply shock is scaled to induce a 25 basis points immediate increase in the excess bond premium.

Looking at the figure, the responses of endogenous variables do vary much across regimes, indicating that the differences among the two regimes in the equation coefficients describing the economy are very large. Regarding the impulse responses of production sector under the tranquil regime (i.e., column 1), after a positive innovation in excess bond premium, the output falls slowly, reaches its minimum, then begins to recover in a steady manner. However, the 68% error bands lie within the negative and positive region, indicating that negative effect on output does not seem to be particularly robust. Similarly, the estimated bands for the response of prices lie also within the negative and positive region. Note, however, that there is a very short-term decline for the first three months.

Regarding the distress regime (i.e., column 2), these impulse responses are remarkably different from the tranquil regime. Output fall immediately and reaches its minimum value (i.e., -3 percent) after 15 months. As the output, the short-term response of inflation is negative, but appears much more persistent and modest; the maximum decline of prices is about -0.20 percent. This is in line with the fact that the United States and the euro area experience a slow and modest decline in inflation during the global financial crisis[12]. For both variables, the 68% probability intervals lie within the negative regime in the short-run, reinforcing the estimated median values.

Under both regimes, the monetary authority responds by lowering the policy rate, EONIA, in order to mitigate the negative impact of the credit supply shock on the real economy. Interestingly this response turns out to be much more aggressive in the distress regime.

Finally, the last column of the figure shows how robust are the differences in the impulse responses between the normal and distress regimes. When looking at the 16% and 64% percentiles, the responses of output, prices and EONIA are remarkably different between the tranquil and distress regimes. In each panel of the third column, and except for the excess bond premium, the error bands lie within the same region as the estimated at the median in the short-run, indicating that the differences between regimes are apparent.

Summarizing, there is strong evidence of nonlinearities in the responses of the economy to credit supply shocks.

[12]Del Negro, Giannoni, and Schorfheide (2015) uses a New-Keynesian model and explains the behavior of inflation during the Great Recession to a low frequency of price changes.

V.3. **Relative importance of credit supply shocks.** Using variance decompositions, we now assess the relative importance of credit supply shocks in driving fluctuations in endogenous variables. Table 7 reports the percentage of the variances of the error made (at the median) in forecasting each endogenous variable due to credit supply shocks across regimes at forecasting horizons between the sixth (6M) and the thirty-sixth months (36M) after the initial shock. The 68 percent error bands are indicated in brackets. Because the model consists of two independent Markov-switching processes, for each of which two regimes are defined, the economy can be classified into four regimes: low-stress coefficients + low-volatility; high-stress coefficients + low-volatility; low-stress coefficients + high-volatility; and high-stress coefficients + high-volatility.

Variance decompositions show that the contribution of disturbances to the financial intermediation to business cycle fluctuations differs dramatically across regimes. When we associate the low-stress coefficients regime with the low-volatility regime (i.e., the first block of the table), these shocks does not explain much of the variations in output, prices and EONIA. Interestingly, when moving to the high-volatility regime (i.e., the third block of the table), while keeping the low-stress coefficients regime, these shocks are still unimportant in driving key macroeconomic variables. Note, however, that our credit supply shock explains for a substantial part of fluctuations in EONIA.

In contrast, when switching to the high-stress coefficients regime, the shock explains a dramatic fraction of business cycle fluctuations. When we combine this regime with the low-volatility regime (i.e., the second block of the table), our shock turns out to be the primary source of long-run output variation (about 43 percent), and a non-negligible source for long-run prices variation (about 19 percent). These fractions increase dramatically when switching to the high-volatility regime (i.e., the fourth block of the table), reaching a value of about 74 percent for output and about 46 percent for prices[13].

Overall, our estimates reveal that the role played by credit supply shocks turns out to be important only when a regime of financial distress is in place.

V.4. **Counterfactual analysis.** One of the most interesting assets to employ in a regime-switching framework is to quantify what would have happened if regime switches had not occurred at particular historical dates. This is a natural exercise to allow us to discover the quantitative implications of changes in the systematic behavior of the system to fluctuations. Prior to asserting the role of changes in the transmission mechanism in cyclical fluctuations, we first look at the historical contribution of credit supply shocks.

[13]When looking at the smoothed probabilities in Figure 3, the state that combines the high-stress regime and the high-volatility regime lasts for only a few months. This explains why the estimated error bands in brackets are so large.

V.4.1. *Suppressing credit supply shocks.* The first counterfactual simulation is to suppress credit supply shocks throughout the sample in order to quantify their importance. To do so, we simply set the disturbances in the financial sector equation to zero. Figure 6 reports the actual data (solid line), the median counterfactual paths (dotted blue line) with the 68% error bands in yellow areas for endogenous variables.

Prior the beginning of 2007, the differences between actual and counterfactual variables' paths are negligible. Industrial production and prices would not have been substantially lower or higher, indicating that the non-systematic part of financial behavior ("credit supply shocks") is not the dominant source of the poor economic performances in this period. However, in the two most recent recessions, credit supply shocks play a crucial role. Without those shocks, the counterfactual path of output would have been much higher; although they did not prevent the deepest collapse in 2008-2009. More specifically, the output decline in the absence of these shocks was about 4.62 in log units instead of 4.5, indicating that credit supply shocks accounted for about half of output decline in this period. The counterfactual path of the price level closely follows the actual series, except for the 2014-2016 period, where the counterfactual path of prices are remarkably above the actual prices, indicating once again the important role of credit shocks during this period.

Interestingly, the counterfactual path of the policy rate would have reached 2 percent, which is close to the ECB's primary objective. Regarding the financial sector, excess bond premium would not have rocketed to the highest levels of 2008-2009 and 2010-2012.

V.4.2. *Placing the tranquil regime throughout.* We run a similar exercise but, instead of suppressing credit supply shocks[14], we place the estimated equation coefficients of the tranquil regime throughout the entire period.

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 B.2. For each draw, we recover the sequence of structural disturbance variances in the model. We then simulate the history (i.e., a set of new series) with those time series of shocks, but replace the equation coefficients of the distress regime with those of the tranquil regime. As a result, the counterfactual simulations report what would have happened if the transmission mechanism of distress regime had not occurred. Results are shown in Figure 7.

Looking at the figure, the model attributes clearly the fall in output to changes in transmission mechanism. In particular, the large drop in 2009 would have never existed, as well as the decline in 2010-2012. Furthermore, the effects of changes in the systematic component

[14]Note that we have also run a simulation in which the tranquil regime prevailed throughout the sample, while suppressing credit supply shocks. This simulation affects variables in the same way.

on price level are remarkable. Once again, the estimated error bands, which are far from the actual series, reinforce our results.

Regarding the counterfactual path of EONIA, it seems that ECB would have kept its policy rate at 4 percent, much higher than ECB's goal, meaning that the euro area would have experienced an overheated economy. Interestingly, the high peaks of the excess bond premium are largely attributed to changes in the systematic behavior of the economy. Under the tranquil regime throughout, our indicator of financial intermediaries' conditions would have been much lower.

Overall, the large differences across these equation coefficients' regimes mean that our best-fit model implies that changes in transmission mechanism during financial crises are crucial in shaping business cycle fluctuations. These fundamental changes in transmission mechanism reveals that linear models are inappropriate to capture dynamics of the euro area economy. Results like this clearly imply that macro-finance models should go beyond linearity to better understand this history.

VI. Robustness Analysis

In order to assess the robustness of results, we study a number of other relevant models. First, we examine how the main results change if the prior duration of each regime is lower than twenty-five months. Second, we propose alternative identification scheme. Third, only changes in the equation coefficients are allowed to vary across time. All of these exercises reinforce the findings in the previous sections. These results of this section are available in an online appendix.[15]

VI.1. **Prior duration.** How important is prior duration for our results? In Section V, we have shown the large persistence of each regime over time. That persistence may be due to the prior about the average duration of each regime is about 25 months. Several other prior durations were examined to determine if these results deliver different outcomes. The prior about the average duration of each regime is about (1) 10 months; (2) 15 months; and (3) 20 months. Clearly, the changes in prior duration do not affect the main conclusions. The economic implications of the $\mathfrak{M}_{\rm 2c2v}$ model, which are not shown, are strictly the same as those reported in previous sections.

VI.2. **Alternative identification schemes.**

[15]The online appendix is available via the following link: `http://www.stephanelhuissier.eu/L17_OnlineAppendix.pdf`

VI.2.1. *recursive ordering: p_t, ip_t, r_t and ebp_t.* In our benchmark identification, prices are ordered after output, meaning that prices react contemporaneously to output variation. One may ask how sensitive the results are with an alternate recursive ordering. Thus, we also estimate our $\mathfrak{M}_{\mathrm{2c2v}}$ model in which endogenous variables are ordered as follows: p_t, ip_t, r_t and ebp_t. Clearly, there is still evidence of nonlinear effects of credit supply shocks on aggregate activity.

