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CREDIT SUPPLY DYNAMICS AND ECONOMIC ACTIVITY IN EURO AREA COUNTRIES

A TIME-VARYING PARAMETER VAR ANALYSIS

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In 2014 all ECB publications feature a motif taken from the €20 banknote.

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Abstract

This paper aims to shed light on the role of credit supply shocks in euro area countries during the recent pre-crisis, bust, and post-crisis periods. A time-varying parameter vector autoregression (TVP-VAR) with stochastic volatility à la Primiceri (2005) is estimated for each country, and the structural shocks are identified by imposing sign restrictions on impulse response functions based on the theoretical model by Gerali et al. (2010). The results suggest that credit supply shocks have been an important driver of business cycle fluctuations in euro area countries, and that their effects on the economy have generally increased since the recent crisis. Moreover, we report evidence that credit supply shocks contributed positively to output growth during the pre-crisis period and negatively during the downturn in economic activity in 2008-2009 in all the countries considered. In the post-crisis period, by contrast, we observe a strong rise in cross-country heterogeneity, reflecting financial fragmentation in the euro area. Although this heterogeneity across euro area countries seems to have declined since around 2012, the contribution of credit supply shocks to GDP growth and credit growth remains negative in most euro area countries, suggesting that constraints in the supply of credit continue to weaken economic activity.

KEYWORDS: credit supply shocks, euro area, TVP-VAR, sign restrictions

JEL Classification: C11, C32, E32, E51

Non-technical summary

The global financial crisis has been accompanied by weakness in the growth of bank lending in recent years and this has been considered as an important factor behind the sluggishness of output growth. A key question in this regard is to what extent the weakness in bank lending is due to tight credit supply conditions or weak demand for credit. Understanding the relative role of credit supply and demand is important as they have different implications for macroeconomic conditions. If the sluggishness in bank lending reflects bottlenecks in the supply of credit rather than a lack of demand, weak lending is more likely to dampen economic activity. For example, the fact that demand for credit cannot be met implies that investment projects cannot be undertaken, which would otherwise help the economy to recover. In countries facing weakness in lending, the correct identification of credit supply dynamics is thus crucial for policy makers.

Researchers have attempted to identify the factors explaining the weakness in bank lending in a variety of ways, such as via bank lending surveys or econometric methods to identify credit supply and demand shocks. This paper contributes to this literature by identifying credit supply shocks for euro area countries through vector autoregressions (VAR) using sign restrictions on impulse responses. In other words, the shocks are identified according to assumptions about how they are likely to affect the variables in the model. These assumptions are based on economic theory. In addition, we allow for changes in the estimated relationships between the variables in our model by using time-varying coefficients and stochastic volatility. Allowing for time variation is important as there is evidence that relationships between the real and financial side of the economy may change over time.

Our main results suggest that credit supply shocks have played an important role in business cycle fluctuations in euro area countries, and that their effects on the economy have generally increased since the global financial crisis. We find that in all countries in our sample, credit supply shocks contributed positively to output growth in the pre-crisis phase and negatively during the downturn in economic activity in 2008-2009. In the post-crisis period, by contrast, we find a strong rise in cross-country heterogeneity, especially between stressed and non-stressed euro area economies. In the aftermath of the crisis, credit supply shocks contributed to the divergence in real GDP growth across countries, reflecting financial fragmentation in the euro area. More specifically, in Greece, Ireland, Italy, Portugal and Spain credit supply shocks exacerbated the downturn, whereas in Austria, Belgium, Germany and the Netherlands credit supply shocks contributed positively to output growth. Although this heterogeneity across euro area countries seems to have declined during the past few years, the contribution of credit supply shocks to GDP growth remains negative in most countries, suggesting that constraints in the supply of credit continue to weaken economic activity.

In addition, we report evidence that credit supply shocks have also been a driver of fluctuations in loan growth during the past decade. In line with our findings for GDP growth, we find a high degree of cross-country heterogeneity in the contribution of credit supply shocks to credit volume movements in the aftermath of the crisis. While bottlenecks in the supply of credit have progressively become less important in constraining output in most stressed euro area economies, particularly since mid-2012, this pattern cannot be observed for loan volume growth, which remains persistently subdued partly because of bottlenecks in the supply of credit.

"Credit weakness appears to be contributing to economic weakness in these [stressed] countries. Our analysis suggests that credit constraints are putting a brake on the recovery in stressed countries, which adds to the disinflationary pressures. And heterogeneity becomes a factor in assessing low inflation in the euro area."

Mario Draghi, ECB Forum on Central Banking,
Sintra, Portugal, 26 May 2014

1 Introduction

Credit markets play a key role in the business cycle of advanced economies. The weakness of bank lending in many economies in the wake of the global financial crisis has led to an intensive debate about its economic implications. A key question in this regard is to what extent the weakness in bank lending is due to tight credit supply conditions or weak demand for credit. Understanding the relative role of credit supply and demand is important as they have different implications for macroeconomic conditions. If the sluggishness in bank lending reflects bottlenecks in the supply of credit rather than a lack of demand, weak lending is more likely to dampen economic activity (Bijsterbosch and Dahlhaus, 2011; Darvas, 2014). For example, the fact that demand for credit cannot be met implies that investment projects cannot be undertaken, which would otherwise help the economy to recover. In countries facing weakness in lending, the correct identification of credit supply dynamics is thus crucial for policy makers. Moreover, it is also important to understand how credit markets contribute to the propagation of macroeconomic disturbances arising in other sectors of the economy, and how they can be a source of disturbance by themselves.

Inspired by recent events, this paper attempts to shed light on the role of credit supply shocks in euro area countries during the past decade, focusing on developments in output and credit volumes. To this purpose, a time-varying parameter VAR (TVP-VAR) with stochastic volatility à la Primiceri (2005) is estimated for each country in our sample (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal and Spain). Quarterly data covering the period 1980Q1-2013Q2 are used, with the exception of Greece (1985Q1-2012Q4), Ireland (1990Q1-2013Q2) and Italy (1995Q1-2013Q2). Time-variation in the coefficients and stochastic volatility are necessary ingredients to control for the non-linearities associated with the structural economic changes and heteroscedastic macroeconomic shocks usually occurring over long time spans. To tackle the high dimensionality of the parameter space, the estimation is carried out using Bayesian methods. The structural shocks are then identified by imposing sign restrictions on impulse response functions based on the DSGE model proposed by Gerali et al. (2010). The identification of structural shocks via sign restrictions is appealing, as it allows us to avoid the usual recursive assumptions on the contemporaneous effects between endogenous variables.

A fast growing literature has attempted to identify credit supply shocks through vector autoregressions (VAR) by imposing sign restrictions on impulse responses (Halvorsen and Jacobsen, 2009; Busch et al., 2010; De Nicolò and Lucchetta, 2011; Eickmeier and Ng, 2011; Tamási and Világi, 2011; Gambetti and Musso, 2012; Hristov et al., 2012; Barnett and Thomas, 2013; Darracq Paries and De Santis, 2013; Houssa et al., 2013; Darracq Paries et al., 2014; Kick, 2014), or by using other identification schemes (Ciccarelli et al., 2010; Abildgren, 2012; Darracq Paries and De Santis, 2013).[1] A constant parameter approach, as adopted in almost all these studies, might not do full justice to the time-varying nature of macroeconomic relationships that these models try to capture. The only paper adopting a TVP-VAR approach with stochastic volatility to study credit supply shocks is due to Gambetti and Musso (2012), who present a systematic comparison across the euro area, the UK and the US. Analyses at the euro area country-level are scarce (see, for example, Hristov et al. (2012)) and rely on estimations of models with fixed parameters and constant volatility.

The contribution of this paper to the existing literature is twofold. First of all, to the best of our knowledge this is the first paper that applies time-varying parameter VAR methods at the euro area country-level to identify credit supply shocks, allowing us to compare the recent experiences of the countries considered. Second, the paper gives a special emphasis on the role of credit supply shocks over the boom-bust-recovery phases characterizing the past decade.

The main results suggest that credit supply shocks have played an important role in business cycle fluctuations in most euro area countries, and that their effects on the economy have generally increased since the recent crisis. A counterfactual exercise conducted through historical decomposition analysis indicates that in all countries credit supply shocks contributed positively to output growth in the pre-crisis phase and negatively during the downturn in economic activity in 2008-2009. In the post-crisis period, by contrast, we find a strong rise in cross-country heterogeneity. In the aftermath of the crisis, credit supply shocks contributed to the divergence in real GDP growth across countries, reflecting financial fragmentation in the euro area. More specifically, in Greece, Ireland, Italy, Portugal and Spain credit supply shocks exacerbated the downturn, whereas in Austria, Belgium, Germany and the Netherlands credit supply shocks contributed positively to output growth. Although this heterogeneity across euro area countries seems to have declined during the most recent period, the contribution of credit supply shocks to GDP growth remains negative in most countries, suggesting that constraints in the supply of credit continue to weaken economic activity.

In addition, we report evidence that credit supply shocks have also been a driver of fluctuations in loan growth during the past decade. In line with our findings for GDP growth, a high degree of cross-country heterogeneity in the contribution of credit supply shocks to credit volume movements is observable during the immediate post-crisis period. Our estimates also show that, while bottlenecks in the supply of credit have progressively become a less important factor constraining output in most stressed euro area countries, in particular since mid-2012, this pattern cannot be observed for lending, which remains persistently subdued partly because of constraints in credit supply. Finally, we show that the main findings of the paper are robust to an alternative identification scheme used in the literature.

The remainder of the paper is organized as follows. Section 2 describes the econometric model. Section 3 presents the main findings. In Section 4 we perform a robustness check. Sections 5 concludes the paper.

[1] There have also been attempts in the theoretical literature to better capture shifts in the supply of credit by expanding the focus beyond borrowing constraints in collateral markets and emphasizing the role of constraints on lenders (Justiniano et al., 2014).

2 The Empirical Methodology

This section describes our econometric approach. Our model follows closely that used by Gambetti and Musso (2012), to which the reader may refer to for the technical details on the estimation.

2.1 The Econometric Model

The analysis is performed by estimating the time-varying parameters VAR model with stochastic volatility employed by Gambetti and Musso (2012). Pioneered by Cogley and Sargent (2005) and Primiceri (2005), TVP-VARs with stochastic volatility have recently become of increasing interest for economists (Baumeister et al., 2008; Benati, 2008; Benati and Surico, 2008; Canova and Gambetti, 2009; Clark and Terry, 2010; Fernández-Villaverde and Rubio-Ramírez, 2010; Franta, 2011; Mumtaz et al., 2011; Nakajima, 2011; Nakajima et al., 2011; Baumeister and Benati, 2013; Prieto et al., 2013). The ability to capture the potential time-varying nature of the underlying structure of the economy and the volatility of macroeconomic shocks in a flexible and robust way is what makes this method particularly appealing to macroeconomists.[2] In what follows, a formal description of the model is provided.

Consider the following reduced-form VAR model:

$$Y_t = B_{0,t} + B_{1,t}Y_{t-1} + \cdots + B_{p,t}Y_{t-p} + \epsilon_t \equiv X_t'\theta_t + \epsilon_t \tag{1}$$

where Y_t is an $n \times 1$ vector containing our endogenous variables, $Y_t = [y_t, \pi_t, l_t, clr_t, str_t]'$, i.e. the real GDP growth rate, the inflation rate, the growth rate of the stock of credit, a composite lending rate and the short-term market interest rate, respectively; $B_{0,t}$ is an $n \times 1$ vector of time-varying coefficients that multiply constant terms; $B_{i,t}$ $(i = 1, \ldots, p)$ are $n \times n$ matrices of time-varying coefficients; ϵ_t are the VAR's reduced-form innovations with zero mean and time-varying covariance matrix Σ_t, which is factorized in a standard way:

$$\Sigma_t = A_t^{-1} H_t \left(A_t^{-1}\right)' \tag{2}$$

where A_t is the lower triangular matrix of simultaneous relations

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 & 0 \\ \alpha_{51,t} & \alpha_{52,t} & \alpha_{53,t} & \alpha_{54,t} & 1 \end{bmatrix} \tag{3}$$

[2] For a comprehensive overview of the TVP-VAR technique, with both methodological and empirical applications, see Nakajima (2011).

and H_t is the diagonal matrix

$$H_t = \begin{bmatrix} \sigma_{1,t} & 0 & 0 & 0 & 0 \\ 0 & \sigma_{2,t} & 0 & 0 & 0 \\ 0 & 0 & \sigma_{3,t} & 0 & 0 \\ 0 & 0 & 0 & \sigma_{4,t} & 0 \\ 0 & 0 & 0 & 0 & \sigma_{5,t} \end{bmatrix} \tag{4}$$

Let us collect in a vector α_t the non-zero and non-one elements of matrix A_t, and in another vector σ_t the diagonal elements of matrix H_t. Following Primiceri (2005), the model's time-varying parameters are assumed to evolve as random walks:

$$\alpha_t = \alpha_{t-1} + \xi_t \tag{5}$$

$$\theta_t = \theta_{t-1} + \eta_t \tag{6}$$

and geometric random walks:

$$\log \sigma_t = \log \sigma_{t-1} + \tau_t \tag{7}$$

where ξ_t, η_t, and τ_t are white Gaussian noises with zero mean and covariance matrix S, Q, and W, respectively. As in Primiceri (2005), we assume the vector of the innovations to be jointly normally distributed with the following assumptions on the covariance matrix:

$$\mathrm{Var}\left(\begin{bmatrix} u_t \\ \xi_t \\ \tau_t \\ \eta_t \end{bmatrix}\right) = \begin{bmatrix} I_5 & 0 & 0 & 0 \\ 0 & S & 0 & 0 \\ 0 & 0 & Q & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \tag{8}$$

where u_t is such that $\epsilon_t = A_t^{-1} H_t^{\frac{1}{2}} u_t$. Lastly, to simplify the estimation we assume S to be block diagonal, i.e. the coefficients of the contemporaneous relations among variables are assumed to evolve independently in each equation (Primiceri, 2005).

To summarize the most meaningful findings of the model the following functions of the VAR coefficients are reported: the impulse response functions (IRFs), the forecast error variance decomposition and the historical decomposition. The impulse response functions and the variance decomposition at every point in time are computed using the estimated coefficients and volatilities corresponding to these points in time, under the assumption that they will not change in the future. The impulse response functions trace out the MA representation of the system, and are derived as follows (Canova and Gambetti, 2009; Gambetti and Musso, 2012):

$$Y_t = \mu_t + \sum_{k=1}^{\infty} C_{k,t} \epsilon_{t-k} \tag{9}$$

where $C_{0,t} = I$, $\mu_t = \sum_{k=0}^{\infty} C_{k,t} B_{0,t}$, $C_{k,t} = \mathcal{S}_{n,n}(\mathbf{B}_t^k)$, $\mathbf{B}_t = \begin{pmatrix} & B_t & \\ I_{n(p-1)} & & 0_{n(p-1),n} \end{pmatrix}$, and $\mathcal{S}_{n,n}(X)$ is a function that selects the first n rows and n columns of matrix X.

The variance decomposition describes the contribution of each shock to the variance of the forecast error in $Y_{t+\tau}$ $(\tau = 1, 2, \dots)$. The historical decomposition measures the contribution of each shock to the deviations of $Y_{t+\tau}$ from its baseline forecasted path $(\tau = 1, 2, \dots)$.

Estimation is conducted using Bayesian methods, which are particularly efficient in treating the high dimensionality of the parameter space and the non-linearities of the model. More specifically, we use a variant of Markov Chain Monte Carlo (MCMC) methods, the Gibbs sampling, to draw from conditional distributions to approximate joint and marginal distributions. To evaluate posteriors we specify the prior distributions consistently with Primiceri (2005). The priors for the initial states of the time-varying coefficients B, simultaneous relations A and log volatilities H are assumed to be normally distributed. The priors for the hyperparameters S, Q and W are assumed to be distributed as independent inverse Wishart. Ordinary least square estimates of a time invariant model, based on a small initial subsample, are used for the specification of the prior distributions.[3] Gibbs sampling is performed in different steps, drawing in turn volatilities (H), simultaneous relations (A), time-varying coefficients (B), and hyperparameters (S, Q, W). Technical details on the Gibbs sampling algorithm used can be found in Gambetti and Musso (2012).[4] A sample of 15000 iterations of the Gibbs sampler is employed, discarding the first 10000 and collecting one out of five draws. As reported in Appendix A, the convergence diagnostics are satisfactory, as they reveal the convergence of the algorithm.

The model is estimated for each country in our sample using quarterly data. The countries considered in the analysis are the initial euro area countries (excluding Luxembourg), i.e. Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal and Spain, as well as Greece. The sample period differs among countries, and its length depends on data availability. We use quarterly data covering the period 1980:1-2013:2 for all countries, with the exception of Greece (1985:1-2012:4), Ireland (1990:1-2013:2) and Italy (1995:1-2013:2). Details on the variables used are reported in Appendix B.

For computational reasons, and consistently with other papers in the literature (Primiceri, 2005; Franta, 2011; Gambetti and Musso, 2012; Baumeister and Benati, 2013), we limit the number of lags to 2 $(p = 2)$.

2.2 The Identification Strategy

The scheme to identify structural shocks is based on sign restrictions, which allows us to avoid the usual recursive assumptions on the contemporaneous effects between endogenous variables. Since it is problematic to impose sign restrictions directly on the coefficients of the VAR, identification of the structural shocks is achieved *ex-post* by imposing sign restrictions on impulse response functions. More specifically, we check whether the impulse responses satisfy our sign restrictions. Sign restrictions on impulse responses have been frequently used in the literature to identify VAR structural shocks (Faust, 1998; Uhlig, 2005) and, in particular, credit supply shocks (Busch et al.,

[3]For more details on the calibration of the prior distributions refer to Gambetti and Musso (2012).

[4]The algorithm used takes into account the correction to the ordering of steps suggested by Del Negro and Primiceri (2013).

