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Monetary Policy and Macroprudential Policy: Rivals or Teammates?

Simona Malovaná and Jan Frait *

Abstract

This paper sheds some light on situations in which monetary and macroprudential policies may interact (and potentially get into conflict) and contributes to the discussion about the coordination of those policies. Using data for the Czech Republic and five euro area countries we show that monetary tightening has a negative impact on the credit-to-GDP ratio and the non-risk-weighted bank capital ratio (i.e. a positive impact on bank leverage), while these effects have strengthened considerably since mid-2011. This supports the view that accommodative monetary policy contributes to a build-up of financial vulnerabilities, i.e. it boosts the credit cycle. On the other hand, the effect of the higher bank capital ratio is associated with some degree of uncertainty. For these and other reasons, coordination of the two policies is necessary to avoid an undesirable policy mix preventing effective achievement of the main objectives in the two policy areas.

Abstrakt

Článek se zabývá situacemi, ve kterých může docházet k interakci (a potenciálnímu konfliktu) mezi měnovou a makroobezřetnostní politikou, a přispívá k diskuzi o jejich koordinaci. S využitím dat pro Českou republiku a pět zemí eurozóny ukazujeme, že měnové zpřísnění má negativní dopad na poměr úvěrů k HDP a rizikově nevážený kapitálový poměr bank (tj. pozitivní dopad na finanční páku bank), přičemž tento efekt výrazně zesiluje od poloviny roku 2011. Tyto výsledky podporují názor, že uvolněná měnová politika přispívá k budování finančních nerovnováh, resp. posouvá úvěrový cyklus směrem nahoru. Na druhé straně, efekt vyššího kapitálového poměru bank je spojen s určitým stupněm nejistoty. Nejen z těchto důvodů je koordinace obou politik nezbytná, aby bylo možné předejít jejich nežádoucí kombinaci, která by zabránila účinnému dosažení hlavních cílů obou politik.

JEL Codes: E52, E58, E61, G12, G18.
Keywords: Bayesian estimation, financial stability, macroprudential policy, monetary policy, time-varying panel VAR model.

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Nontechnical Summary

Following the economic and financial crisis of 2008–2013 it was accepted that price stability alone is not enough for maintaining financial stability. Consequently, macroprudential policy was instituted in addition to microprudential capital and liquidity regulations. The incorporation of macroprudential policy into the framework for the functioning of central banks has created new questions regarding the form of coordination that will secure the desired complementarity of macroprudential and monetary policy. The need for such coordination stems from the observation that monetary and macroprudential policy tools are not independent, as they affect both the monetary and credit conditions via their effect on credit growth. In some situations, the two can come into conflict because of the need for them to work in opposite directions, while in other situations it may be desirable for them to act in the same direction. This makes it necessary to analyse their interactions at different stages of the financial and business cycle and to coordinate them where appropriate.

This paper studies the extent to which monetary policy may contribute to a build-up of financial vulnerabilities and the effect of macroprudential capital regulation on the macroeconomy and the credit cycle. The analysis is conducted for the Czech Republic and five euro area countries (Germany, France, Italy, Austria and Belgium), allowing for international spillovers and dynamic interdependencies. Monetary policy is proxied by a monetary conditions index estimated using dynamic factor analysis. The non-risk-weighted bank capital ratio represents macroprudential capital regulation.

Our results show that monetary tightening has a negative impact on both the credit-to-GDP and capital ratios (i.e. a positive impact on bank leverage). Unconventional monetary policy contributes to the persistence of the responses, while the impact of conventional monetary policy has gradually been dying out in recent years. The significantly larger effect on bank credit than GDP supports the view that accommodative monetary policy contributes to a build-up of financial vulnerabilities, i.e. it boosts the credit cycle. Further, we argue that the stronger impact on banks' equity than overall assets results mainly from the effect on loan loss provisions, which are deductions from net interest income and consequently bank capital. Higher interest rates boost loan loss provisions through their impact on debt service costs and default probabilities. Moreover, the effect has strengthened in recent years, indicating that a prolonged period of unusually low rates contributes to higher sensitivity of some financial variables to changes in monetary policy.

The response to the higher bank capital ratio differs considerably across countries. We observe both a counter-cyclical and pro-cyclical impact with respect to credit-to-GDP and real GDP growth. This may be a result, for example, of the omission of non-bank lenders or a lack of observations of when macroprudential capital regulation was actively used. All in all, the effect is associated with uncertainty. Therefore, it is desirable to discuss and coordinate changes in the two policies to avoid potential surprises and conflicts. Information sharing between the two authorities and coordination of the two policies are necessary to avoid an inappropriate policy mix preventing effective achievement of the main objective of each authority.

1. Introduction

Monetary policy based on inflation targeting has proved to be effective in combating inflation since it was first introduced in the 1990s. Following the economic and financial crisis of 2008–2013, however, many monetary economists and central bankers have started to ask whether the main postulates of this form of monetary policy should be revised and supplemented. It has been accepted that price stability alone is not enough for maintaining financial stability. In this context, there has been renewed discussion about whether the central bank should take risks to financial stability into account in setting its monetary policy tools even when the current forecast does not indicate any risks to price stability over the monetary policy horizon (Woodford, 2012; Frait et al., 2011). A consensus on this issue has not been reached so far.

A consensus has emerged on the need to establish macroprudential policy as an essential addition to microprudential capital and liquidity regulations. At present, the monetary and macroprudential functions represent autonomous parts of central bank policies, with their own objectives and toolkits. The incorporation of macroprudential policy into the framework for the functioning of central banks has given rise to new questions regarding the form of coordination between macroprudential and monetary policy. The need for such coordination stems from the observation that monetary and macroprudential policy tools are not independent, as they affect both the monetary and credit conditions via their effect on credit growth. At the same time, the best economic outcomes can be expected if both policies are used in a complementary manner (Agénor et al., 2014). However, in some situations the desired complementarity can be achieved by the two working in opposite directions, while in other situations it may be desirable for them to act in the same direction. This makes it necessary to analyse their interactions at different stages of the financial and business cycle and to coordinate them where appropriate (Borio, 2014).

A fierce debate on the interaction of the two policies erupted in 2013 in response to the highly accommodative monetary policy being pursued by the Federal Reserve, the ECB and the Bank of England coupled with a strong recovery in property markets and some financial market segments. Some national authorities have already responded by setting non-zero counter-cyclical capital buffer rates or tightening their regulations on property exposures. The prevailing conclusion is that the potential undesirable effects of easy monetary policy on the risks to financial stability can be largely mitigated by applying suitable macroprudential tools sufficiently early. However, concerns have been voiced that more aggressive use of such tools could neutralise the effects of accommodative monetary policy and foster deflationary pressures.

From the conceptual perspective, there is no doubt about the need to coordinate the two policies in such a situation. From the practical point of view, however, it will be very difficult for the monetary authority to decide, especially if the two policies are conducted by different authorities. This is due to different probabilities of failure to fulfil the two main objectives (Adrian and Liang, 2014). It is highly likely that the macroeconomic forecast will imply failure to hit the inflation target in the short-to-medium run, whereas at any given moment in time systemic risk will have the potential to materialise in the medium-to-long run only. The monetary authority's natural response will thus be to prioritise the inflation target. Preference is unlikely to be given to the financial stability objective, as this would require a consensus that the risk of a future financial crisis has exceeded a critical level. No such consensus was reached before the recent financial crisis. On the contrary, the rising systemic risks were downplayed. It is the difference between expected risks and merely potential vulnerabilities that makes the two types of policy often very difficult to coordinate in practice. A better understanding of the interactions between economic and financial cycles and between monetary and macroprudential policies is therefore needed.

This paper studies the extent to which monetary policy may contribute to a build-up of financial vulnerabilities and the effect of macroprudential capital regulation on the macroeconomy and the credit cycle. The analysis is conducted for the Czech Republic and five euro area countries connected with the Czech economy through trade and financial links (Germany, France, Italy, Austria and Belgium). This collection of countries allows us to study possible spillover from abroad to the Czech economy, capture interdependencies and compare the dynamics of the Czech and closely related economies. The objective here is to provide a flexible framework capable of estimating dynamic interdependencies and measuring changes in the effect of monetary and macroprudential policies over time. For this purpose, we employ a time-varying parameter panel VAR model.

We have identified a few patterns and reached a few conclusions. First, monetary tightening has a negative impact on both the credit-to-GDP and capital ratios (i.e. a positive impact on bank leverage). This result is robust to model specification (factor selection, time variation and variable ordering) and to alternative monetary policy proxies. Unconventional monetary policy contributes to the persistence of the responses, while the impact of conventional monetary policy has gradually been dying out in recent years. The fall in the credit-to-GDP ratio indicates that monetary tightening leads to a significantly larger drop in bank credit than GDP. The decrease in the capital ratio reflects a stronger impact on banks' equity than overall assets. Second, the response to the higher bank capital ratio differs considerably across countries. We observe both a counter-cyclical and pro-cyclical impact with respect to credit-to-GDP and real GDP growth. This may be a result, for example, of the omission of non-bank lenders or a lack of observations of when macroprudential capital regulation was actively used. All in all, the effect is associated with uncertainty.

The remainder of this paper is organised as follows. The next section presents the empirical methodology. Section 3 describes the data, prior specification and alternative monetary policy proxy. Section 4 deals with model selection and reports our main findings. Section 5 discusses the results in a broader context and possible policy issues. In section 6 we provide a robustness and sensitivity analysis to different model specifications. Section 7 concludes.

2. Empirical Methodology

The main purpose of this paper is to analyse the dynamics of particular Czech variables (related to monetary policy and financial stability), allowing for international spillovers, and to compare them with the dynamics of closely related countries (through trade and financial links). The Czech Republic ranks among the most open economies in Europe,[1] with a banking sector dominated by foreign capital, particularly from EU countries.[2] Failure to recognise spillovers and transmission channels between countries may lead to the formulation of inappropriate policies. Panel VARs are a suitable framework for capturing these characteristics, as they allow for modelling of dynamic interdependencies and cross-sectional heterogeneities.

The model parameters are allowed to be time-varying, reflecting our expectations of increased sensitivity and higher responsiveness to monetary policy and financial shocks in recent years (in a

[1] According to the World Bank openness index ((exports+imports)/GDP), the Czech Republic ranked 11th in the world and 5th in Europe in 2015.

[2] At the end of 2015, foreign owners directly or indirectly controlled 91.8% of the assets of the Czech banking sector. Foreign owners from EU Member States accounted for 88.9% of assets. This refers to the share of the banking sector's assets controlled by foreign entities (i.e. foreign owners holding directly or indirectly at least 50% of the bank's shares) in the total assets of the banking sector.

prolonged period of very accommodative monetary conditions).[3] Rather than a discrete break, we expect the effect to increase smoothly over time. Even in the case of a discrete shift, the time-varying model is able to pick up breaks relatively quickly, as suggested by Baumeister and Peersman (2013).

2.1 Panel VAR with Time-varying Parameters

Given the aforementioned considerations, we employ a time-varying parameter multi-country panel VAR model with G endogenous variables and N countries of the form

$$y_{it} = A_{it}(L)Y_{t-1} + e_{it} \tag{1}$$

where y_{it} is a $G \times 1$ vector of dependent variables for each country i at time t; $i = 1,...,N$; $t = 1,...,T$. $Y_t = (y'_{1t}, y'_{2t}, ..., y'_{Nt})'$ is an $NG \times 1$ vector of endogenous variables, A_{it} is a $G \times G$ matrix of coefficients and $e_{it} \sim N(0,\Omega)$ is a vector of random errors where Ω is a full $NG \times NG$ covariance matrix.

Let $X_t = I_{NG} \otimes \mathbf{X_t'}$; $\mathbf{X_t} = (I, Y'_{t-1}, Y'_{t-2}, ..., Y'_{t-p})'$ with p lags of endogenous variables, let $\alpha_t = (\alpha'_{1t}, ..., \alpha'_{Nt})'$, where α_{it} are $Gk \times 1$ vectors of G rows of the matrix A_{it}, and let E_t be a $NG \times 1$ vector. We can then rewrite (1) as

$$Y_t = X_t \alpha_t + E_t \tag{2}$$

Since α_t varies with cross-sectional units and time, the number of coefficients for estimation rapidly increases with N, G and T. In particular, we have $k = NGp$ coefficients in each equation and NGk in total to be estimated in each time period. This prevents any meaningful unconstrained estimation. Canova and Ciccarelli (2009) suggested reformulating (2) into a parsimonious SUR model where the regressors are the averages of the VAR right-hand side variables and their lags. Assume that α_t depends on a much lower dimension vector θ_t (i.e. is factorised) as follows

$$\alpha_t = \sum_f \Xi_f \theta_{ft} + u_t \tag{3}$$

where θ_{ft} are $s \times 1$ low-dimensional vectors (factors) with $s << NGk$, Ξ_f are $K \times s$ matrices of zeros and ones,[4] and $u_t \sim N(0,\Psi)$ is a vector of random errors; $\Psi = \Omega \otimes (\sigma^2 I_K)$. The factors capture components in the coefficient vector which are common in some way, for example, across units, variables, lags or groups thereof, while u_t captures all the unmodelled features. We can then rewrite (2) as

$$\begin{aligned} Y_t &= X_t(\Xi\theta_t + u_t) + E_t \\ &= \mathscr{X}_t \theta_t + \gamma_t \qquad\qquad \gamma_t = X_t u_t + E_t \sim N(0, \Upsilon_t) \end{aligned} \tag{4}$$

where $\Upsilon_t = \sigma_t \Omega$; $\sigma_t = (1 + \sigma^2 \mathbf{X_t'} \mathbf{X_t})$.

Reformulating the model in terms of common factors significantly reduces the problem of estimating NGk coefficients into s factors. Such parsimonious use of the cross-sectional information provides more accurate coefficient estimates than individual country VARs, reduces the standard errors and is able to capture the effect of international shocks which might be a result of a complicated structure of interdependencies.

[3] Many authors provide convincing evidence that the effect of monetary policy changes varies considerably over time (see e.g. Primiceri, 2005; Baumeister and Peersman, 2013).

[4] See Canova and Ciccarelli (2009, 2013) for a detailed discussion and illustrative examples.

The time variation is modelled through the law of motion of factors θ_t, which follows a random walk

$$\theta_t = \theta_{t-1} + \eta_t \qquad \eta_t \sim N(0,B) \tag{5}$$

This specification is similar to that used traditionally in the time-varying coefficient VAR literature, but it is parsimonious, as θ_t is of much smaller dimension than α_t, and it allows us to explore permanent coefficient changes.

The covariance matrix Ω is assumed to be constant, which might be seen as a strong assumption. However, as argued by Canova and Ciccarelli (2009), making E_t and u_t correlated allows us to capture the conditional heteroscedasticity in y_t. In particular, the forecast error $\gamma_t = Y_t - \mathscr{X}_t\theta_t$ has a prior distribution $(\gamma_t|\sigma^2) \sim N(0|\sigma_t\Omega)$ and thus an unconditional multivariate t distribution with location 0, a scale matrix Ω and v_γ degrees of freedom. As a result, innovations of (4) are allowed endogenously to have fat tails.

This model can be estimated using classical methods.[5] Nevertheless, due to the short sample size we take a Bayesian approach to estimating the model, which requires a prior distribution for Ω, B, σ^2 and $\theta_{0|0}$. We let $p(\Omega,B) = p(\Omega)\prod_f p(B_f)$, where

$$\begin{aligned} p(\Omega) &= iW(V_1,n_1) \\ p(B_f) &= iW(V_{2f},n_{2f}) \qquad f = 1,...,F \end{aligned} \tag{6}$$

$iW(.)$ stands for inverse Wishart distributions; the hyperparameters (V_1,V_{2f},n_1,n_{2f}) and σ^2 are treated as fixed.[6] As the analytical distribution is unfeasible, MCMC methods have to be used to obtain the posterior quantities. For known values of Ω, σ^2 and B, the standard method for a state space model based on the Kalman filter is employed to obtain a posterior distribution of θ_t.[7]

Shock identification. To compute the impulse response functions and forecast error variance decomposition, we fix the time-varying coefficients at their values at the point in time when the statistics are computed. Shock identification is performed assuming Ω is diagonal, with restrictions based on Cholesky decomposition, which implies that the variables may react with a lag both within and across units.

3. Data and Prior Specification

The sample covers the Czech Republic and five euro area countries – Germany, France, Italy, Belgium and Austria. This selection is purely pragmatic. Germany is the closest trading partner of the Czech Republic[8] and the largest economy in Europe. Furthermore, the Czech banking system is mostly foreign owned, with parent companies mainly from France, Italy, Belgium and Austria. This set of euro area countries together account for about 70% of euro area banks' total assets and 72% of euro area GDP. This collection of countries allows us to (i) study possible spillover from abroad

[5] In particular, if the factorisation in (4) is exact (i.e. $\sigma^2 = 0$), OLS can be employed, as the error term is uncorrelated with the regressors.
[6] Note that a typical Bayesian analysis would involve using MCMC methods to draw σ^2 (see e.g. Canova and Ciccarelli, 2009). However, as suggested by Koop and Korobilis (2015), we use a grid of values for σ^2, while each value should represent a particular model (see section 4.1).
[7] For more details see the technical appendix.
[8] On average, more than 32% of exports and 27% of imports since 2005 have been to/from Germany.

to the Czech economy, (ii) capture interdependencies and (iii) compare the dynamics of the Czech and closely related economies.