VI.2.2. *non-recursive approach: monetary policy reacts with delay.* The identification scheme employed in this paper assumes a recursive economic structure by imposing the policy variable does respond contemporaneously to fluctuations in production sector. In this section, we relax this assumption and assume that the policy rate responds with one lag, making our identification non-recursive. These identifying assumptions, established by Leeper, Sims, and Zha (1996) and Leeper and Zha (2003), is based on the fact that macroeconomic variables such as final goods prices and output can be evaluated only with substantial delay. The rest of identification remains unchanged, namely that production sector still responds with a delay to financial markets variables and excess bond premium depends contemporaneously on everything in the system. We estimate our $\mathfrak{M}_{\mathrm{2c2v}}$ model with a non-recursive identification and we find that economic implications produced from this model remain unchanged.

VI.3. **Change only in coefficients.** An interesting exercise is to allow only equation coefficients to vary across time. Although Sims (2001) and Lhuissier and Zabelina (2015) use 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 for the absence of changes in equation coefficients. However, the estimated MDD for the model in which coefficients switch between two regimes (i.e., 3622.741) remain far below the levels of the MDDs in Table 2.

VII. The role of ECB policies

The previous sections suggest that adverse credit supply shocks and changes in the mechanism transmission played an important role during the recent Great Recession and the European debt crisis.

In the face of these damaging events, the ECB responded by several unconventional measures. The ECB measures included the Securities Markets Programme (SMP) that implies the purchase of government debt, the Outright Monetary Transactions (OMT) that induces the conditional purchase of government debt, and long-term funding to banks (LTROs). The primary objective of ECB policies was to reduce long-term interest rates and to restore financial integration of euro area financial markets in order to support the supply of credit, which in turn stimulates investment spending and economic activity.

Indeed, as can be seen from Figure 8, these events were characterized by important differences in credit conditions across euro area countries, and especially between German bond yields and those in Greece, Ireland, Italy, Portugal and Spain. The figure reports that the 10-year sovereign yield in the euro area countries relative to corresponding German yield peaks around 100 basis points in the early 2009, while the bond spread rises above 200 basis points in the late 2011.

The objective of this section is to assess the role of government bond purchases on the macroeconomy. As a first step, it is crucial to understand to what extent these unconventional monetary policy announcements have put downward pressure on the 10-year euro area sovereign spread. There is a literature that has documented the effects of ECB interventions on yields. Notable examples include Eser and Schwaab (2013), Krishnamurthy, Nagel, and Vissing-Jorgensen (2014), and Szcerbowicz (2015). Although all of these studies employ different econometric approaches, they all concludes that ECB actions, except for LTROs, have significantly cut the 10-year euro area sovereign spread. As a second step, we use the estimates of the effects of ECB actions on the sovereign spread as given and we generate a sequence of new credit supply shocks that undo the ECB announcements on sovereign spread to calculate what would have happened on inflation and output if ECB had not implemented these programs. This procedure follows closely Baumeister and Benati (2013).

Our approach is based on the fact that ECB interventions, which primarily aimed at influencing the financial intermediation sector, should be reflected by unexpected changes in the supply of bank credit, and so by the historical path of estimated structural credit supply shocks, reported in Figure 4. Of course, the historical path of this series does not only incorporate ECB interventions, but also crisis-related factors such as the lack of liquidity and credit crunch. This is why we need to purge credit supply shocks from ECB interventions.

VII.1. **A near MS-SBVAR model.** As a first step, we extend our best-fit model by introducing the 10-year euro area sovereign bond spread as a "periphery" VAR variable. This "near-VAR" approach is very similar to Zha (1999) and Peersman and Smets (2003), except that we are applying it to a time-variation parameters SVAR model, as opposed to a constant-parameters SVAR. As mentioned previously, the inclusion of such a variable is crucial to evaluate the macroeconomic effects of ECB policies. The model becomes as follows

$$\begin{bmatrix} y_t' & y_t^* \end{bmatrix} \underbrace{\begin{bmatrix} A_0(s_t) & \underset{n\times 1}{b_0} \\ \underset{n\times n}{0} & \underset{1\times 1}{c_0} \end{bmatrix}}_{\tilde{A}_0(s_t)} = \begin{bmatrix} x_t' & x_t^* \end{bmatrix} \underbrace{\begin{bmatrix} F(s_t) & b \\ \underset{(k*n+1)\times n}{0} & c \end{bmatrix}}_{\tilde{F}(s_t)} + \begin{bmatrix} \varepsilon_t' & \varepsilon_t^* \end{bmatrix} \underbrace{\begin{bmatrix} \Xi^{-1}(s_t) & \underset{n\times 1}{0} \\ \underset{1\times n}{0} & \underset{1\times 1}{\xi} \end{bmatrix}}_{\tilde{\Xi}^{-1}(s_t)}, \tag{8}$$

with y_t^* is the 10-year euro area government bond; and $x_t{}^* = \begin{bmatrix} y_{t-1}{}^* & \cdots & y_{t-\rho}{}^* & 1 \end{bmatrix}$; $\varepsilon_t{}^*$ is a standard normal distribution. As before, the $n \times 1$ vector y_t consists of the endogenous variables and x_t the lagged endogenous variables. We impose neither zero-restrictions on b_0, c_0, b and c to avoid "incredible restrictions" (Sims, 1980) and neither time-variation restrictions to keep a parsimonious model. The system (8) assumes that the inclusion of the sovereign spread does not affect the block of the benchmark endogenous variables. As a result, the estimated matrices, $A_0(s_t)$, $F(s_t)$ and $\Xi(s_t)$, remain unchanged with respect to our benchmark model.

To facilitate the estimation procedure, we can easily re-write the above form as follows

$$\tilde{y}_t'\tilde{A}(s_t) = \tilde{x}_t'\tilde{F}(s_t) + \tilde{\varepsilon}_t{}'\tilde{\Xi}^{-1}(s_t), \tag{9}$$

with $\tilde{y}_t' = [y_t' \quad y_t^*]$ and $\tilde{x}_t' = [x_t' \quad x_t^*]$. Using Dynare, the overall system (9) can be easily estimated under the prior of Sims and Zha (1998), even with zero restrictions on the parameters in $\tilde{A}_0(s_t)$ and $\tilde{F}(s_t)$. Alternatively, one can estimate only the last equation of the system as the (Markov-switching) parameters of the remaining equations have already been estimated in the previous sections. This results directly from Propositions 1 and 2 in Chen, Higgins, Waggoner, and Zha (2016).

Figure 9 reports the impulse responses of the 10-year sovereign bond spread to a positive credit supply shock. The results suggest that a disruption in financial intermediation triggers a deterioration of government borrowing costs. Under each regime (i.e., column 1 and 2), the sovereign spread increases, reaches its maximum after three months and then recovers in a steady manner. The impulse response under the distress regime is clearly more persistent than that under the tranquil regime. This is confirmed by the last column of the figure that reports a negative difference in impulse responses between the two regimes.

VII.2. **Historical Counterfactuals.** As a second step, we now quantify the impact of ECB actions by using the sovereign spread as point of reference. Szcerbowicz (2015) uses an event-based regressions to measure the impact of ECB policies on sovereign bond market. Following the SMP announcement on May 2010, the author conclude that

> "The most striking result in the euro zone is the impact of the ECB longer-term sovereign bond purchase program (SMP), which reduced the spreads by 16 basis points."

Another SMP were announced on August 2011, and the author finds that

> "The overall effect of the benchmark euro-zone spread is significant (-26 bp)."

In what follows, we take the Szcerbowicz (2015)'s finding as our benchmark measure of ECB policies on the 10-year sovereign spread and we ask what would have happened on output and inflation if the ECB announcements had not allowed such a reduction in the sovereign bond. Figure 10 reports the results from the following counterfactual simulation[16]

(1) Generate a sequence of draws, $\tilde{A}_0^{(i)}$, $\tilde{F}^{(i)}$ and $\tilde{\Xi}^{(i)}$ from the posterior distribution;
(2) For each draw and conditional on equations' coefficients, keep all the historical path of structural shocks, except for the one to the credit supply shocks;
(3) Recomputing the credit supply shocks such that the counterfactual path for the ten-year sovereign bond spread is, from May 2010 to July 2011, 16 basis points higher than the actual historical path, and, from August 2011 to December 2011, $16 + 26$ basis points higher than the actual historical path.

We can see that (year-over-year) industrial production output growth would have reached a lower value by around four percentage points at its peak, and the (annual) inflation level would have lowered by around half a percentage point. This counterfactual simulation implies that ECB's unconventional monetary policies have mitigated the large decline in output, although they could not have prevented to reach negative values.