2010; De Nicolò and Lucchetta, 2011; Eickmeier and Ng, 2011; Gambetti and Musso, 2012; Hristov et al., 2012; Barnett and Thomas, 2013; Houssa et al., 2013). As shown by Paustian (2007), sign restrictions can be a useful tool for recovering structural shocks from VAR residuals as long as the imposed restrictions are sufficiently numerous. Moreover, the identification of additional shocks contributes to a better identification of the shocks under scrutiny, as the orthogonality between the structural shocks represents itself an additional restriction (Uhlig, 2005). Lastly, the imposed sign restrictions must be mutually exclusive to uniquely identify the structural shocks. In light of these considerations, we set our sign restrictions as follows.

We identify four structural shocks, leaving one shock unidentified in order to capture the effects of any further remaining disturbance. The strategy to identify aggregate supply shocks, aggregate demand shocks and monetary policy shocks is the same as in Gambetti and Musso (2012), who set their restrictions on the basis of standard DSGE models. Table 1 summarizes the set of sign restrictions we impose on the impulse responses. In particular, aggregate supply shocks drive real GDP and inflation in opposite directions. Expansionary aggregate demand shocks are assumed to move real GDP, inflation, the short-term interest rate and the lending rate up. Finally, we define an expansionary monetary policy shock as a shock that has a positive impact on real GDP and inflation and a negative impact on the short-term interest rate.[5]

[Table 1 about here]

Our strategy for identifying credit supply shocks relies on the impulse response functions generated by the theoretical model proposed by Gerali et al. (2010), reported in Figure 1, and employed by Busch et al. (2010) and Gambetti and Musso (2012). The implied sign restrictions do not hinge on this model only, but match the commonly agreed intuition of the effects of credit supply shocks. As in the case of an aggregate demand shock, an expansionary credit supply shock leads to an increase in output, inflation and the short-term interest rate. What distinguishes these two shocks is that credit volume changes are assumed to be driven by credit supply shocks if the lending rate moves in the opposite direction in comparison with the rate of credit growth. We will stick to this intuitive identification structure for credit supply shocks throughout the paper. Some restrictions on the other shocks will be changed when performing the sensitivity analysis in Section 4.

[Figure 1 about here]

From a practical point of view, to obtain impulse response functions that satisfy our sign restrictions, we assume that $\mathcal{P}_t$ is the unique lower triangular Cholesky matrix such that $\mathcal{P}_t\mathcal{P}_t' = \Sigma$. For any $\mathcal{H}_t$ such that $\mathcal{H}_t\mathcal{H}_t' = I$, we have that $\Sigma = \mathcal{P}_t\mathcal{P}_t' = \mathcal{P}_t\mathcal{H}_t\mathcal{H}_t'\mathcal{P}_t'$. Therefore, we can construct a new decomposition and orthogonalize the shocks by using $\mathcal{P}_t\mathcal{H}_t$ and check whether the generated impulse response functions, given by $IRF(t,k) = C_{k,t}\mathcal{P}_t\mathcal{H}_t$, satisfy simultaneously the restrictions imposed. $\mathcal{H}_t$ is chosen by means of rotation matrices, as described by Canova and De Nicoló (2002) and Canova (2007). If a particular rotation matrix generates impulse

[5] As our model is estimated country-by-country, monetary policy shocks are identified using country data, which may not be fully appropriate for the period after the advent of the euro. However, we believe that this is not a major issue as we use the same euro area short-term interest rate for all countries from 1999 onwards (2002 for Greece) and the correlation of the business cycles across euro area countries was generally high. We do not believe that this has a significant impact on our conclusions regarding the role of credit supply shocks.

responses compatible with our sign restrictions, the impulse responses are stored. Otherwise, we discard them. Restrictions on impulse responses are imposed only upon impact, as in Gambetti and Musso (2012).

3 Results

Developments in credit and economic activity in the euro area over the past decade have been dominated by the impact of the global financial crisis. After growing strongly in the years preceding the financial crisis, credit growth declined abruptly and real GDP contracted significantly in 2008-2009. In the aftermath of the crisis, economic activity started to pick up again gradually although credit growth remained subdued. As credit and output dynamics were different before, during and in the aftermath of the crisis, we distinguish three sub-periods in our analysis: the pre-crisis, the bust and the post-crisis period (Table 2). The terms bust and crisis are used interchangeably in this paper and refer to the downturn in real GDP growth around 2008-2009 (see Table 2 for the precise dates). Although these three periods broadly coincide for all countries, their precise timing is country-specific. The bust period starts with the first quarter-on-quarter decline in real GDP in 2007-2008 and the start of the post-crisis period is defined by the first subsequent increase in quarterly GDP.

[Table 2 about here]

3.1 Evidence of Time-Varying Coefficients and Variance

Before we present our results on the effect of credit supply shocks, we first provide evidence of the appropriateness of using time-varying coefficients and stochastic volatility in order to validate the choice for our econometric approach. Figure 2 plots the time-varying variance of the residuals for the five variables in our model and for each country in the sample. Substantial time variation is evident for all the countries, especially during the 1980s and the recent global financial crisis, reflecting structural economic changes and the fact that these economies were hit by extraordinary shocks.

[Figure 2 about here]

In order to investigate the presence of time variation in coefficients and volatility formally, we perform three statistical tests. Table 3 reports three tests to check the presence of time-varying coefficients in the matrices A, B and H. The trace test (Cogley and Sargent, 2005) checks whether the trace of the prior variance-covariance matrix is significantly smaller than the posterior of the variance-covariance matrix. The Kolmogorov-Smirnov test verifies the equality of two distributions for each parameter of the matrices A, B and H. This test is performed between three different points in time. Finally, a t-test for equal means of two distributions is conducted for the parameters of matrices A, B, and H. The test is again performed between three different points in time. The three tests on matrices A and B all reveal strong time-variation in the coefficients, supporting our approach of using time-varying coefficients. In addition, the Kolmogorov-Smirnov test and the t-test on matrix H further confirm our preference for using a specification that allows for stochastic volatility.[6]

[Table 3 about here]

3.2 Credit Supply Shocks over the Entire Sample Period

Before moving to the main results for the three sub-periods considered, we provide a brief overview of the average effect of credit supply shocks in our countries of interest. The impulse response functions to an expansionary credit supply shock over the entire sample period look intuitive. Figure 3 reports the median of the responses (blue line) and the associated confidence interval represented by the shaded area (showing the 16th and 84th percentiles of the distribution). The confidence intervals are generally narrow, confirming the significance of the responses.

The impulse responses show a similar pattern across the euro area countries in our sample. An expansionary credit supply shock has a significant but short-lived positive impact on real GDP growth, lasting for around three quarters in most countries. The positive effect on inflation is more persistent than on output, lasting up to five years in some countries (although it is substantially shorter in most countries). There is more variation across countries for inflation than for GDP growth, with a relatively persistent impact on inflation observed for Belgium, Finland, Greece and Spain. Regarding loan volume growth, credit supply shocks seem to have on average a longer-lasting impact in France, Ireland, Italy, Portugal and Spain, amounting to up to two to three years in these countries while being substantially shorter in the rest of the euro area. The decline in the lending rate seems to be short-lived in all euro area countries, with a significant negative effect lasting for only two to three quarters. The positive responses in the short-term interest rate reflect the increase in inflation resulting from an expansionary credit supply shock and are similar across countries (with Greece standing out to some extent).

[Figure 3 about here]

Appendix C reports the impulse response functions of aggregate supply shocks, aggregate demand shocks and monetary policy shocks (Figures 11-13). The impact of the other structural shocks exhibits a plausible pattern, suggesting that we correctly identify them as well as credit supply shocks. Our impulse responses are broadly in line with the findings in related studies, in particular with those in Gambetti and Musso (2012). Comparing the results for individual countries with those for the euro area in Gambetti and Musso (2012), we can observe that, perhaps unsurprisingly, the impulse responses for Germany are relatively similar to those for the euro area average. Particularly for Greece and Portugal, by contrast, the impulse responses look relatively different from the euro area average, although the differences are not large.

[6] A comparison between our TVP-VAR with stochastic volatility and two alternative VARs with time-invariant coefficients (a country-specific VAR and a panel VAR à la Hristov et al. (2012)) shows that our model generates indeed much more plausible results. These findings are available upon request from the authors.

3.3 Credit Supply Shocks before, during and in the aftermath of the Crisis

3.3.1 Impulse Response Analysis

One of the main advantages of modeling time-variation is the possibility to track the effects of structural shocks over time. The evolution of the short-term impact of credit supply shocks during the last decade shows a substantial time variation in all the countries of interest. Two statistical tests provide evidence of the changing impact of credit supply shocks over the three periods considered (Table 4). Both a t-test and a Wilcoxon rank sum test, testing for equal means and medians, respectively, show that for most countries and variables in our model the impact of credit supply shocks has significantly increased over time (the green cells in Table 4), especially during the crisis period. Only in a small number of cases, the impact has not changed significantly (white cells) or has declined (red cells). As credit supply shocks were relatively large during the crisis, this is an indication that the short-term impact of these shocks may become larger with the size of the credit supply shock. These results are broadly in line with those in Gambetti and Musso (2012) for the euro area, who also observe a larger short-term impact of credit supply shocks around the global financial crisis, particularly for real GDP and inflation.

[Table 4 about here]

The same information conveyed through charts provides further evidence of the changing impact of credit supply shocks over the three periods considered (Appendix D, Figure 14). Credit supply shocks had a stronger impact on GDP growth during the crisis than before and afterwards, in particular in Austria, Belgium, Germany, Ireland, Italy and Spain. A similar pattern can be observed for inflation. The impact of credit supply shocks peaked during the crisis, particularly in Ireland and Spain. The evolution of the effect of credit supply shocks on loan volumes exhibits a less clear pattern during the three sub-periods. In some countries (such as Belgium, Finland, France and the Netherlands), the impact of credit supply shocks on credit seems to have gradually declined over time. In others, by contrast, the impact of these shocks has increased (such as in Germany, Ireland, Italy and Spain). Regarding interest rates, there is an increase over time in the absolute value of the short-term impact of credit supply shocks on both lending rates as well as the money market rate in most countries.

3.3.2 Forecast Error Variance Decomposition

The forecast error variance decomposition measures the contribution of a specific shock to the variability of the forecast error for the variables in our model. The evolution of the variance decomposition (at a 20-quarter horizon) suggests that the contribution of credit supply shocks to the variability of our variables declined during the downturn of 2008-2009, before picking up in the aftermath of the crisis in many euro area countries (Table 5 reports the results of a t-test and a Wilcoxon rank sum test. A significant larger impact of credit supply shocks is marked in green, whereas the red cells represent a significant lower impact). The decrease in the relative importance of credit supply shocks during the recession reflects the greater role of demand shocks during that period. A more heterogeneous picture emerges in the post-crisis period, with the share of the variance explained by credit supply shocks increasing in some countries while decreasing in others (columns 1-3 in Table 5). More specifically, after the crisis the fraction of the variance of our variables that can be explained by credit supply shocks increased especially for Greece, Ireland and Italy, whereas a decline occurs particularly in Finland and France.

Looking at the variance decomposition for the five variables in our model in more detail, it is worth highlighting the increase in the variance of credit volume growth due to credit supply shocks from the pre-crisis to the post-crisis period in several countries. The same applies to the composite lending rate, suggesting that credit supply shocks had an impact on lending conditions and the evolution of credit volumes in particular after 2009, rather than during the downturn in 2008-2009. The results of the variance decomposition analysis are confirmed by Figure 15 (Appendix D), which reports graphically the evolution of the relative contribution (in percentage points) of credit supply shocks to the variance of the endogenous variables.

[Table 5 about here]

3.3.3 Historical Decomposition

The historical decomposition decomposes actual data into a trend and the accumulated effects of the structural shocks. Therefore, it allows economists to perform counterfactual exercises by providing a picture of the estimated impact of structural shocks during the period of interest. Table 6 shows the average rate of real GDP growth in euro area countries during the three periods considered, with and without the effect of credit supply shocks. The counterfactual series indicates how a variable would have evolved in the absence of credit supply shocks. Focusing on real GDP, it appears that credit supply shocks made a positive contribution to output growth in the pre-crisis phase and a negative contribution during the crisis in all our countries, whereas in the aftermath of the crisis there was a strong rise in cross-country heterogeneity. Before the crisis, credit supply shocks pushed up real GDP growth in all countries in our sample (green cells represent a positive contribution), particularly in Austria, Greece and Portugal (dark green cells). Once the crisis started, this impact turned negative in all countries (red cells). The negative contribution of credit supply shocks was particularly large (in relative terms) in Austria, Ireland, Italy, Portugal and Spain (dark red cells). Hence, there is some evidence that the larger the positive contribution of credit supply shocks was before the crisis, the more sizeable the subsequent negative impact of these shocks was during the bust. In the aftermath of the crisis, credit supply shocks contributed to the divergence in real GDP growth across the countries in our sample, reflecting financial fragmentation in the euro area. Especially in Greece, Ireland, Italy, Portugal and Spain, credit supply shocks added to the downturn, whereas in Austria, Belgium, Germany and the Netherlands credit supply contributed positively to output growth.

These results are consistent with the prevalent narratives of the crisis in euro area countries. In particular in Ireland, which was confronted with a banking crisis, economic activity suffered substantially as a result of declines in credit supply. Table 6 shows that, in the absence of credit supply shocks, annual real GDP growth in Ireland would have been 1.6 percent higher on average in 2010-2013. Although less than in Ireland, also in Italy and Spain credit supply contributed relatively strongly to the contractions in economic activity during the post-crisis period. Together with Greece and Portugal, the economies of Italy and Spain are characterized by high shares of small and medium-sized companies (SMEs). As these companies tend to rely relatively heavily on bank credit, the high share of SMEs may have made it more difficult for economic activity in these countries to recover from the financial tensions associated with the crisis (Klein, 2014).

The above findings contrast with those documented in Hristov et al. (2012). Also in that study there is a rise in cross-country heterogeneity after the crisis, but it involves different groups of countries. The first one, which comprises Austria, Finland, Ireland, Italy and Portugal, is characterized by negative contributions of credit supply shocks during the first half of the crisis (2007Q3-2008Q4) and positive contributions in the second period (2009Q1-2010Q2). By contrast, in the second group of countries, composed of Belgium, France, Germany, Greece, the Netherlands and Spain, the contribution of credit supply shocks to GDP growth was positive in the first period and negative in the second. A possible explanation for these conflicting findings may be related to the different empirical approach that these authors follow (i.e. a panel VAR with constant coefficients).

[Table 6 about here]

Looking at the contribution of credit supply shocks to real GDP growth during the aftermath of the crisis in more detail, differences across euro area countries seem to have declined recently. Figure 4 shows the evolution of actual GDP growth and its counterfactual (i.e. without the effect of credit supply shocks) on a quarterly basis. The most pronounced differences across countries emerged in the immediate aftermath of the crisis (during 2010-2012), with credit supply shocks reducing on average real GDP growth in most euro area countries with Austria, Belgium, Germany and the Netherlands as the main exceptions. The downward impact of these shocks on output growth in several countries, including France, Greece, Italy, Portugal and Spain has waned in the most recent period. In some countries, the start of this decline seems to have coincided with the drop in sovereign bond yields, which started in mid-2012. In almost all countries, however, the contribution of credit supply shocks to GDP growth remains negative, suggesting that constraints in the supply of credit continue to contribute to the weakness in economic activity.

[Figure 4 about here]

In order to obtain a clearer picture of the relative importance of credit supply shocks, Figure 5 plots the contributions to real GDP growth of all the structural shocks identified in the model. This picture shows that, in addition to those associated with credit supply, also other shocks have played an important role in shaping the business cycle in euro area countries. Not surprisingly, aggregate demand shocks have been a major driver of fluctuations in output growth during the crisis. Moreover, monetary policy shocks have played an important role in the evolution of GDP growth in Belgium, Finland, France, Ireland, Italy and Portugal, whereas aggregate supply shocks have only played a minor role during the past decade. Compared with the other structural innovations, credit supply shocks have also played a leading role, reducing real GDP during the crisis particularly in Austria, Ireland, Italy, Portugal and Spain. But also in the aftermath of the crisis (i.e. since 2010), credit supply shocks continued to be a key factor dragging down output growth in Ireland, Italy and Spain.

[Figure 5 about here]

Credit supply shocks have also played an important role in credit volume movements during the past decade. Figure 6 shows the evolution of actual loan growth and its counterfactual, in which credit supply shocks are set to zero. In line with our earlier findings for real GDP growth, the expansionary credit supply shocks before the crisis added to new lending in all countries until 2008, although the degree to which these shocks contributed positively to credit growth differed across countries. Our estimates also show that in the aftermath of the crisis bottlenecks in the supply of credit weakened new lending especially in Ireland, Italy, Portugal and Spain. As in the case of GDP growth, we observe a relative high degree of cross-country heterogeneity during the period immediately after the downturn in economic activity (i.e. during 2009 and 2010). This heterogeneity seems to have declined during the more recent period with a gradual increase in the dampening effect of credit supply shocks on new lending in several euro area countries. Compared with the picture for real GDP in Figure 4, however, the improvement for loan volumes seems to be negligible or even absent in the most recent period, suggesting that credit supply bottlenecks are more severe for new lending than for output growth.

[Figure 6 about here]

The historical decomposition of the structural shocks identified confirms that credit supply was a major constraining factor for credit growth in the last decade in most of our countries (Figure 7). Our model suggests that constraints in the supply of credit have been a key factor holding back credit growth in France, Ireland, Italy, Portugal and Spain during the past few years. In most countries (e.g. in Austria, Finland, Belgium, France, Germany, Greece, Ireland, Portugal and Spain) also demand-related factors seem to have played an important role in the evolution of credit growth, especially since the crisis. Although this suggests that subdued credit demand may also explain part of the weakness in credit growth, our framework does not enable us to disentangle pure credit demand shocks from other demand-related forces.

