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Credit Spreads and the Links between the Financial and Real Sectors in a Small Open Economy: The Case of the Czech Republic*

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Abstract

Various approaches have been employed to explore the possibility of non-linear feedback between the real and financial sectors. The present study focuses on the impact of real shocks on selected financial sector indicators and the responses of the real economy to impulses emanating from the financial sector. We estimate a threshold Bayesian VAR with block restrictions and the credit spread as a threshold variable using the example of the Czech Republic. We find that while there is no evidence of asymmetric effects across positive and negative shocks, the responses of the financial sector to real shocks tend to differ below and above the credit spread threshold. Responses in the opposite direction (i.e. from the financial sector to the real economy) are pro-cyclical and similar irrespective of regime. A positive shock to credit and a negative shock to the NPL (non-performing loans) increase industrial production over the entire time horizon. The direct impact of foreign factors on lending seems to be rather limited.

1. Introduction

The persistent financial market vulnerability in Europe has raised pressing questions about the viable options for policymakers and the operability of "traditional" policy instruments. Given the recent crisis and post-crisis experience, the momentum of the debate has from the outset centered on the interactions between the real and financial sectors. The efforts by researchers, industry experts and policymakers have ultimately been transformed into a number of both theoretical and empirical studies (for a detailed survey, see, for example, BIS, 2011), which either build upon existing channels or develop novel ones linking the real and financial sides of the economy. The influential balance sheet or "financial accelerator" framework of Bernanke and Gertler (1995) emphasizes capital market frictions, including moral hazard, asymmetric information and imperfect contract enforcement problems, and the subsequent need for collateral to access credit. As a result, shocks to collateral value arising in the real economy might in turn feed back from the banking sector into real economic activity.[1] The bank lending and bank capital channels instead focus on banks' asset and liability structure. The former channel relies on the inability of banks to fully substitute for lost liabilities in the event of a monetary contraction

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[1] Given the dominant position of bank credit in the financing of Czech corporates and households, the authors use the terms banking sector and financial sector interchangeably.

(Bernanke and Blinder, 1988), while the latter reflects banks' incentives given exogenous shocks to capital and interactions of capital with regulatory requirements. In such a setting, adverse changes to bank capital can have a pronounced impact on the lending of less capitalized banks (van den Heuvel, 2002; Meh and Moran, 2010). The literature on capital requirements has identified additional feedback effects of regulation through shifts in risk-weighted assets in the capital-asset ratio (Borio *et al.*, 2001; Goodhart *et al.*, 2004). The liquidity channel, as discussed, for example, by Brunnermeier and Pedersen (2009), has received considerable attention, especially due to the spillover mechanisms amplifying the recent financial crisis.[2]

Most of the literature on the impact of the financial sector on economic activity and *vice versa* assumes a linear relation between these two sectors. However, the interactions between them are not necessarily linear. The endogeneity of credit markets in the financial accelerator mechanism, the propagating sectoral dynamics of the liquidity channel and, for example, the relevance of the bank capital channel for a subset of (less capitalized) banks each point to the potential importance of non-linearities in applied work. The role of non-linearities increased after the Lehman collapse, when the financial sector and economic activity passed through a period characterized by increased financial turbulence and a drop in economic activity worldwide. Schleer and Semmler (2015) confirm this hypothesis and stress the importance of non-linearities. The authors find that euro-area output has amplified the reaction to shocks in periods of high financial stress.

The contribution of this paper is the following: First, the present study aims to gauge the non-linear interactions between the real sector and the financial sector in a simple reduced-form model taking separate perspectives on (i) the responses of the financial sector to real shocks and ii) the impact of financial shocks on the real economy. To our knowledge, this is the only study on the interactions between the real and financial sectors in the Czech Republic which accounts for non-linearities. Given that most of the related empirical studies have focused on developed economies (the sole exception being Çatik and Martin, 2012), this study provides complementary evidence on the role of non-linearities for a small emerging economy. Our model incorporates a simple form of non-linearity. By allowing for regime shifts depending on credit market conditions, we impose greater flexibility than in the case of a linear system so that the potential non-linearities in the transmission of shocks from the financial system can be evaluated. The second contribution of the present study is methodological, as we extend the single-equation Bayesian threshold model by Chen and Lee (1995) into the multiple-equation setting with block restrictions to account for external factors in a small open economy.

The remainder of the paper is organized as follows: Section provides a brief overview of the empirical evidence on real sector-finance linkages. Section 3 describes the data and methodology. Section 4 presents estimated generalized impulse responses for key variables of interest and discusses the results. Section 5 concludes the paper.