We have also run a similar simulation but with two other major ECB announcements, namely the Mario Draghi's "whatever-it-takes" speech on July 2012 and the OMT programme announced on September 2012. Szcerbowicz (2015) shows that these two announcements have reduced the sovereign euro-area spread by 19 and 14 basis points, respectively. We recompute the credit supply shocks in such a way that the counterfactual path for the ten-year sovereign bond spread is, from July and August 2012, 19 basis points higher than the actual series, and, from September to December 2012, $19+14$ basis points higher than the actual historical path. We obtain the results shown in Figure 11. As can be seen from the figure, our counterfactual simulation leaves the time path of output and inflation almost unchanged, suggesting that the historical paths of both macroeconomic variables are attributed almost entirely to non-credit market sources. These results are not surprising given that our credit supply shocks

[16] As mentioned in Baumeister and Benati (2013), our counterfactual simulation is not subject to the Lucas critique since we only manipulate structural shocks while leaving all coefficients unchanged.

have only modest effects on aggregate activity during 2012, the year where the tranquility regime was in place.

VIII. Conclusion

The purpose of this paper was twofold; 1) To examine how crises manifest themselves; and 2) To understand the differences in the role played by credit supply between crisis and non-crisis episodes. To do so, this paper has considered the European historical experience and has confronted a number of structural Bayesian vector autoregressions with several possible patterns of time variation in coefficients and in disturbance variances. These regime switches follow a Markov-switching process along the line of Hamilton (1989) and Sims and Zha (2006). We use the term "credit supply shock" to refer to a shock to the excess bond premium that is orthogonal to the current state of the economy. These shocks directly affect the risk appetite in the corporate bond market. Using the best-fit model, we reach the following conclusions:

- After taking into account heteroskedasticity, the differences in the behavior of the economy between tranquil and financial distress periods (e.g., the Great Recession and the sovereign debt crisis) reflect variations in the transmission mechanism.
- The transmission of credit supply shocks to the economy appears strongly nonlinear over time. A positive shock that causes a 25 basis points increase in the excess bond premium implies a three percent output decline in periods of financial distress, but effects that are close to zero in tranquil periods. In periods of financial distress, these disturbances are the most important shock driving the business cycle.
- Our counterfactual simulations implies that variations in the transmission mechanism was central during the periods of financial distress.
- There is evidence that ECB policies had beneficial output effects during the 2010-2012 meltdown.

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APPENDIX A. DATA

All data are organized monthly from October 1999 to June 2016. Data comes from the ECB - Statistical Data Warehouse, with the exception of the excess bond premium which was generously given by Roberto De Santis.

- ip_t: output is the industrial production index (working day and seasonally adjusted).
- p_t: Prices is the harmonized index of consumer price (HICP). The series has been deseasonnalized with the *Jdemetra+* software.
- r_t: the policy rate is EONIA taken at the end of each month.

- ebp_t: Excess bond premium by De Santis (2016). This is a measure of credit supply conditions in the euro area.

Appendix B. Markov-switching Structural Bayesian VAR model

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

B.1. **The posterior.** Before describing the posterior distribution, we introduce the following notation: θ and q are vectors of parameters where θ contains all the 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 denoting 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), we employ a class of Markov-switching structural VAR models of the following form:

$$y_t' A_0(s_t) = x_t' F(s_t) + \varepsilon_t' \Xi^{-1}(s_t), \tag{10}$$

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 $A_0(k)$, $f_j(k)$ be the jth column of $F(k)$, and $\xi_j(k)$ be the jth diagonal element of $\Xi(k)$. The conditional likelihood function is as follows:

$$p(y_t|s_t, Y_{t-1}) = |A_0(s_t)| \prod_{j=1}^{n} |\xi_j(s_t)| \exp\left(-\frac{\xi^2(s_t)}{2} \left(y_t' a_j(s_t) - x_t' f_j(s_t)\right)^2\right). \tag{11}$$

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

$$|A_0(s_t)| \prod_{j=1}^{n} |\xi_j(s_t)| \exp\left(-\frac{\xi^2(s_t)}{2} \left((y_t' + x_t' W_j) U_j b_j(s_t) - x_t' V_j g_j(s_t)\right)^2\right), \tag{12}$$

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 matrices with orthonormal columns and W_j is a matrix. See Waggoner and Zha (2003) 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), we exploit the idea of a Litterman's random-walk prior from structural-form parameters. Dummy observations are introduced as a component of the prior. The n first dummy observations 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 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 $\bar{\Sigma}_{b_j}$, $\bar{\Sigma}_{\psi_j}$, and $\bar{\Sigma}_{\delta_j}$ denotes the prior covariance matrices and $\bar{\alpha}_j$ and $\bar{\beta}_j$ are set to one, allowing 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 using VARs is that conditional distributions like $p(S_T|Y_T, \theta, q)$, $p(q|Y_T, S_T, \theta)$, and $p(\theta|Y_T, q, S_T)$ can be obtained in order to exploit the idea of Gibbs-sampling by sampling alternatively from these conditional posterior distributions.

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

$$
\begin{aligned}
p(b_j(k)|y_t, S_t, b_i(k)) = & \\
& \exp\left(-\frac{1}{2}b_j'(k)\bar{\Sigma}_{b_j}^{-1}b_j(k)\right) \\
& \times \prod_{t\in\{t:s_t=k\}} \left[|A_0(k)|\exp\left(-\frac{\xi^2(s_t)}{2}(y_t'a_j(k) - x_t'f_j(k))^2\right)\right], \qquad (24)
\end{aligned}
$$

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

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

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

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

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

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

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

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

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

where

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

Then, in order 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. *Conditional posterior densities, $p(q|Y_T, S_T, \theta)$.* 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 $p(\theta)$ are the priors. One usually employs 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 us to evaluate the integral on the right hand side of (32) as follows

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

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 those 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 multimodal and 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. This method, which we employ in this paper, combines the MCMC draws from the posterior probability density function with the draws from the weighting function. Their method is based on the following result:

$$h(\theta) = \frac{\chi_{\Theta_L}(\theta)}{q_L} g(\theta), \tag{35}$$

where $g(.)$ is an elliptical distribution centered at the mode $\hat{\theta}$ and scaled by the sample covariance matrix $\hat{\Omega} = \frac{1}{N}\sum_{i=1}^{N}(\theta^{(i)} - \hat{\theta})(\theta^{(i)} - \hat{\theta})'$; $\chi_{\Theta_L}(\theta)$ is an indicator function that is equal to one if θ fall in Θ_L and zero otherwise; and q_L is the probability that draws from the elliptical distribution lies in the region Θ_L defined as follows

$$\Theta_L = \{\theta : p(Y_T|\theta)p(\theta) \geq L\}, \tag{36}$$

where L is defined so that 90% of draws from the posterior distribution lies in Θ_L.

The procedure for implementing the method can be done in the following way

(1) Generate a sequence of draws from the posterior distribution $\theta^{(i)}$. The value of L should be lie between the minimum and maximum values of the posterior probability density.
(2) Generate draws of θ from the function $g(\theta)$ and compute the fraction, denoted $\hat{q}_L$, of these draws that belongs to Θ_L.
(3) Evaluate the marginal data density according to (34).

Appendix D. Tables

Table 1. Property statistics: output growth and excess bond premium.

	Bench. (1)	Bench.(20%) (2)	CEPR Recession (3)	BB (1971) (4)
Panel A: Distress Periods				
vol(EBP)	0.9280	0.8978	1.0465	1.2316
vol(IP)	1.5977	1.7136	1.3780	1.2306
cov(EBP,IP)	−0.7279	−0.7953	−0.6654	−0.8884
Panel B: Non-distress Periods				
vol(EBP)	0.4196	0.4993	0.5604	0.6632
vol(IP)	0.4558	0.6043	0.7320	0.8381
cov(EBP,IP)	−0.0391	−0.0366	−0.0087	−0.0861

Note: Standard deviations (vol) and covariances (cov) for industrial production growth rate (IP) and excess bond premium (EBP). Column (1) uses the benchmark (bench.) classification (the highest one-third realizations of the excess bond premium are used as distress periods). Column (2) uses the highest one-fifth realizations of the excess bond premium are used as distress periods). Column (3) uses CEPR recession dates. Column (4) uses the Bryan and Boschan (1971) procedure on the log of monthly industrial production.

Table 2. Measure of fit

Model	Specification	Log MDD
$\mathfrak{M}_{\text{constant}}$	Time-invariant model	3563.099
$\mathfrak{M}_{\text{2v}}$	2-regimes in shock variances	3618.094
$\mathfrak{M}_{\text{3v}}$	3-regimes in shock variances	3633.290
$\mathfrak{M}_{\text{4v}}$	4-regimes in shock variances	***
$\mathfrak{M}_{\text{2c2v}}$	2-regimes in all equation coefficients and 2-regimes in shock variances	3644.183
$\mathfrak{M}_{\text{2c3v}}$	2-regimes in all equation coefficients and 3-regimes in shock variances	***
$\mathfrak{M}_{\text{2Fc2v}}$	2-regimes in coefficients of the financial sector equation and 2-regimes in shock variances	3633.106
$\mathfrak{M}_{\text{2Pc2v}}$	2-regimes in equation coefficients describing production sector, and 2-regimes in shock variances	3632.316

Note: The method for computing the marginal data densities (MDDs) is the Sims, Waggoner, and Zha (2008) method.