[Figure 7 about here]

3.4 Are the Identified Credit Supply Shocks Plausible? A Comparison with Survey Data

A successful identification of the structural shocks is one of the key challenges when using the VAR approach. Recent papers quantifying the impact of credit supply shocks have used two types of identification strategies (see Section 1): those based on sign restrictions and those based on survey data such as Ciccarelli et al. (2010). The latter study uses survey data from the ECBs Bank Lending Survey (BLS) as a proxy for credit supply and demand. In this approach, credit supply is based on survey replies to the BLS questions on changes in lending standards applied by banks. In order to investigate the plausibility of the structural shocks identified by our model, we follow Ciccarelli et al. (2010) and construct a credit supply index based on changes in bank lending standards associated with the ability of banks to lend in relation to their balance sheet constraints and competitive pressure. Survey data are available for all countries in our sample, except Finland and Greece. Appendix B reports in detail how we calculate the credit supply index.

The evolution of our credit supply index based on survey data is very similar to the structural credit supply shocks identified by our model (Figure 8). The correlation between both measures is positive and high for all countries, in particular for Austria, Italy, Portugal and Spain. With the exception of Ireland, both measures indicate a sharp tightening of credit supply standards during the crisis in 2008 and 2009. Both measures also show improved credit supply conditions in 2012 and 2013 in many countries. This exercise thus confirms the plausibility of the structural credit supply shocks identified in our model. However, it should be stressed that the advantage of a model-based approach is twofold. First of all, it is rooted in economic theory, and it allows us to calculate credit supply shocks also for periods for which the BLS is not available. Second, survey indicators may be partly endogenous, reflecting movements due to changing economic conditions.

[Figure 8 about here]

4 A Robustness Check: Alternative Sign Restriction Identification

We check the robustness of our results by modifying the sign restriction identification, and, in particular, adopting the identification used by Hristov et al. (2012). According to this alternative identification strategy, summarized in Table 7, the short-term interest rate declines in response to an expansionary aggregate supply shock, and the lending rate decreases in response to an expansionary monetary policy shock. We do not change the imposed restrictions on credit supply shocks, which remain consistent with the DSGE model by Gerali et al. (2010).

[Table 7 about here]

We evaluate the difference between this specification and our baseline model in terms of impulse response functions and historical contribution of credit supply shocks to GDP growth. The impulse responses of a credit supply shock are almost identical to those obtained using the baseline model (Figure 9). Appendix E compares the impulse responses for the other shocks that we identify (Figures 16-18). Whereas the results for the aggregate demand shock are very close to those of our baseline model, the main differences arise for the aggregate supply shock and monetary policy shock. This is not surprising, as we have changed our identification strategy for those two shocks. These differences do, however, not have any impact on the conclusions of this paper.

[Figure 9 about here]

The counterfactual exercise performed through historical decomposition analysis confirms that our results do not change when we use the alternative identification strategy. Both counterfactual scenarios for real GDP growth are virtually the same in both models (Figure 10). To sum up, our results seem to be very robust to the main alternative identification strategy used in the literature.

[Figure 10 about here]

5 Concluding Remarks

This paper aims to shed light on the role of credit supply shocks in euro area countries during the recent pre-crisis, bust, and post-crisis phases. We estimate a time-varying parameter vector autoregression (TVP-VAR) with stochastic volatility following Primiceri (2005) and Gambetti and Musso (2012) for each country, and the structural shocks are identified by imposing sign restrictions on impulse response functions based on the theoretical model developed by Gerali et al. (2010).

The findings suggest that credit supply shocks have played an important role in business cycle fluctuations in the euro area, and that their effects on the economy have generally increased since the recent crisis. The counterfactual exercises carried out in the paper indicate that in all the countries considered credit supply shocks contributed positively to output growth in the pre-crisis phase and negatively during the downturn in economic activity in 2008-2009. In the post-crisis period, by contrast, we observe a strong rise in cross-country heterogeneity between stressed economies on the one hand and non-stressed economies on the other. More specifically, in the aftermath of the crisis, credit supply shocks contributed to the divergence in real GDP growth across countries, reflecting financial fragmentation in the euro area. In Greece, Ireland, Italy, Portugal and Spain credit supply shocks exacerbated the downturn, whereas in Austria, Belgium, Germany and the Netherlands credit supply shocks contributed positively to output growth. Although this heterogeneity across euro area countries seems to have declined during the most recent period, the contribution of credit supply shocks to GDP growth remains negative in most euro area countries, suggesting that constraints in the supply of credit continue to weaken economic activity.

In addition, we report evidence that credit supply shocks have also played a role for fluctuations in loan growth during the last decade in most of our countries. In line with our findings for GDP growth, a high degree of cross-country heterogeneity can be observed for credit volumes during the immediate post-crisis period. Our estimates also show that, whereas bottlenecks in the supply of credit have progressively become a less important factor constraining output in most stressed euro area countries, in particular since mid-2012, tight credit supply conditions continue to restrain lending in most euro area countries and in stressed economies in particular.

This paper suggests several potential avenues for future research. Two are worth mentioning here. The first one would be to further analyze the determinants of credit supply shocks in order to come to more precise policy recommendations. The second avenue would be to distinguish the effects of credit supply shocks originating in different sectors, such as households and non-financial corporations. A disaggregation of credit into loans for mortgages and consumption and loans for investment would enable researchers to gain deeper insights into the mechanisms driving economic activity and credit volumes.

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Tables and Figures

Table 1: Sign restrictions

	Responses to an expansionary shock				
Shock	Real GDP	GDP deflator	Short-term rate	Lending rate	Credit
Aggregate supply	+	−	unrestricted	unrestricted	unrestricted
Aggregate demand	+	+	+	+	unrestricted
Monetary policy	+	+	−	unrestricted	unrestricted
Credit supply	+	+	+	−	+

Notes: Sign restrictions are imposed for one quarter on the impulse responses to expansionary shocks.

Table 2: Pre-crisis, bust, and post-crisis periods

	Pre-crisis period	Bust period	Post-crisis period
Austria	2005Q1-2008Q1	2008Q2-2009Q2	2009Q3-2013Q2
Belgium	2005Q1-2008Q2	2008Q3-2009Q1	2009Q2-2013Q2
Finland	2005Q1-2007Q4	2008Q1-2009Q2	2009Q3-2013Q2
France	2005Q1-2008Q1	2008Q2-2009Q2	2009Q3-2013Q2
Germany	2005Q1-2008Q1	2008Q2-2009Q1	2009Q2-2013Q2
Greece	2005Q1-2008Q3	2008Q4-2010Q4	2011Q1-2012Q4
Ireland	2005Q1-2007Q1	2007Q2-2009Q4	2010Q1-2013Q2
Italy	2005Q1-2008Q1	2008Q2-2009Q2	2009Q3-2013Q2
Netherlands	2005Q1-2008Q1	2008Q2-2009Q2	2009Q3-2013Q2
Portugal	2005Q1-2007Q4	2008Q1-2009Q1	2009Q2-2013Q2
Spain	2005Q1-2008Q1	2008Q2-2009Q4	2010Q1-2013Q2

Notes: The bust period starts with the first QoQ GDP reduction in 2007/2008; the post-crisis period with the first subsequent QoQ GDP increase. Exception: Ireland 2007Q3.

Table 3: Testing time variation in coefficients and volatility

	Trace test[1]				Kolmogorov-Smirnov test[2]						t-test[3]					
					A		B		H		A		B		H	
	trace	16% perc.	50% perc.	84% perc.	1-2	2-3	1-2	2-3	1-2	2-3	1-2	2-3	1-2	2-3	1-2	2-3
Austria	0.08	0.88	1.21	1.67	10/10	10/10	55/55	49/55	5/5	5/5	9/10	10/10	52/55	46/55	5/5	5/5
Belgium	0.13	1.97	3.92	8.27	10/10	10/10	54/55	52/55	5/5	5/5	9/10	9/10	54/55	50/55	5/5	4/5
Finland	0.39	2.88	3.98	5.68	10/10	10/10	55/55	41/55	5/5	5/5	10/10	8/10	50/55	37/55	3/5	5/5
France	0.03	0.42	0.58	0.83	10/10	10/10	54/55	49/55	5/5	5/5	9/10	10/10	53/55	45/55	5/5	5/5
Germany	0.10	1.24	1.72	2.56	10/10	10/10	55/55	54/55	4/5	5/5	10/10	10/10	52/55	46/55	4/5	4/5
Greece	0.17	1.69	2.75	4.58	10/10	9/10	55/55	53/55	5/5	5/5	9/10	8/10	51/55	49/55	5/5	5/5
Ireland	0.18	2.95	5.11	11.54	10/10	10/10	54/55	39/55	5/5	5/5	9/10	9/10	50/55	37/55	5/5	4/5
Italy	0.09	1.77	2.83	4.63	10/10	10/10	49/55	43/55	4/5	5/5	10/10	7/10	49/55	44/55	5/5	5/5
Netherlands	0.06	2.82	4.66	7.34	10/10	8/10	55/55	53/55	5/5	5/5	9/10	7/10	53/55	48/55	5/5	5/5
Portugal	0.40	2.22	3.08	4.41	10/10	9/10	54/55	54/55	5/5	5/5	10/10	8/10	53/55	47/55	5/5	4/5
Spain	0.18	1.17	1.54	2.09	10/10	9/10	53/55	46/55	5/5	5/5	10/10	8/10	49/55	39/55	5/5	5/5

Notes: [1]**Trace test** (Cogley and Sargent, 2005). The second column reports the trace of the prior variance-covariance matrix (Q). The third, fourth and fifth columns reports the 16%, 50% and 84% percentiles of the posterior of Q. If the trace of the prior variance-covariance matrix is significantly smaller than the posterior of Q, there is evidence of time-variation in the parameters. [2]**Kolmogorov-Smirnov test for equality of two distributions.** Columns 6-11 report the proportion of parameters for which the null hypothesis that they are from the same continuous distributions is rejected at the 5% significance level. For each country, the sample period is divided into three sub-periods: period 1, period 2 and period 3. The test is performed between period 1 and 2, and between period 2 and 3. The matrices that contain time-varying parameters, i.e. A, B and H, are considered. [3]***t*-test for equal means of two distributions.** Columns 12-17 report the proportion of parameters for which the null hypothesis that they are from distributions with equal means is rejected at the 5% significance level. For each country, the sample period is divided into three sub-periods: period 1, period 2 and period 3. The test is performed between period 1 and 2, and between period 2 and 3. The matrices that contain time-varying parameters, i.e. A, B and H, are considered.

Table 4: Has the impact effect of credit supply shocks changed over time?

	t-test[1]										Wilcoxon rank sum test[2]									
	y		π		l		clr		str		y		π		l		clr		str	
	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3
Austria	$\neq$	$=$	$\neq$	$\neq$	$=$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$=$	$=$	$=$	$\neq$	$=$	$\neq$	$\neq$
Belgium	$\neq$	$=$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$=$	$\neq$	$=$	$\neq$	$=$	$\neq$	$\neq$	$=$	$=$	$=$	$=$
Finland	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$=$
France	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$=$	$=$	$\neq$	$\neq$
Germany	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$=$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$=$	$=$	$\neq$	$\neq$
Greece	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$=$	$=$	$=$	$=$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$=$	$=$	$=$	$=$	$=$
Ireland	$\neq$	$=$	$\neq$	$=$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$=$	$\neq$	$=$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$
Italy	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$
Netherlands	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$=$	$\neq$	$\neq$	$=$	$=$	$\neq$	$\neq$
Portugal	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$=$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$=$
Spain	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$

Notes: [1]***t*-test for equal means of two distributions.** A $\neq$ ($=$) symbol indicates that the null hypothesis that the vectors are from distributions with equal means is (not) rejected at the 5% significance level. A green (red) colored cell indicate that the absolute value of the median has increased (decreased). For each country, three dates (1, 2 and 3) are considered: 2005Q1, 2009Q1 and 2013Q2 (2012Q4 for Greece). The test is performed between period 1 and 2, and between period 1 and 3. [2]**Wilcoxon rank sum test for equal medians of two distributions.** A $\neq$ ($=$) symbol indicates that the null hypothesis that they are from the same continuous distributions is (not) rejected at the 5% significance level. A green (red) colored cell indicate that the absolute value of the median has increased (decreased). For each country, three dates (1, 2 and 3) are considered: 2005Q1, 2009Q1 and 2013Q2 (2012Q4 for Greece). The test is performed between period 1 and 2, and between period 1 and 3.

Table 5: Has the variance decomposition of credit supply shocks at horizon = 20 changed over time?

	t-test[1]										Wilcoxon rank sum test[2]									
	y		π		l		clr		str		y		π		l		clr		str	
	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3	1-2	1-3
Austria	$=$	$\neq$	$=$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$=$	$\neq$	$\neq$	$=$	$=$	$=$	$\neq$	$\neq$	$=$	$\neq$	$=$
Belgium	$=$	$=$	$\neq$	$=$	$=$	$=$	$=$	$\neq$	$=$	$=$	$=$	$\neq$	$=$	$=$	$=$	$\neq$	$=$	$=$	$=$	$=$
Finland	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$=$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$=$	$\neq$	$=$
France	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$
Germany	$\neq$	$=$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$
Greece	$=$	$=$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$=$	$=$	$=$	$\neq$	$=$	$=$	$\neq$	$=$	$\neq$	$\neq$	$=$	$\neq$
Ireland	$=$	$\neq$	$\neq$	$=$	$=$	$\neq$	$=$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$=$	$\neq$	$=$	$\neq$	$=$	$\neq$
Italy	$=$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$=$	$=$	$\neq$	$\neq$	$\neq$	$\neq$
Netherlands	$\neq$	$=$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$=$	$\neq$	$=$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$=$
Portugal	$=$	$=$	$=$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$=$	$=$	$=$	$=$	$=$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$	$\neq$
Spain	$=$	$=$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$=$	$=$	$=$	$\neq$	$=$	$\neq$	$\neq$	$\neq$	$=$	$\neq$	$=$

Notes: [1]***t*-test for equal means of two distributions.** A $\neq$ ($=$) symbol indicates that the null hypothesis that the vectors are from distributions with equal means is (not) rejected at the 5% significance level. A green (red) colored cell indicate that the median has increased (decreased). For each country, three dates (1, 2 and 3) are considered: 2005Q1, 2009Q1 and 2013Q2 (2012Q4 for Greece). The test is performed between period 1 and 2, and between period 1 and 3. [2]**Wilcoxon rank sum test for equal medians of two distributions.** A $\neq$ ($=$) symbol indicates that the null hypothesis that they are from the same continuous distributions is (not) rejected at the 5% significance level. A green (red) colored cell indicate that the median has increased (decreased). For each country, three dates (1, 2 and 3) are considered: 2005Q1, 2009Q1 and 2013Q2 (2012Q4 for Greece). The test is performed between period 1 and 2, and between period 1 and 3.

Table 6: Average YoY GDP growth without credit supply shocks (TVP-VAR)

	Pre-crisis period		Bust period		Post-crisis period	
	Actual	Counterf.	Actual	Counterf.	Actual	Counterf.
Austria	3.49	3.05	−4.22	−2.75	1.53	1.47
Belgium	2.35	2.32	−5.82	−5.08	1.09	1.07
Finland	4.02	3.90	−7.32	−7.15	1.17	1.22
France	2.05	1.96	−3.57	−3.35	1.05	1.11
Germany	3.90	3.74	−6.22	−5.22	3.73	3.62
Greece	3.11	2.80	−4.64	−4.10	0.81	0.95
Ireland	6.46	6.06	−4.19	−1.88	0.69	2.31
Italy	1.57	1.46	−5.97	−4.33	−0.50	0.07
Netherlands	3.44	3.38	−4.14	−3.71	0.23	0.21
Portugal	1.83	1.56	−3.40	−2.73	−0.83	−0.77
Spain	3.52	3.43	−2.91	−2.24	−0.77	−0.59

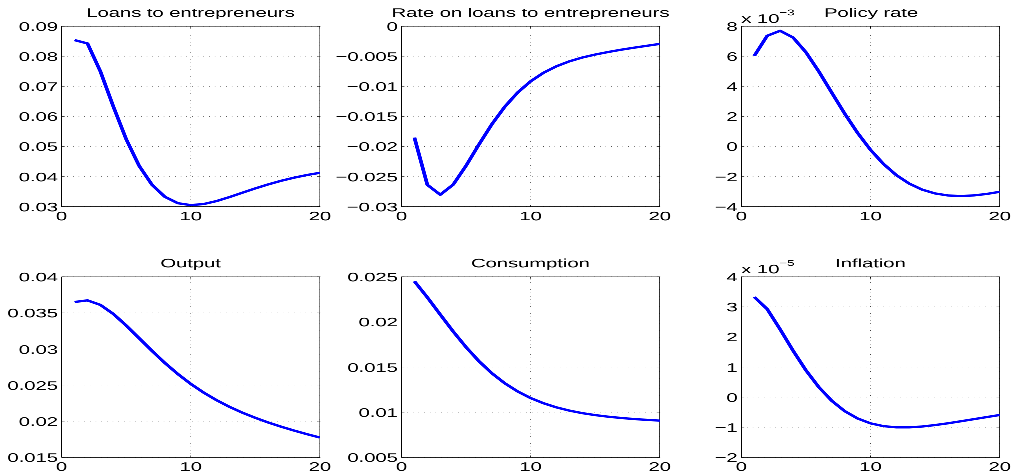
Notes: Green (red) cells indicate that the contribution of credit supply shocks to the average YoY GDP growth is positive (negative). , , indicate that the percentage difference between actual and counterfactual GDP growth is, respectively: between 0 and 10 percent; between 10 and 20 percent; larger than 20 percent. , , indicate that the percentage difference between actual and counterfactual GDP growth is, respectively: between 0 and 10 percent; between 10 and 20 percent; larger than 20 percent.

Table 7: Alternative sign restrictions

	Responses to an expansionary shock				
Shock	Real GDP	GDP deflator	Short-term rate	Lending rate	Credit
Aggregate supply	+	−	−	unrestricted	unrestricted
Aggregate demand	+	+	+	+	unrestricted
Monetary policy	+	+	−	−	unrestricted
Credit supply	+	+	+	−	+

Notes: Sign restrictions are imposed for one quarter on the impulse responses to expansionary shocks.