2. Empirical Literature

The empirical links between the real economy and the financial sector have been studied extensively within distinct analytical frameworks and from different

[2] Other studies on market and funding liquidity include Wagner (2010) and Strahan (2008).

perspectives. Most empirical studies on feedback effects rely on the vector autoregression (VAR) methodology, which links key macroeconomic variables with a selected indicator, or selected indicators, of financial sector performance. These studies typically emphasize the link from the real sector to the financial sector using aggregate-level data within standard (possibly cointegrated) vector autoregressions.[3]

The literature, focused largely on credit risk, emphasizes the role of macroeconomic aggregates in the modeling of default rates or other dimensions of credit risk, and addresses possible feedback effects from banks to the real sector with more or less frequent reference to stress-testing. Alves (2005) and Åsberg Sommar and Shahnazarian (2008) employ cointegration techniques to find a significant relationship between the expected default frequencies published by Moody's and selected macro-variables. Aspachs *et al.* (2007) use panel VAR techniques to measure the impact of banks' default probabilities on the GDP variables of seven industrialized economies, while global VAR studies by Pesaran *et al.* (2006) and Castrén *et al.* (2008) establish links between global macroeconomic and financial factors and firm-level default rates.

Literature building upon the standard monetary policy framework augmented by financial sector variables typically investigates the monetary policy mechanisms and the transmission channels from finance to the real economy. This includes Gilchrist and Zakrajšek (2011), Helbling *et al.* (2011) and Meeks (2012), who model the links from credit spreads to business cycle indicators, and de Bondt (1998, 1999), Favero *et al.* (1999), Altunbas *et al.* (2002), Hristov *et al.* (2012) and Milcheva (2013), who focus on the bank lending channel in Europe. Research on Central European economies includes Franta *et al.* (2011), who study the monetary transmission mechanism in the Czech Republic using a time-varying parameters VAR model, and Vilagi and Tamási (2011), who use Hungarian data and rely on a Bayesian structural VAR model to consider different types of credit shocks. Égert and MacDonald (2009) provide a detailed survey covering the region of Central and Eastern Europe.

While the empirical literature spans a long list of macro-studies on feedback effects between the real economy and the banking sector, the role of non-linearities has been studied to a somewhat lesser extent. As the precise nature of the non-linearities in most situations is not known, authors have opted for different estimation frameworks. Among the most prominent are the threshold and Markov-switching VAR models (TVAR and MS-VAR, respectively). A frequently cited study by Balke (2000) adopts a structural TVAR model with tight and regular credit regimes using quarterly US GDP data over the period 1960–1997. The model finds a larger effect of monetary policy shocks on output in the "tight" credit regime and a more pronounced effect of contractionary monetary shocks compared to expansionary ones. In a similar TVAR exercise for the UK, Atanasova (2003) supports the evidence on the asymmetry of monetary policy effects in credit constrained and unconstrained regimes as well as different output effects of monetary contractions and expansions. Finally, Calza and Sousa (2006) employ Balke's framework to investigate the role of credit shocks in the euro area and conclude that, while present, the non-linearities

[3] As DSGE models have only recently moved away from a highly stylized treatment of the financial sector, the present section does not provide a detailed treatment of the DSGE literature (for a survey, see Brázdik *et al.*, 2011).

and asymmetric responses seem to be less pronounced than those found by Balke (2000) for the US.

Kaufmann and Valderrama (2007), on the other hand, estimate an MS-VAR model for the euro area and the US. The results for the euro area show that, depending on the regime, lending is supply-driven (low credit growth regime) or demand-driven (high credit growth regime). In the case of the United States, periods of low volatility in GDP growth, inflation and asset price growth are associated with rapid credit growth. In another comparative study by Kaufmann and Valderrama (2008) focusing on German and UK bank lending, the authors apply the MS-VAR model to corporate and household sector data and conclude that shocks to real variables and interest rates differently impact lending both across regimes within countries and across countries for a given regime.

Studies outside the TVAR and MS-VAR frameworks include higher-order approximation of a non-linear VAR by Drehmann *et al.* (2006). The authors relate aggregate credit risk in the UK to macroeconomic variables and find that credit risk responds strongly to macro developments, especially for large shocks. De Graeve *et al.* (2008) introduce an integrated micro-macro framework at the bank level based on German bank data linked to macroeconomic variables. Utilizing the parameters from a micro-based logit model in a macro VAR, the authors identify feedback effects between the banking sector and the real economy which are impossible to obtain from the standard linear specification. A study of the euro area by Gambacorta and Rossi (2010) employing the asymmetric vector error correction model addresses possible asymmetries in the transmission mechanism and concludes that the effect of a monetary policy tightening on credit, GDP and prices is larger than the effect of a monetary policy easing.

A common feature of all the above-mentioned studies allowing for non-linearities is their focus on developed market economies. To the best of our knowledge, Çatik and Martin (2012) is the only published study focusing on the non-linear feedback effect from the real economy to the financial sector in an emerging market economy. Using TVAR, the study investigates changes to the macroeconomic transmission mechanism in Turkey after a change of monetary policy regime in the early 2000s and finds sharp changes in transmission mechanisms after 2004, when the reforms were implemented.