Table 3. Contemporaneous coefficient matrix, $A(s_t^c = 1)$.

Prod. ip	Prod. p	Policy R	Financial F
128.92 [114.99;141.95]	3.34 [−7.62;13.30]	−5.75 [−14.52;2.60]	8.12 [−6.73;22.61]
0.00 [0.00;0.00]	739.99 [660.40;815.96]	62.89 [8.26;121.90]	36.89 [−45.10;115.03]
0.00 [0.00;0.00]	0.00 [0.00;0.00]	693.85 [587.82;823.61]	−152.48 [−249.54;−61.51]
0.00 [0.00;0.00]	0.00 [0.00;0.00]	0.00 [0.00;0.00]	1703.27 [1414.28;1935.96]

Note: Contemporaneous coefficient matrix for the tranquil regime in the $\mathfrak{M}_{\mathrm{2c2v}}$ model, computed from the posterior median. The 68 percent probability intervals are indicated in brackets.

Table 4. Contemporaneous coefficient matrix, $A(s_t^c = 2)$.

Prod. ip	Prod. p	Policy R	Financial F
112.10 [95.13;130.73]	−5.66 [−27.91;13.79]	−4.46 [−24.58;13.68]	5.53 [−21.73;31.64]
0.00 [0.00;0.00]	561.74 [481.64;653.28]	−49.22 [−143.58;41.53]	65.74 [−60.24;185.81]
0.00 [0.00;0.00]	0.00 [0.00;0.00]	261.73 [219.51;318.12]	2.25 [−51.56;57.57]
0.00 [0.00;0.00]	0.00 [0.00;0.00]	0.00 [0.00;0.00]	818.19 [558.35;988.28]

Note: Contemporaneous coefficient matrix for the distress regime in the $\mathfrak{M}_{\mathrm{2c2v}}$ model, computed from the posterior median. The 68 percent probability intervals are indicated in brackets.

TABLE 5. Relative shock variances across regimes when the diagonal of $A_0(s_t^{\mathrm{c}} = 1)$ is normalized to a vector of ones

	Private y	Private p	Policy R	Financial F
$s_t^{\mathrm{v}} = 1$	4.5868E-05 [3.8262E-05;5.6662E-05]	1.3770E-06 [1.1623E-06;1.6531E-06]	8.6379E-07 [6.5472E-07;1.0998E-06]	5.0263E-07 [4.1522E-07;6.4103E-07]
$s_t^{\mathrm{v}} = 2$	9.5019E-05 [7.7973E-05;1.1602E-04]	2.6884E-06 [2.3007E-06;3.2158E-06]	4.0131E-06 [3.1913E-06;5.5825E-06]	8.7658E-07 [7.3079E-07;1.1352E-06]

Note: Relative shock variances across the two regimes of s_t^{v} from $\mathfrak{M}_{2c2v}$ model, computed from the posterior median, when the diagonal of $A_0(s_t^{\mathrm{c}} = 1)$ is normalized to a vector of ones. The 68 percent probability intervals are indicated in brackets.

TABLE 6. Relative shock variances across regimes when the diagonal of $A_0(s_t^{\mathrm{c}} = 2)$ is normalized to a vector of ones

	Private y	Private p	Policy R	Financial F
$s_t^{\mathrm{v}} = 1$	4.1798E-05 [2.7916E-05;6.9172E-05]	1.7319E-06 [1.2096E-06;2.5542E-06]	3.3464E-06 [1.7542E-06;5.0471E-06]	2.9314E-06 [1.7723E-06;4.7722E-06]
$s_t^{\mathrm{v}} = 2$	8.5580E-05 [6.3197E-05;1.2763E-04]	3.2216E-06 [2.6553E-06;4.8734E-06]	1.5835E-05 [1.0938E-05;2.1770E-05]	5.2493E-06 [3.9028E-06;7.1075E-06]

Note: Relative shock variances across the two regimes of s_t^{v} from $\mathfrak{M}_{2c2v}$ model, computed from the posterior median, when the diagonal of $A_0(s_t^{\mathrm{c}} = 2)$ is normalized to a vector of ones. The 68 percent probability intervals are indicated in brackets.

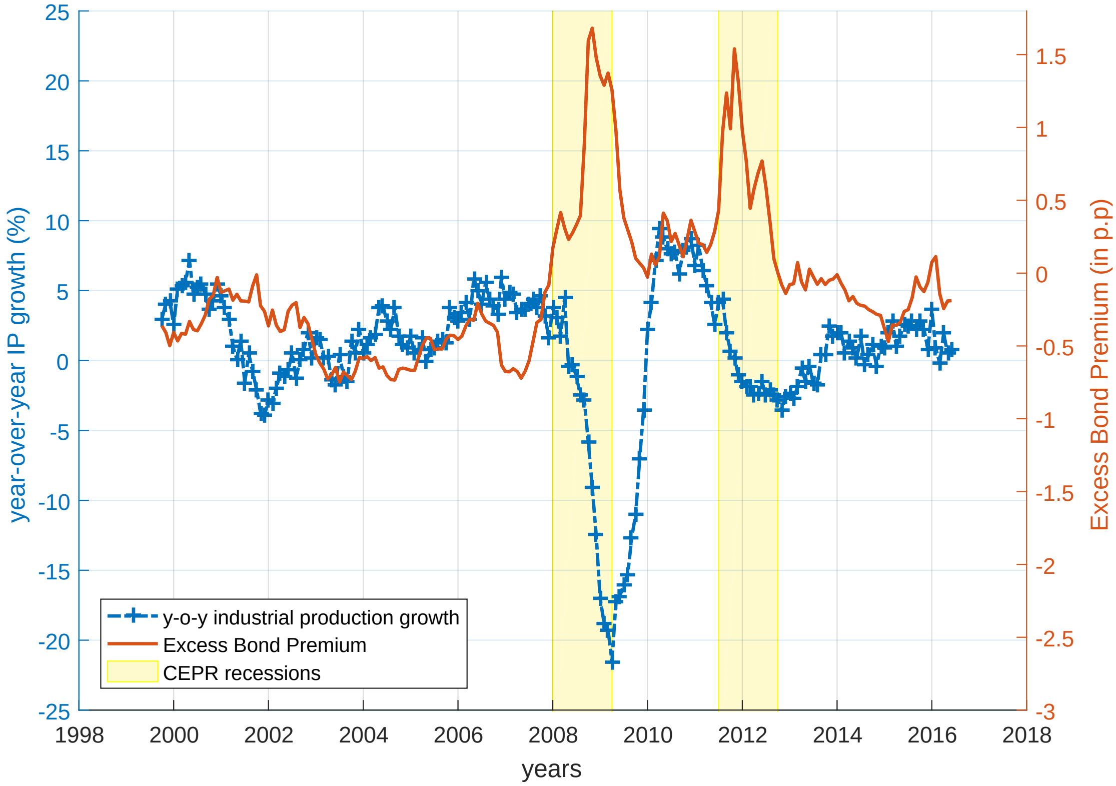
TABLE 7. Variance decomposition of endogenous variables — fractions explained by credit supply shocks