Figure 1: Impulse response functions to a shock to the loan rate of entrepreneurs (Gerali et al., 2010)

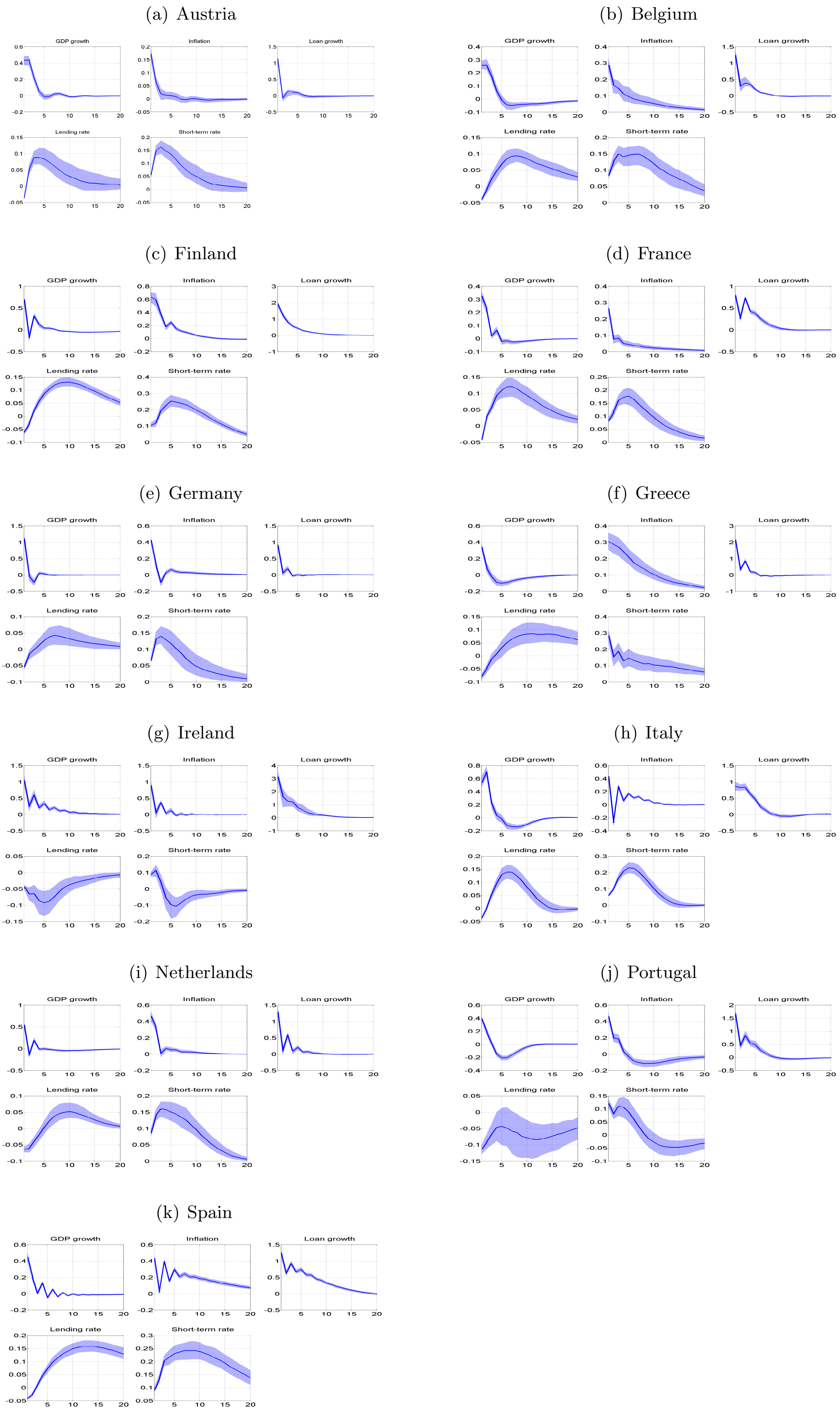


Notes: The rates are shown as absolute deviations from the steady-state, expressed in percentage points. The other variables are percentage deviations from the steady-state.

Figure 2: Stochastic volatility

Notes: The red line indicates the median of the VAR residual variances. The shaded area indicates the 16 and 84 percentiles.

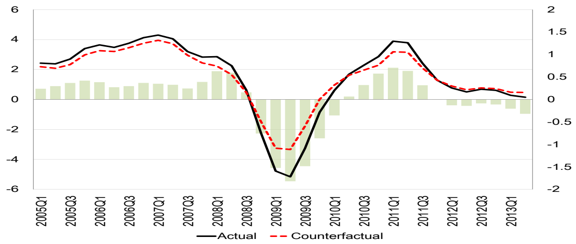
Figure 3: Impulse response functions to a credit supply shock



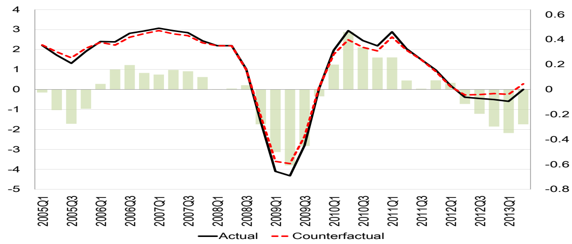
Notes: The blue line denotes the median of the impulse responses to a credit supply shock. The shaded area indicates the 16 and 84 percentiles. The impulse responses are normalized to an expansionary one-standard deviation shock and are expressed in percent terms.

Figure 4: Evolution of YoY real GDP growth in the absence of credit supply shocks

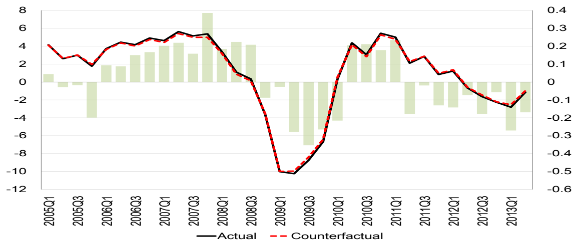
(a) Austria



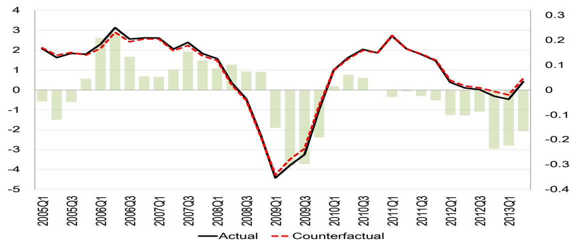
(b) Belgium



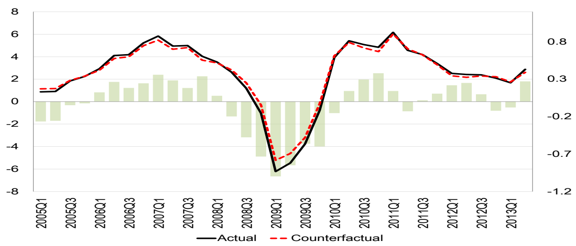
(c) Finland



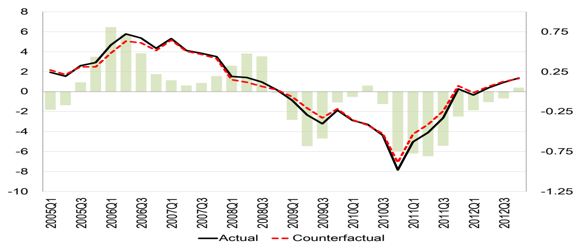
(d) France



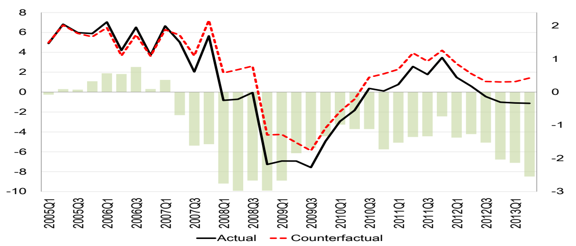
(e) Germany



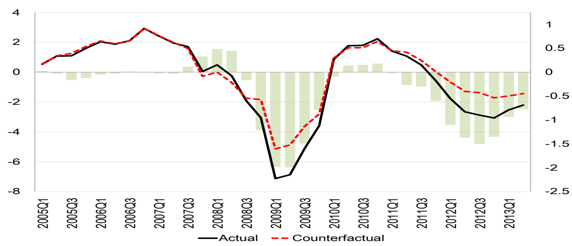
(f) Greece



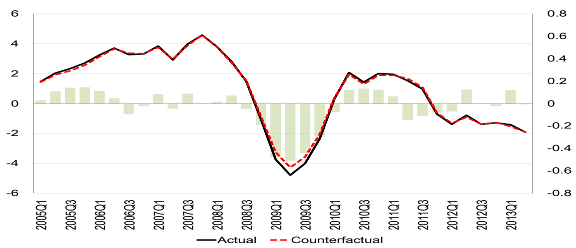
(g) Ireland



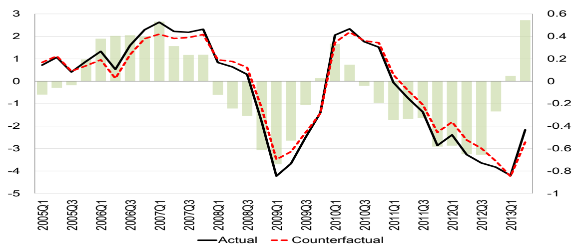
(h) Italy



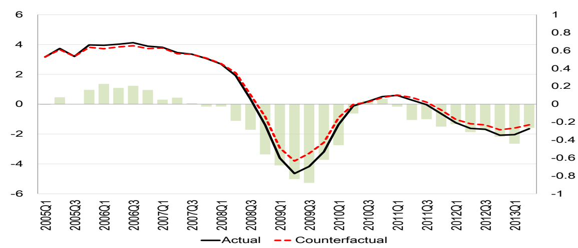
(i) Netherlands



(j) Portugal

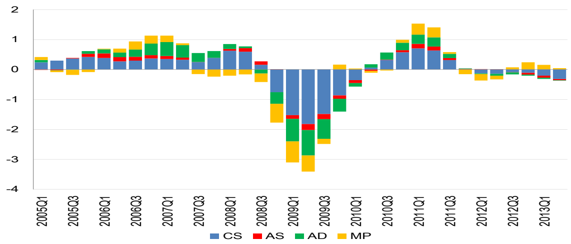


(k) Spain

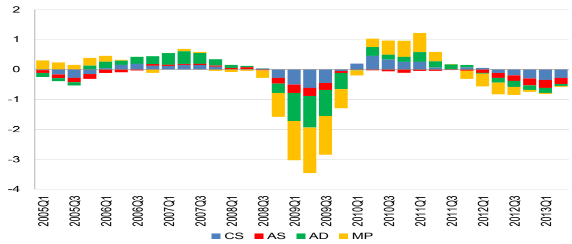


Notes: Actual and counterfactual evolution of real GDP growth (left axis). The green bars indicate the median of the contribution of credit supply shocks to GDP growth (right axis).

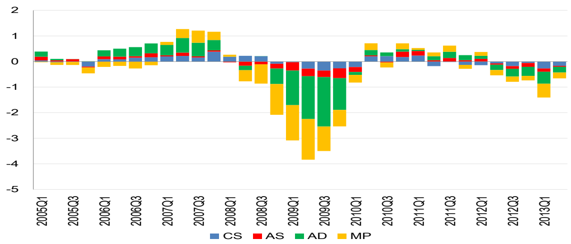
Figure 5: The contribution of the identified shocks to GDP growth



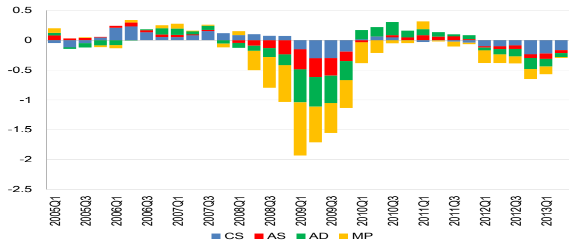
(a) Austria



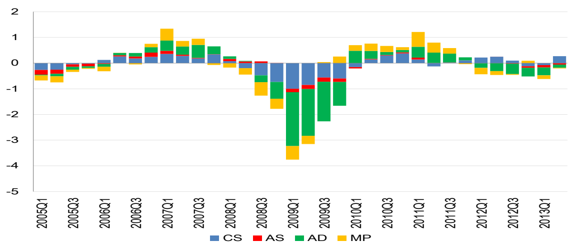
(b) Belgium



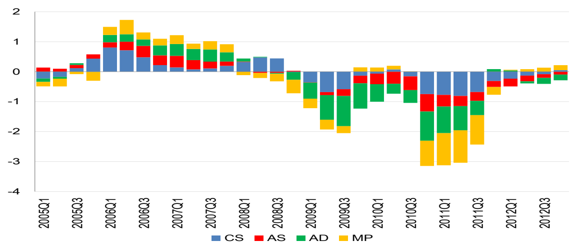
(c) Finland



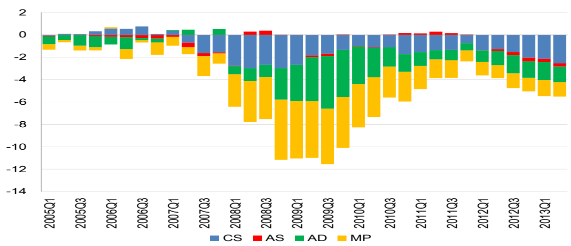
(d) France



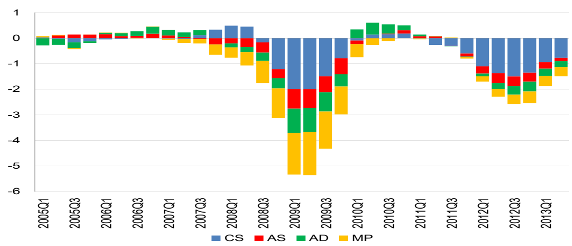
(e) Germany



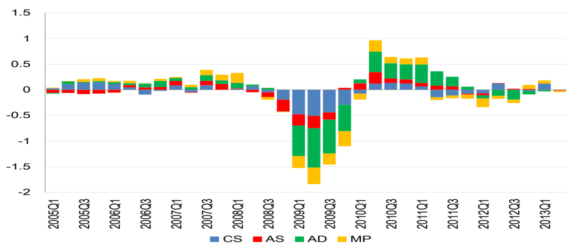
(f) Greece



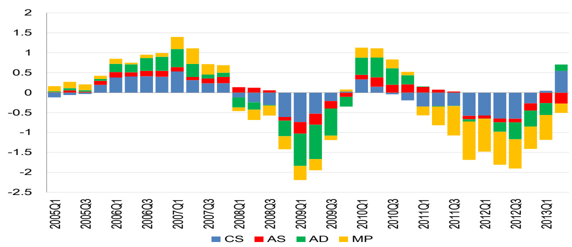
(g) Ireland



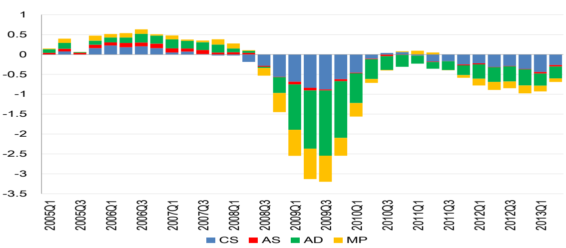
(h) Italy



(i) Netherlands



(j) Portugal

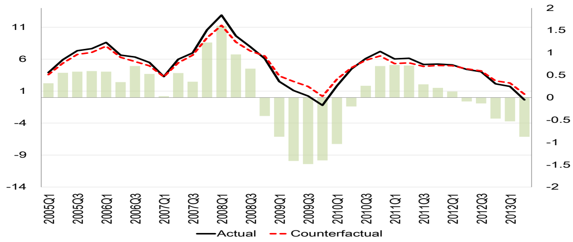


(k) Spain

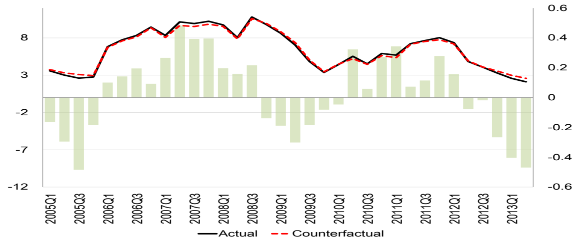
Notes: Contribution of the identified shocks to GDP growth (median). CS indicates Credit Supply shocks, AS Aggregate Supply shocks, AD Aggregate Demand shocks, MP Monetary Policy shocks.