3. Methodology and Data

3.1 Bayesian Threshold VAR

The potentially non-linear nature of the feedback effects between the real and financial sectors is addressed within the threshold VAR framework.[4] The advantage of TVAR is that it allows for endogenous switching between different regimes as a result of shocks to the modeled variables. Furthermore, the framework is a convenient and straightforward tool for the treatment of certain types of non-linearities, such as regime switching or multiple equilibria (Balke, 2000). The selection of the threshold variable provides an intuitive reference to the source driving the non-

[4] One possible alternative is the MS-VAR framework, which examines the exogenous (random) transitions between regimes. Time-varying coefficient VARs, on the other hand, are more suited to tracking gradual changes in transmission over time (Boivin *et al.*, 2010).

linearities. Potential disadvantages include the omission of other drivers, especially in cases where the nature of the non-linearity is uncertain, and the linearity restriction within a given regime.

Given the limited length of the time series, we assume the existence of a single threshold value. Nonetheless, despite the available evidence of distinct feedback effects between regular and “tight” or “crisis” regimes, one should note that it is still not clear to what extent models allowing for single switching of parameters (i.e. a unique threshold) capture the actual nature of the non-linearities.

The model contains three blocs of variables: (i) the domestic real sector and domestic monetary policy, as represented by the volume of industrial production, the price level and the short-term interest rate, (ii) the domestic financial sector, as measured by the volume of aggregate credit and the share of non-performing loans (NPLs), and (iii) the external sector, approximated by the nominal exchange rate, the volume of foreign industrial production and the foreign interest rate (foreign industrial production and the foreign interest rate enter the model first). We use the Bayesian threshold VAR (BTVAR) framework with block restrictions on exogenous foreign industrial production, and the interest rate to account for the small open economy assumption. The application of the Bayesian framework in the present setting was motivated among other things by its lower sensitivity to sample size relative to the frequentist framework.

$$\mathbf{y}_t = \mathbf{\Pi}_1 \mathbf{x}_t \mathbf{I}\left[y_{t-d}^{thr} < r \right] + \mathbf{\Pi}_2 \mathbf{x}_t \mathbf{I}\left[y_{t-k}^{thr} \geq r \right] + \boldsymbol{\varepsilon}_t \qquad t = 1,..,T \qquad \boldsymbol{\varepsilon}_t \approx NI_p(\mathbf{0},\mathbf{\Omega}) \tag{1}$$

where

$\mathbf{x}_t$ stands for a $p \times 1$ vector of endogenous variables, $\mathbf{x}_t = \left[1, x_{t-1}^1, .., x_{t-1}^p, .., x_{t-k}^1 .., x_{t-k}^p \right]$ is a $pk+1$ vector of lagged endogenous variables, and $\mathbf{\Pi}_i$ is a $p \times (1+pk)$ matrix of coefficients with block exogeneity restrictions such that for n foreign and m domestic variables we have

$$\mathbf{\Pi}_i = \begin{bmatrix} \mathbf{\Pi}_{nn} & \mathbf{0} \\ \mathbf{\Pi}_{nm} & \mathbf{\Pi}_{mm} \end{bmatrix} \tag{2}$$

The block exogeneity assumption postulates that domestic shocks should not impact on foreign covariates and has been employed by a number of studies on small open economies (e.g. Cushman and Zha, 1997; Zha, 1999; Maćkowiak, 2006; Havránek *et al.*, 2010). The threshold selection in BTVAR accounts for potential volatility shifts across regimes, replacing the restrictive assumption of constant volatility in the TVAR model by Balke (2000) and his successors. Neglecting the heteroscedasticity of shocks might cause changes in the magnitude of shocks to be confused with changes in the transmission mechanism (Primiceri, 2005).

The model is estimated in levels that, following the argument by Sims *et al.* (1990), avoids inconsistencies that might possibly occur if we incorrectly impose cointegration restrictions. Using specification without a cointegration relation also helps to save degree of freedom, which is important for our relatively small sample length. Furthermore, a Bayesian framework has a significant advantage in terms of the treatment of non-stationarity, since the presence of unit roots in the data does not affect the likelihood function (again Sims *et al.*, 1990).

The identification of shocks relies on recursive (Cholesky) decomposition. The ordering of the variables proceeds from a measure of economic activity, the price level, the interest rate, the exchange rate and a measure approximating the Czech financial sector (Goodhart and Hofmann, 2008; Havránek *et al.*, 2010). For the foreign variables, we assume ordering from output to the interest rate.