Horizon	IP	Prices	EONIA	EBP
		$s_t^{\mathrm{c}} = 1$, $s_t^{\mathrm{v}} = 1$ (Tranquil regime, Low-volatility regime)		
6M	0.3168 [0.0748;1.1355]	0.3494 [0.1092;1.1174]	0.9334 [0.1586;2.4224]	80.4524 [68.1174;90.0109]
12M	0.5908 [0.1143;2.1430]	0.4316 [0.1298;1.5170]	1.5514 [0.2976;3.9027]	77.0075 [62.2632;87.9086]
24M	1.0381 [0.1241;4.6880]	0.5203 [0.1174;2.3915]	2.3717 [0.3931;6.0567]	74.3048 [58.4554;86.8342]
36M	1.2836 [0.1306;5.9551]	0.5906 [0.1418;2.6802]	2.6199 [0.3739;7.3430]	72.6036 [55.2321;85.9430]
		$s_t^{\mathrm{c}} = 2$, $s_t^{\mathrm{v}} = 1$ (Distress regime, Low-volatility regime)		
6M	28.9452 [13.1323;54.6333]	3.1226 [0.4432;11.9601]	17.6958 [7.1800;36.5413]	75.9087 [57.3310;88.6727]
12M	43.0059 [18.8279;67.4156]	5.7991 [1.3584;20.0806]	33.2809 [15.0570;57.8241]	70.2481 [49.4109;86.9563]
24M	43.1416 [19.5516;70.9020]	13.5041 [2.9097;35.9915]	45.8231 [20.5778;69.2853]	67.8165 [43.0236;84.6329]
36M	40.4303 [19.6162;68.4762]	19.1287 [5.1239;49.5882]	48.7594 [21.2938;72.7606]	66.7800 [39.1488;83.7157]
		$s_t^{\mathrm{c}} = 1$, $s_t^{\mathrm{v}} = 2$ (Tranquil regime, High-volatility regime)		
6M	0.9029 [0.2182;3.3836]	1.2264 [0.3382;3.8088]	6.5133 [0.6385;17.7084]	95.6166 [88.8379;97.9371]
12M	1.6725 [0.3452;6.8545]	1.6283 [0.3991;5.7092]	9.8361 [1.1171;26.4835]	94.6614 [85.9832;97.5171]
24M	3.1199 [0.3831;12.3268]	1.9116 [0.4460;8.0624]	13.1362 [1.5543;37.0390]	94.0556 [84.7595;97.1347]
36M	3.4757 [0.3942;15.3528]	2.3892 [0.5439;9.9348]	14.0623 [1.9104;43.2442]	93.5401 [84.1299;96.7591]
		$s_t^{\mathrm{c}} = 2$, $s_t^{\mathrm{v}} = 2$ (Distress regime, High-volatility regime)		
6M	58.1045 [32.0537;77.1144]	10.3009 [1.5846;30.2938]	52.1325 [27.8072;74.9259]	92.8229 [77.4035;97.8747]
12M	71.4276 [42.1918;88.1773]	17.3061 [3.9647;48.1338]	70.4118 [39.7955;87.2082]	90.8584 [69.5613;97.3807]
24M	74.7914 [38.6102;91.5756]	32.7260 [8.4333;67.2717]	77.8177 [46.1793;92.3343]	89.5002 [64.8392;97.0726]
36M	73.7653 [37.2874;90.7350]	46.2479 [13.4826;77.8974]	78.8827 [44.5358;93.4808]	88.7524 [64.0002;96.7557]

Note: Fraction of variances (computed from the posterior median) of each endogenous variables explained by credit supply shocks at various horizons under each regime from the $\mathfrak{M}_{2c2v}$ model. The 68 percent probability intervals are indicated in brackets.

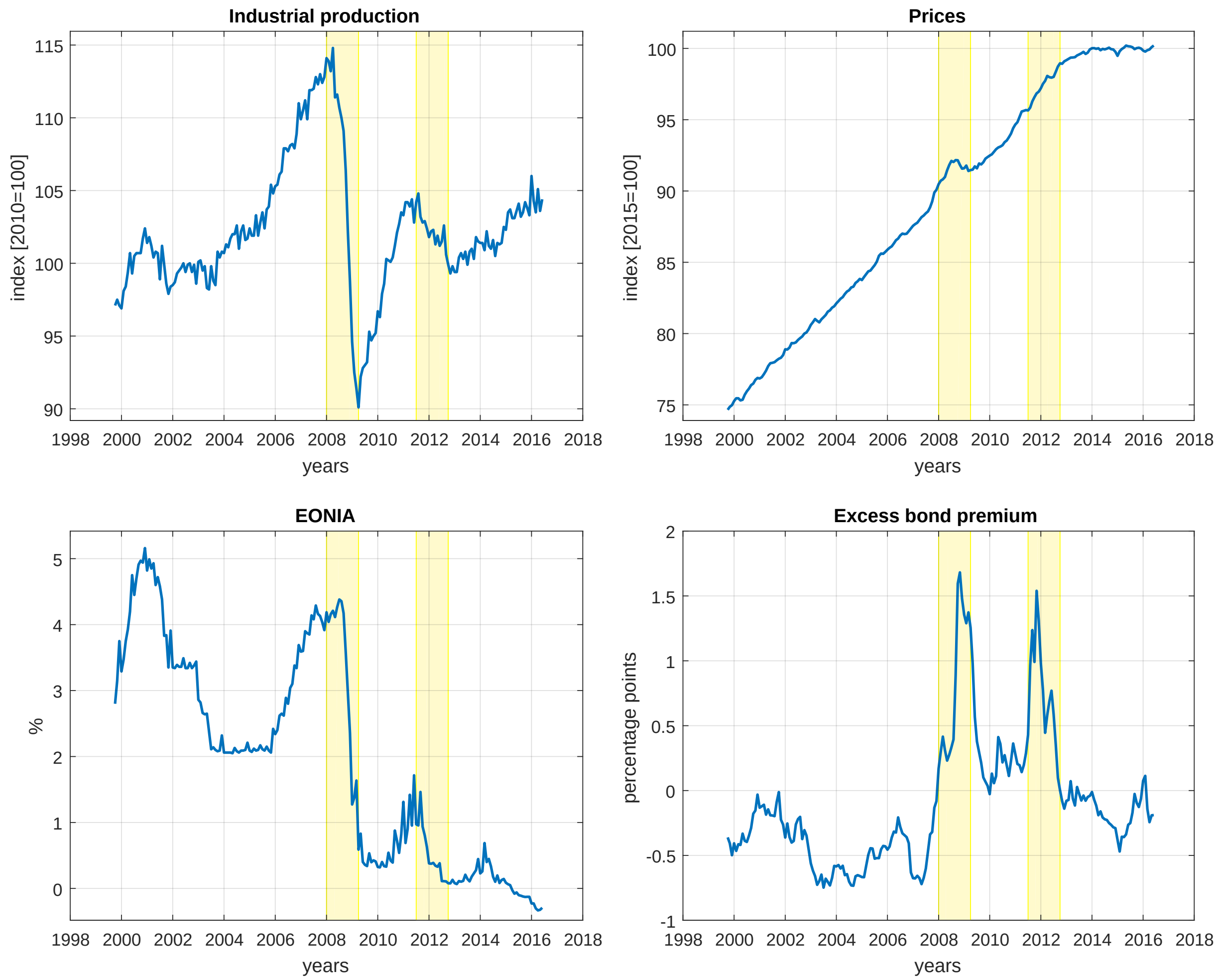
Appendix E. Graphs

Figure 1. Output growth and excess bond premium.



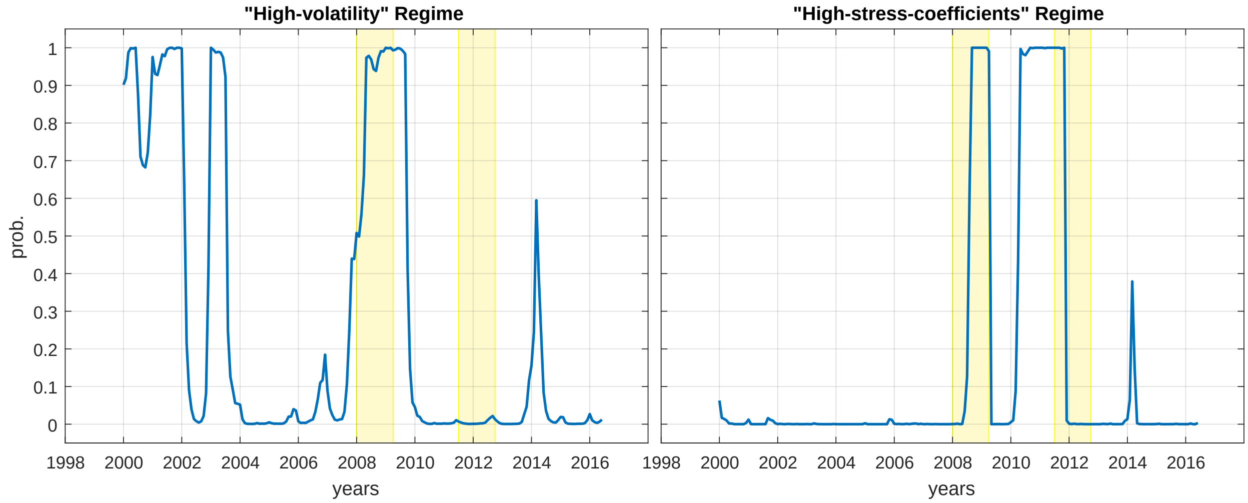
Note: Sample period: October 1999 - June 2016. The year-over-year industrial production growth rate (dotted blue line) is labeled on the left. The De Santis (2016) excess bond premium (solid red line) is labeled on the right. The yellow areas denote the CEPR recessions of the euro area.