For each country we have chosen five endogenous variables – real GDP, CPI, bank credit to the private non-financial sector in relation to GDP, the aggregate non-risk-weighted bank capital-to-asset ratio and a monetary policy variable on a sample from 2000 Q1 to 2015 Q3. Real GDP growth is used as a proxy for the business cycle and the credit-to-GDP ratio for the credit cycle.[9] The rationale for using credit-to-GDP as a cycle variable stems from one of the key conclusions of post-crisis studies of the financial cycle, namely that sharp growth in this ratio is strongly correlated with subsequent banking crises (Aikman et al., 2015; Borio, 2012; Schularick and Taylor, 2012). Moreover, similar approximation is used in other research studies (see e.g. Brei and Gambacorta, 2014).

GDP is measured using Eurostat seasonally adjusted real GDP at 2010 prices and CPI using the OECD index (2010 = 100). The credit-to-GDP ratio, published quarterly by the BIS, is measured at market value. The non-risk-weighted capital ratio is constructed using series from national central bank databases and the ECB database.[10] Monetary policy is proxied by the monetary conditions index and its individual parts (see section 3.1).

The Czech credit-to-GDP ratio is affected by a fall in the credit volume in 1998–2002 caused by a banking crisis in the 1990s and the clean-up of bank balance sheets ahead of the privatisation of large banks. This prevents any meaningful estimation using the series covering this period without appropriate adjustment. To obtain useful and robust information from the credit-to-GDP ratio, we employ local extreme analysis and compute an adjusted credit indicator as the difference between the current ratio and the minimum ratio attained in past quarters. By construction, the indicator captures the expansionary phase of the credit cycle. As the Czech economy did not experience any serious credit contraction in the period covered, we consider this indicator appropriate for describing the Czech credit cycle. Moreover, the conclusions drawn on its basis are consistent with the assessment of the Czech aggregate financial cycle indicator.[11]

The capital ratio applied here differs from the usual regulatory capital ratio, where assets are adjusted by regulatory risk weights designed to capture their relative risk. The non-risk-weighted ratio is closer to the regulatory leverage. There are two main reasons for using this series. The first is simply connected with data availability. Second, using non-risk-weighted assets prevents the results from being affected by potential balance sheet adjustments and IRB risk weight adjustments made by banks in order to reduce the risk weights and obtain more favourable regulatory treatment.

[9] The credit-to-GDP ratio may not be an optimal proxy for the credit cycle for a converging economy with financial deepening. The gap between the ratio and its long-term trend should be used instead. However, the Czech economy entered into transition in the 1990s with a very high level of corporate debt. As a result, there has been no upward-sloping trend so far. Credit-to-GDP may thus be a good proxy for the credit cycle.
[10] Capital and reserves comprise equity capital, non-distributed benefits or funds, and specific and general provisions against loans, securities and other types of assets.
[11] The CNB uses the FCI to some extent to complement the recommended credit-to-GDP ratio. The FCI combines signals of cyclical risks from various segments of the economy. These signals cover both supply and demand factors (such as credit growth, property prices, the speed of private sector borrowing and interest rate spreads). The FCI methodology is described in detail in Plašil et al. (2014).

The variables are scaled by their standard deviations. For all variables except the monetary policy proxies, the growth rates are computed quarter-on-quarter and annualised. We use one lag for the endogenous variables[12] and a constant.

Prior distribution. Due to the short sample size we are not able to tune our prior choice using a training sample. In order to minimise its influence, we select relatively loose and less informative (but appropriate) priors rather than flat ones

$$p(\Omega) \sim iW(k_{\Omega}^{2} \cdot \Omega_{OLS} \cdot (T-k), n_1) \tag{7}$$

$$p(B_f) \sim iW(k_B^2 \cdot I_{dim(\theta_t^f)}, n_{2f}) \tag{8}$$

where Ω_{OLS} is the OLS estimate from the time-invariant regression, $n_1 = k+1$ and $n_{2f} = dim(\theta_t)+1$. Ω_{OLS} is multiplied by $(T-k)$ because in the inverse-Wishart distribution, the scale matrix has the interpretation of the sum of the squared residuals. The prior degrees of freedom equal the dimension of matrix Ω and B respectively, plus one (as this is the necessary minimum for the inverse-Wishart to be properly defined). The initial value of $\theta_{0|0}$ equals its OLS estimate from the time-invariant regression; the variance $R_{0|0}$ is set to $0.25I$. The benchmark results presented in section 4.2 are obtained using $k_{\Omega} = 10$ and $k_B = 0.01$. This choice is consistent with the literature and the formal model selection (see section 4.1). The justification of the prior selection and its sensitivity to alternative specifications is discussed in section 6.

3.1 Alternative Monetary Policy Proxy

Regarding the monetary policy variable, there was a consensus in academia and the central banking community in the pre-crisis period that the short-term policy rate is a good measure of both the monetary policy stance and the policy instrument. It thus became a standard proxy for monetary policy shocks in studying transmission and for the monetary policy stance in core structural macro-models. However, this began to be questioned once policy rates reached their lower bounds and unconventional measures were implemented.

Given this, it would be appropriate to provide some alternative measure that is informative of the monetary policy stance in such a situation. The recent literature suggests several possibilities, as presented in detail by Lombardi and Zhu (2014). One option is to convert the degree of unconventional monetary policy into the monetary policy interest rate or its equivalent (the interbank rate), i.e. to estimate the shadow rate.[13] This measure is directly comparable with the conventional shift in central banks' monetary policy. Another possibility is to construct a monetary conditions index as a combination of variables describing monetary policy and the monetary stance.[14] Both measures are driven by the dynamics of the set of monetary variables representing conventional and unconventional policies.

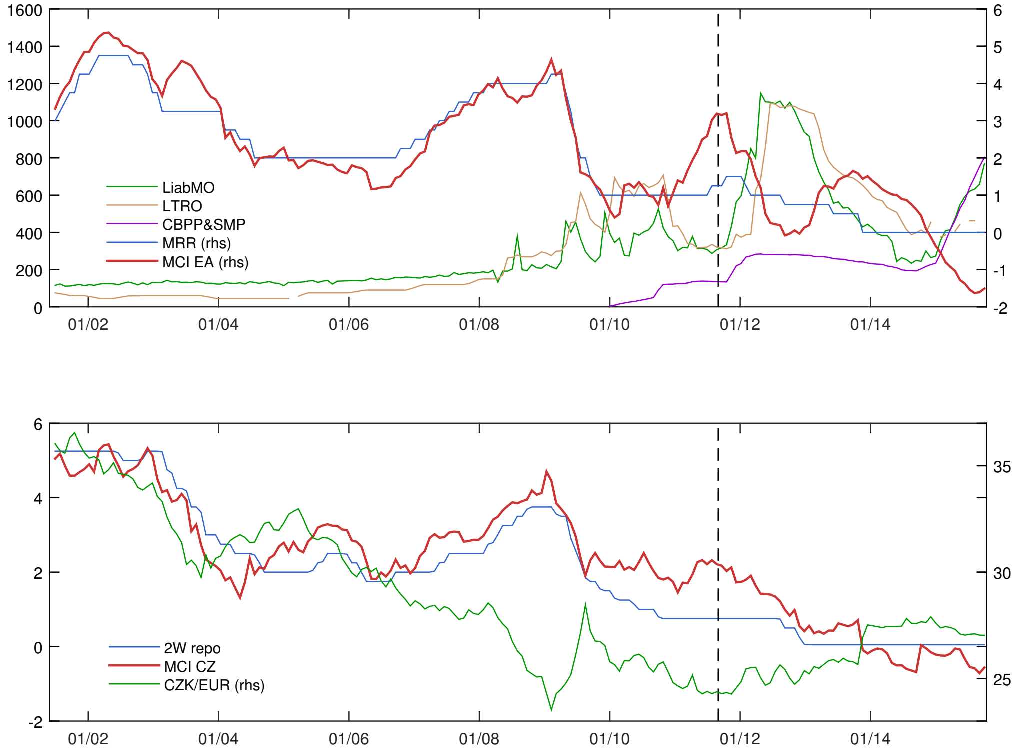
[12] One lag is selected because of the relatively short length of our dataset and because the regressors average over the lags of the endogenous variables in the SUR model.

[13] To our knowledge there are three approaches to estimating shadow rates as an indicator of the monetary policy stance. The first approach is based on model simulation of the theoretical effects of unconventional policies on 3-month money market rates. The second approach is based on option-pricing models and on calculating the price of a call option on cash at the ZLB, which is then subtracted from the yield curve (Krippner, 2012; Wu and Xia, 2014). The third approach is based on estimating the unobservable shadow rate using a dynamic factor model and a set of monetary variables representing conventional and unconventional policies (Lombardi and Zhu, 2014).

[14] The idea of the MCI dates back to the 1990s, with the Bank of Canada usually credited as having been the first to use it. The very first version was constructed as a simple linear combination of a small set of variables. Later, monetary policy was assumed to be an unobserved variable which might be extracted using a dynamic factor model (see e.g. Babecká-Kucharčuková et al., 2016).

We chose to construct a monetary conditions index (MCI) on the basis of Babecká-Kucharčuková et al. (2016), as the estimated shadow rates were not robust to the model specification.[15] Moreover, the MCI allows us to disentangle the effect of conventional and unconventional monetary policy through individual factors. The estimation procedure and robustness analysis is summarised in the technical appendix.

Figure 1: Monetary Conditions Index for the Euro Area and the Czech Republic



Note: The monetary indexes are standardised; an increase means tightening of the monetary conditions.

Estimated monetary conditions indexes. The final indexes are shown in Figure 1. The evolution of the euro area MCI is similar to that obtained by Babecká-Kucharčuková et al. (2016). Our estimation, however, extends beyond mid-2014. Before the global financial crisis and before the period of strong monetary easing, the index closely tracks the main ECB policy rate and the 3-month Euribor, while from 2011 we observe a significant deviation from these rates. This is not surprising given that monetary policy was dominated by conventional measures. In the first half of 2011, the overall monetary conditions in the euro area are significantly tighter than indicated by the main refinancing rate and the 3-month Euribor. This is driven by the variability of the ECB's balance sheet items. As from the second half of 2011, there is a rapid easing of monetary conditions related to the implementation of the Securities Markets Programme (SMP) and the Long-Term Refinancing Operations (LTRO) programme. The significant decrease in the ECB's balance sheet as from the second quarter of 2012 is then reflected in a considerable tightening of the monetary conditions. This

[15] According to simulations (not reported), the estimated ECB and CNB shadow rates (on the basis of Lombardi and Zhu (2014)) differ considerably with respect to the number of factors, lags and variables included. This is in contrast to Lombardi and Zhu (2014), who provide successful robustness checks for the federal funds shadow rate. This, however, might be due to short data samples relative to the US.

tightening occurs even when the main policy rate is at a historical low, which may point to disrupted monetary transmission (Orphanides, 2012; Babecká-Kucharčuková et al., 2016). Subsequently, in the first three quarters of 2015 we observe an accommodative effect of the expanded asset purchase programme announced in January 2015.

Similarly to the euro area MCI, the Czech version tracks the main CNB policy rate and the 3-month Pribor very closely until 2010. Between the beginning of 2010 and mid-2011 the index more or less stagnates at a significantly tighter level, despite further cuts in policy rates. This reflects gradual exchange rate appreciation, which reverts to slow depreciation at the end of 2012. Together with very low rates and further cuts, the slight exchange rate weakening is reflected in an easing of the monetary conditions until policy rates hit the zero lower bound in November 2012. After that, the index stagnates for a few months and then starts to increase. This short tightening was interrupted by the adoption of the exchange rate commitment by the CNB in November 2013, which led to a further rapid decline in the index.

4. Empirical Results

4.1 Model Selection and Estimation

Each equation of the model has $k = 6 \cdot 4 + 2 + 1 = 27$ coefficients, and there are 26 equations in the system, which leads to $27 \cdot 26$ parameters to be estimated at each t in the unrestricted regression. Thus, as discussed in section 2.1, we parametrise the coefficient vector α_t with three factors

$$\alpha_t = \Xi_1 \theta_{1t} + \Xi_2 \theta_{2t} + \Xi_3 \theta_{3t} \tag{9}$$

where θ_{1t} is a 6 x 1 vector of country-specific common factors, θ_{2t} is a 5 x 1 vector of variable-specific common factors and θ_{3t} is a 1 x 1 vector of common factors for all coefficients.

An incorrect choice of factor structure may come at a cost (see Koop and Korobilis, 2015). In order to determine which specification fits the data best, we compare the marginal log-likelihood of the sample data under the factorisation produced by four different models. Model 0 includes all three factors. Model 1 excludes the common component for all coefficients, Model 2 excludes the variable-specific component and Model 3 excludes the country-specific component. Additionally, we compare specifications with different degrees of time variation and heteroscedasticity of errors: $k_B = \{0.1, 0.01, 0\}$[16] and $\sigma^2 = \{0\ 0.001\ 0.005\ 0.01\}$.

The marginal log-likelihood is calculated from the Gibbs output based on Chib's method (Chib, 1995).[17] In doing so, we produce ten independent runs of the Gibbs sampler, each consisting of 7,000 draws, where the first 1,500 draws are discarded. In total, we obtain 70,000 draws and keep 55,000. Convergence was safely achieved with about 1,000 draws.[18]

The results in Table 1 suggest that Model 3 without the country-specific factor is preferred to all other combinations. This indicates that the dynamics of the variables within a country (e.g. output and prices) are different, while the dynamics of the same variables across countries (e.g. output

[16] The comparison was not made for values $k_B > 0.01$, as these lead to explosive impulse response functions and poor forecasts (see section 6).
[17] There are also other methods for calculating the marginal likelihood, but these are not suitable due, for example, to instability (the harmonic mean estimator; Newton and Raftery (1994)) or would be hard to implement due to model complexity. Details on the computation based on Chib's method are presented in the technical appendix.
[18] For more details on convergence see the technical appendix.

in Germany and France) are similar. This is not surprising given the high cyclical alignment of economic activity and the cyclical component of unemployment between the Czech Republic and the euro area.[19] Furthermore, the Czech economy has strong trade and ownership links with the euro area, and the alignment of financial markets (the money, foreign exchange, bond and stock markets) has long been mostly high and comparable with the euro area countries (CNB, 2015).[20]

Moreover, the model with no time variation ($k_B = 0$) is the worst across all factor specifications, which justifies our choice of the time-varying-parameter approach. The model with exact factorisation ($\sigma^2 = 0$) is preferred to models with heteroscedastic errors. These patterns are consistent with Canova and Ciccarelli (2009). The dynamic analysis presented in the next section is therefore based on the model without the country-specific factor, with $k_B = 0.01$ and $\sigma^2 = 0$. The comparison with different specifications is discussed in section 6.

Table 1: Marginal Log-likelihood – Chib's Method

σ^2	k_B	Model 0	Model 1	Model 2	Model 3
0	0.01	-685 (0.51)	-1449 (0.35)	-606 (0.47)	-497 (0.40)
0	0.001	-698 (0.54)	-1438 (0.33)	-618 (0.49)	-519 (0.55)
0	0	-992 (0.55)	-1743 (0.30)	-807 (0.42)	-662 (0.41)
0.001	0.01	-660 (0.52)	-1440 (0.32)	-622 (0.40)	-518 (0.40)
0.001	0.001	-690 (0.41)	-1438 (0.31)	-631 (0.44)	-509 (0.44)
0.001	0	-995 (0.53)	-1721 (0.27)	-813 (0.42)	-648 (0.34)
0.005	0.01	-688 (0.51)	-1453 (0.34)	-625 (0.33)	-506 (0.33)
0.005	0.001	-697 (0.52)	-1444 (0.30)	-615 (0.42)	-509 (0.47)
0.005	0	-992 (0.46)	-1739 (0.30)	-802 (0.42)	-671 (0.37)
0.01	0.01	-724 (0.56)	-1438 (0.30)	-612 (0.33)	-532 (0.42)
0.01	0.001	-669 (0.49)	-1456 (0.27)	-635 (0.48)	-518 (0.39)
0.01	0	-1006 (0.52)	-1737 (0.26)	-826 (0.54)	-640 (0.42)

Note: Numerical standard errors are reported in parenthesis.

[19] Analyses conducted by the CNB indicate a sustained above-average degree of alignment in terms of overall economic activity, exports and also industrial production, even when adjusted for the external shock in the form of the global financial and economic crisis.

[20] The result which prefers the model without the country-specific common factor may suggest estimating the model with the aggregate euro area instead of five different euro area countries. This approach is not preferable for at least two reasons. First, data on the capital ratio are available neither for the euro area as a whole, nor for all the individual countries for a sufficiently long period. Second, the responses to the monetary policy shock are accompanied by those to the bank capital shock. In the latter case, the impulse responses are different for each country.