We adopt normal-diffuse priors for the autoregressive coefficients following Kadiyala and Karlsson (1997), which are commonly used in the literature on Bayesian VARs:[5]

$$\boldsymbol{\pi}_i \approx N\left(\tilde{\boldsymbol{\pi}}, \tilde{\mathbf{V}}_i^{pr}\right) \text{ and } p\left(\boldsymbol{\Sigma}_i\right) \propto \left|\boldsymbol{\Sigma}_i\right|^{-(p+1)/2} \qquad \text{for } i = 1,2, \tag{3}$$

where $\boldsymbol{\pi}_i$ is a vector of stacked coefficients of the matrix $\boldsymbol{\Pi}_i$, $\tilde{\boldsymbol{\pi}}_i$ is a zero column vector with $p(1+pk)$ rows, $\tilde{\mathbf{V}}_i^{pr}$ are matrices with elements corresponding to the coefficients on their own lags equal to φ_0 / l^2 and elements on other lags equal to $\varphi_0\varphi_1\sigma_{i,q}^{2} \big/ \left(l^2\sigma_{i,r}^{2}\right)$, where $\sigma_{i,q}^{2}$ corresponds to the standard error of an AR(1) process of a variable q estimated separately for each variable. The values of the hyperparameters are set to $\varphi_0 = 0.2$, $\varphi_1 = 0.5$.[6] The prior on the residual variance-covariance matrix is diffuse and independent of the priors on the autoregressive coefficients.

The prior on the threshold parameter is assumed to follow a uniform distribution on the interval $\left[r_{\underline{q}}, r_{\overline{q}}\right]$, where $\underline{q}$ represents the 10% quantile and $\overline{q}$ the 90% quantile of the threshold variable r. Employing the simple Metropolis-Hastings algorithm (e.g. Chen and Lee, 1995; Koop and Potter, 2014), the candidate draws r^* are accepted with the probability $p = \min\left(1, \dfrac{f\left(r^*\right)}{f\left(r\right)}\right)$, where $f(\cdot)$ is the log-likelihood function.[7] Finally, the prior for the delay parameter accounts for possible lagged effects of the shift to another regime and i_t is assumed to follow a multinomial distribution generating the probability of a particular delay equal to $1/d_0$, where d_0 represents the maximum number of lags considered.

The likelihood function and the conditional posterior distributions for the individual parameters can be found in the *Appendix*. For the analysis of feedback between the real sector and the banking sector, we computed generalized impulse response functions (GIRFs) based on Koop, Pesaran and Potter (1996). The nonlinear GIRFs abandon the symmetry and history independence properties of linear impulse response functions and take into account the size (and sign) of the shock, as well as its evolutionary path. The practical computation of the GIRFs is based

[5] See Koop and Korobilis (2010) for an excellent survey on Bayesian macroeconometrics and Giannone *et al.* (2012) for a discussion focused specifically on prior selection.

[6] A detailed exposition is provided in (Canova, 2007).

[7] See the *Appendix* for the likelihood function of the threshold parameter.

on the repeated simulation of impulse responses with and without the initial shock to an i-th variable of concern. In particular, after the specification of the initial shock to an i-th variable corresponding to one standard deviation, we pick a history Ω_{t-1}^{r} of the m-dimensional time series over the period k. In the following step, we impose a sequence of shocks of the same length k drawn with replacement from the estimated BTVAR residuals and calculate the implied system dynamics. In the next step, we impose an alternative sequence of shocks, which is identical to the previous one except for the addition of one standard deviation to the relevant variable in period 0, and again simulate the implied impulse responses. The GIRF is then the difference between the two simulated paths. The whole procedure was repeated for $R = 1{,}000$ histories Ω_{t-1}^{r} and $B = 200$ drawn shocks and the ultimate GIRF was calculated as the average impulse response function over the BR rounds.[8]

There would be little justification for applying the threshold model if no statistically significant evidence of non-linearities was present. Before embarking on the BTVAR estimation, we tested for non-linearities using the procedure by Hansen (1996). The procedure uses the standard F_n-statistic

$$F_n = \sup_{r \in \Gamma_n} F_n(r) \tag{4}$$

which, given that the threshold r is not identified under the H_0, does not have the chi-square distribution. The appropriate asymptotic distribution can nonetheless be approximated by means of a bootstrap procedure. We ran 1,000 realizations of the standard F_n statistic under the null hypothesis of symmetry for each grid point and then obtained its empirical distribution by collecting the statistics over the grid space of the threshold values.[9]

3.2 Data

The sample has a monthly frequency spanning 2004m1–2012m3. The choice of model variables was guided by similar studies on a small open economy (e.g. Borys-Morgese *et al.*, 2009; Havránek *et al.*, 2010; Franta *et al.*, 2011). We prefer industrial production as a proxy for the level of economic activity, given that more traditionally used measures such as real GDP and the output gap are available only at quarterly frequency.[10] In the literature on real sector-finance feedback, industrial production was used, for example, by Atanasova (2003). The three-month PRIBOR approximates the monetary policy rate and the cost of funds in the economy. The remaining variables in the standard monetary policy model for a small open economy include the price level and the nominal exchange rate.[11] Given that more than three-quarters of Czech foreign trade is invoiced in euros, we use the bilateral

[8] For more details, see also Atanasova (2003).