Figure 6: Evolution of YoY credit volume growth in the absence of credit supply shocks

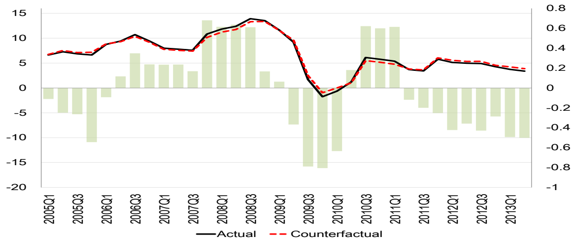
(a) Austria



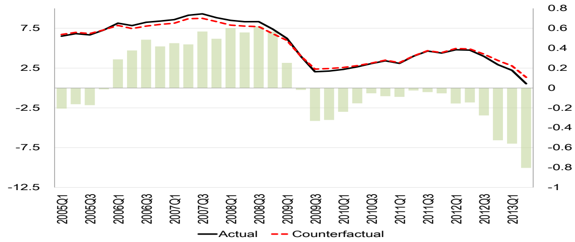
(b) Belgium



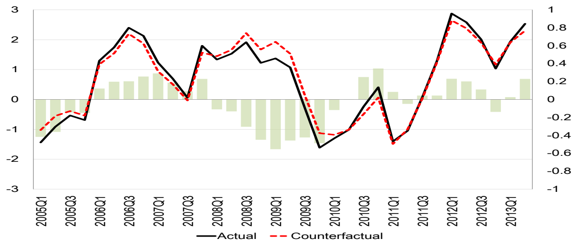
(c) Finland



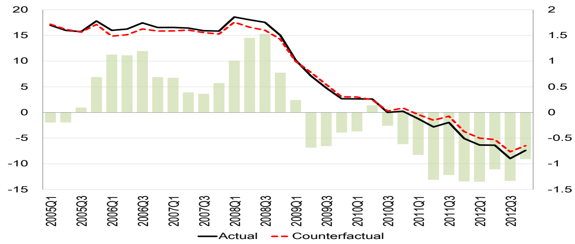
(d) France



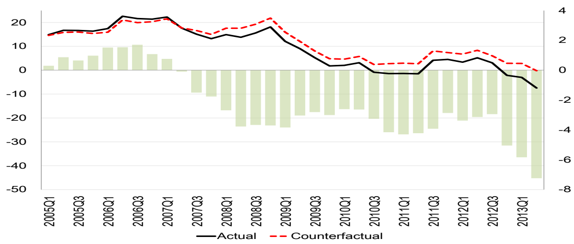
(e) Germany



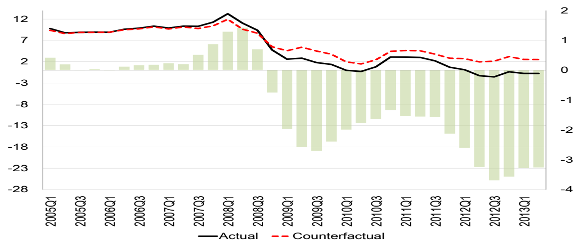
(f) Greece



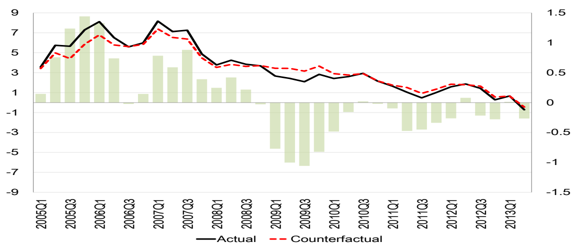
(g) Ireland



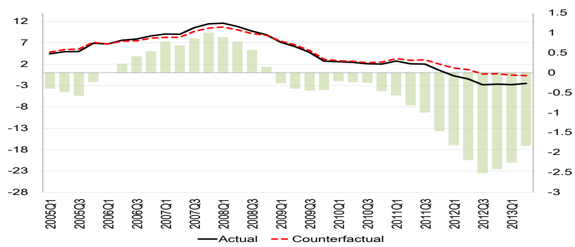
(h) Italy



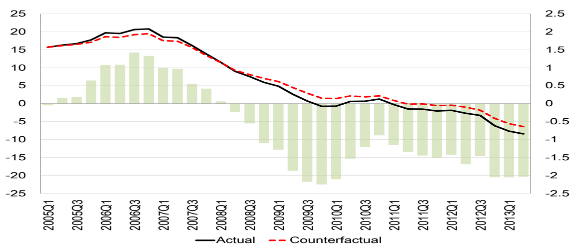
(i) Netherlands



(j) Portugal



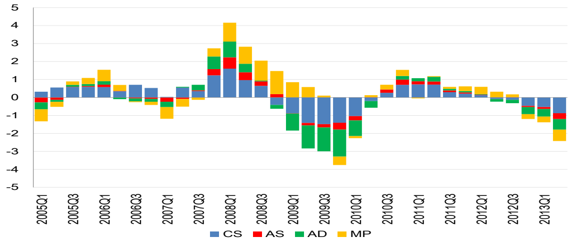
(k) Spain



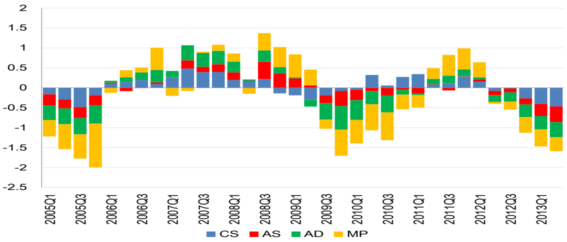
Notes: Actual and counterfactual evolution of credit volume growth (left axis). The green bars indicate the median of the contribution of credit supply shocks to credit volume growth (right axis).

Figure 7: The contribution of the identified shocks to credit volume growth

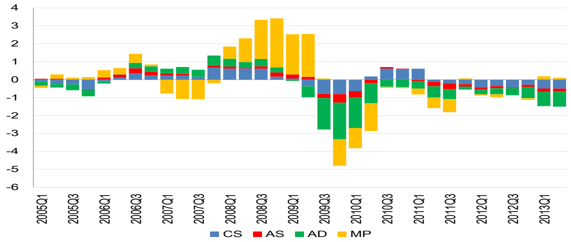
(a) Austria



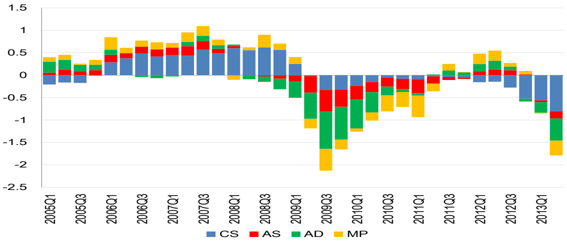
(b) Belgium



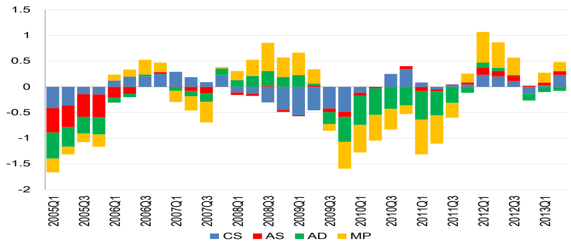
(c) Finland



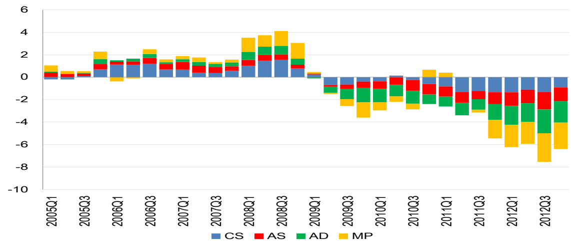
(d) France



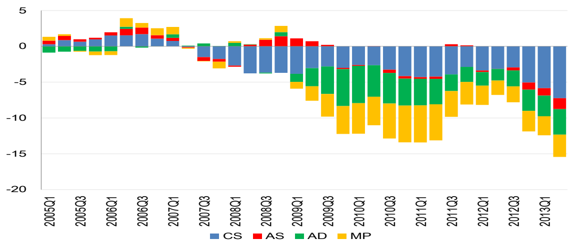
(e) Germany



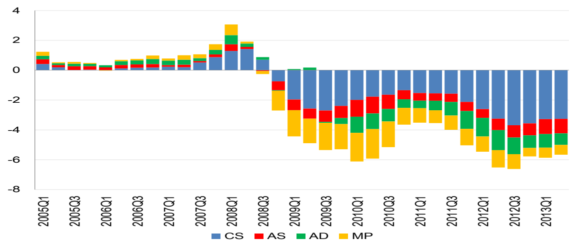
(f) Greece



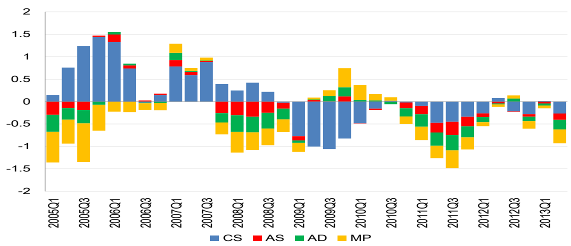
(g) Ireland



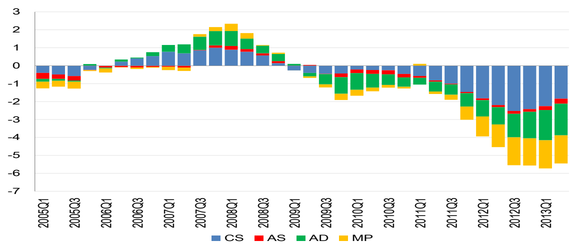
(h) Italy



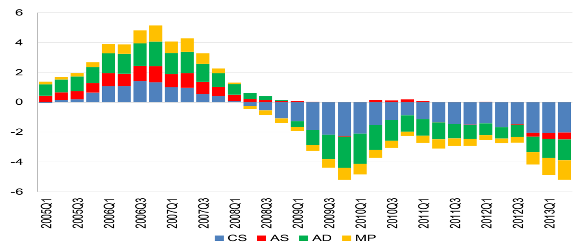
(i) Netherlands



(j) Portugal



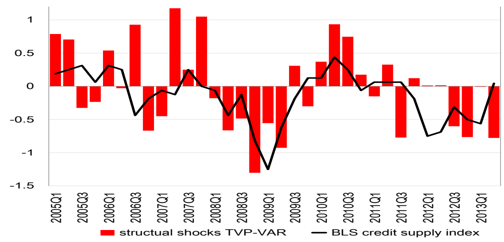
(k) Spain



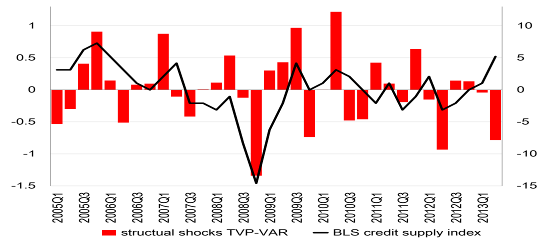
Notes: Contribution of the identified shocks to credit volume growth (median). CS indicates Credit Supply shocks, AS Aggregate Supply shocks, AD Aggregate Demand shocks, MP Monetary Policy shocks.

Figure 8: Evolution of structural credit supply shocks and BLS credit supply index

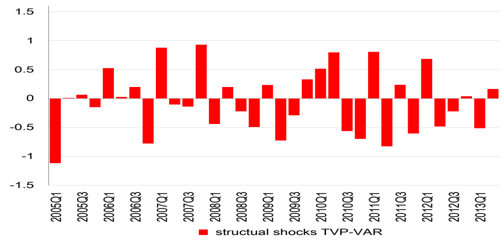
(a) Austria



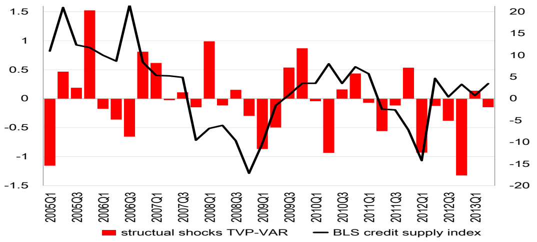
(b) Belgium



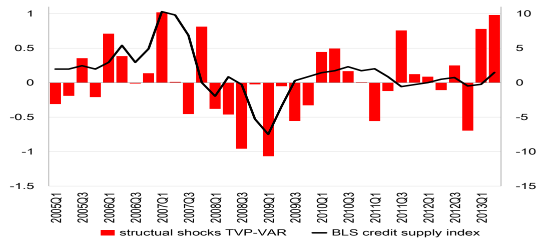
(c) Finland



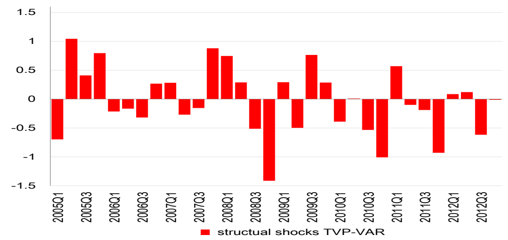
(d) France



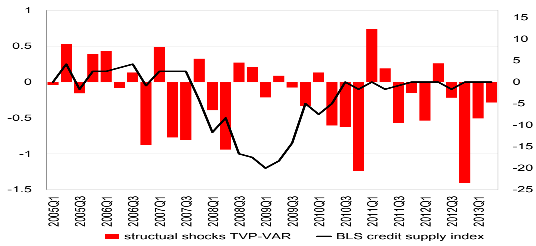
(e) Germany



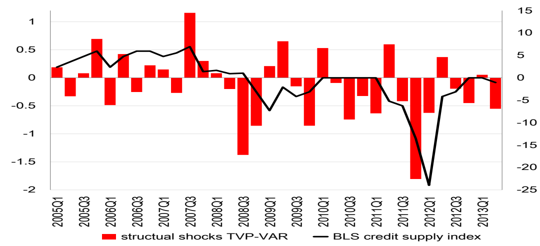
(f) Greece



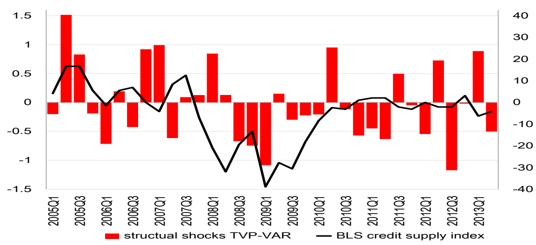
(g) Ireland



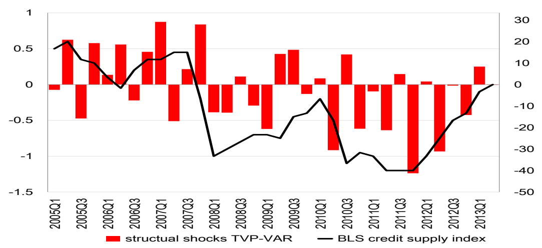
(h) Italy



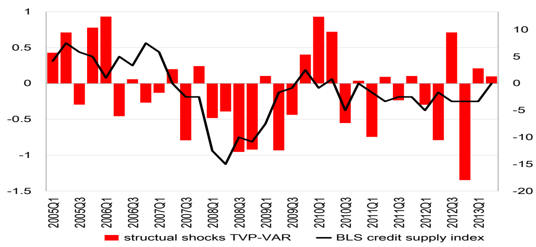
(i) Netherlands



(j) Portugal



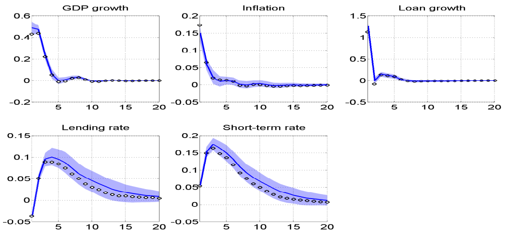
(k) Spain



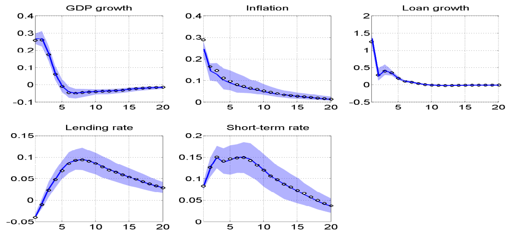
Notes: Comparison between the identified structural credit supply shocks (left axis, red bars) and the BLS credit supply indicator (right axis, black line).

Figure 9: Impulse response functions to a credit supply shock (model with alternative identification)

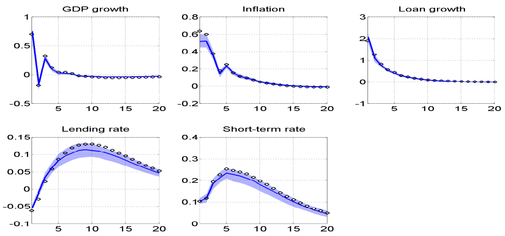
(a) Austria



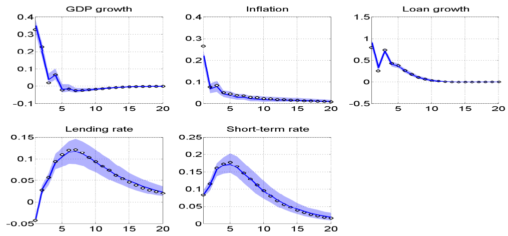
(b) Belgium



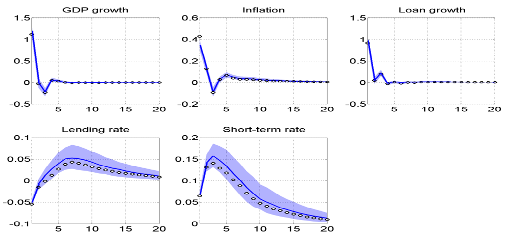
(c) Finland



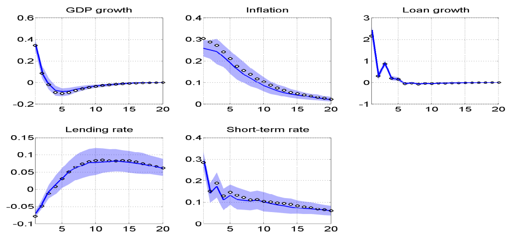
(d) France



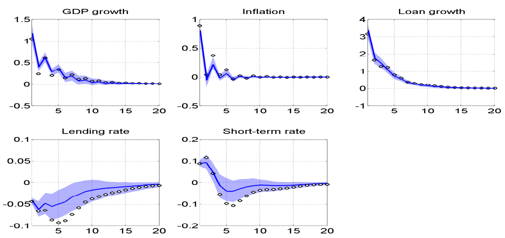
(e) Germany



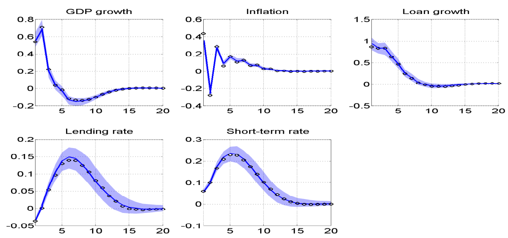
(f) Greece



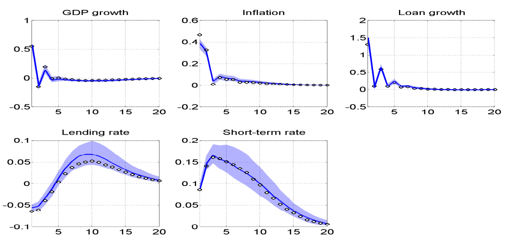
(g) Ireland



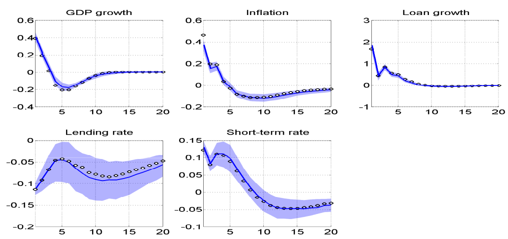
(h) Italy



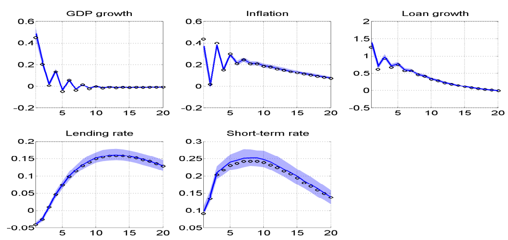
(i) Netherlands



(j) Portugal



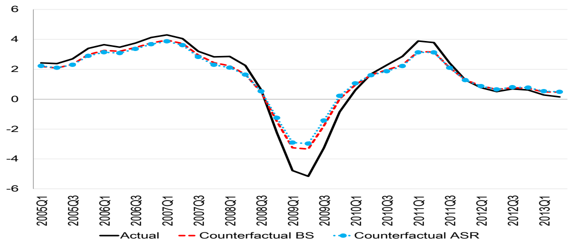
(k) Spain



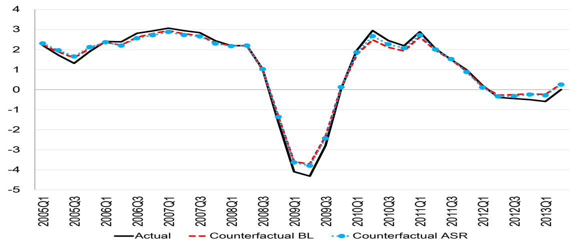
Notes: The blue line and blue areas denote, respectively, the median and confidence bands (16 and 84 percentiles) of the impulse responses to a credit supply shock using the alternative identification. The dotted line denotes the median of the baseline model. The impulse responses are normalized to an expansionary one-standard deviation shock and are expressed in percent terms.