4.2 Transmission of CNB and ECB Monetary Policy to Banks' Capital and Credit Ratios

In this section we study the dynamics of the capital-to-asset and credit-to-GDP ratios in response to a positive monetary policy shock. We report the 32th and 68th percentiles of the distribution of the impulse response functions after 1, 4, 8 and 16 quarters over the whole time period between 2001 Q2 and 2015 Q3. A crucial assumption for our identification approach is the ordering of countries and variables. Countries are ordered based on their GDP – DE, FR, IT, BE, AT and CZ. Variables are ordered within each country following the usual practice in the macroeconometric literature, with real GDP in first place followed by CPI. The ordering of the remaining variables (the monetary policy variable and the credit-to-GDP and capital ratios) may be a bit tricky. First, we assume that the monetary authority takes into account all the available information when setting its policy (and reacts contemporaneously), while the rest of the economy responds to these monetary policy actions with a delay. Thus, the monetary policy variable is ordered last (i.e. after the block of all variables for the euro area countries and after the block of Czech variables). Second, the capital ratio is ranked behind credit-to-GDP. This reflects the assumption that the capital ratio has a delayed effect on the real economy and lending, whereas variables characterising the real economy and credit aggregates affect capital ratios immediately (see e.g. Berrospide and Edge, 2010).

Given the model specification and the factors selected, the response to a euro area monetary policy shock is the same across all the euro area countries. This is because the monetary policy variable is common to all the euro area countries and the factor specification does not include a country-specific factor. Figure 2 shows the impulse responses of the first difference of the bank capital and credit ratios to a 1 pp increase in the Czech and euro area monetary conditions indexes. The effect is negative for both ratios in all time periods and at all reported horizons, peaking after 1–2 quarters.[21] After that, the immediate impact quickly disappears. The fall in the credit-to-GDP ratio indicates that monetary tightening leads to a significantly larger drop in bank credit than GDP. The decrease in the capital ratio reflects a stronger impact on banks' equity than overall assets. The strength of responses is very similar for the Czech Republic and the euro area countries, with a slightly weaker effect for CZ. This is mainly due to the lower persistence of the monetary policy shock in the very first quarters.[22]

Furthermore, the estimated impulse responses indicate significant time variation in both the capital and credit ratios, with a gradually strengthening impact from 2011 Q3 onwards. This is more or less consistent with the point identified in the estimated MCI as the beginning of the period of pronounced monetary easing, given a combination of unusually low interest rates and unconventional monetary policy. The immediate effect of a 1 pp point increase in the MCI is about three times higher at the end of the sample than at the beginning. The cumulative effect is then twice as high.[23]

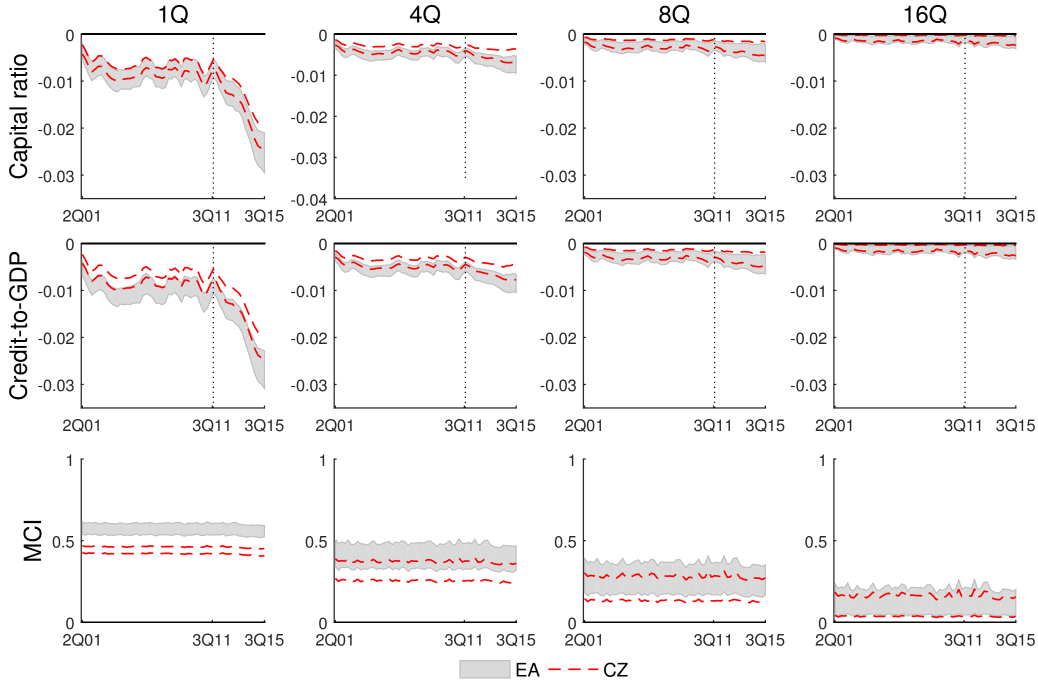
[21] The effect remains negative for both ratios even if we assume 3-month interbank rates as proxies for monetary policy.

[22] Furthermore, monetary tightening results in a rapid and persistent fall in output and prices. After 16 quarters, the cumulative effect on GDP and CPI is very similar for the Czech Republic and the euro area countries (see Figure B2 in appendix). This is more or less consistent with other studies on monetary policy transmission in euro area countries and the Czech Republic.

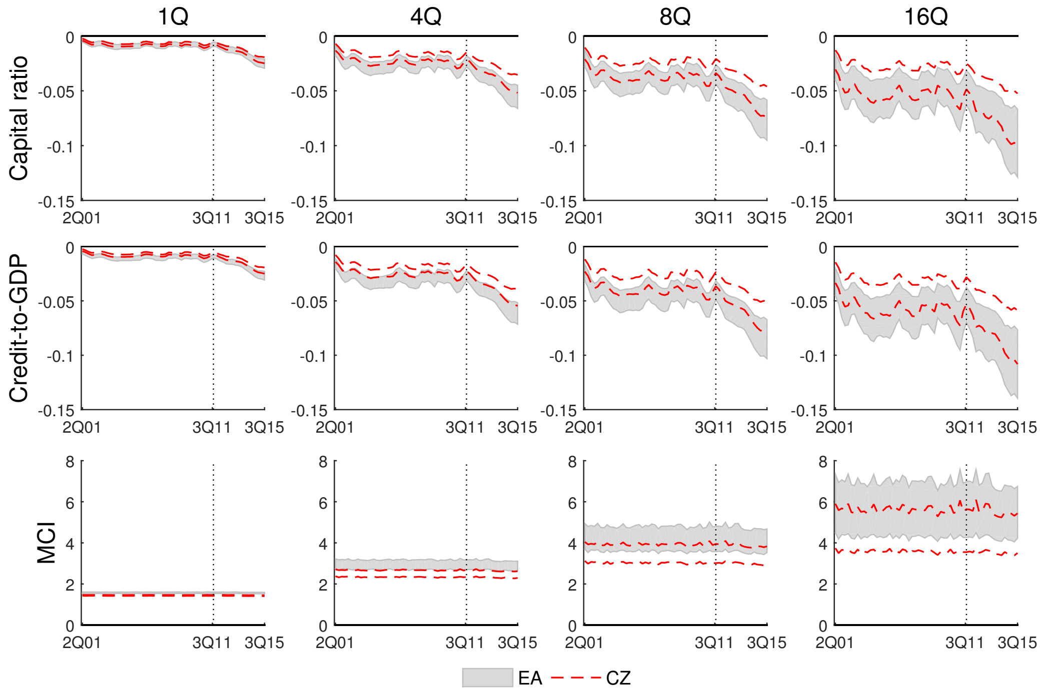
[23] As from mid-2011, we observe a significantly stronger response to the monetary policy shock for GDP and CPI as well.

Figure 2: Impulse Responses – Shock to the MCI

(a) Non-cumulative



(b) Cumulative



Note: Responses after 1, 4, 8 and 16 quarters to a 1 pp shock at $Q = 0$; 32th and 68th percentiles of the distribution reported. Except for the monetary policy proxies, the variables are in quarter-on-quarter changes, annualised.

The transmission of monetary policy through the credit channel is widely explored in the literature. It is generally accepted that easier monetary policy leads to an expansion of credit, as lower interest rates encourage borrowing (Adrian and Liang, 2014; Peek and Rosengren, 2013).[24] For example, Angeloni et al. (2003) provide evidence for the credit channel in some of the largest euro area countries during 1993–1999. Maddaloni and Peydró (2013) investigate the importance of the risk-taking channel in the euro area. A significantly stronger effect of a monetary policy shock on credit than GDP is supported by Laséen and Strid (2013), who use a Bayesian VAR-model on Swedish data.

The negative impact of monetary tightening on the bank capital ratio, i.e. the positive impact on bank leverage, can be explained in several ways. In general, banks mainly profit from a spread between the rates they receive on assets and those they pay on deposits. Higher policy rates are usually associated with a flattening of the yield curve,[25] which may be motivated by imperfect pass-through along the term structure of interest rates given that short-term rates are temporarily higher (Baumeister and Benati, 2013).[26] Since assets have longer maturity than deposits, a flatter yield curve usually reduces this spread and, therefore, banks' profits. Numerous studies have demonstrated a significant relationship between bank profitability and the yield curve slope. Recently, Alessandri and Nelson (2015) show that the effect might be different in the short and the long run. In the long run, both the level and the slope of the yield curve contribute positively to profitability, while in the short run higher market rates compress interest margins, consistently with loan pricing frictions.

Higher rates also reduce the discounted value of the fixed-income assets the bank holds, which can harm its profitability and overall equity. The higher the duration gap is, the higher the revaluation losses would be. The final impact of revaluations is highly dependent on accounting practices. The revaluation of "marked to market" and "available for sale" assets will be reflected in equity almost immediately, while assets "held to maturity" will only have an impact if they are realised.

Abstracting from changes in the real economy, a monetary tightening and the subsequent rise in market rates should be reflected in higher loan losses and recognised loan loss provisions. Since such charges are deductions from net interest income, higher provisions may reduce banks' retained earnings and consequently their capital, assuming a fixed ratio of dividend payouts. As pointed out by Borio et al. (2015), monetary policy shocks may transmit to loan loss provisions through at least two channels working in opposite directions. The first channel works through the stock of loans, as higher interest rates increase the debt service burden and hence the probability of default. The speed of transmission through this channel depends on the residual fixation of the existing loan portfolio – with higher residual fixation the transmission is slower. The second channel works through new loans. Higher interest rates might increase the perceived riskiness of new clients and induce less risk-taking on new loans through the risk-taking channel (Borio and Zhu, 2012). Assuming that the existing stock of loans with variable rates or short residual fixation periods is much larger than the flow of new loans, the overall impact would be positive.

[24] Transmission through the credit channel has traditionally been characterised by two separate channels – the balance sheet channel and the bank lending channel (Bernanke and Gertler, 1995). The balance sheet channel of monetary policy acts through asset prices and the net worth of borrowers, which affects the ability of households and firms to obtain credit. The bank lending channel works through the banking sector and bank credit supply. This paper, however, does not set out to disentangle these two channels.

[25] Monetary policy easing is usually expected after a period of monetary tightening. The longer end of yield curves reflects these expectations and rises by less than short-term rates.

[26] The current situation contradicts this common wisdom. The prolonged period of extremely low interest rates and the zero lower bound on nominal interest rates has flattened yield curves and compressed banks' margins and profits.

Beyond this, our methodology allows us to study the effect in a dynamic setting under changing macroeconomic conditions which might play a non-negligible role in provisioning. It is generally accepted that bank loan losses tend to follow economic cycles, falling during expansions and rising during downturns. Assuming that banks are aware of this, they might increase (reduce) their provisions in anticipation of worsening (improving) economic conditions. An expected increase in credit risk may therefore motivate banks to engage in forward-looking provisioning. The motivation for doing so could be smoothing of income and taxes over the cycle.

Transmission through loan loss provisions is also supported by a significant increase in responsiveness to monetary policy shocks in recent years, indicating some form of non-linearity as suggested by Borio et al. (2015). In particular, the sensitivity of loan loss provisions to monetary policy changes is expected to be higher in a low interest rate environment, pointing to such practices as "evergreening" of loans.[27] Overall, the effect of higher policy rates on banks' capital is expected to be negative, assuming a negative impact on banks' net interest income (at least in the short run) and a positive impact on their provisions. In the long run, when we might expect higher rates to have a positive impact on banks' net interest income (see e.g. Borio et al., 2015), the effect on bank capital would only remain negative if the impact on loan loss provisions is relatively stronger.

Given that the responses to positive and negative shocks are symmetric, monetary easing is associated with a fall in bank leverage, i.e. an increase in the capital ratio. This might be seen as inconsistent with the current specific situation of zero or even negative market rates where banks' margins are compressed and their net interest income is falling, speaking more in favour of transmission through change in loan loss provisions. To explore the relationship between loan loss provisions and the capital ratio, we compute simple statistics using individual bank data.[28] Table 2 presents the correlations over time between the variables of interest – loan loss provisions (as a share of net interest revenues and in levels) and the non-risk-weighted capital ratio. The final correlations are computed between aggregated variables constructed as a weighted average of the individual banks' series, with weights determined by the banks' assets. The results suggest a negative correlation (stronger or weaker).

Table 2: Correlations over Time

	E/A	E/A (y-o-y change)
LLP/NIR (y-o-y change)	-0.22	-0.09
LLP (y-o-y change)	-0.37	-0.11

Note: Adjusted for outliers. LLP = loan loss provisions; E/A = equity to total assets; NIR = net interest revenues.

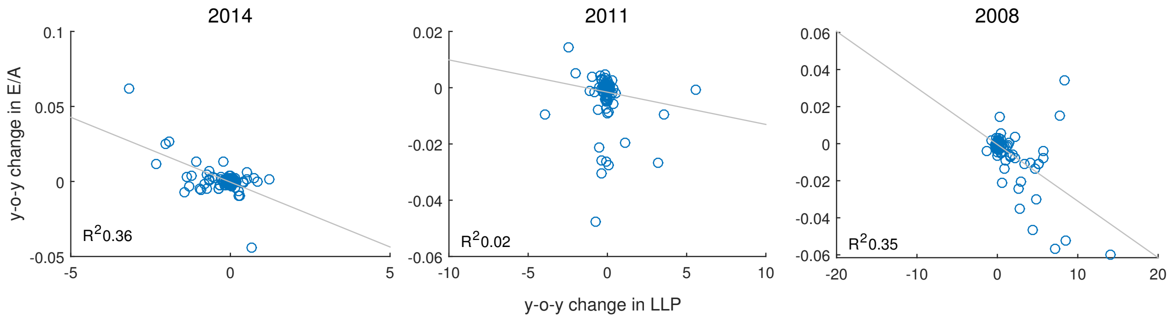
A potential weakness of the reported "over-time" correlation is the relative short series for individual banks (yearly observations between 2000 and 2014). Therefore, we explore the cross-sectional correlations in different years and compare the weighted year-on-year change in loan loss provisions

[27] Monetary policy easing usually comes after a period of recession or crisis in which there has been a deterioration in bank balance sheets. This may reduce banks' willingness to accept further losses and cause them to delay the recognition of losses in their credit portfolios by rolling over loans (Albertazzi and Marchetti, 2010; Peek and Rosengren, 2005).

[28] The sample comprises the 200 largest banks (based on total assets) from DE, FR, IT, BE, AT and CZ between 2000 and 2014, retrieved from the BankScope database. The search strategy and other conditions used to determine the final sample are described in the appendix.

and the capital ratio, with weights determined by the share of individual banks' assets in the total assets of the whole sample. The indicators suggest a negative relationship in all reported years (see Figure 3).

Figure 3: Scatter Plots – Individual Banks



Note: Weighted sample; the weights are equal to the share of the assets of each institution in the whole sample. LLP = loan loss provisions; E/A = equity to total assets. Adjusted for outliers.

The effect of conventional and unconventional monetary policy. Next, the monetary conditions index is supplemented by its individual factors representing conventional and unconventional policy.[29] In particular, the first factor is used as a proxy for conventional policy because its dynamics is driven mainly by interest rate developments in the euro area and the Czech Republic. The second and third factors are driven by ECB balance sheet items in the case of the euro area and by CNB foreign reserves and the exchange rate in the case of the Czech Republic. Thus, a weighted average of the two factors (with weights determined by the explained variance) is used as a proxy for unconventional policy. The final impulse responses are presented in Figure 4.