FIGURE 2. Data



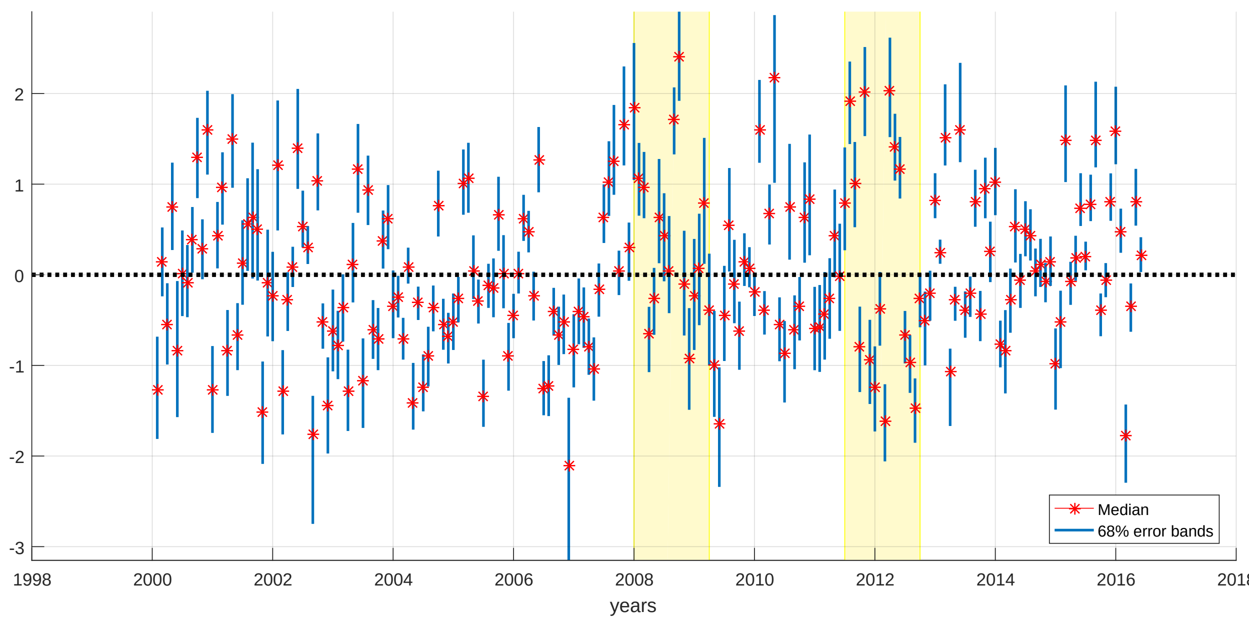
Note: Sample period: October 1999 - June 2016. The solid lines depict the four series: industrial production, prices, EONIA, and excess bond premium. These series have been transformed before estimating each model. All the variables, except EONIA and excess bond premium, enter as log-levels. The yellow areas denote CEPR recessions in the euro area.

FIGURE 3. Smoothed probabilities.



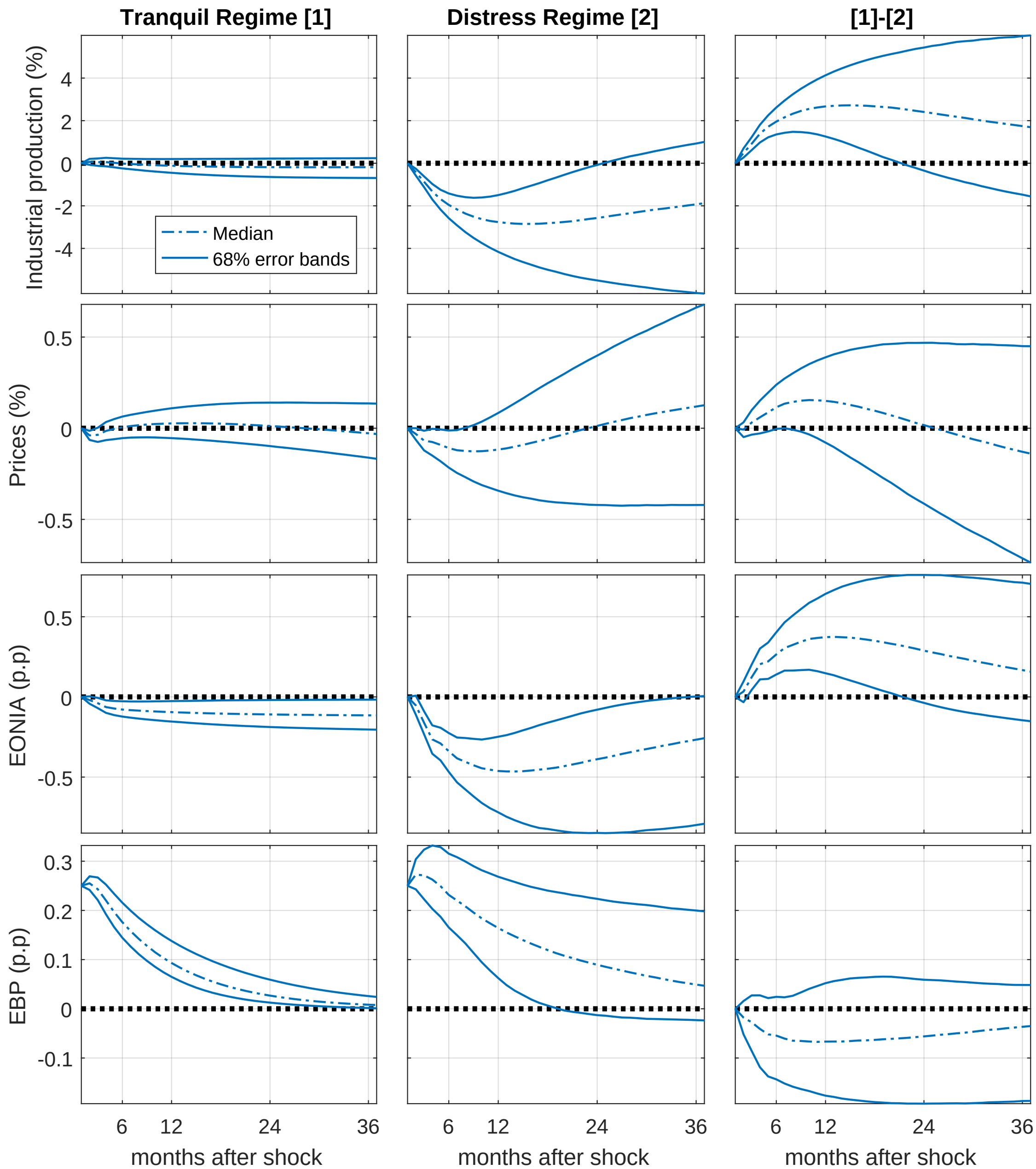
Note: Smoothed probabilities (at the mode) produced from the best-fit model, $\mathfrak{M}_{2c2v}$, in which equation coefficients and variances of structural disturbances evolve independently according to two-states Markov-switching processes, s_t^c and s_t^v, respectively. The yellow areas denote CEPR recessions in the euro area.

FIGURE 4. Time series of credit supply shocks.



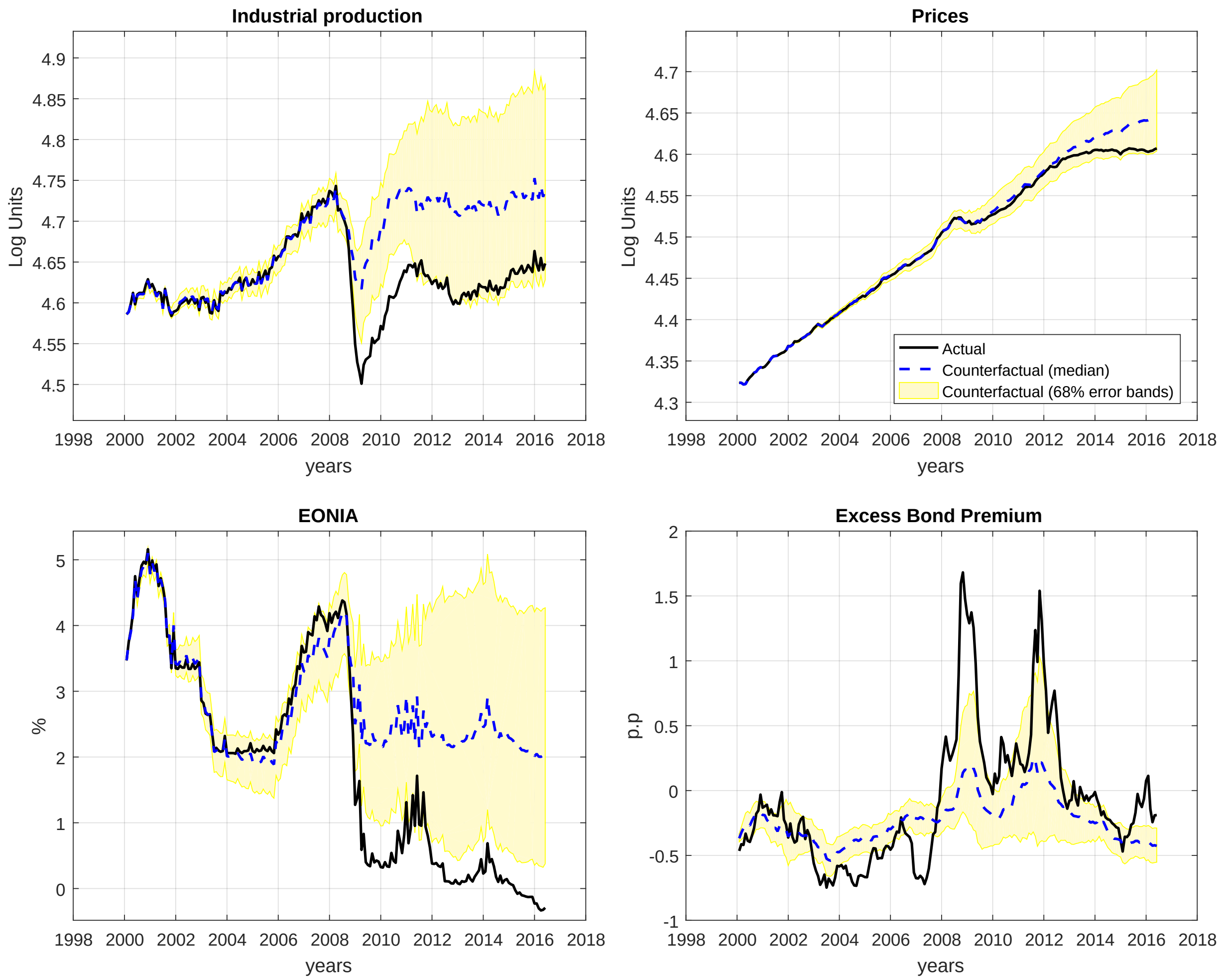
Note: Sample period: February 2000 - June 2016. Time series produced from the $\mathfrak{M}_{2c2v}$ model. A positive bar means an adverse credit supply shock. The red star represents the median and the blue lines denotes the 68 percent probability interval. The yellow areas denote CEPR recessions in the euro area.