[9] The original Gauss code for the testing procedure was obtained from Atanasova (2003).

[10] Borys-Morgese, Horváth and Franta (2009) originally used quarterly data transformed into monthly frequency using the Hodrick-Prescott filter.

[11] We use the nominal interest rate as in Mojon and Peersman (2001). In a low and stable inflation environment, nominal interest and exchange rates could be more informative than the respective real variables, which, in contrast to nominal rates, are not available in real time (immediately) but are published with a lag.

Table 1 Threshold Estimates and Test for Non-Linearity

Model	Estimated *r*	Hansen (1996)'s chi-square *p*-value
Credit	3.2821	0.003
NPLs	2.733	0.010

exchange rate against the euro instead of the effective rate. Aggregate nominal credit and the share of non-performing loans in total loans represent alternative measures of banking sector performance. To save on degrees of freedom, each financial indicator is employed in a separate model. As the Czech Republic is a small open economy, one needs to control for the external environment. We do so by using the three-month Euribor and the index of the real volume of industrial production of the 17 members of the euro area.

Empirical studies relying on the TVAR framework use a measure of the credit spread (Balke, 2000; Atanasova, 2003) or credit growth (Calza and Sousa, 2006) as a threshold variable to gauge credit market conditions. Balke (2000) employs three alternative indicators of credit market conditions, namely the commercial paper to T-bill spread, the mix of bank loans and commercial paper in firms' total external finance, and the difference between the growth rates in the short-term debt of small and large manufacturing firms. Atanasova (2003) uses the corporate bond spread defined as the redemption yield on ten-year investment-grade corporate bonds minus the equivalent maturity yield on risk-free government debt.[12]

Given the small size of the corporate bond market in the Czech Republic, the present study cannot rely on a measure based on corporate bond spreads. Instead, we define the credit spread as a difference of the average rate charged on newly issued loans and the one-year PRIBOR. The average rate is calculated as a weighted average of rates applied to corporate and household loans, with volumes of newly issued corporate and household loans as respective weights. The PRIBOR is a key reference rate for the cost of funds on the interbank market and serves as an approximation of a risk-free interest rate.[13]

Industrial production, the price level, the exchange rate, credit and EU GDP are expressed in natural logarithms and seasonally adjusted at the source where necessary. For the aggregate data on the real economy, we use the information published by the Czech Statistical Office and the ARAD database of the Czech National Bank. Variables capturing the external environment are from Eurostat and Bloomberg. Plots of all the series are available in *Figure 1A* in the *Appendix*.

4. Empirical Results

The results of Hansen's (1996) procedure indicate a strong presence of non-linearities for both specifications with credit and the non-performing loan ratio (see *Table 1*). The estimated thresholds correspond to a credit spread of 3.28% for the BTVAR specification with the credit variable and 2.73% for the specification

[12] Kaufmann and Valderrama (2008) employ the MS BVAR framework and thus do not need to consider a threshold variable. Nonetheless, they relate the two regimes identified to the general economic conditions.

[13] We do not adopt the Czech government debt yield as an alternative risk-free rate given the impact of the recent sovereign crisis on the volatility of sovereign bonds across Europe.

Figure 1 Credit Spread and Estimated Threshold from BTVAR with Credit

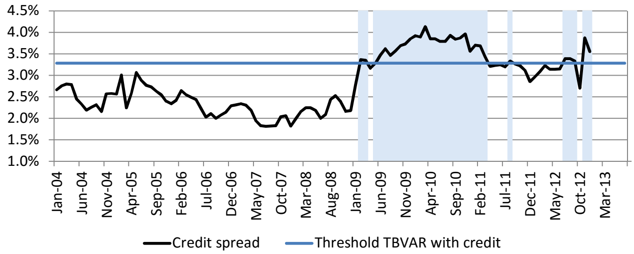
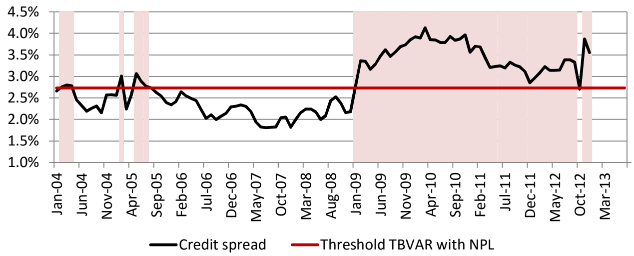


Figure 2 Credit Spread and Estimated Threshold from BTVAR with Non-Performing Loans



with NPLs.[14] The estimated threshold from the specification with credit highlights the importance for credit developments of the (postponed) advent of the post-Lehmann economic crisis in February 2009 and the following two and a half years of pronounced economic downturn (*Figure 1*). The threshold from the BTVAR specification with NPLs, on the other hand, points to a pronounced impact of the financial crisis on banks' credit losses extending over the whole post-2009 period (*Figure 2*). For simplicity, the regime where the credit spread is above the threshold level is called the "high credit spread regime" or "high regime", and that where the spread is below the threshold is referred to as the "low credit spread regime" or "low regime".