At first glance, the impacts of the conventional and unconventional parts of the MCI differ significantly in terms of time variation, persistence and uncertainty, while the sign of the responses remains negative in all periods.[30] The impact of the unconventional part on the capital and credit ratios is more time variant and more persistent, due to higher persistence of the shock itself. On the other hand, the effect of the conventional part of the MCI is more stable over time, while it has been gradually dying out in recent years. This is not surprising given that conventional policy has exhausted its room for manoeuvre. In the very last quarters of the sample, the effect of unconventional policy shocks plays the dominant role, as the ECB and CNB have reached the effective ZLB.[31]

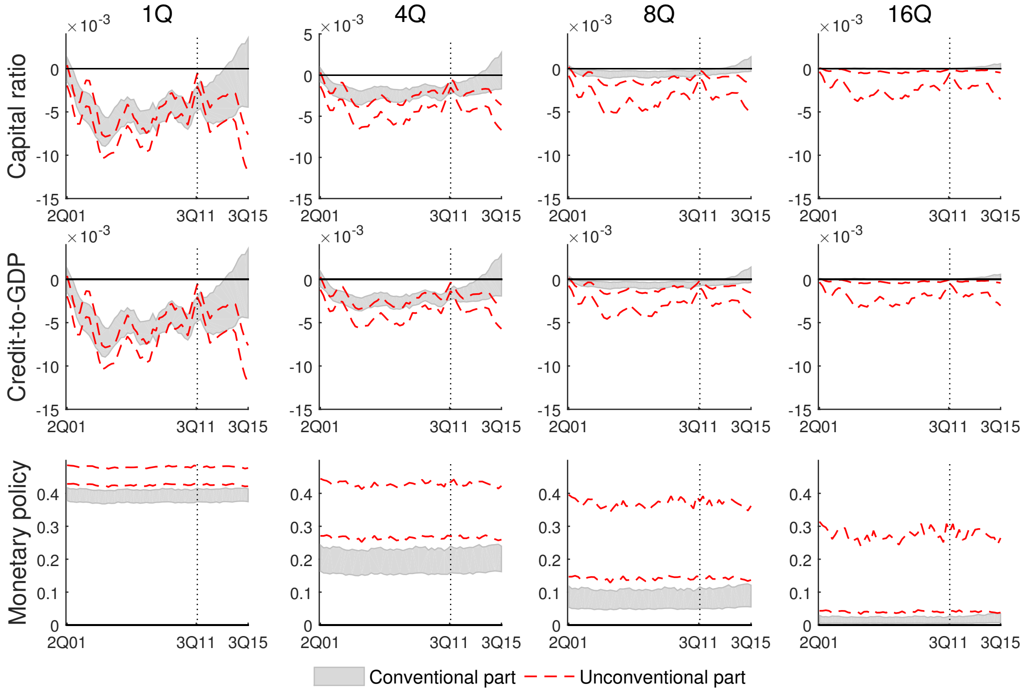
[29] A similar approach is used by Babecká-Kucharčuková et al. (2016).

[30] The effect on bank lending is in line with the existing empirical evidence. Boeckx et al. (2014) show that the unconventional monetary policy measures of the ECB did support bank lending to households and firms during the financial crisis for a given policy rate. This finding is consistent with Lenza et al. (2010), who show that unconventional monetary policy positively influences bank lending mainly through reduction of interest rate spreads.

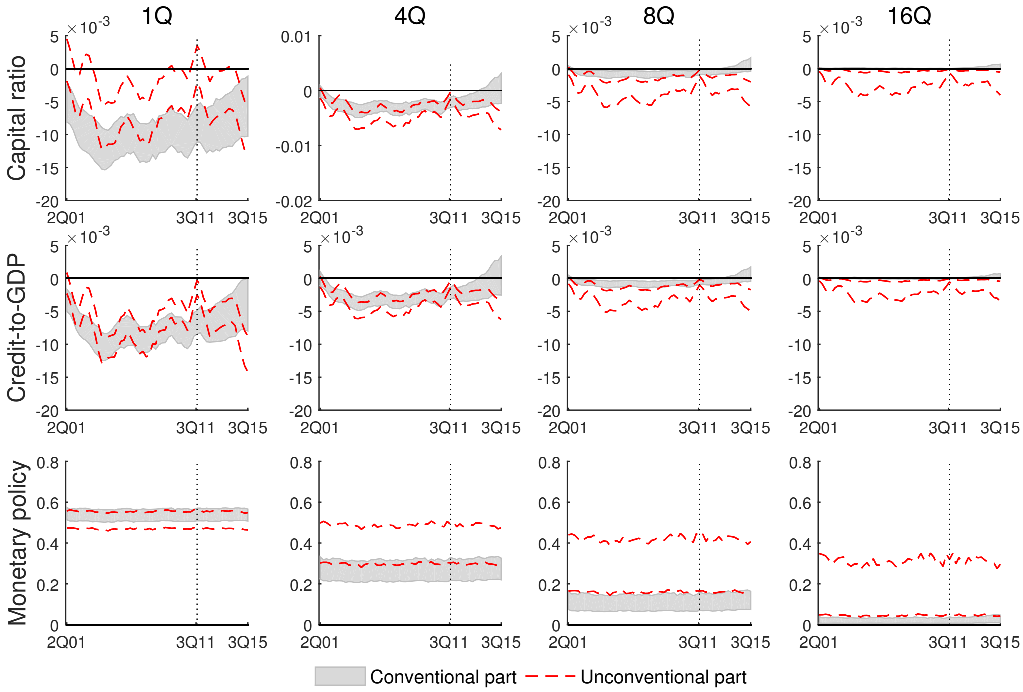
[31] The impact is similar for GDP and CPI. The response to the conventional policy shock gradually weakens, while the unconventional policy shock takes over the role. For euro area countries, the higher persistence of unconventional monetary policy is apparent mainly at the very end of the sample period. Surprisingly, the impact of the unconventional monetary policy shock on output is initially positive and is negative from the second quarter onwards. For the Czech Republic, the effect of the unconventional monetary policy shock on prices and output is rather stronger between 2001 and 2006, and in the very last quarters it has a more persistent effect on output (see Figure B4 in appendix). The cumulatively stronger and more persistent impact of the unconventional monetary policy shock on output than prices is in line with other studies (see e.g. Gambacorta et al., 2014).

Figure 4: Impulse Responses – Conventional and Unconventional Monetary Policy Shock

(a) CZ, non-cumulative



(b) EA, non-cumulative



Note: Responses after 1, 4, 8 and 16 quarters to a 1 pp shock at $Q = 0$; 32th and 68th percentiles of the distribution reported. Except for the monetary policy proxies, the variables are in quarter-on-quarter changes, annualised.

4.3 Shock to the Non-risk-weighted Capital Ratio

A natural extension of the presented analysis is to study the impact of macroprudential capital regulation on the real economy and bank credit. Such an analysis, however, is associated with a high degree of uncertainty, since macroprudential policy tools have only recently started to be used actively in many countries and we have very few observations for a proper estimation. The time-varying framework may help us partially overcome this problem, as we can focus on the more recent period. However, the estimation is still also based on the period when no or limited macroprudential tools were applied.[32] Another potential weakness of our analysis is the fact that changes in the aggregate measure of capital may reflect other things in addition to regulatory changes.

Figures 5 and 6 display the cumulative impulse responses to a 1 pp positive shock to the first difference of the non-risk-weighted capital ratio[33] in each country. The impulse responses of the individual countries differ considerably not only in sign, but also in the strength of the response. The effect of the capital shock can be divided into three categories: (i) a counter-cyclical impact with respect to both credit-to-GDP and real GDP growth (CZ), (ii) a counter-cyclical impact with respect to credit-to-GDP, but a pro-cyclical impact with respect to real GDP growth (DE, FR, AT), and (iii) a pro-cyclical impact with respect to credit-to-GDP, but a counter-cyclical impact with respect to real GDP growth (BE, IT).

The first case was more or less expected, as it is broadly in line with the literature. Existing empirical evidence suggests that higher capital ratio requirements reduce bank lending (Aiyar et al., 2016), but also lower GDP growth for a number of years (BCBS, 2010). Such an impact is desirable in terms of reducing growth in the credit-to-GDP ratio, but undesirable in terms of lowering real GDP growth.

The second case seems on first inspection to be the most desirable given the higher economic activity and the reduction in credit-to-GDP growth. There are at least two channels through which a higher bank capital ratio may lead to output growth. First, it may increase confidence in under-capitalised banks, reduce banks' overall funding costs and, consequently, help underpin a sustained recovery in credit growth and boost output growth. Assuming that credit increases less than output, the credit-to-GDP ratio will decrease (or slow down). In addition, banks are likely to pass on the lower funding costs to borrowers by reducing interest rates on loans. This is consistent with the response of Austria given an endogenous easing of the monetary conditions.

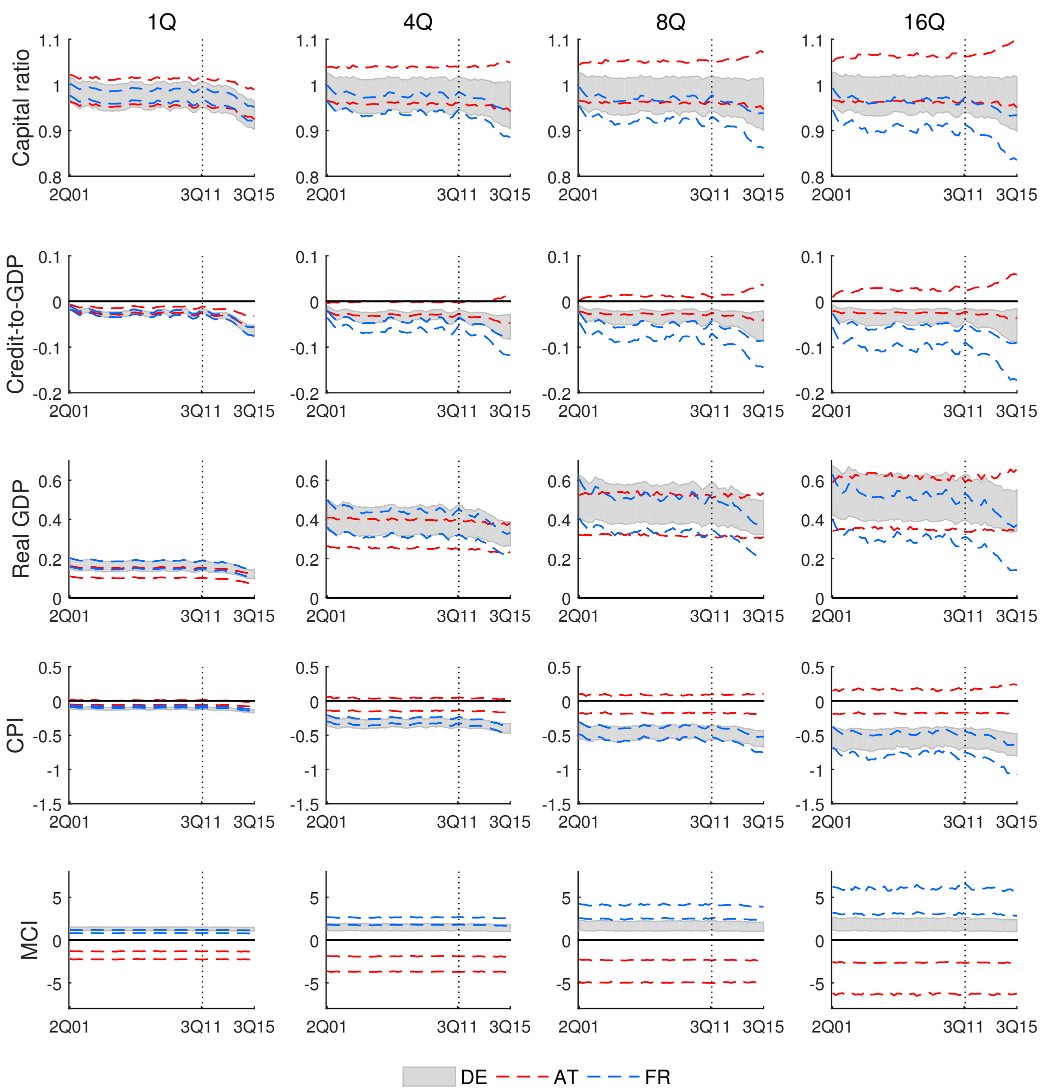
Second, the impact of the higher capital ratio on credit supply may be limited if borrowers can borrow from foreign branches and non-bank institutions. For capital regulation to be effective in controlling the aggregate credit supply it must not only affect the supply of loans by regulated banks, but also ensure that unregulated entities are not able to offset these changes in the credit supply. For example, Aiyar et al. (2012) estimate that about a third of the initial reduction in credit supply in response to higher microprudential capital ratio requirements applying to UK-regulated banks was offset by increased lending by foreign branches. A similar explanation is given by Bernanke and

[32] In this respect the analysis is subject to the Lucas critique.

[33] Generally, the conduct of macroprudential policy is based on an extensive set of instruments (capital based and liquidity based, LTV, LTI, DSTI, etc.), which may be difficult to express as a single variable. One alternative is to use an index that reflects the macroprudential policy stance (see e.g. Cerutti et al., 2015; Akinci and Olmstead-Rumsey, 2015). Such an index would be difficult to construct with sufficient length and frequency for the Czech Republic given the limited use of such macroprudential tools. The non-risk-weighted capital ratio is close to the regulatory leverage ratio, which is intended to counterbalance the build-up of systemic risk by limiting the effects of risk weight compression during booms and to restrict the build-up of leverage in the banking sector (Altunbas et al., 2014).

Lown (1991) and Driscoll (2004) in terms of US non-banks, which are able to lend to corporates and thus reduce the potential impact on output.[34] Constrained banks are likely to reduce credit supply and pass on their higher funding costs (usually associated with raising equity[35]) to borrowers by increasing interest rates on loans. In our analysis, Germany and France seem to match these patterns given an endogenous tightening of the monetary conditions.

Figure 5: Cumulative Impulse Responses – Shock to the Bank Capital Ratio (1)

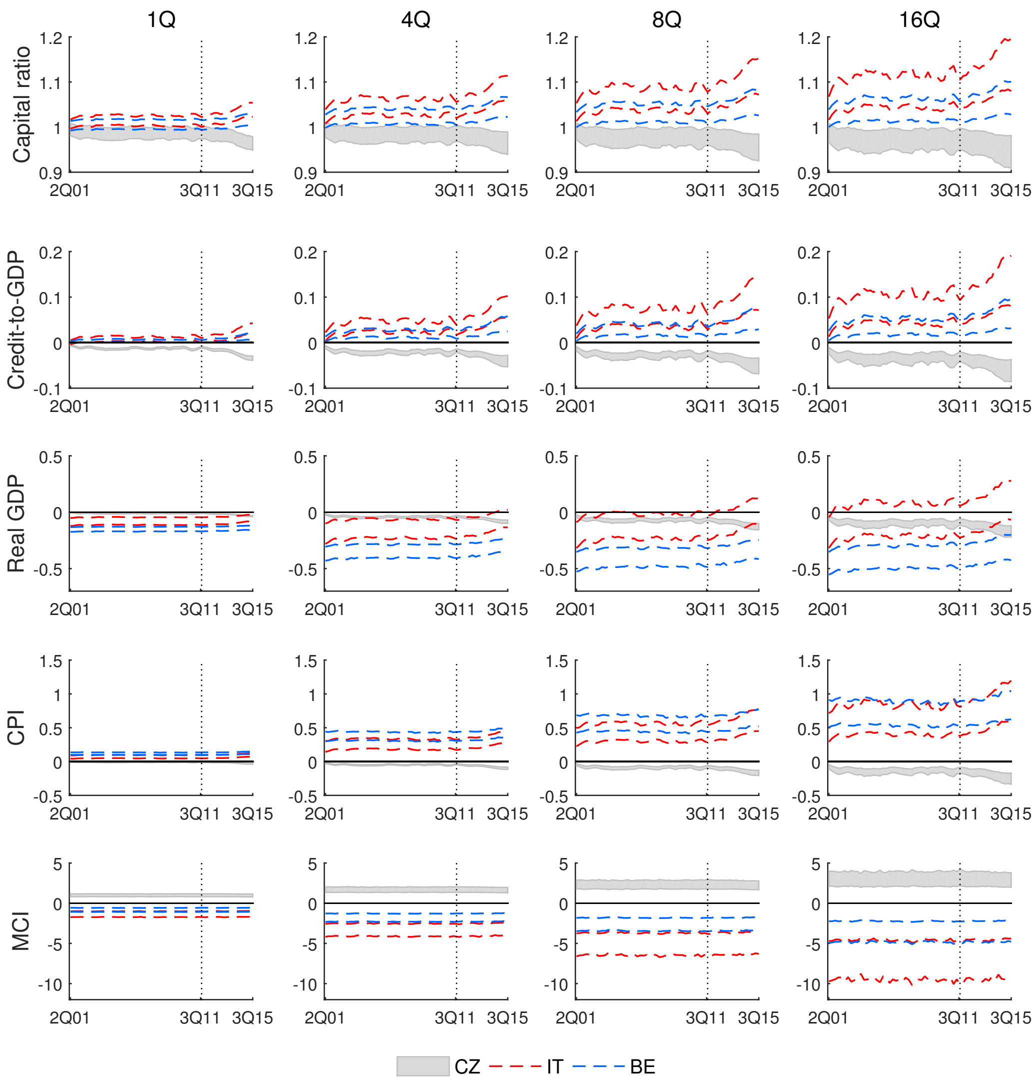


Note: Responses after 1, 4, 8 and 16 quarters to a 1 pp shock at $Q = 0$; 32th and 68th percentiles of the distribution reported. Except for the monetary policy proxies, the variables are in quarter-on-quarter changes, annualised.

[34] The international reciprocity arrangements under Basel III may help mitigate this problem.
[35] Generally, banks may increase their capital ratio by issuing new equity or by increasing retained earnings. Assuming a risk-weighted capital ratio, the third option is to reduce risk-weighted assets. Some evidence suggests that banks are more willing to raise new equity than to reduce dividend payouts or cut remuneration (Giese et al., 2013).

The last case, in which a drop in real GDP growth is accompanied by higher credit-to-GDP, is the least desirable outcome. There are two potential sources of this effect: (i) the fall in output is stronger than the fall in credit (the more likely scenario) or (ii) the fall in output is accompanied by higher credit growth (the less likely scenario). To sum up, the effect of a shock to the non-risk-weighted bank capital ratio is associated with uncertainty, and the interpretation of the presented results should take into account the limited number of observations for when macroprudential capital regulation was applied. Nevertheless, it may shed some light on the possible dynamics of financial and macroeconomic variables.