FIGURE 5. Impulse responses to a credit supply shock.



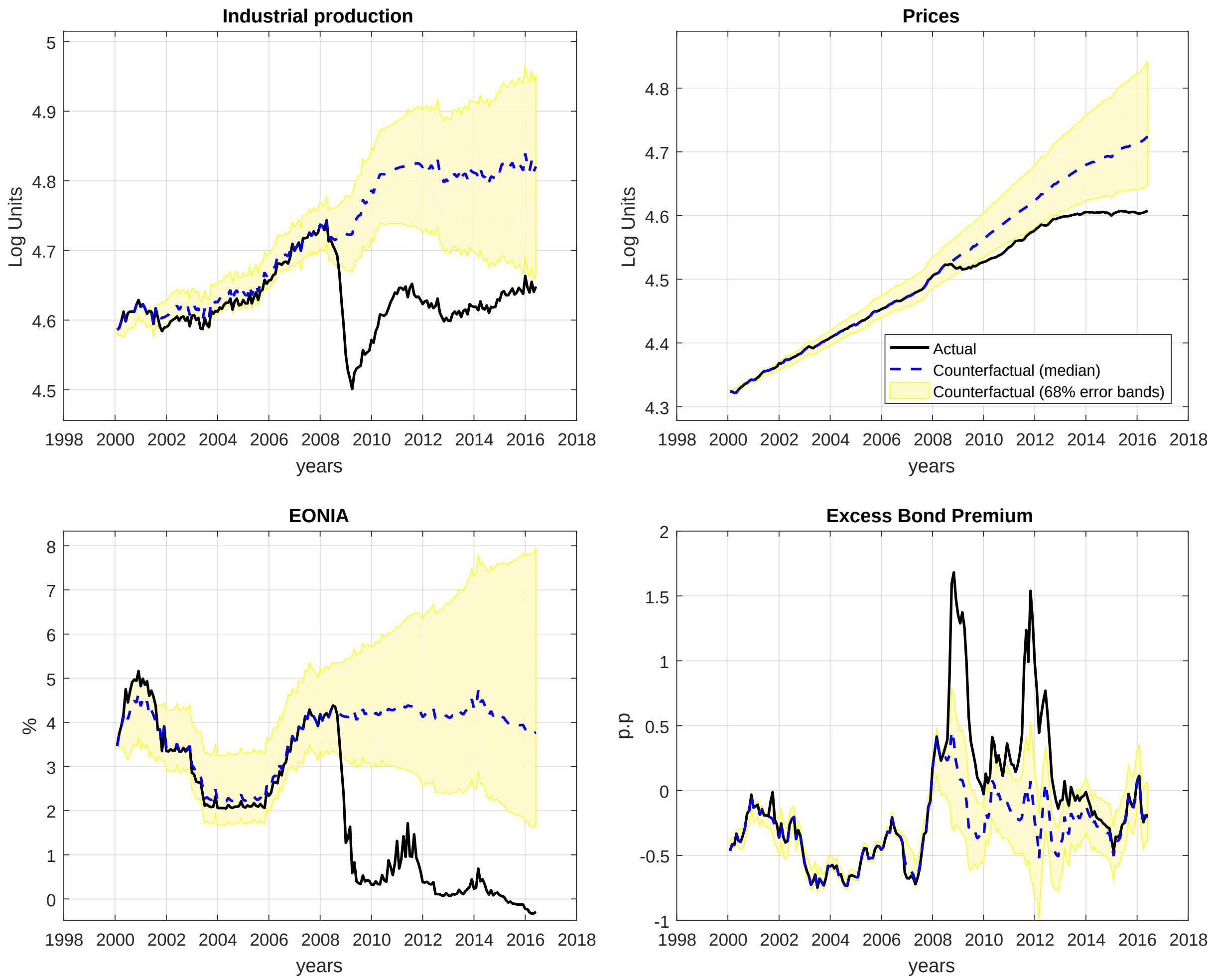
Note: Impulse-response functions to credit supply shock under both regimes from the best-fit model. The first and second column report impulse responses of endogenous variables under tranquil et distress regimes, respectively. The last column displays the difference between the two regimes. In each case, the median is reported in dotted line and the 68% error bands in solid lines.

FIGURE 6. Suppressing credit supply shocks.



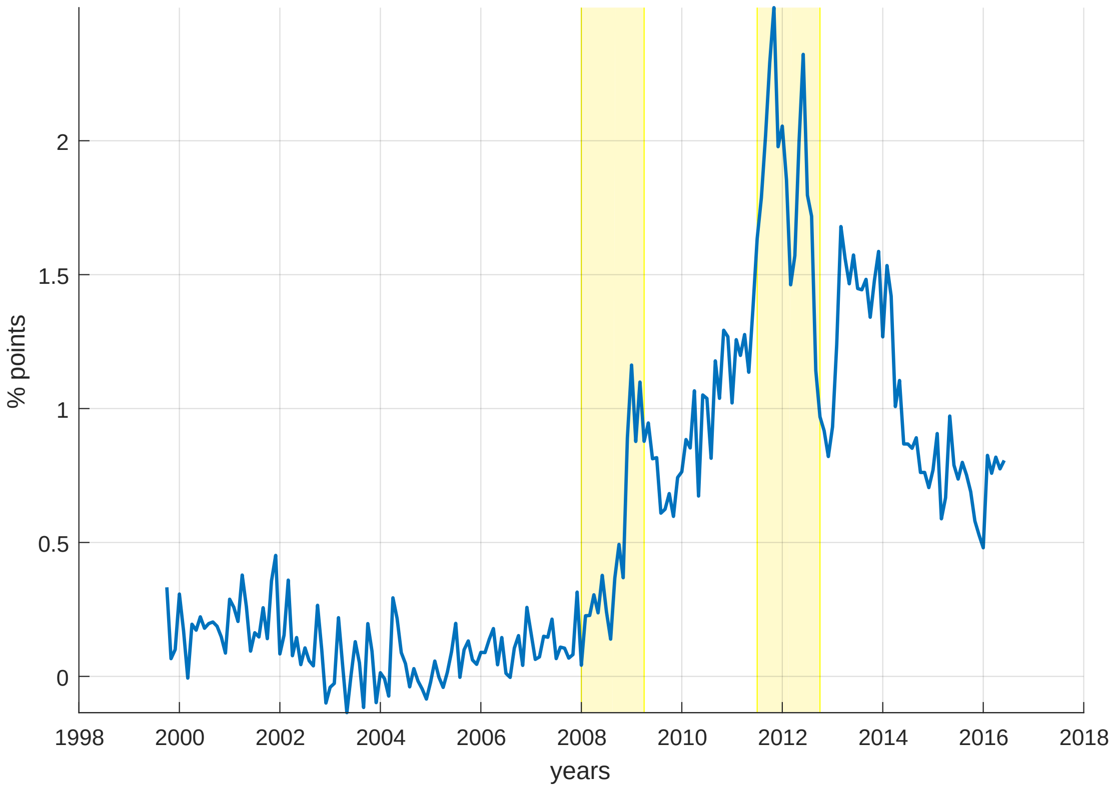
Note: Sample period: February 2000 - June 2016. Counterfactual — i.e., supressing credit supply shocks throughout the entire period — produced from the $\mathfrak{M}_{2c2v}$ model; that is, two independent Markov-switching processes: 1) Two-states process governing equation coefficients; and 2) Two-states process governing all variance shocks. Actual and median counterfactual paths of endogenous variables are in solid black line and in dotted blue line, respectively. The yellow areas denote the counterfactual's 68% error bands.