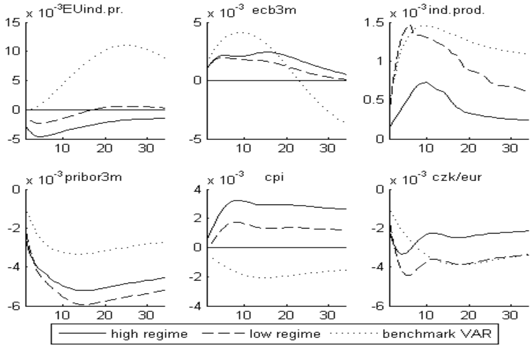
The figures containing the empirical results present generalized impulse response functions conditional on the initial state (*high* or *low* credit spread regime) and the impulse response functions from a symmetric BVAR model without a threshold (benchmark VAR). The size of the permanent shocks corresponds to a positive standard deviation at time $t = 0$. The impulse responses are evaluated over a period of 36 months. We do not report results for negative shocks, as our estimates do not find significant asymmetry in the impulse responses, i.e. the impulse responses have broadly the same magnitude in the case of positive and negative shocks.[15,16] An increase in industrial production, the domestic price level and the three-month PRIBOR are the domestic shocks, and an increase in EU industrial production, a rise in the three-month Euribor and exchange rate depreciation are the external shocks.

[14] The mean of the credit spread is 2.8%.

[15] The impulse responses for a negative shock can be provided upon request.

[16] Our results are consistent with Atanasova (2003), who did not find asymmetric responses for UK data. Balke (2000) and Gambacorta and Rossi (2010), on the other hand, find asymmetric effects for the US and the euro area respectively.

Figure 3 Impulse Response Functions from Real Sector Variables to Credit



4.1 Responses of the Financial Sector

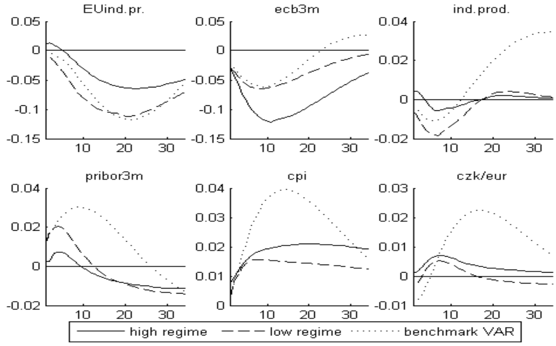
Figure 3 plots the impulse responses of credit to the three domestic and three external shocks. The comparison of the impulse responses from the benchmark VAR and BTVAR provide a mixed picture, with some responses showing a markedly different level and, in the case of CPI, even direction. These mixed results might point to potential restrictiveness of the benchmark VAR framework, which can be understood as a variant of the BTVAR with identical regimes. The subdued response of aggregate credit to a positive shock to industrial production in the *high* credit spread regime might be partly due to uncertainty about the net present value of potential investment projects of firms and/or the future income streams of households and a resulting unwillingness to take on loans. The credit response to the interest rate shock is, as expected, negative and more pronounced in the threshold specification as compared to the benchmark linear VAR.[17] Our results in some cases indicate notably different GIRFs as compared to the baseline VAR. For example, the negative response of credit to a positive shock to CPI obtained from the benchmark VAR is somewhat counterintuitive, given that credit is expressed in nominal terms. This result may be related to the tightness of firms' and households' budget constraints. An increase in the domestic price level might raise input costs more than revenues in a small open economy with a large proportion of exporting companies. Similarly, a higher price level reduces households' ability to service debt and reduces banks' willingness to lend. The more flexible BTVAR framework, on the other hand, generates responses that are in line with expectations.

Similarly, the responses of credit to a positive shock to foreign industrial production vary depending on the estimation framework. While the benchmark VAR indicates a positive and long-lasting reaction of credit, the BTVAR results suggest a mild and only transitory response path reverting quickly to zero.[18] Given that the overwhelming majority of loans in the Czech financial system are denominated in the domestic currency, the positive response to an increase in the Euribor probably

[17] The results indicate relatively high sensitivity of credit to interest rate shifts. *Table 1A* in the *Appendix* lists the peak responses of credit and non-performing loans with respect to industrial production and the three-month PRIBOR, respectively.

[18] Given the relatively small size of the impulse responses from the BTVAR, the counterintuitive negative sign in this case might point to low precision of the estimates rather than model misspecification.

Figure 4 Impulse Response Functions from Real Sector Variables to Non-Performing Loans



reflects a systemic response of the European Central Bank to inflation pressures rather than shifts in the costs of funds.[19]

The uniformly negative response of aggregate credit to the exchange rate depreciation can be explained by the convergence process of the Czech economy during the sample period, marked by steady appreciation of the Czech koruna, expansion of the Czech financial sector and corresponding growth of credit.