Figure 6: Cumulative Impulse Responses – Shock to the Bank Capital Ratio (2)

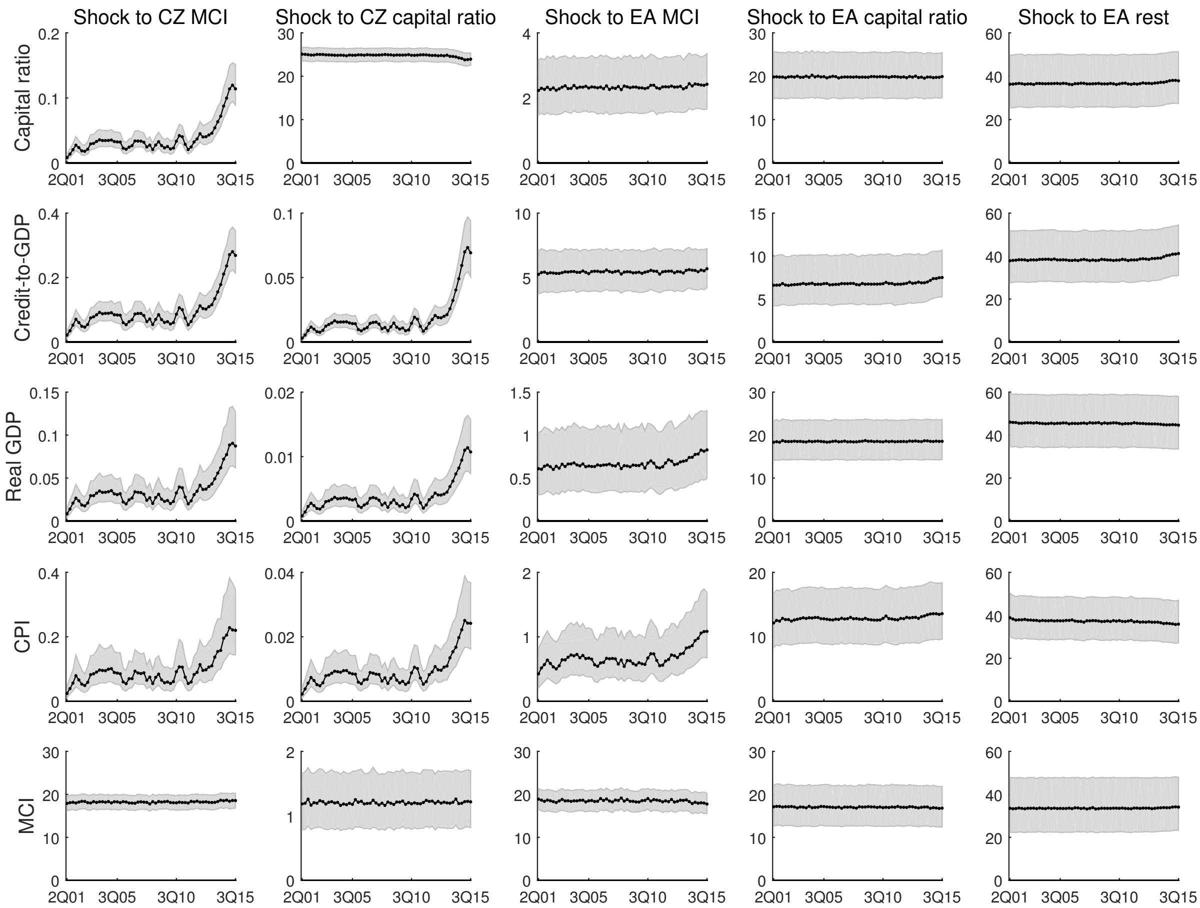


Note: Responses after 1, 4, 8 and 16 quarters to a 1 pp shock at $Q = 0$; 32th and 68th percentiles of the distribution reported. Except for the monetary policy proxies, the variables are in quarter-on-quarter changes, annualised.

4.4 Spillovers from Euro Area Countries to the Czech Economy

Figure 7 show the median contribution of various disturbances to the forecast error variance (FEVD) of the Czech variables after 16 quarters, along with 32th and 68th percentiles of the distribution.Unlike the impulse response functions, the FEVD can tell us how important the shocks are on average.

Figure 7: Forecast Error Variance Decomposition of Czech Variables



Note: Median contributions of different shocks to the forecast error variance of the Czech variables after 16 quarters; 32th and 68th percentiles of the distribution reported. Except for the monetary policy proxies, the variables are in quarter-on-quarter changes, annualised.

The contribution of the shocks from the euro area countries to the variance of all the Czech variables is stable over time and very high, ranging between 50% and 70%. A considerable share is attributed to bank capital disturbances, which explain about 20% of the Czech capital ratio and MCI variance and about 7% of the Czech credit-to-GDP variance. More than 50% of the variation of the Czech MCI is explained by the shocks to output, CPI, the credit-to-GDP ratio and the capital ratio coming from euro area countries, and an additional 20% is explained by the shock to the euro area MCI. Together, about 70% of the forecast error variance of the Czech MCI is attributed to disturbances from euro area countries. This is not surprising given that the Czech economy is highly open and the Czech banking system is mainly foreign owned.

The fraction of the variance of the Czech variables explained by the domestic monetary policy shock is rather small, despite an increase as from mid-2011. The shock to domestic MCI is not even the main contributor to the forecast error variance of the variable itself. This indicates that the CNB's monetary policy does not represent an exogenous monetary policy shock. The endogenous reaction to the shocks from the euro area countries is therefore the main factor behind the CNB's monetary policy. Similarly, the share of the Czech capital ratio variance explained by the variable itself is about 25%, while the contribution of the euro area shocks is more than 60%.

To conclude, shocks coming from the external environment are more important determinants of domestic financial and macroeconomic fluctuations than shocks coming from the domestic environment. These findings have unsurprising but still important implications for both monetary and macroprudential policies, specifically that the configuration of those policies should account for risks coming from the external environment.

5. Discussion

Despite the desirable complementarity of monetary and macroprudential policies, conflicts may arise between them. The existence of a potential conflict, the strength of that conflict, and the optimum policy mix for minimising it, all depend on which phase of the financial and business cycle the economy is in (Borio, 2014) and on what sorts of shocks the economy is currently exposed to (Brunnermeier and Sannikov, 2014). In Table 3 we suggest suitable combinations of responses of the two policies to different stages of the business and credit cycles.[36] Some of these combinations may seem logical and uncontroversial. However, in some cases it can be very hard to decide on the right policy mix. If the economy is starting to climb out of recession and emerge from a banking crisis, easing both policies works in a single, common direction, since inflation pressures and risk-taking are both at a low level. The easy monetary policy does not compress risk premia and does not encourage excessive risk-taking. If the economy is in a phase where credit growth is accelerating and financial imbalances are starting to form, maintaining easy monetary policy may initially help further improve the current financial risk indicators, but may simultaneously generate latent risks that could later manifest as a sharp deterioration in loan portfolio quality. Both policies should be kept neutral, or one of them – macroprudential policy – should be tightened.

A specific problem arises when the recovery is more sustained and output is near its potential but the inflation pressures are very weak and interest rates therefore stay very low. If this situation persists, credit growth is likely to recover and demand for risky assets will increase, leading to a surge in their prices.[37] The US and some other advanced countries (including the Czech Republic) started to get into a similar situation in 2013–2014. Our results indicate that monetary tightening leads to a significant drop in the credit-to-GDP ratio of the private non-financial sector and in banks' capital ratio, with a pronounced effect in recent years. Given the symmetry of the impulse response functions, monetary easing leads to a significant increase in both ratios. This supports the view that accommodative monetary policy may contribute to a build-up of financial vulnerabilities, i.e. it may boost the credit cycle (Adrian and Liang, 2014).

[36] The policy combinations in Table 3 should be regarded as dominant, but not always optimal and attainable. Other combinations may be desirable or necessary in some circumstances.

[37] Jorda et al. (2013) show that a combination of excessive credit growth and strong business cycle expansion leads to more severe recessions and crises followed by slower recoveries. They use cross-sectional data on more than 200 recession episodes in 14 advanced countries between 1870 and 2008. Similar results are presented by Aikman et al. (2016). Using a threshold VAR model, they show that a shock to the non-financial credit-to-GDP gap may lead to a recession (if the gap is already too high) or to an expansion (if the gap is still low).

Table 3: Interaction of Policies at Different Stages of the Credit and Business Cycle

		Economic Expansion		**Economic Recession**	
		Inflationary Pressures	Disinflationary Pressures	Inflationary Pressures	Disinflationary Pressures
Credit Boom	Monetary	Tightening > IT	Easing < IT	Tightening	Easing
	MacroPru	Tightening	Tightening	Tightening	Tightening
Credit Bust	Monetary	Tightening	Easing	Tightening < IT	Easing > IT
	MacroPru	Easing	Easing	Easing	Easing

Note: Some combinations are more likely than others, and some are very unlikely (e.g. a combination of a recession, inflationary pressures and a credit boom). Less likely combinations are shown in light grey colour. The symbols > IT and < IT denote monetary policy responses that are, respectively, stronger and weaker than those needed to attain the inflation target. Combinations where inflation is close to the target, loans are growing at a reasonable rate and asset prices are at normal levels are not shown in the table, as in these cases the responses of the two policies will be moderate and will not interact significantly.
Source: Frait et al. (2015)

The deepening of this effect in recent years may speed up the leveraging of the private sector, shift the economy to an expansionary phase of the financial cycle and compress the reaction time of macroprudential policy. While central banks' monetary policy independence enables them to deploy monetary tools quickly, it may take time for them to negotiate with other authorities, overcome political resistance or change the law before they can apply macroprudential policy tools. The delay in the final effect itself adds to the delay in implementation. If the macroprudential policy reaction time is significantly compressed, this policy may not have the capacity to act preventively and minimise potential losses.

From the conceptual perspective, the right response in such a situation is to tighten macroprudential policy, as there is an increasing risk of households and firms becoming overleveraged and the financial sector becoming more vulnerable. If this step is ineffective, the monetary policy authority may be faced with the dilemma of whether to support the achievement of the financial stability objective by preventively tightening the monetary conditions at the cost of missing the inflation target in the short run, i.e. whether to "lean against the wind".[38] Leaning against the wind as a safeguard against growth in the vulnerability of the system is supported by the existence of the "bank" channels of monetary policy transmission, especially the risk-taking channel. Woodford (2012) states that taking financial stability into account when setting monetary policy rates is merely a natural extension of flexible inflation targeting. He concludes that conflicts can arise between the price stability and financial stability objectives, but they also arise between the price stability and economic stability objectives, which are covered by flexible inflation targeting in its conventional sense.

Higher sensitivity to monetary policy shocks also poses a risk in the opposite direction (i.e. in the case of monetary tightening). For example, in a simultaneous economic and credit boom monetary tightening would have the desired effect of slowing down credit-to-GDP growth, but the undesired one of reducing the capital ratio. In such case, the suitable policy mix may depend, among other things, on the capitalisation and overall condition of the banking sector. Assuming that banks are

[38] A problem can arise if this strategy would de-anchor inflation expectations, which might make it more difficult for inflation to return to the target. With greater uncertainty about the central bank's inflation target (for example in response to the "leaning against the wind" strategy), market expectations about future inflation would become more sensitive to news and changes in the outlooks for key macroeconomic variables.

operating close to the capital requirements, monetary tightening should be accompanied by macroprudential tightening (i.e. additional capital charges) in order to prevent a loss of resilience of the banking sector. In doing so, both policies are likely to work in the same direction to mitigate inflationary pressures and to rein in risks arising from rapid credit growth (for evidence on the mutually reinforcing effects of the two policies in Asian-Pacific economies see Bruno and Shin (2016)).

Given the presented findings, the conduct of monetary policy should not be completely separated from that of macroprudential policy. As suggested by the estimated impulse responses, a prolonged period of monetary easing increases the sensitivity of banks to a subsequent monetary tightening. On the other hand, the effect of macroprudential capital regulation is associated with uncertainty. Therefore, it is desirable to discuss and coordinate changes in monetary policy in both directions to avoid potential surprises and conflicts. Information sharing between the two policy areas in the central bank (or between the two authorities if the policies are conducted separately) and coordination of the two policies are necessary to avoid an inappropriate policy mix preventing effective achievement of the main objective of each authority.

6. Sensitivity and Robustness Analysis

The benchmark factor specification and prior belief about the amount of time variation were chosen based on a formal model selection. In this section we justify this choice and discuss the sensitivity and robustness to different specifications.[39]

Factor specification. The impact of monetary tightening on the capital ratio and credit-to-GDP remains negative for all the euro area countries regardless of specification. The signs of the other responses also remain more or less similar to the benchmark case. They differ mainly in intensity and persistence. On the other hand, the responses of the Czech variables under alternative factor specifications have counterintuitive signs given an increase in GDP growth and inflation in response to monetary tightening. This speaks in favour of our benchmark choice without a country-specific factor.

Prior distribution. First, the choice of priors for the initial states does not affect the results. The selection of k_Ω and k_B, however, turns out to be important. This is due to a high number of free parameters.[40]

The conditional posterior means of $\Omega|Y^T, \Theta_{-\Omega}$ and $B_f|Y^T, \Theta_{-B_f}$, distributed as inverse-Wishart, are of the following forms

$$E(\Omega|Y^T, \Theta_{-\Omega}) = \frac{n_1}{n_1+T}\frac{V_1}{n_1} + \frac{T}{n_1+T}\Omega_{MLE} \tag{10}$$

$$E(B_f|Y^T, \Theta_{-B_f}) = \frac{n_{2f}}{n_{2f}+T}\frac{V_{2f}}{n_{2f}} + \frac{T}{n_{2f}+T}B_{f,MLE} \tag{11}$$

where $V_1 = k_\Omega^2 \cdot \Omega_{OLS} \cdot (T-k)$ and $V_{2f} = k_B^2 \cdot I_{dim(\theta_t^f)}$ are scale matrices, and n_{2f}, n_1 are the degrees of freedom of the prior distribution. Ω_{MLE} and $B_{f,MLE}$ are the maximum likelihood estimates of those covariance matrices. The conditional posterior mean is a combination of the prior and likelihood, with weights determined by the relative size of the prior degrees of freedom and the sample size T. In this framework, the prior distribution of both covariance matrices parametrises the amount of time

[39] Estimation results are not reported but are available upon request.
[40] For a detailed discussion see Primiceri (2005).

variation in the model – $p(B_f)$ directly and $p(\Omega)$ indirectly through the variance of the prediction error in the Kalman filter recursion of θ_t.

First, focus on $p(\Omega)$. With $n_1 \to \infty$ and $V_1 \to 0$, the prior becomes very tight, i.e. Ω and Υ_t will converge to zero. The variance of the prediction error simplifies to $f_{t|t-1} = \mathscr{X}_t P_{t|t-1} \mathscr{X}_t{}'$, which causes $P_{t|t} = 0$ and forces the Kalman gain to be equal to the observation matrix $\mathscr{X}_t$. Consequently, $\theta_{t|t} = \theta_{t|t-1}$ and $\alpha_t = \Xi\theta_{t-1}$ (as we assume exact factorisation). As such, the hyperparameters n_1 and V_1 control the overall tightness of the prior distribution around the random walk assumption and thus the amount of time variation. Therefore, a less informative prior on Ω (i.e. a higher k_Ω) allows us to parametrise the amount of time variation directly through k_B. Moreover, a rather looser prior on Ω is needed to achieve fast convergence and low sample autocorrelation of draws at higher lags. An experiment with a tighter prior (i.e. $k_\Omega = \{1, 0.1\}$) shows that convergence to a stable distribution can be achieved, but with a much longer chain, a larger burn-in period and thinning. As this is not efficient, we opt for $k_\Omega = 10$.

Next, with higher k_B coefficients we try to capture the high-frequency variation and explain the outliers of the data. With lower k_B the coefficients are not allowed to change considerably over time and the time-varying-parameter regression loses its sense. Thus, in the benchmark specification we set $k_B = 0.01$, which is consistent both with the literature (Primiceri, 2005) and with the formal model selection discussed in section 4.1. Moreover, the amount of in-sample time variation is important as regards subsequent sensible impulse responses and forecasts. Models with high time variation often exhibit exploding responses with counterintuitive signs and provide poor forecasts (Stock and Watson, 1996). Our experiments with higher k_B (not reported) support this conclusion.

6.1 Shock Identification

The sheer dimensionality of the large-scale matrix Ω makes proper shock identification difficult. In particular, it would be very hard to find enough constraints to achieve identification for all shocks. There are several possible ways of handling it – basic zero restrictions and Cholesky decomposition for Ω (as in our case), a block structure, long-run restrictions (Blanchard and Quah, 1989) and others. In many cases, however, it is difficult to justify a particular choice economically. For example, a block structure would not be appropriate if we would like to allow shocks to be transmitted across units within a time period. We therefore opt for the commonly used Cholesky format and perform a robustness analysis with respect to variable and country ordering.