Figure 10: Evolution of YoY real GDP growth in the absence of credit supply shocks (model with alternative identification)

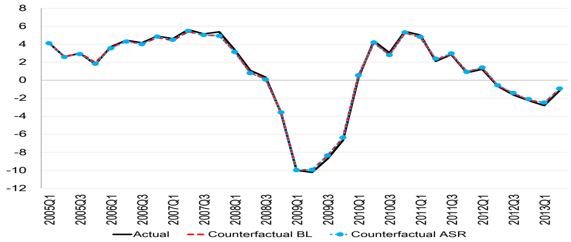
(a) Austria



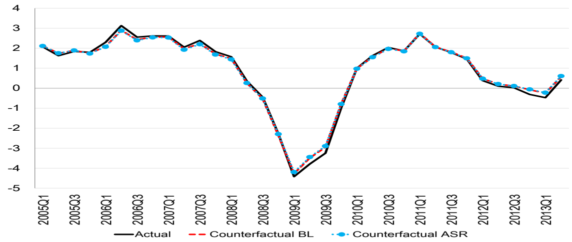
(b) Belgium



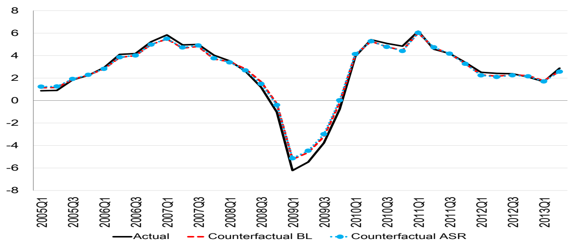
(c) Finland



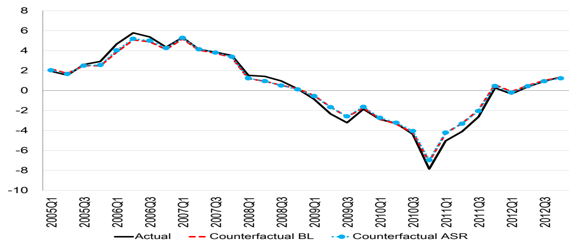
(d) France



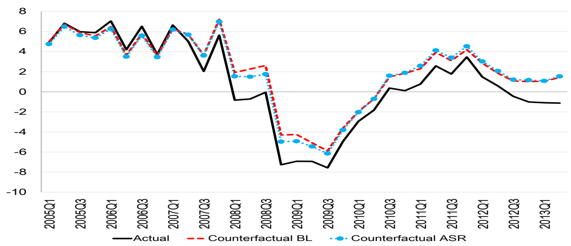
(e) Germany



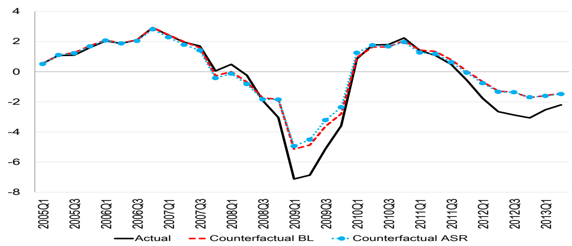
(f) Greece



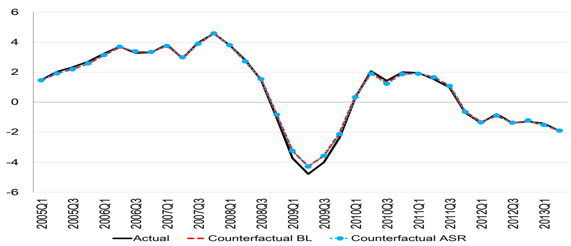
(g) Ireland



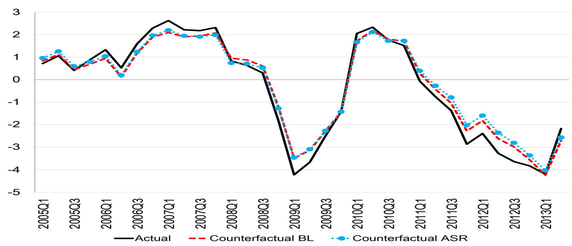
(h) Italy



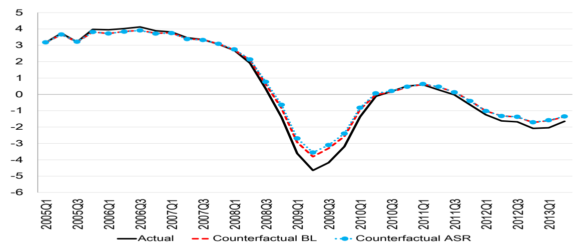
(i) Netherlands



(j) Portugal



(k) Spain



Notes: Actual and counterfactual evolution of real GDP growth. BL denotes the baseline model; ASR denotes the model with alternative sign restrictions.

Appendix A: Convergence Diagnostics

The Markov Chain Monte Carlo (MCMC) algorithm estimates 1575 hyperparameters (20 for S, 1540 for Q, 15 for W) and $70 \times t$ coefficients ($5 \times t$ for H, $10 \times t$ for A, and $55 \times t$ for B). In order to assess the convergence of the algorithm, we consider three convergence statistics for the estimated parameters:

- **Autocorrelation of the chain at lag = 20.** Low autocorrelation indicates that the draws are almost independent, and, therefore, the algorithm is efficient.

- **Inefficiency factors.** The inefficiency factor is computed as $1 + 2\sum_{k=1}^{\infty} \rho_k$, where ρ_k is the sample autocorrelation at lag k, and quantifies the relative efficiency loss in the computation of the variance from correlated versus independent samples (Chib, 2001). Its inverse is the relative numerical efficiency proposed by Geweke (1992), As in Primiceri (2005), we use a 4% tapered window for the estimation of the spectral density at frequency zero. Values of the inefficiency factors below or around 20 are considered as satisfactory.

- **Raftery and Lewis (1992) diagnostic.** It indicates the total number of runs required to achieve a certain precision. As in Primiceri (2005), we test the precision for the 0.025 and 0.0975 quantiles of marginal posteriors, and set the desired accuracy to 0.025 and the probability of achieving the required accuracy to 0.95. A satisfactory level of accuracy of the sampling algorithm is obtained if the required number of runs is lower than the number of iterations actually used.

The results of the three tests are reported in Table 8. They suggest that the convergence of the sample algorithm is achieved for all countries. In fact, for the hyperparameters and coefficients the 20th order sample autocorrelation is generally very low, the inefficiency factors are lower than 20 (with the exception of a few cases), and the Raftery and Lewis (1992) required runs are always far less than the total number of iterations used (15000).

Table 8: Convergence diagnostics

		20th order sample autocorrelation				Inefficiency factors				RL runs			
		Median	Mean	Min	Max	Median	Mean	Min	Max	Median	Mean[1]	Min	Max
Austria	S	0.008	0.026	−0.037	0.302	5.849	6.812	4.074	18.687	188	192	148	260
	Q	0.020	0.022	−0.121	0.239	5.610	5.862	1.561	14.647	283	311	148	2800
	W	−0.006	−0.013	−0.073	0.027	1.990	2.060	1.436	2.735	188	192	160	239
	H	−0.002	0.000	−0.092	0.142	1.246	1.307	0.494	3.646	161	170	143	350
	A	0.008	0.010	−0.101	0.190	1.394	1.697	0.551	11.407	160	165	143	462
	B	0.004	0.009	−0.103	0.236	2.918	3.435	0.606	13.118	173	185	143	1470
Belgium	S	0.002	0.010	−0.033	0.076	8.132	8.453	6.612	11.945	196	199	160	260
	Q	0.089	0.107	−0.120	0.444	10.233	10.404	2.881	21.295	309	376	160	2544
	W	−0.029	−0.020	−0.058	0.065	1.706	1.843	1.072	2.756	173	185	160	239
	H	0.000	0.002	−0.087	0.100	1.504	1.610	0.802	4.362	160	170	143	283
	A	0.007	0.007	−0.097	0.123	1.574	1.710	0.651	4.972	160	168	143	1184
	B	0.060	0.084	−0.100	0.395	5.713	6.792	0.893	20.340	188	220	143	4302
Finland	S	−0.014	−0.007	−0.059	0.055	7.911	8.096	3.484	11.472	173	178	148	239
	Q	0.054	0.067	−0.142	0.498	8.705	8.814	2.245	23.588	309	361	148	2318
	W	−0.007	0.000	−0.054	0.063	1.656	1.572	0.787	2.340	173	179	148	220
	H	−0.005	−0.004	−0.089	0.094	1.251	1.344	0.665	4.309	160	163	143	220
	A	−0.006	−0.006	−0.098	0.083	1.302	1.350	0.518	2.742	160	164	143	924
	B	0.058	0.072	−0.097	0.479	5.564	6.205	0.787	21.520	173	214	143	2660
France	S	−0.023	−0015	−0.052	0.077	7.119	7.425	1.658	11.251	184	182	148	220
	Q	0.071	0.078	−0.138	0.345	9.011	9.189	2.228	16.428	309	373	148	1400
	W	0.005	0.012	−0.036	0.073	1.489	1.511	1.190	1.856	173	173	148	220
	H	0.003	0.004	−0.086	0.102	1.228	1.278	0.531	3.459	160	162	143	239
	A	0.000	0.000	−0.092	0.108	1.294	1.431	0.606	4.477	160	160	143	239
	B	0.040	0.059	−0.095	0.367	4.773	5.811	0.671	17.349	173	199	143	1230
Germany	S	−0.006	0.002	−0.075	0.154	4.889	4.593	3.073	6.237	203	263	173	804
	Q	0.006	0.008	−0.152	0.176	4.756	4.891	2.040	10.155	309	326	148	1212
	W	−0.005	0.004	−0.040	0.052	1.731	1.902	0.987	3.347	188	180	148	220
	H	0.002	0.004	−0.081	0.122	1.192	1.236	0.607	2.342	160	167	143	283
	A	−0.002	−0.003	−0.094	0.097	1.312	1.398	0.535	3.749	160	165	143	800
	B	0.003	0.006	−0.101	0.188	2.320	2.632	0.626	8.405	173	175	143	816
Greece	S	0.006	−0.007	−0.055	0.028	3.298	3.171	1.536	4.161	173	179	148	220
	Q	0.004	0.004	−0.124	0.154	4.209	4.394	1.021	11.145	239	252	143	1200
	W	0.027	0.021	−0.033	0.074	1.844	2.009	0.989	3.444	188	190	148	239
	H	−0.004	−0.002	−0.066	0.098	1.184	1.233	0.518	2.946	160	166	143	239
	A	0.002	0.003	−0.083	0.114	1.194	1.209	0.544	2.548	160	161	143	220
	B	0.018	0.019	−0.094	0.144	3.575	3.887	0.910	11.215	173	196	143	1094

Table 8 (continued): Convergence diagnostics

		20th order sample autocorrelation				Inefficiency factors				RL runs			
		Median	Mean	Min	Max	Median	Mean	Min	Max	Median	Mean[1]	Min	Max
Ireland	S	−0.011	−0.006	−0.067	0.053	5.875	6.206	1.936	10.980	188	190	148	283
	Q	0.152	0.179	−0.127	0.641	11.929	12.684	1.766	28.096	346	466	148	5136
	W	0.000	0.005	−0.040	0.046	2.480	2.532	1.829	3.599	188	196	154	260
	H	0.003	0.005	−0.066	0.142	1.638	1.797	0.702	4.866	173	180	143	494
	A	0.006	0.007	−0.075	0.099	1.574	1.742	0.529	5.739	160	164	143	368
	B	0.104	0.165	−0.088	0.616	7.399	9.389	0.953	25.651	188	257	143	4315
Italy	S	−0.022	−0.019	−0.067	0.035	2.744	2.962	1.086	7.110	173	182	148	239
	Q	0.020	0.026	−0.178	0.380	6.230	6.667	1.783	19.151	309	348	144	2946
	W	−0.011	−0.006	−0.050	0.053	1.365	1.453	1.063	2.349	173	178	148	260
	H	0.000	0.000	−0.074	0.098	1.228	1.366	0.644	3.183	160	171	148	576
	A	−0.001	0.000	−0.091	0.081	1.370	1.571	0.431	3.779	160	165	148	260
	B	0.020	0.024	−0.090	0.200	2.951	3.303	1.033	10.902	173	182	143	933
Netherlands	S	−0.032	−0.008	−0.076	0.114	6.795	6.943	1.769	13.312	203	201	160	260
	Q	0.060	0.072	−0.153	0.401	8.927	9.354	2.341	19.140	354	419	148	2544
	W	0.000	0.008	−0.029	0.069	1.964	2.332	1.636	4.034	173	190	148	338
	H	0.003	0.005	−0.087	0.131	1.445	1.550	0.675	4.187	160	168	143	692
	A	0.000	−0.001	−0.103	0.095	1.542	1.611	0.759	4.304	160	164	143	513
	B	0.055	0.074	−0.082	0.389	5.044	5.861	0.851	19.695	173	200	96	1130
Portugal	S	−0.006	−0.004	−0.057	0.062	2.147	2.654	1.229	7.975	188	204	148	408
	Q	0.014	0.020	−0.126	0.255	3.810	4.295	0.742	14.865	239	249	148	838
	W	−0.005	−0.008	−0.080	0.039	1.369	1.540	0.945	2.502	173	179	148	239
	H	−0.001	0.000	−0.095	0.126	1.228	1.268	0.604	2.808	160	166	148	239
	A	−0.003	−0.004	−0.104	0.083	1.202	1.371	0.447	3.622	160	163	143	548
	B	0.025	0.035	−0.117	0.223	3.607	4.710	0.677	14.693	173	210	143	2325
Spain	S	−0.004	−0.007	−0.065	0.042	1.468	1.544	1.073	2.312	167	167	148	188
	Q	−0.006	−0.006	−0.110	0.086	1.870	1.929	0.578	4.125	188	203	143	824
	W	−0.010	−0.011	−0.071	0.040	1.462	1.444	0.822	1.987	173	183	160	239
	H	−0.005	−0.005	−0.078	0.103	0.973	1.014	0.500	1.879	160	160	143	220
	A	0.000	0.000	−0.091	0.079	0.979	1.011	0.517	1.926	160	160	143	239
	B	−0.007	−0.006	−0.102	0.113	1.190	1.219	0.478	2.833	160	160	143	306

Notes: [1] The mean of the RL runs is rounded to the closest integer.

Appendix B: The Data

To estimate the VAR we use quarterly data covering the period 1980:1-2013:2, with the exception of Greece (1985:1-2012:4), Ireland (1990:1-2013:2) and Italy (1995:1-2013:2).

- **Real GDP (y_t):** Nominal gross domestic product at market prices, seasonally adjusted (OECD Economic Outlook - Datastream mnemonic: (CC)OCFGPNB)[7] divided by the GDP deflator (see description below). For Germany the series has been adjusted for the break of 1990.

- **GDP Deflator (π_t):** GDP deflator index, seasonally adjusted (OECD Economic Outlook - (CC)OCFDGDE; For Germany: OECD Main Economic Indicators - Datastream mnemonic BDQNA057E).

- **Short-term interest rate (str_t):** Money market interest rates, 3-month rates (Eurostat Statistics Database - Codes: irt_st_q, irt_h_mr3_q).

- **Credit to the non-financial private sector (l_t):** Credit to non-financial private sector, lending sector: All sectors, adjusted for breaks (BIS Long series on credit to private non-financial sectors). The series have been seasonally adjusted using a 5-order Henderson filter.

- **Composite lending rate (clr_t):** Calculated as the weighted average of interest rates on lending to households for house purchase, quarterly average of monthly data, new business (ECB MFI Interest Rate Statistics - Code: MIR.M.(CC).B.A2C.A.R.A.2250.EUR.N) and lending to non-financial corporations, quarterly average of monthly data, new business (ECB MFI Interest Rate Statistics - Code: MIR.M.(CC).B.A2A.A.R.A.2240.EUR.N). For Greece these data are complemented with Eurostat data, and the lending rate to non-financial corporations is relative to loans up to and including EUR 1 million. The weights are based on outstanding amounts of loans to households for house purchase (ECB Balance Sheet Items - Code: BSI.Q.(CC).N.A.A22.A.1.U2.2250.Z01.E) and loans to non-financial corporations (ECB Balance Sheet Items - Code: BSI.Q.(CC).N.A.A20.A.1.U2.2240.Z01.E).