Figure 7. Imposing the "tranquility" regime.



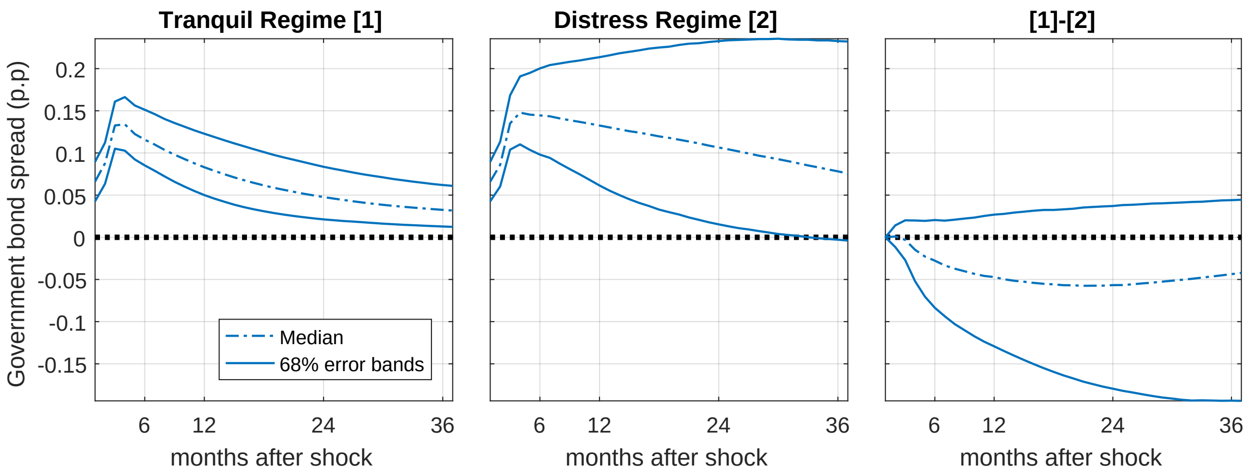
Note: Sample period: February 2000 - June 2016. Counterfactual — i.e., placing the "tranquility" regime throughout the entire period — produced from the $\mathfrak{M}_{2c2v}$ model; that is, two independent Markov-switching processes: 1) Two-states process governing equation coefficients; and 2) Two-states process governing all variance shocks. Actual and median counterfactual paths of endogenous variables are in solid black line and in dotted blue line, respectively. The yellow areas denote the counterfactual's 68% error bands.

Figure 8. Euro area bond yield - German bond yield (10-year Government).



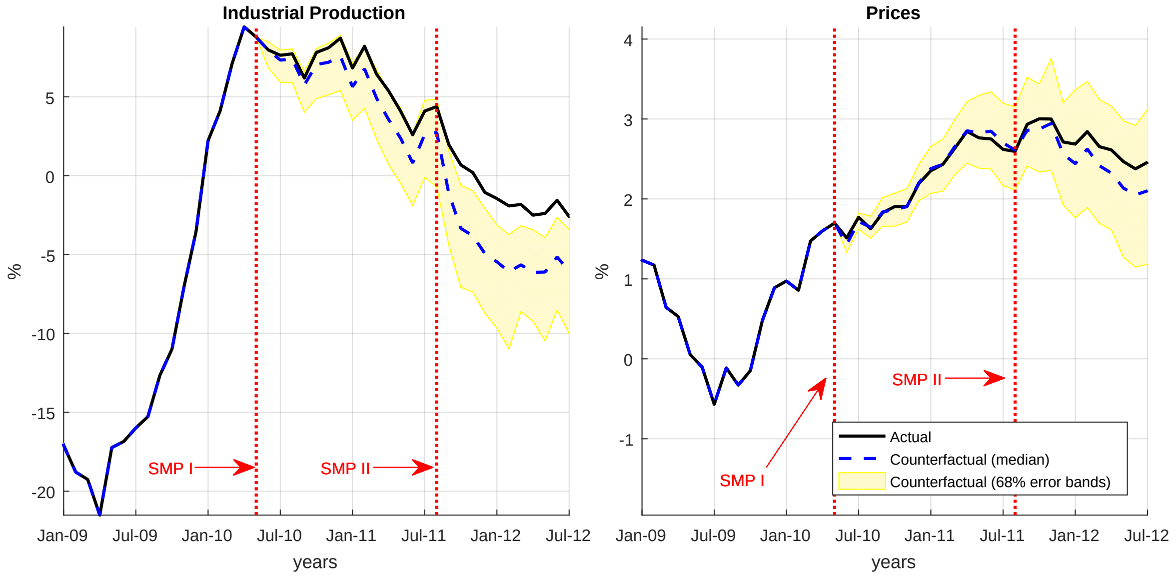
Note: Sample period: October 1999 - June 2016. The blue line reports the difference between the euro area 10-year bond yield and the German 10-year bond yield. The yellow areas denote the CEPR recessions of the euro area.

Figure 9. Impulse responses of the 10-year government bond spread to a credit supply shock.



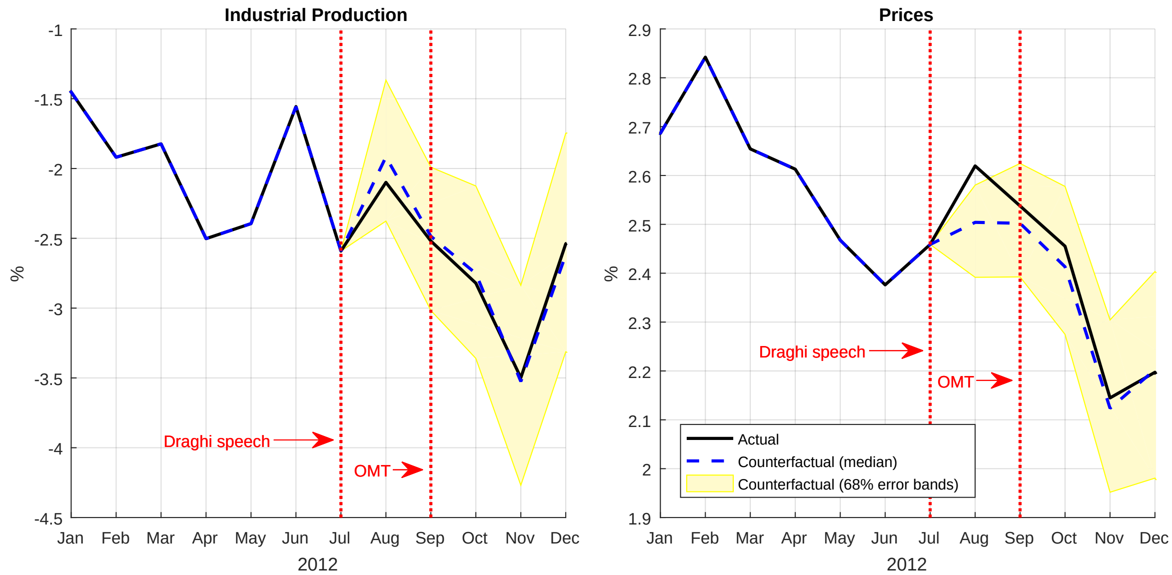
Note: The first and second column report impulse responses of the 10-year government bond spread under tranquil et distress regimes, respectively. The last column displays the difference between the two regimes. In each case, the median is reported in dotted line and the 68% error bands in solid lines.

FIGURE 10. Eliminating the impact of Securities Markets Programme (SMP) announcements.



Note: Sample period: January 2009 - July 2012. For each panel (on the left, year-over-year industrial production growth rate; and on the right, year-over-year inflation),the black solid line reports the actual series, the blue dotted line reports the counterfactual path of the series and the yellow areas display the counterfactual's 68% error bands. The SMP are announced on May 2010 and August 2011, respectively.

FIGURE 11. Eliminating the impact of Outright Monetary Transactions (OMT) announcement and M. Draghi speech.



Note: Sample period: January 2012 - December 2012. For each panel (on the left, industrial production; and on the right, prices),the black solid line reports the actual series, the blue dotted line reports the counterfactual path of the series and the yellow areas display the counterfactual's 68% error bands. M. Draghi gave his "whatever it takes" speech on July 2012. The OMT is announced on September 2012.

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