Figure 4 plots the impulse responses of non-performing loans to the macroeconomic variables. The responses of non-performing loans are qualitatively the same regardless of the estimation framework and initial regime, yet in the case of domestic macroeconomic variables, they show a distinctly muted pattern in the BTVAR setup. A one-time positive shock to industrial production leads to intuitively negative and transitory responses from the threshold estimates as compared to the benchmark VAR, implying a positive effect over the long term. The tamed results particularly in the *high* credit spread regime might possibly be driven by the insufficient size of the economic upturn and uncertainty about the length of the recovery over the crisis years.

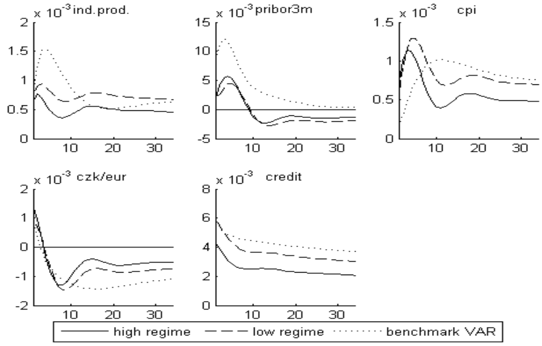
Price and interest rate increases are likewise notably less pronounced using the BTVAR estimates (similarly to the case of industrial production[20]). Conforming to expectations, NPLs initially rise following an interest rate hike.[21] A shock to the CPI might proxy for the worsening economic environment with negative repercussions in the level of NPLs, especially in the *high* regime. The depreciation of the domestic currency boosts the profits of exporters and connected supply chains, but the impact of the shock for the BTVAR impulse responses is nonetheless not strong enough to support all the beneficiaries of the depreciation and the effect on NPLs fades away in the second half of the response period.

[19] Foreign inflation has not been included in our model due to degrees-of-freedom considerations.

[20] Furthermore, the peak responses to a shock from industrial production listed in *Table 1A* in the *Appendix* are arguably smaller as opposed to the interest rate. These results could reflect the fact that industrial production captures a narrower part of the economy compared to aggregate credit, which covers the corporate and household (housing and consumer) components. In turn, relatively strong responses to PRIBOR3M, which is also a part of the real economy, and the relatively restrictive nature of the measure of industrial production are additional arguments for avoiding the cointegration approach.

[21] See *Table 1A* for the (purely indicative) quantification of a 10 bps rise in the interest rate.

Figure 5 Impulse Response Functions from Credit to Real Sector Variables



A shock to the EU17 industrial production index lowers NPLs, but to a lesser extent in the *high* regime. The negative response of NPLs to the Euribor interest rate rise might conform to the systemic reaction of the ECB to rising inflation and strong demand pressures. We do not think though that there is a clear parallel between domestic and foreign inflation and domestic NPLs, as time lags play a significant role.

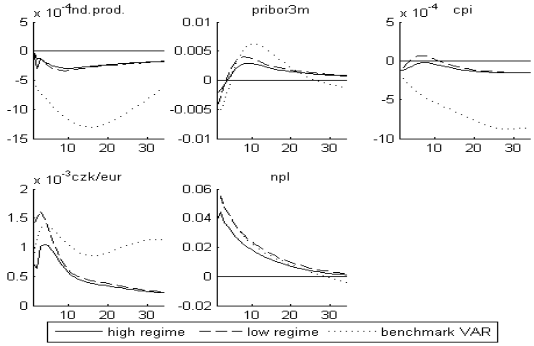
4.2 Responses of the Real Economy

The response of the domestic economy and the exchange rate to the shocks to credit and NPLs are shown in *Figure 5* and *Figure 6*.[22] The impulse responses for credit in *Figure 5* are of similar size and shape irrespective of regime. A positive shock to credit boosts industrial production over the entire time horizon. The benchmark VAR generates a strong procyclical effect over the first twelve months, which nonetheless returns to the response levels obtained from the BTVAR framework. The response of industrial production tends to be somewhat more pronounced in the *low* as opposed to *high* credit spread regime. While not directly comparable, our finding differs from that of Balke (2000), who finds that a credit spread shock approximating credit market conditions has substantially larger effects on output growth when the system is in the tight credit regime. Calza and Sousa (2006) likewise report the response of real GDP to a positive shock to real loan growth to be somewhat bigger but less persistent in the low credit growth regime than in the high credit growth regime.

The price level increases as more credit flows into the economy. The positive response of the interest rate tends to reflect the efforts of the monetary authority to curb the inflationary pressures spurred by credit inflows. The policy response is nonetheless smaller in the BTVAR framework in comparison to the benchmark case, where the initial interest rate reaction is elevated. The exchange rate appreciation following a positive shock to credit can be explained by the convergence process of the Czech economy during the sample period, similarly as in the case of the impulse response function from the exchange rate to credit.