To construct our BLS credit supply index we collect data from the euro area Bank Lending Survey (BLS). Following Ciccarelli et al. (2010), we define changes in credit supply as factors related to bank balance sheet capacity and competition pressures. In particular, we consider factors A and B in the BLS questions Q2, Q9 and Q11. The index is calculated as the additive inverse of the average of the net percentage of banks answering A and B. For France, the weighted net percentage is used. For Austria and Ireland, the diffusion index is used. For Belgium, BLS data are collected from the National Bank of Belgium, and the index is calculated as the average of the net percentage of banks answering A and B. No data are available for Finland and Greece.

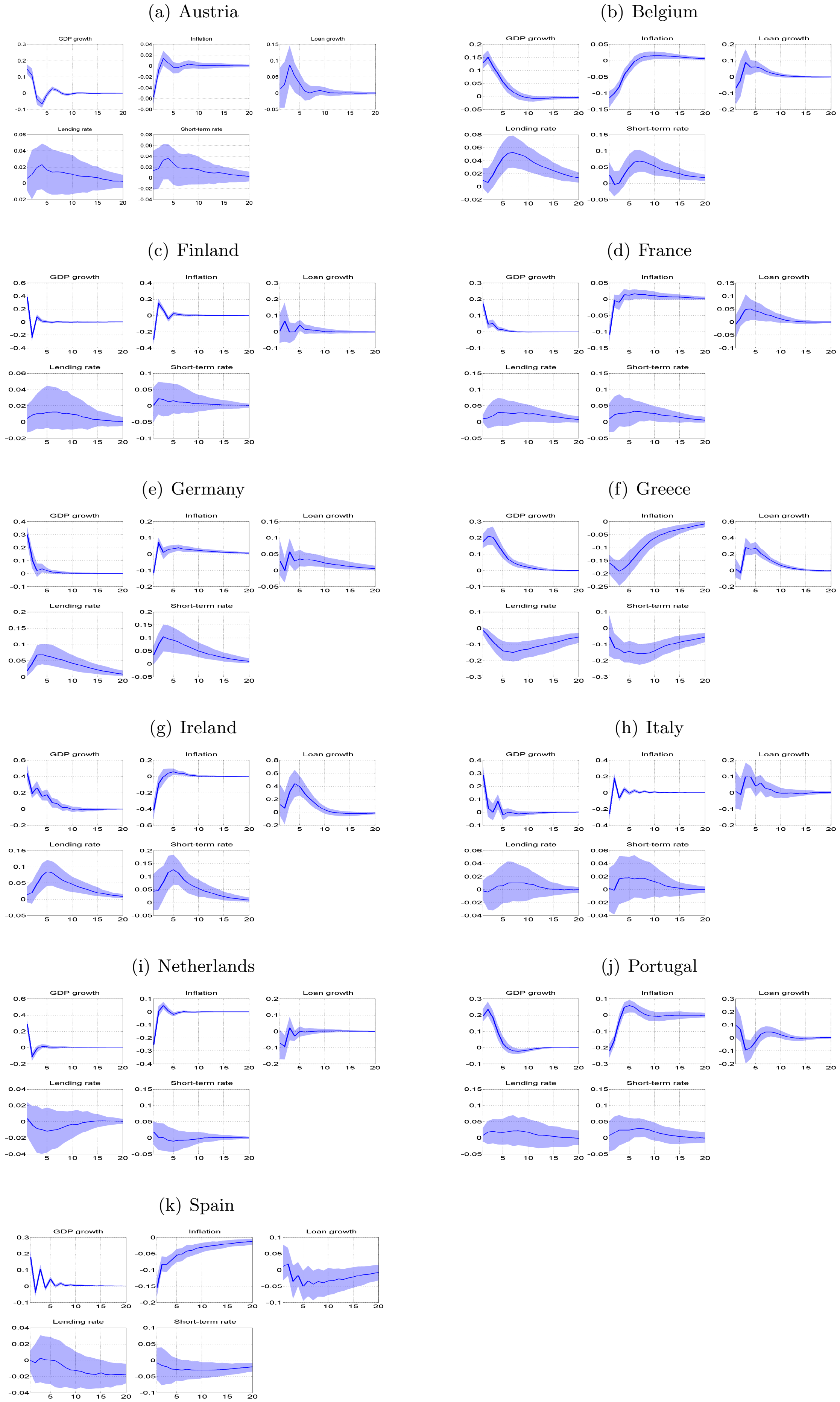
[7] CC stands for Country Code.

Appendix C

The impulse response functions of other shocks

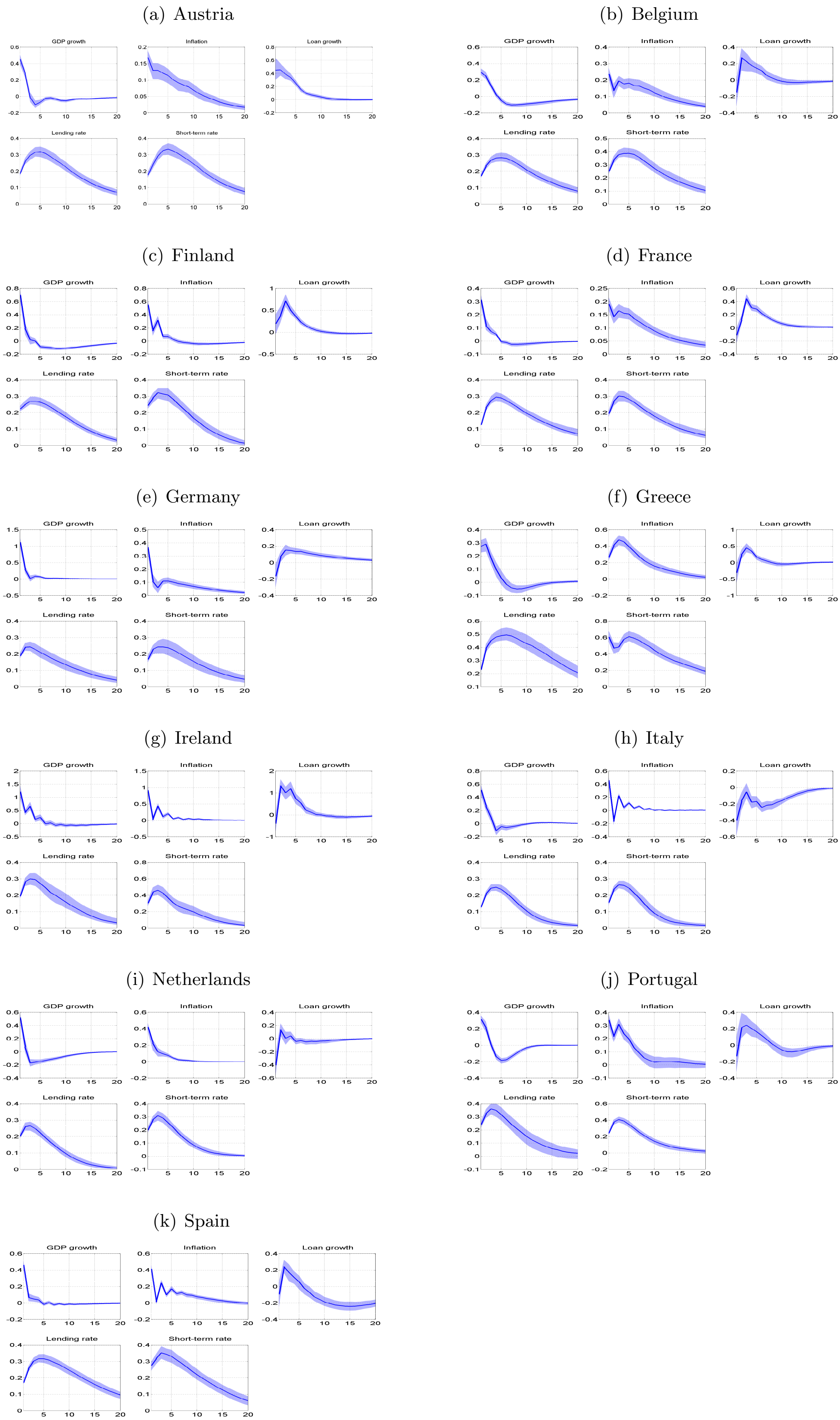
(baseline model)

Figure 11: Impulse response functions to an aggregate supply shock



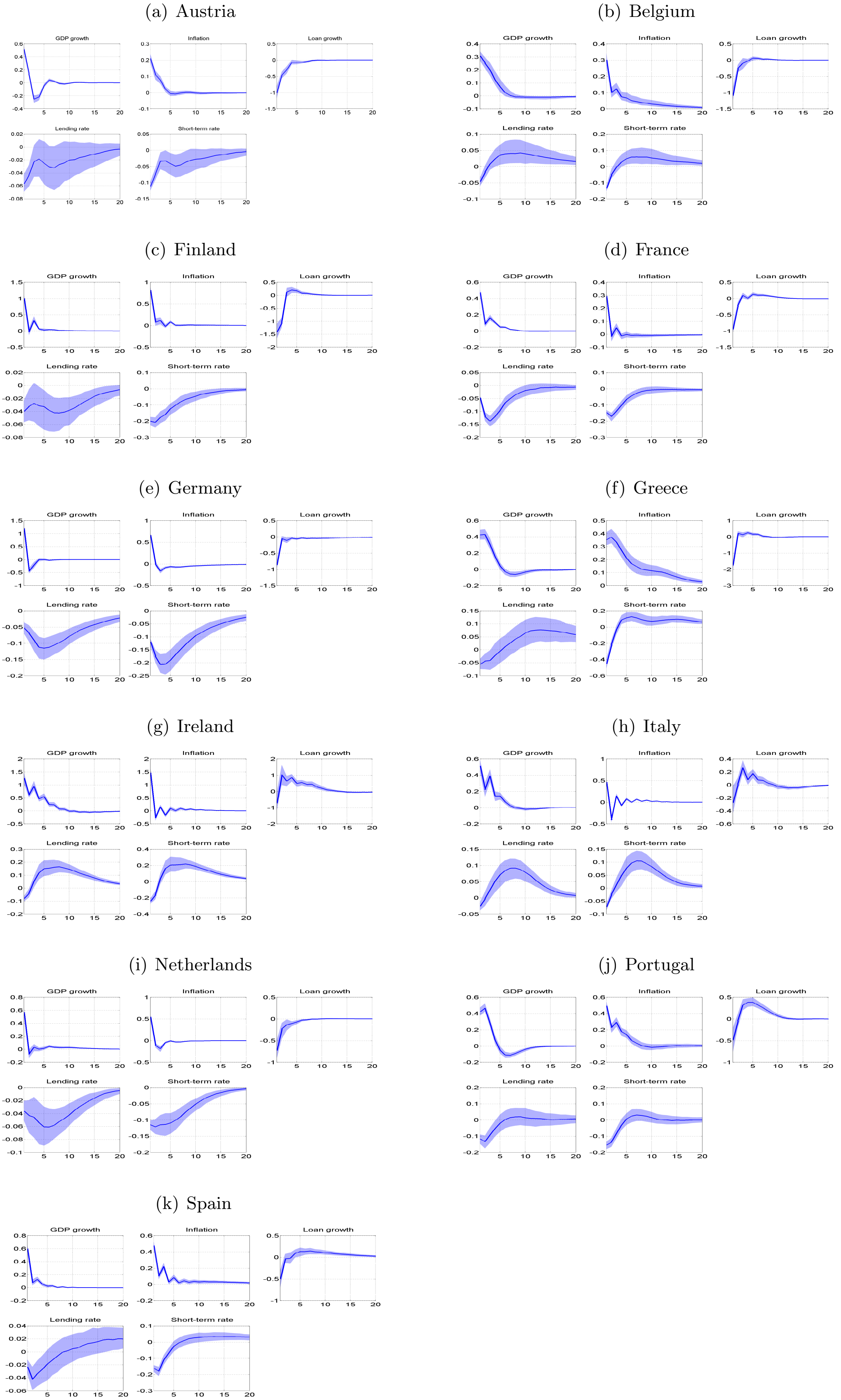
Notes: The blue line denotes the median of the impulse responses to an aggregate supply shocks. The shaded area indicates the 16 and 84 percentiles. The impulse responses are normalized to an expansionary one-standard deviation shock and are expressed in percent terms.

Figure 12: Impulse response functions to an aggregate demand shock



Notes: The blue line denotes the median of the impulse responses to an aggregate demand shock. The shaded area indicates the 16 and 84 percentiles. The impulse responses are normalized to an expansionary one-standard deviation shock and are expressed in percent terms.

Figure 13: Impulse response functions to a monetary policy shock

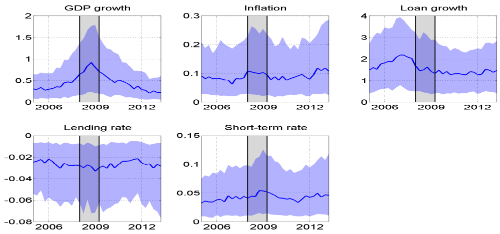


Notes: The blue line denotes the median of the impulse responses to a monetary policy shock. The shaded area indicates the 16 and 84 percentiles. The impulse responses are normalized to an expansionary one-standard deviation shock and are expressed in percent terms.

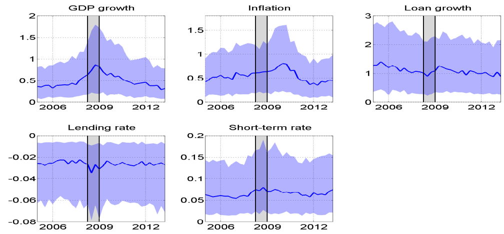
Appendix D
IRFs and FEVD over time

Figure 14: Impact effect of credit supply shocks over time

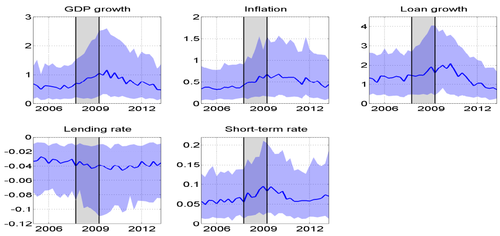
(a) Austria



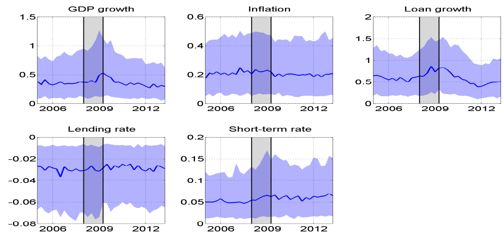
(b) Belgium



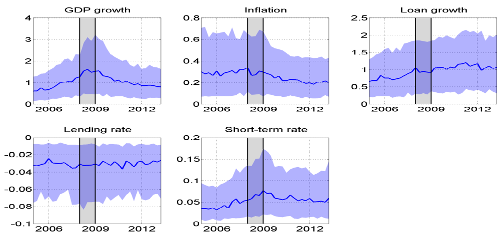
(c) Finland



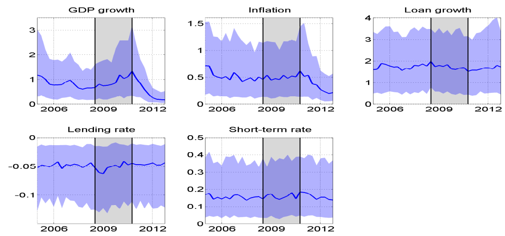
(d) France



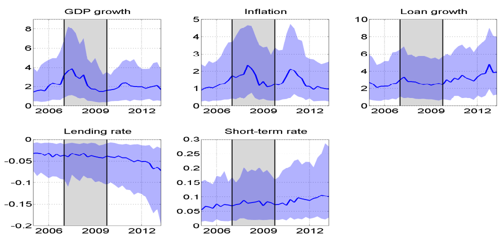
(e) Germany



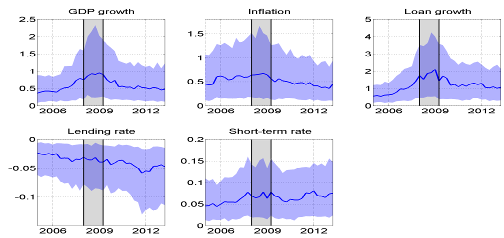
(f) Greece



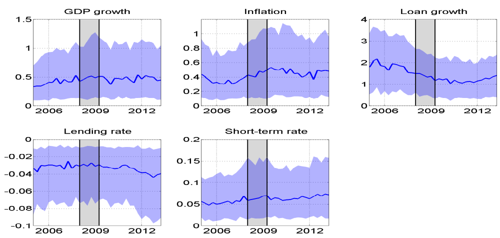
(g) Ireland



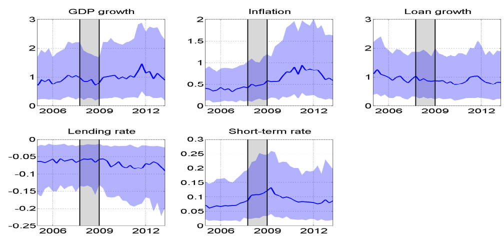
(h) Italy



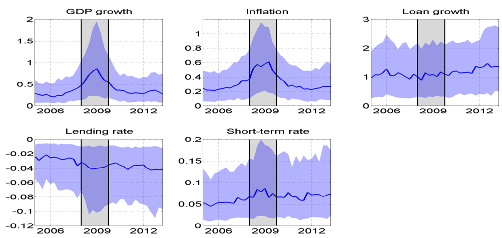
(i) Netherlands



(j) Portugal



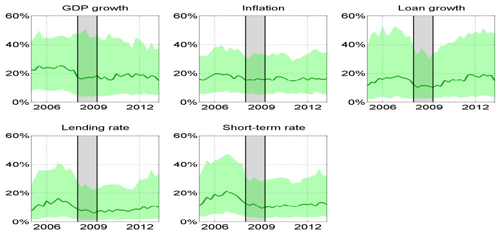
(k) Spain



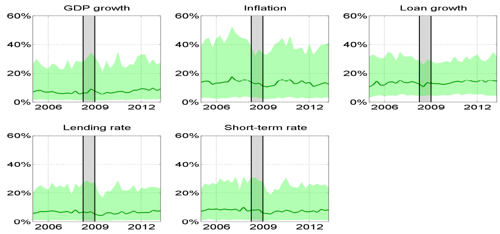
Notes: Evolution of the impulse responses to a credit supply shock at horizon = 1. The blue line indicates the median of the impulse responses. The shaded area indicates the 16 and 84 percentiles. The impulse responses are normalized to an expansionary one-standard deviation shock and are expressed in percent terms.