Variable ordering. Within a banking sector, our benchmark identification assumes that structural innovations to the credit-to-GDP ratio can affect the bank capital ratio immediately, but that innovations to the capital ratio do not have contemporaneous effects on the credit ratio. This assumption suggests that contemporaneous structural innovations to the credit ratio originate from the real economy and not from innovations to the bank capital ratio. Assuming opposite ordering, however, does not change the results presented in section 4.2 significantly. The resulting median impulse responses lie within the 32th and 68th percentiles of the distribution of benchmark impulse responses for all variables.

Country ordering. The Czech Republic is ordered last in all cases, i.e. in all specifications the Czech variables react contemporaneously to innovations in the foreign variables, while the opposite does not hold. We consider this assumption to be reasonable and do not question it. All the other countries are subjected to different ordering. The sign of the responses to monetary policy shocks always remains the same as in the benchmark specification. The sign of the responses to the capital ratio shock is also immune to different country ordering in most cases. The exception is Austria, for which some responses change sign or (more often) the 32th and 68th percentiles of the distribution include zero.

7. Conclusions

This paper studies the extent to which monetary policy contributes to the build-up of financial vulnerabilities and the effect of macroprudential capital regulation on the macroeconomy and the credit cycle. The incorporation of macroprudential policy into the framework for the functioning of central banks has given rise to new questions regarding the form of coordination between macroprudential and monetary policy. The need for such coordination stems from the observation that monetary and macroprudential policy tools are not independent, as they affect both the monetary and credit conditions via their effect on credit growth. This paper sheds some light on situations in which monetary and macroprudential policies may interact (and potentially get into conflict) and contributes to the discussion about the appropriate coordination of the two policies. Methodologically, we use a time-varying coefficient panel VAR model for the Czech Republic and five euro area countries. The model allows for international spillovers and is capable of estimating dynamic interdependencies. Monetary policy is proxied by a monetary conditions index estimated using dynamic factor analysis. The non-risk-weighted bank capital ratio represents macroprudential capital regulation.

Using this methodology, we have identified a few patterns. First, monetary tightening has a negative impact on both the credit-to-GDP and capital ratios (i.e. a positive impact on bank leverage). This result is robust to model specification and to alternative monetary policy proxies. Unconventional monetary policy contributes to the persistence of the responses, while the impact of conventional monetary policy has gradually been dying out in recent years. The fall in the credit-to-GDP ratio indicates that monetary tightening leads to a significantly larger drop in bank credit than GDP. Given the symmetry of the impulse responses, monetary easing leads to a significant increase in both ratios. This supports the view that accommodative monetary policy contributes to a build-up of financial vulnerabilities, i.e. it boosts the credit cycle. The decrease in the capital ratio reflects a stronger impact on banks' equity than overall assets. We argue that this effect results mainly from the effect on loan loss provisions, which are deductions from net interest income and consequently bank capital. Higher interest rates boost loan loss provisions through their impact on debt service costs and default probabilities. Moreover, the effect has strengthened in recent years, indicating that a prolonged period of unusually low rates contributes to higher sensitivity of some financial variables to changes in monetary policy.

Second, the response to the higher bank capital ratio differs considerably across countries. We observe both a counter-cyclical and pro-cyclical impact with respect to credit-to-GDP and real GDP growth. Such different effects may be connected with several issues. First, the proposed credit-to-GDP ratio only covers bank lending to the non-financial sector and completely omits non-bank entities. The impact of the higher capital ratio on credit supply may be limited if borrowers can borrow from foreign branches and non-bank institutions. Second, we focus only on the change in the capital ratio and not on the level of capitalisation of banking sectors. Higher capital requirements would have different effects on well-capitalised and under-capitalised banks. They may increase confidence in an under-capitalised banking sector, reduce banks' overall funding costs and, consequently, help underpin a sustained recovery in credit growth and boost output growth. Third, due to a lack of observations, the estimation is also based on the period when no or limited macroprudential tools were applied. This poses a risk that the estimated effect reflects other things in addition to regulatory changes.

The existence of a potential conflict between monetary and macroprudential policies, the strength of that conflict, and the optimum policy mix for minimising it, all depend on which phase of the financial and business cycle the economy is in and on what sorts of shocks the economy is currently exposed to. As suggested by our results, a prolonged period of very accommodative monetary policy contributes to higher sensitivity of financial variables to a subsequent monetary tightening. On the other hand, the effect of macroprudential capital regulation is associated with uncertainty. Therefore, it is desirable to discuss and coordinate changes in monetary and macroprudential policy to avoid potential surprises and conflicts. Information sharing between the two authorities and coordination of the two policies are necessary to avoid an inappropriate policy mix preventing effective achievement of the main objective of each authority.

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Appendix A: Technical Appendix

A.1 Bayesian Inference

As shown in Canova and Ciccarelli (2009), the likelihood of a factorised SUR model is

$$\mathscr{L}(\theta,\Upsilon|Y) \propto \prod_t |\Upsilon_t|^{-1/2} exp\Big[-\frac{1}{2}\sum_t (Y_t - \mathscr{X}_t\theta_t)'\Upsilon_t^{-1}(Y_t - \mathscr{X}_t\theta_t)\Big] \tag{A1}$$

Let $Y^T = (Y_1,...,Y_T)$ denote the data and $\Theta = (\Omega, B, \theta_{0|0}, \{\theta_t\})$ the unknown parameters whose joint distribution is to be found. Given the data, the conditional posterior distributions are

$$\begin{aligned} p(\Omega|Y^T,\Theta_{-\Omega}) &= iW(\hat{V}_1, n_1 + T) \\ p(B_f|Y^T,\Theta_{-B_f}) &= iW(\hat{V}_{2f}, n_{2f} + T * dim(\theta_t^f)) \end{aligned} \tag{A2}$$

The scale matrices are given by

$$\begin{aligned} \hat{V}_1 &= V_1 + \sum_t (Y_t - \mathscr{X}_t\theta_t)\sigma_t^{-1}(Y_t - \mathscr{X}_t\theta_t)' \\ \hat{V}_{2f} &= V_{2f} + \sum_t (\theta_t^f - \theta_{t-1}^f)(\theta_t^f - \theta_{t-1}^f)' \end{aligned} \tag{A3}$$

where θ_t^f is the f^{th} subvector of θ_t.

The conditional posterior of $(\theta_1,...,\theta_T|Y^T,\Theta_{-\theta_t})$ is obtained using the Kalman filter and the simulation smoother of Chib and Greenberg (1995). Given the starting values for $\theta_{0|0}$ and $P_{0|0}$, the Kalman filter recursion is defined as

$$\begin{aligned} \theta_{t|t} &= \theta_{t|t-1} + (P_{t|t-1}\mathscr{X}_t f_{t|t-1}^{-1})(Y_t - \mathscr{X}_t\theta_t) \\ P_{t|t} &= (I - (P_{t|t-1}\mathscr{X}_t f_{t|t-1}^{-1})\mathscr{X}_t)(P_{t|t-1} + B) \\ f_{t|t-1} &= \mathscr{X}_t P_{t|t-1}\mathscr{X}_t' + \Upsilon_t \end{aligned} \tag{A4}$$

where $P_{t|t}$ is the covariance matrix of the conditional distribution of $\theta_{t|t}$, $(Y_t - \mathscr{X}_t\theta_t)$ is the prediction error and $f_{t|t-1}$ is its variance.

We use the Gibbs sampler to simulate draws from the posterior distribution $p(\Theta|Y^T)$. This can be obtained by cycling through the conditions in (A2) and (A4). First, conditional on the data and hyperparameters, we draw a sample of states $\{\theta_t\}$ from the joint posterior distribution $p(\theta_1,...,\theta_T|Y^T,\Theta_{-\theta_t})$. To do this, the output of the Kalman filter is used to simulate θ_T from $N(\theta_{T|T}, P_{T|T})$, θ_{T-1} from $N(\theta_{T-1}, P_{T-1})$ and θ_1 from $N(\theta_1, P_1)$, where $\theta_t = \theta_{t|t} + P_{t|t}P_{t+1|t}^{-1}(\theta_{t+1} - \theta_{t|t})$ and $P_t = P_{t|t} - P_{t|t}P_{t+1|t}^{-1}P_{t|t}$. Then, conditional on the data and states, we draw hyperparameters from $p(B|Y^T,\{\theta_t\})$ and $p(\Omega|Y^T,\{\theta_t\})$. After the initial set of draws is discarded, the sequence of draws converges to a draw from the joint distribution $p(\{\theta_t\},\Omega,B|Y^T)$.

A.2 Marginal Likelihood Estimation – Chib's Method

The marginal likelihood of a model provides an intuitive and natural objective function for model selection and parameter estimation. If we consider a model M with data Y^T and model parameters Θ, then the marginal likelihood is

$$\mathscr{L}(Y^T|M) = \int p(Y^T|\Theta,M)p(\Theta|M)d\Theta \tag{A5}$$

As the marginal likelihood cannot be evaluated analytically in our case (due to non-conjugacy, high dimensionality and large amounts of data) it is computed numerically using the output of the Gibbs sampler.

Suppose that $p(Y^T|\Theta,M)$ is a likelihood function of data y under model M given parameters Θ. The prior distribution of Θ is given by $p(\Theta|M)$. The posterior distribution is then $p(\Theta|Y^T,M)$ with G draws $\Theta^g \equiv \{\Theta^1,...,\Theta^G\}$ obtained using the Gibbs sampler. The marginal likelihood of model M is then defined as follows

$$m(Y^T|M) = \frac{p(Y^T|\Theta)p(\Theta)}{p(\Theta|Y^T)} \tag{A6}$$

or equivalently on the logarithmic scale

$$ln\ m(Y^T|M) = ln\ p(Y^T|\Theta) + ln\ p(\Theta) - ln\ p(\Theta|Y^T) \tag{A7}$$

The estimate of the posterior distribution is obtained from the Gibbs output (for more details see Chib, 1995).

A.3 Convergence of the MCMC Algorithm

Convergence diagnostics are presented for Model 3 with $k_\Omega = 10$, $k_B = 0.01$, $\sigma^2 = 0$ and the MCI as the monetary policy proxy; other specifications give similar results and are available upon request.

The convergence is assessed based on the sample autocorrelation of the chain of draws, Raftery and Lewis (1992) diagnostics, and the Gelman and Rubin (1992) potential scale reduction factor comparing between and within variances of multiple chains.[41] First of all, different initial values produce the same results. Convergence to a stationary distribution is always achieved after about 1,000 draws. The results are also not sensitive to the total number of iterations and chains (ten chains of 5,500 draws give the same results as two chains of 27,500 draws). Figure A1 plots the sample autocorrelation at the 20th lag for free elements of Ω and B. The entire plot remains below 0.1 and decays quickly with higher lag order. This suggests that the draws are almost independent, which increases the efficiency of the algorithm.

[41] The Gelman and Rubin (1992) statistic is based on the notion that if multiple chains have converged, by definition they should appear very similar to one another.

Figure A1: Convergence Diagnostics – Sample Autocorrelation at the 20th Lag

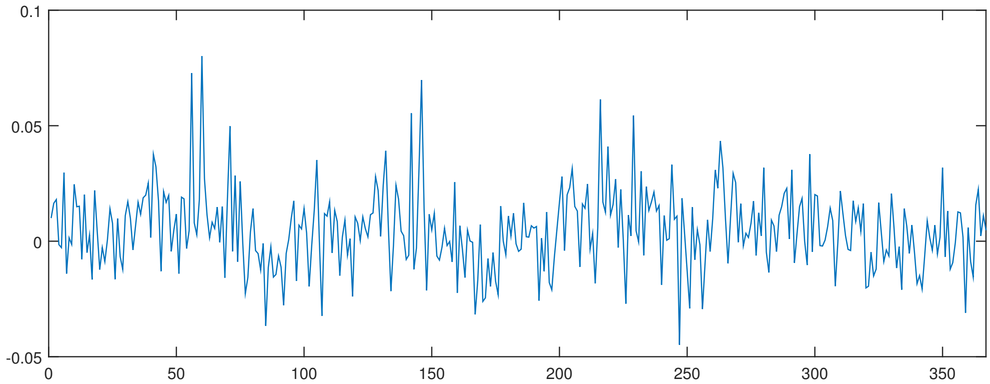
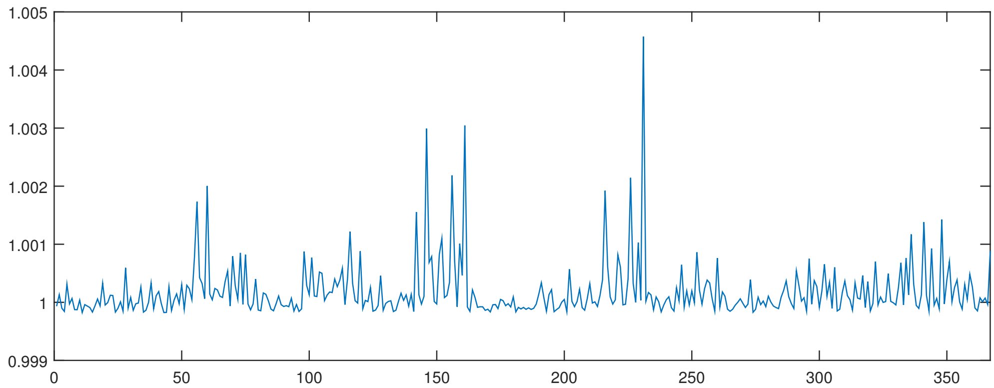


Figure A2 presents the potential scale reduction factor. For all parameters it remains far below the commonly accepted 1.05. As a final check, we compute the Raftery and Lewis (1992) diagnostic, which indicates the number of draws needed to get a stationary distribution from the Gibbs sampler, i.e. to achieve a certain level of precision. The parameters for the diagnostic are specified as follows: quantile = 0.025; desired accuracy = 0.025; probability of attaining required accuracy = $\{0.95, 0.99\}$. The number of runs required is always well below the total number of iterations performed. In particular, the number of draws required to achieve 95% and 99% precision lies in the range of 157–161 and 270–278 respectively. To conclude, all the presented statistics suggest convergence of the sampler to a stable distribution.

Figure A2: Convergence Diagnostics – Potential Scale Reduction Factor



A.4 Monetary Policy Index

A.4.1 Estimation Procedure

The basic idea of factor models is that co-movement of observed series can be explained by a few unobserved common components (factors). The factors are chosen so as to maximise the proportion of the total variation explained. Let $Y_t; t = 1, ..., T$ be an N-dimension vector of stationary series with the following factor representation

$$Y_t = \Lambda F_t + \varepsilon_t \tag{A8}$$

$$F_t = \sum_{i=1}^{p} A_i F_{t-i} + u_t \tag{A9}$$

where F_t is a vector of common factors (unobserved), Λ is a matrix of factor loadings, $\sum_{i=1}^{p} A_i$ are matrices of autoregressive coefficients for p lags, and ε_t and u_t are i.i.d. Gaussian error terms.

We use the expectation-maximisation algorithm to obtain maximum likelihood estimates of the model. Its use was first suggested by Watson and Engle (1983), and most of the recent papers dealing with large-scale models propose it, too. Overall, the approach consists of iterating between two steps – estimating the unobservables (factors) conditional on the observed series, and maximising the likelihood conditional on the factors from the previous iteration.

To construct the monetary conditions index, we put together a monetary dataset for the euro area and the Czech Republic including variables associated with monetary policy (see below). The first block consists of interest rates and yields at various maturities, while the second block is devoted to change in the balance sheet of the central bank and the exchange rate, given the particular unconventional policy employed in each country. The ECB's unconventional tools consist of a set of various measures evolving over time since 2008 (Long-Term Refinancing Operations, Securities Markets Programme, Covered Bond Purchase Programme). The CNB, on the other hand, uses only one additional unconventional tool, that is, intervening on the foreign exchange market to weaken the koruna so as to maintain the exchange rate close to CZK 27 to the euro. The dataset covers the period from January 2000 to December 2015 at monthly frequency. We use month-on-month growth rates for quantities, as the time series need to be stationary for the estimation.

The optimal number of lags is selected according to the Schwarz information criterion and the number of factors according to parallel analysis[42] (see Figure A3). For both the Czech Republic and the euro area, one lag and three factors were chosen. The final indexes are normalised using the mean and standard deviation of the 3-month Euribor and Pribor respectively, and plotted in Figure 1.

The robustness and sensitivity analysis of the final indexes is performed with respect to both the number of lags and the number of factors (see Figure A5). First, using a different lag order does not change the basic dynamics of either index significantly. In particular, a quantitative difference is only apparent for the euro area index with six lags . Second, the optimal number of factors may differ depending on the selection criterion chosen. For example, according to the Kaiser method the optimal number of factors is five for the euro area dataset and four for the Czech Republic

[42] Given the importance of determining the number of factors to retain, different methods have been proposed, e.g. Kaiser's eigenvalue-greater-than-one rule (Kaiser, 1960), the Minimum Average Partial test (Velicer, 1976), the Scree test (Cattell, 1966) and Parallel Analysis (Horn, 1965). Kaiser's method and the Scree test have been criticised for their inefficiency and subjectivity. The MAP test, on the other hand, may display a tendency to underestimate the number of factors under certain conditions. Various studies suggest PA as an appropriate method for determining the number of factors.

dataset. Alternatively, Hallin and Liska (2007) and Bai and Ng (2007) suggest choosing the number of factors according to the share of the variance explained (70% or 90%). Apparently, the monetary conditions index estimates based on just one factor mainly follow the interest rate and miss the information contained in other variables. The estimates based on two or more factors then follow very similar dynamics.