Figure 15: Variance decomposition of credit supply shocks over time (at horizon = 20)

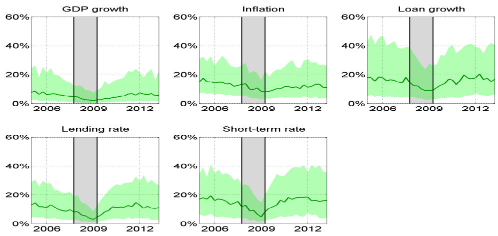
(a) Austria



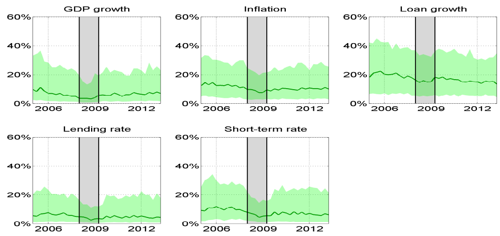
(b) Belgium



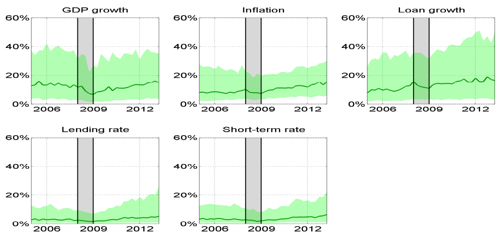
(c) Finland



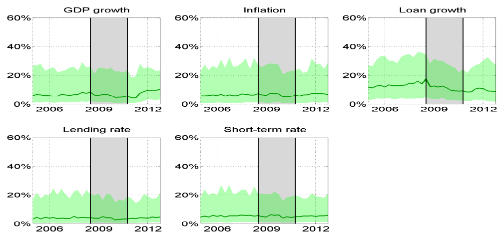
(d) France



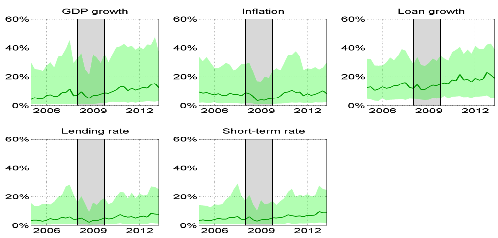
(e) Germany



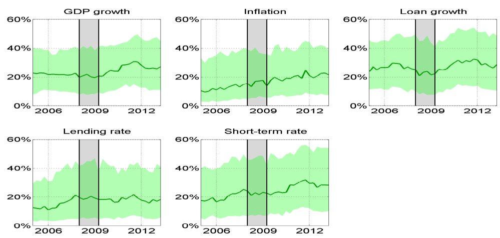
(f) Greece



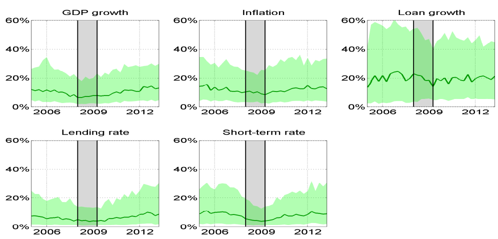
(g) Ireland



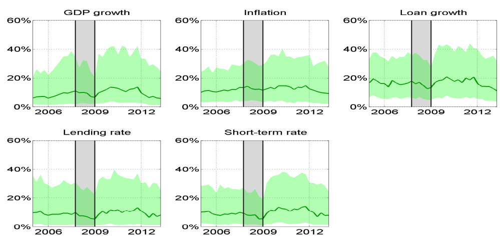
(h) Italy



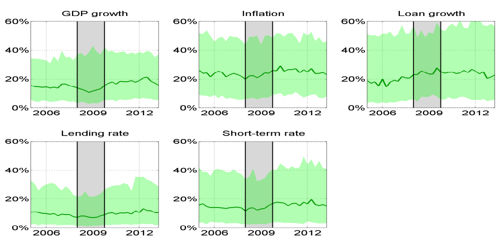
(i) Netherlands



(j) Portugal



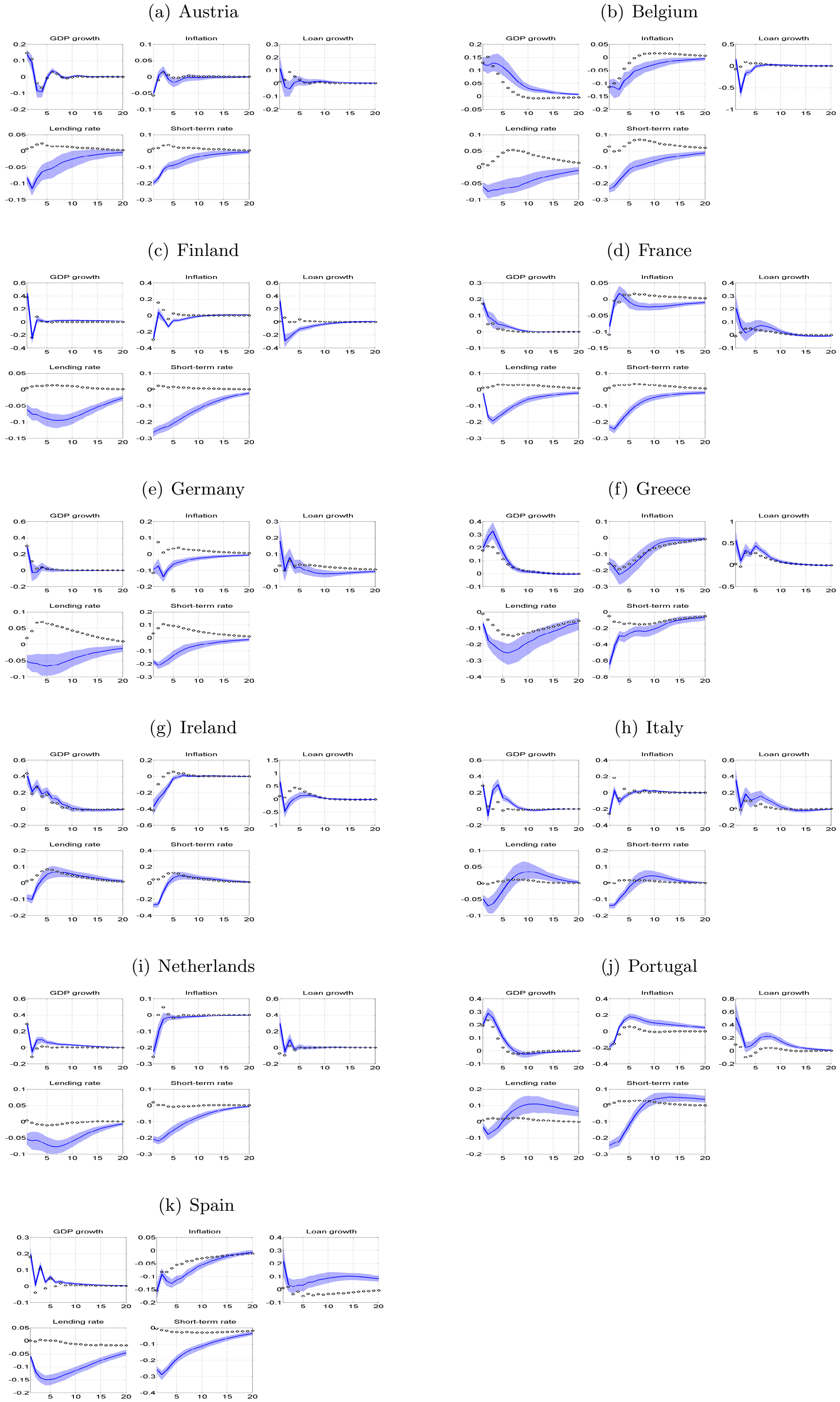
(k) Spain



Notes: Evolution of the variance decomposition of credit supply shocks at horizon = 20. The green line indicates the median of the variance decomposition. The shaded area indicates the 16 and 84 percentiles.

Appendix E
The impulse response functions of other shocks (alternative identification)

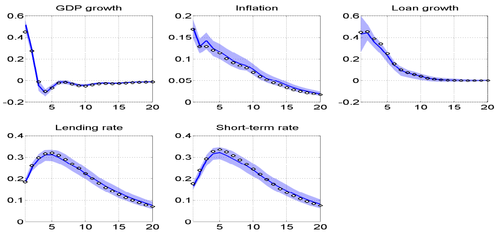
Figure 16: Impulse response functions to an aggregate supply shock



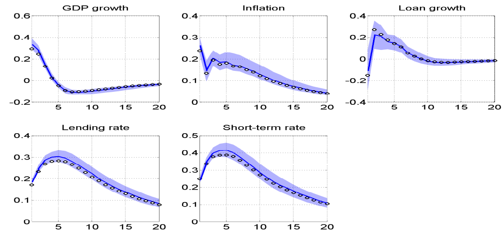
Notes: The blue line and blue areas denote, respectively, the median and confidence bands (16 and 84 percentiles) of the impulse responses to an aggregate supply shock using the alternative identification. The dotted line denotes the median of the baseline model. The impulse responses are normalized to an expansionary one-standard deviation shock and are expressed in percent terms.

Figure 17: Impulse response functions to an aggregate demand shock

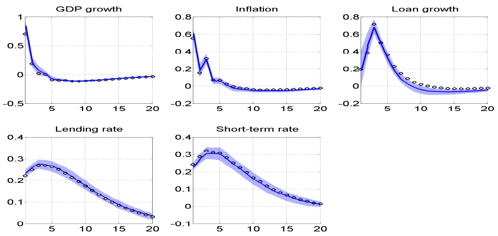
(a) Austria



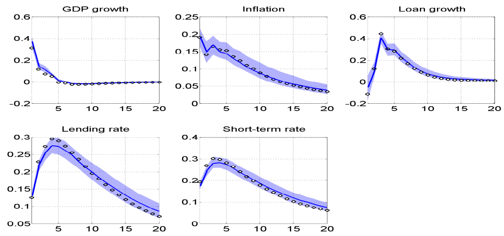
(b) Belgium



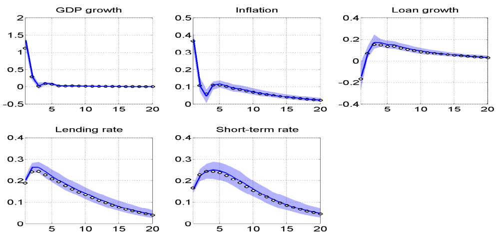
(c) Finland



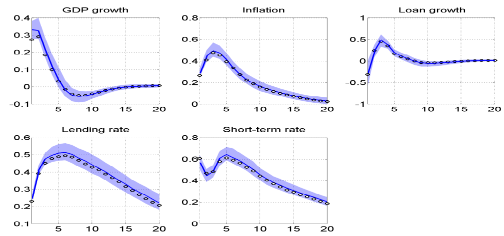
(d) France



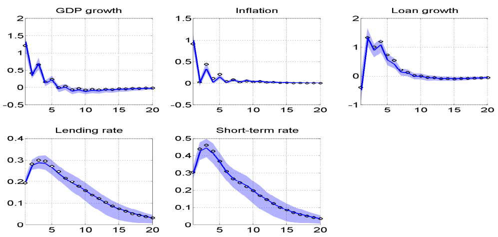
(e) Germany



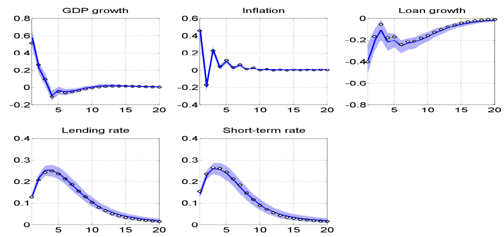
(f) Greece



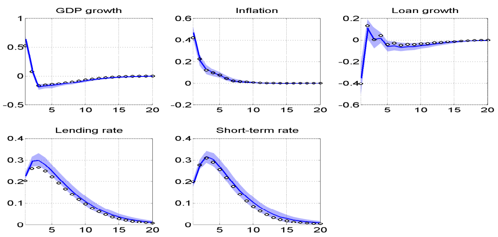
(g) Ireland



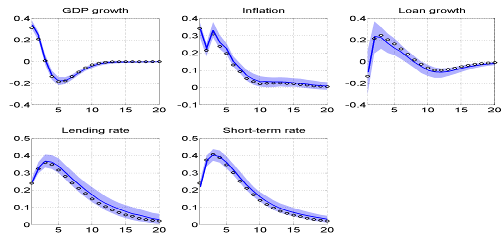
(h) Italy



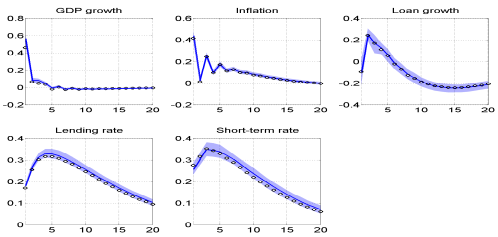
(i) Netherlands



(j) Portugal

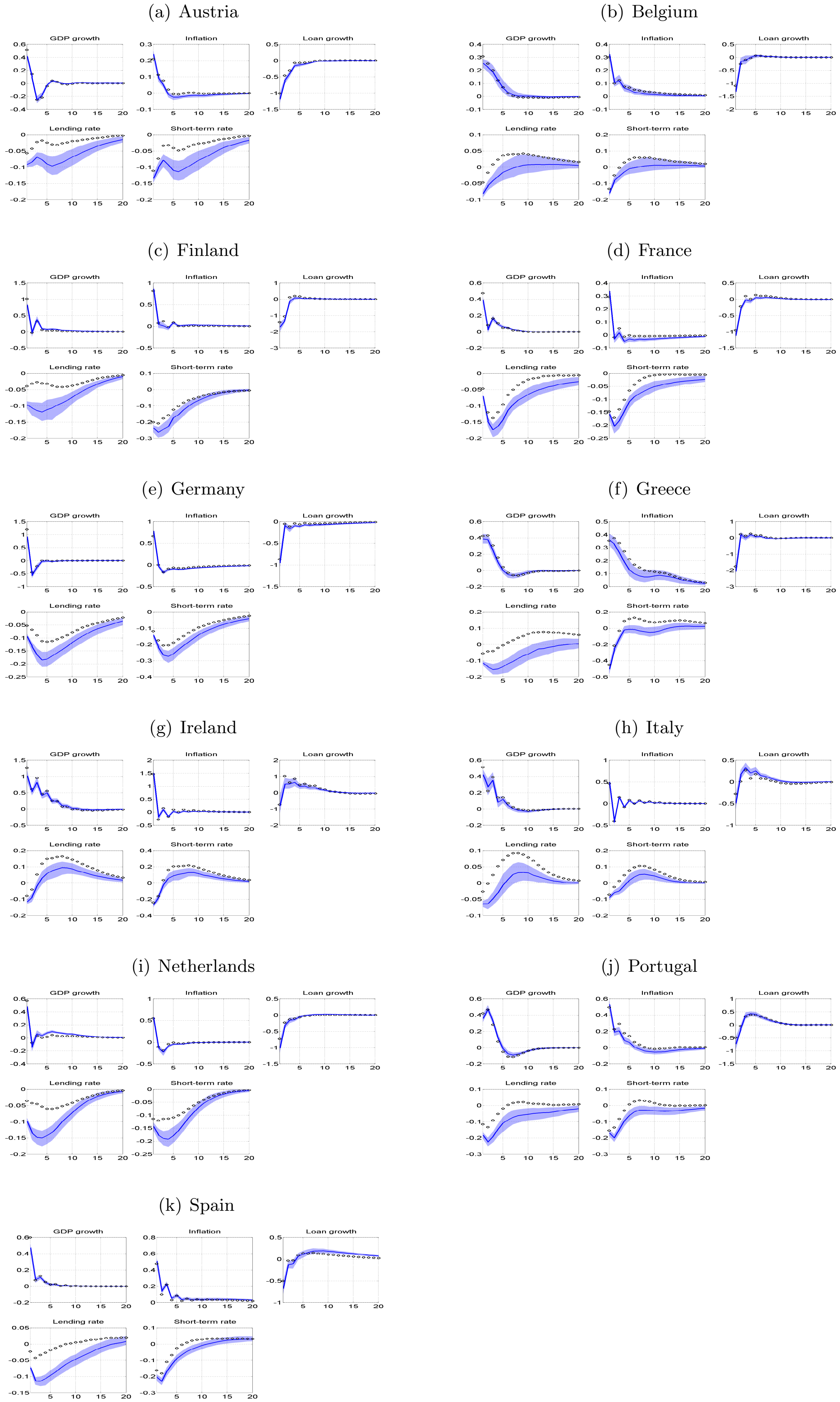


(k) Spain



Notes: The blue line and blue areas denote, respectively, the median and confidence bands (16 and 84 percentiles) of the impulse responses to an aggregate demand shock using the alternative identification. The dotted line denotes the median of the baseline model. The impulse responses are normalized to an expansionary one-standard deviation shock and are expressed in percent terms.

Figure 18: Impulse response functions to a monetary policy shock



Notes: The blue line and blue areas denote, respectively, the median and confidence bands (16 and 84 percentiles) of the impulse responses to a monetary policy shock using the alternative identification. The dotted line denotes the median of the baseline model. The impulse responses are normalized to an expansionary one-standard deviation shock and are expressed in percent terms.