A.4.2 Monetary Datasets

Czech Republic

- Interest rates
  - 2W repo rate, Lombard rate, discount rate
  - Interbank rates (PRIBOR) with maturities of 3, 6 and 12 months
  - Yields on government bonds with maturities of 2, 3, 5, 7 and 10 years
- CZK/EUR exchange rate
- Foreign exchange reserves

Euro Area

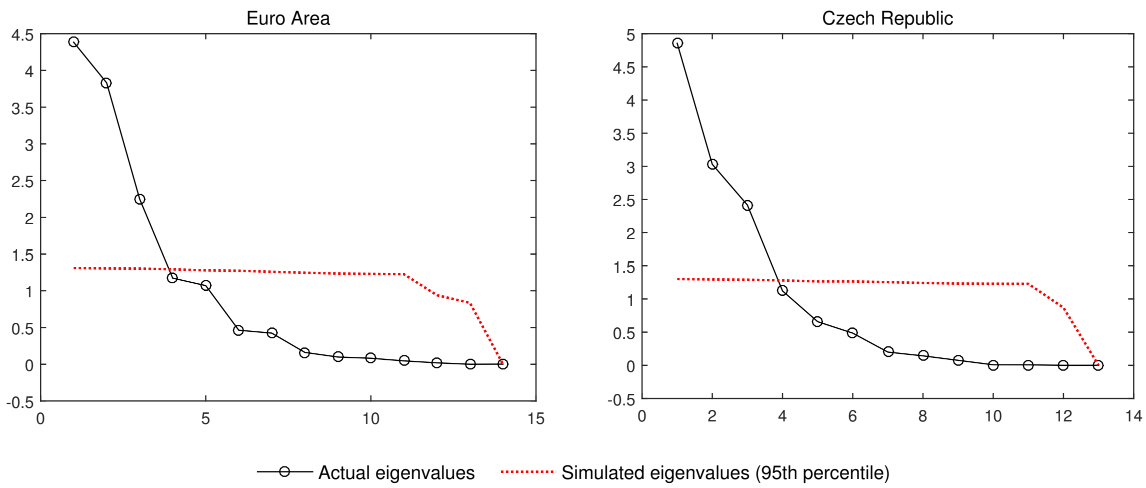
- Interest rates
  - Main refinancing rate, main discount rate, main lending rate
  - Interbank rates (EURIBOR) with maturities of 3 and 12 months
  - Yields on government bonds with maturities of 5 and 10 years
- Monetary and other aggregates
  - M1, M2, M3
- CB's balance sheet
  - Currency in circulation
  - Long-term refinancing operations (LTRO)
  - Securities held for monetary policy purposes (CBPP, SMP)
  - Liabilities of ECB to euro area MFIs related to monetary operations

Table A1: Variance Explained by Factors

	Euro Area			Czech Republic		
Factor	Eigenvalue	% of variance	Cumulative %	Eigenvalue	% of variance	Cumulative %
1	4.38	31.3	31.3	4.86	37.4	37.4
2	3.83	27.4	58.7	3.03	23.3	60.7
3	2.25	16.1	74.7	2.42	18.6	79.3
4	1.17	8.4	83.1	1.12	8.6	87.9
5	1.07	7.6	90.8	0.66	5.1	92.9
6	0.46	3.3	94.1	0.49	3.7	96.7
7	0.42	3.0	97.1	0.20	1.5	98.2
8	0.16	1.2	98.2	0.14	1.1	99.3
9	0.10	0.7	98.9	0.08	0.6	99.9
10	0.08	0.6	99.5	0.01	0.1	99.9
11	0.05	0.3	99.9	0.01	0.1	100.0
12	0.02	0.1	100.0	0.00	0.0	100.0
13	0.00	0.0	100.0	0.00	0.0	100.0
14	0.00	0.0	100.0	-	-	-

Note: The eigenvalues are the variances of the factors. Because we conducted the factor analysis on the correlation matrix, the variables are standardised, which means that each variable has a variance of 1, and the total variance is equal to the number of variables used in the analysis.

Figure A3: Parallel Analysis – Determination of the Optimal Number of Factors



Note: The simulated eigenvalues are based on 1,000 draws.

Figure A4: Factors Used for the Construction of the Monetary Conditions Indexes

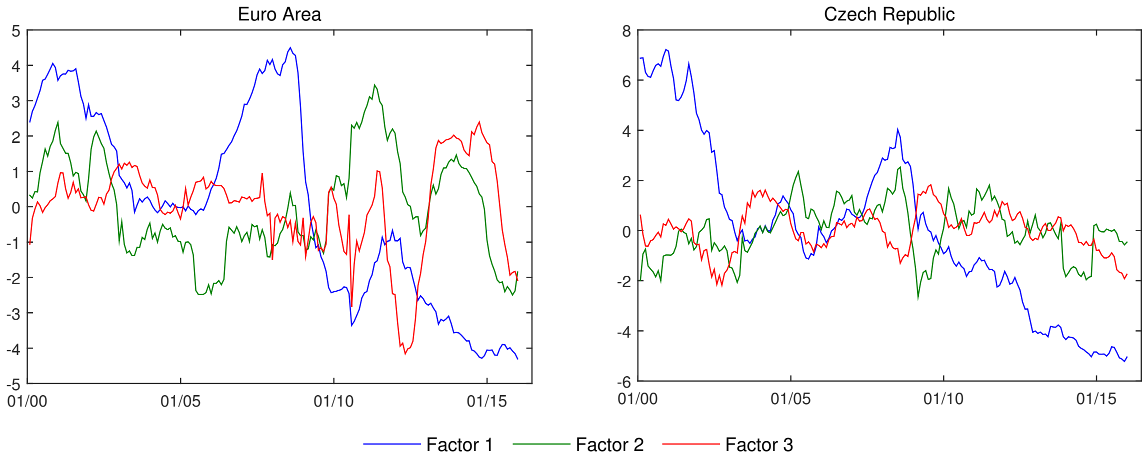
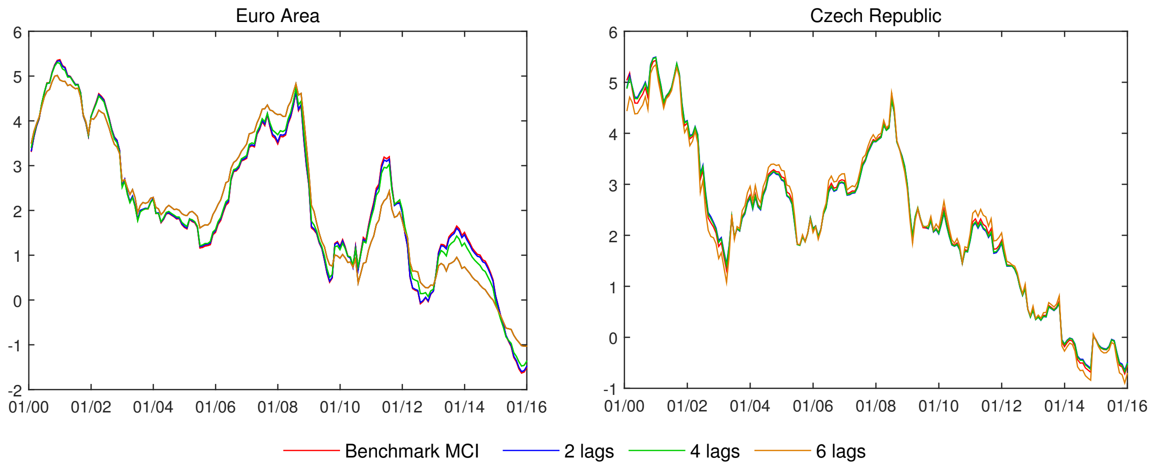
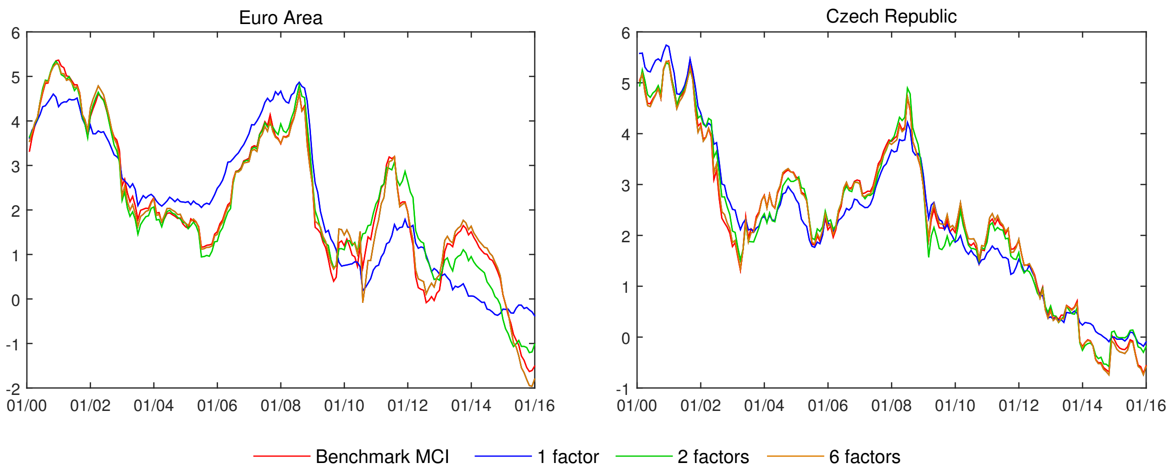


Figure A5: Robustness Check of the MCI

(a) Different lag order



(b) Different number of factors



A.5 BankScope Search Strategy

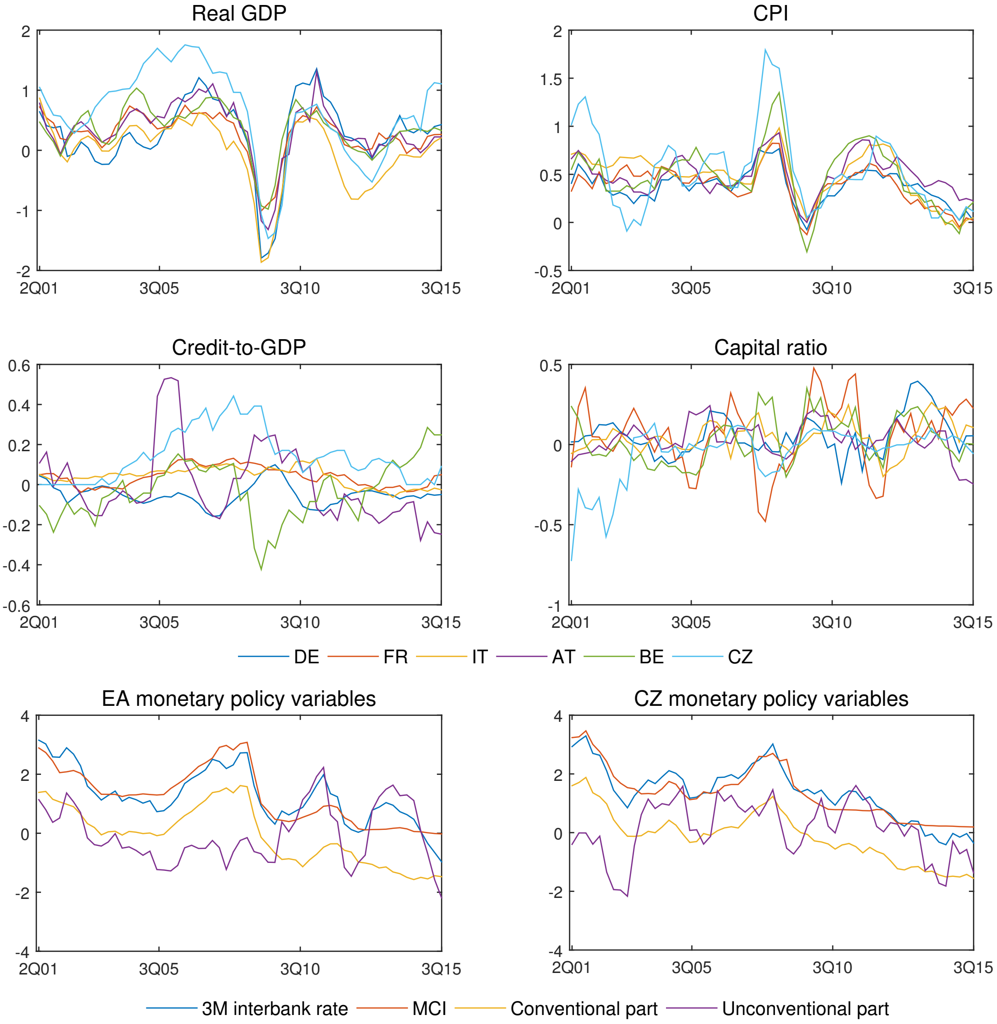
Table A2: BankScope Search Strategy

Status:	Active Banks	30538
Consolidation code:	Institutions (Cons. codes C1, C2, U1 and A1)	32626
Specialisation:	Commercial banks, savings banks, cooperative banks, real estate and mortgage banks, bank holdings and holding companies	35217
World Region/Country:	Austria (AT), Belgium (BE), Czech Republic (CZ), France (FR), Germany (DE), Italy (IT)	7698
Total assets (EUR):	2016, 2015, 2014, 2013, 2012, 2011, 2010, 2009, 2008, 2007, 2006, 2005, 2004, 2003, 2002, 2001, 2000 for at least one of the selected periods, Top 100	220

Note: The sample generated covers the period from 2000 to 2014; it is unbalanced; banks with less than five reported years were discarded; a final sample of 200 banks was used in the subsequent analysis.

Appendix B: Graphical Appendix

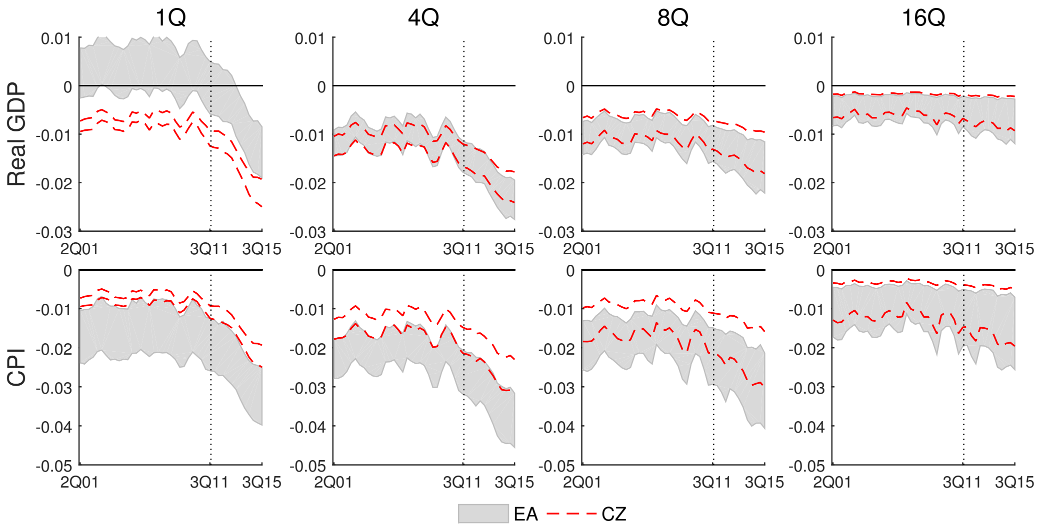
Figure B1: Data Series in the Panel BVAR Model



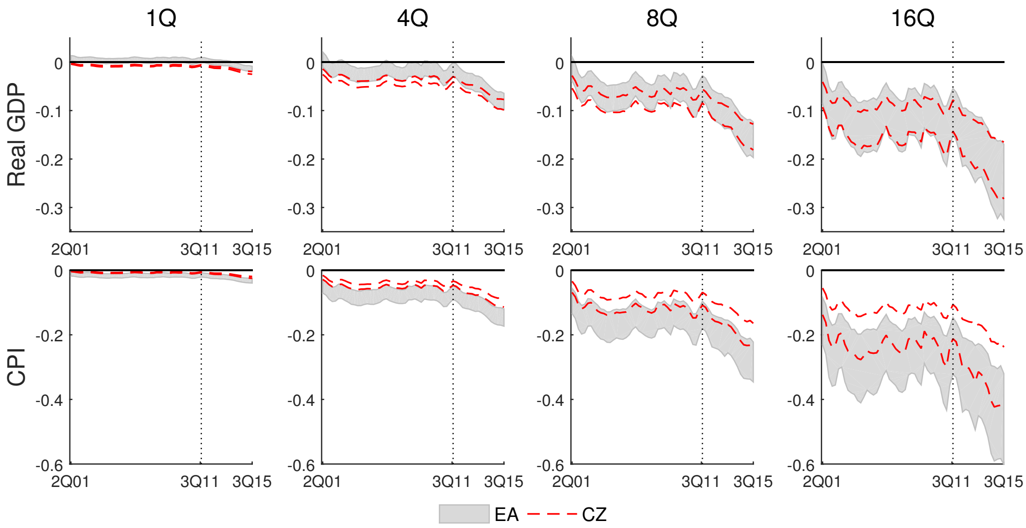
Note: Except for the monetary policy proxies, the variables are in quarter-on-quarter changes, annualised.

Figure B2: Impulse Responses – Shock to the MCI (2)

(a) Non-cumulative



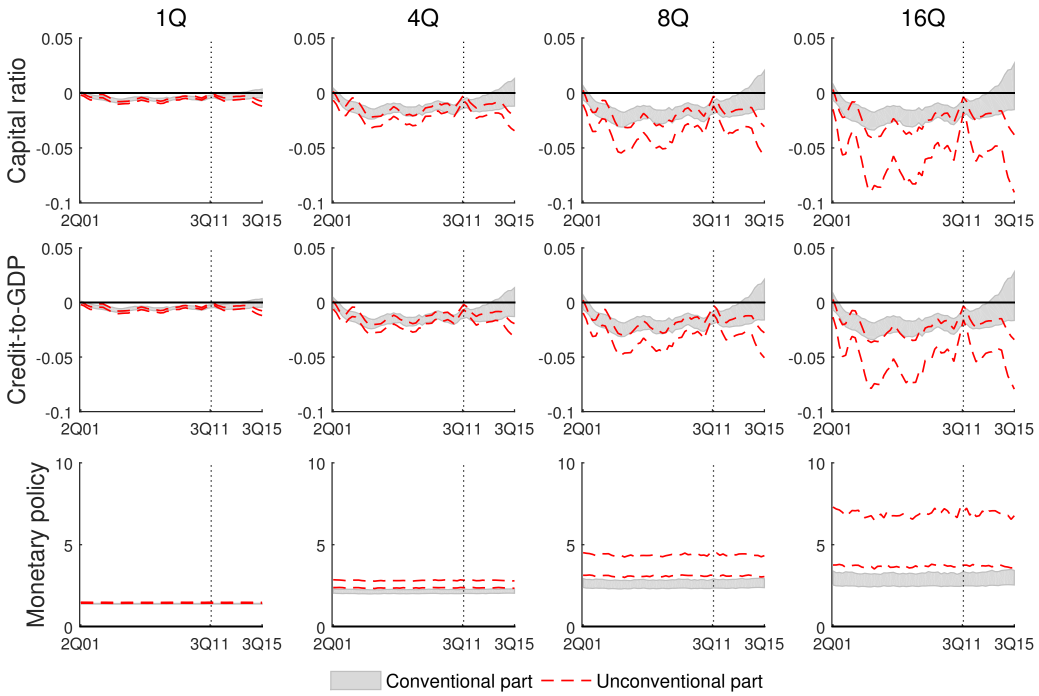
(b) Cumulative



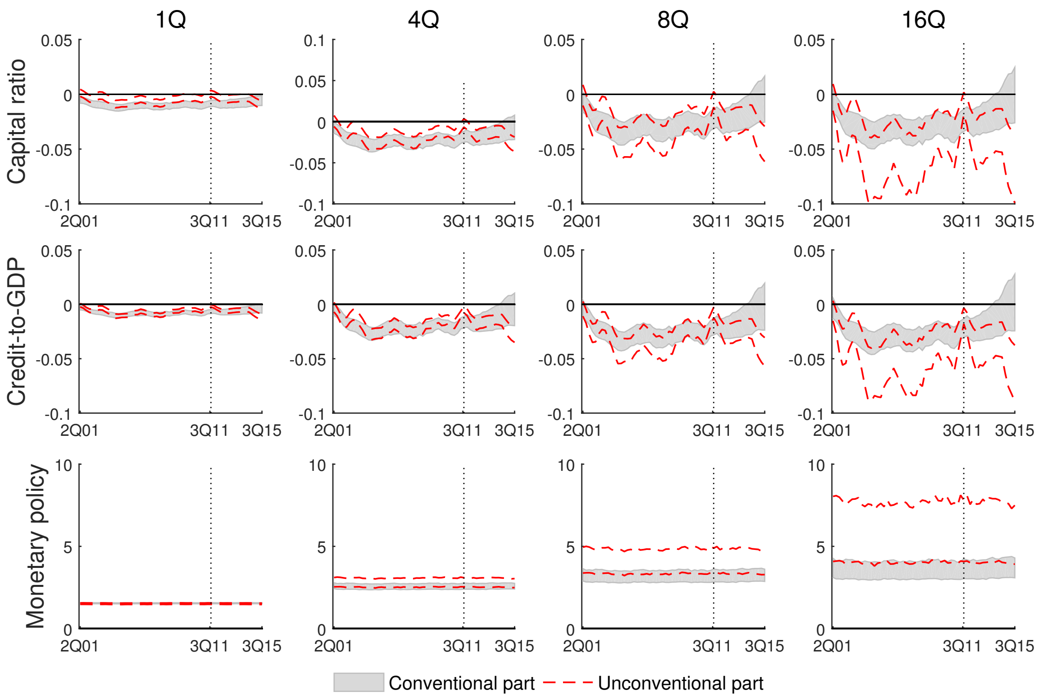
Note: Responses after 1, 4, 8 and 16 quarters to a 1 pp shock at $Q = 0$; 32th and 68th percentiles of the distribution reported. Except for the monetary policy proxies, the variables are in quarter-on-quarter changes, annualised.

Figure B3: Impulse Responses – Conventional and Unconventional Monetary Policy Shock (2)

(a) CZ, cumulative



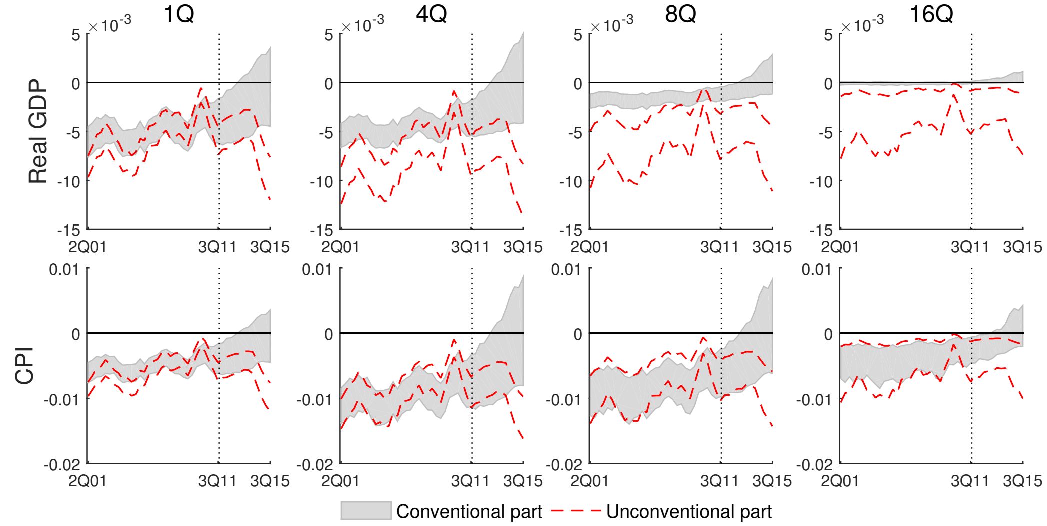
(b) EA, cumulative



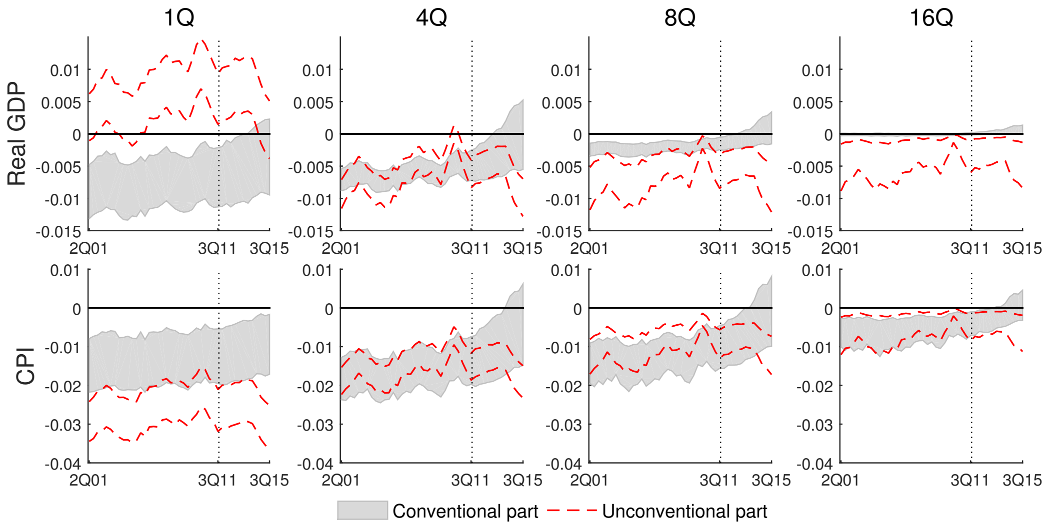
Note: Responses after 1, 4, 8 and 16 quarters to a 1 pp shock at $Q = 0$; 32th and 68th percentiles of the distribution reported. Except for the monetary policy proxies, the variables are in quarter-on-quarter changes, annualised.

Figure B4: Impulse Responses – Conventional and Unconventional Monetary Policy Shock (3)

(a) CZ, non-cumulative



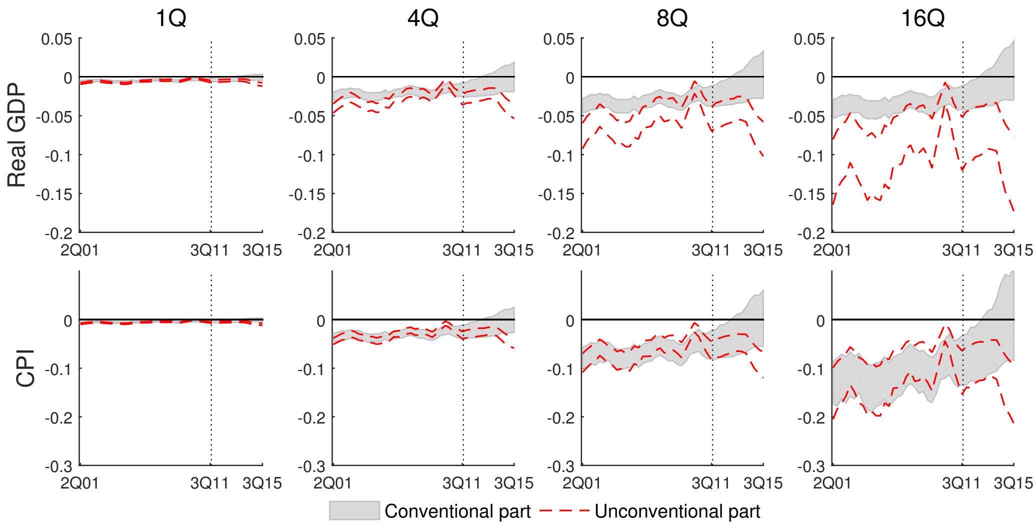
(b) EA, non-cumulative



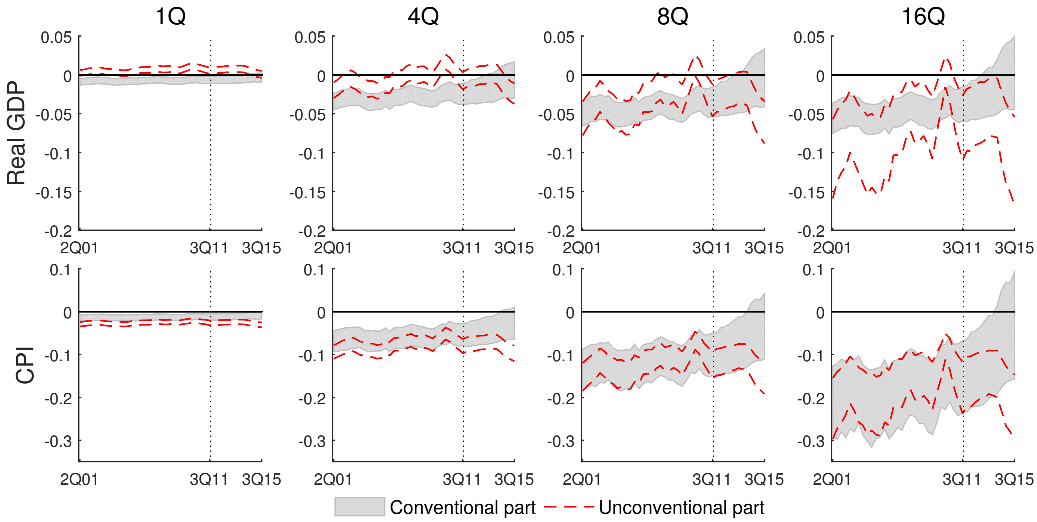
Note: Responses after 1, 4, 8 and 16 quarters to a 1 pp shock at $Q = 0$; 32th and 68th percentiles of the distribution reported. Except for the monetary policy proxies, the variables are in quarter-on-quarter changes, annualised.

Figure B5: Impulse Responses – Conventional and Unconventional Monetary Policy Shock (4)

(a) CZ, cumulative

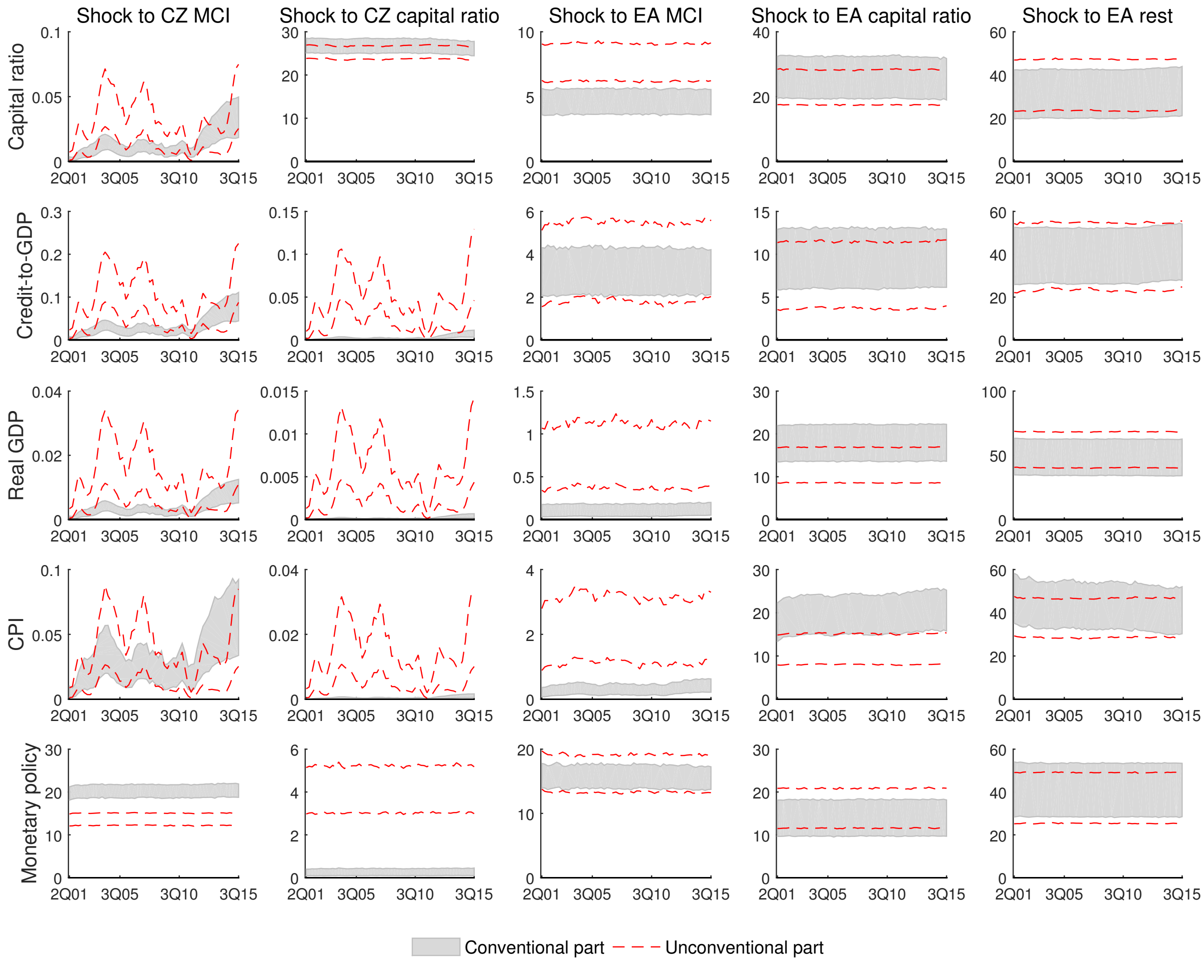


(b) EA, cumulative



Note: Responses after 1, 4, 8 and 16 quarters to a 1 pp shock at $Q = 0$; 32th and 68th percentiles of the distribution reported. Except for the monetary policy proxies, the variables are in quarter-on-quarter changes, annualised.

Figure B6: Forecast Error Variance Decomposition of Czech Variables (2)



Note: Contributions of different shocks to the forecast error variance of the Czech variables after 16 quarters; 32th and 68th percentiles of the distribution reported. Except for the monetary policy proxies, the variables are in quarter-on-quarter changes, annualised.

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