[22] *Table 1B* in the *Appendix* lists the peak responses of industrial production and the interest rate with respect to credit and non-performing loans, respectively.

Figure 6 Impulse Response Functions from Non-Performing Loans to Real Sector Variables



Finally, *Figure 6* reports the impulse responses for a one-time positive shock raising NPLs by one standard deviation. The responses from the BTVAR are unanimously milder in comparison to the benchmark model and do not differ across regimes. Furthermore, the threshold responses imply zero or close to zero long-term effects of an increase in NPLs on the macroeconomy. The results indicate a negative path for industrial production and lower inflation, as well as depreciation of the currency.

5. Conclusions

We test for a non-linear relation between the real and financial sectors using a small empirical model generally applied in studies focusing on the transmission mechanism in a small open economy. We augment this model with financial sector aggregates—aggregate credit and non-performing loans (NPLs)—and estimate it using a BTVAR (Bayesian threshold VAR) model. We combine the BTVAR framework with information on credit and non-performing loans as measures of the stance of the financial sector in an attempt to provide a general picture of the feedback between the real and financial sectors of a small open economy. The estimated thresholds obtained from BTVAR identify different cut-off values for the credit spread, indicating the importance of the initial two and a half years of the global economic and financial crisis for credit developments and the pronounced impact of the financial crisis on banks' credit losses extending over the whole post-2009 period.

Our results indicate that the omission of non-linearities might lead to a possibly simplistic understanding of the interactions and transmission mechanisms between the real economy and the financial sector. In particular, the magnitude and, in some cases, even the direction of the impulse responses differ in the linear benchmark model and BTVAR frameworks. Furthermore, the impulse responses are in some cases strongly dependent on the initial state. This relates, for example, to the tamed response of aggregate credit to a positive shock to industrial production in the *high* credit spread regime.

Despite the absence of asymmetries in the effects of positive and negative shocks, the magnitude and, less frequently, the timing of the impulse responses differ in the *high* (above-threshold) and *low* (below-threshold value) credit spread regimes. We find that procyclicality of the financial sector matters for the real economy. A positive shock to credit and a negative shock to NPLs support industrial production over the entire time horizon, yet the responses to credit shocks do not differ substantially across credit spread regimes. This finding differs from the results of other studies employing the threshold VAR framework, which report asymmetric feedback from credit to the real economy. Asymmetries are likewise absent in the responses of the real economy to shocks to NPLs. The complementary investigation of non-performing loans reveals weak procyclicality of NPLs with respect to industrial production, which, however, vanishes after approximately 18 months. The economic recovery thus needs to be sufficiently robust to translate into lower NPLs. As the financial sector in the Czech Republic is largely bank-based and funded predominantly by domestic deposits, the direct impact of foreign factors on lending seems to be rather limited and credit volumes tend to be affected indirectly through the situation within the production sector of the economy.

Our results imply that policymakers should take into account the unstable transmission mechanism from the real to the financial sector, in particular from output to credit. Moreover, the financial sector feeds procyclically back into the real economy, thus supporting the argument for regulation of the mechanisms amplifying crisis period under study (e.g. Borio *et al.*, 2001).

APPENDIX

Table 1A Peak Responses of Credit and Non-Performing Loans to Shocks from Industrial Production and the Interest Rate

	From industrial production (1% change)		From 3M PRIBOR (10 bps change)	
	credit	**NPLs**	**credit**	**NPLs**
Benchmark	0.017%	-0.13 bps	-2.90%	28.8 bps
High	0.009%	-0.07 bps	-4.92%	7.68 bps
Low	0.017%	-0.25 bps	-5.79%	19.2 bps

Note: Peak responses have been recalibrated as compared to the results presented in *Figure 3* and *Figure 4*, which show impulse responses to a one standard deviation shock.

Table 1B Peak Responses of Industrial Production and the Interest Rate to Shocks from Credit and Non-Performing

	From credit (1% change)		From NPLs (1 pp change)	
	industrial production	**3M PRIBOR**	**industrial production**	**3M PRIBOR**
Benchmark	0.29%	2.43 bps	-1.66%	8.62 bps
High	0.15%	1.17 bps	-0.33%	5.31 bps
Low	0.19%	0.98 bps	-0.33%	3.98 bps

Note: Peak responses have been recalibrated as compared to the results presented in *Figure 5* and *Figure 6*, which show impulse responses to a one standard deviation shock.

The likelihood function for the threshold BVAR follows Kadiyala and Karlsson (1997):

$$L\left(\mathbf{\Pi}_1,\mathbf{\Pi}_2,\mathbf{\Sigma}_1,\mathbf{\Sigma}_2,r,d \mid \mathbf{Y}\right)\propto\left|\mathbf{\Sigma}_1\right|^{-\frac{n_1}{2}}\left|\mathbf{\Sigma}_2\right|^{-\frac{n_2}{2}}\exp\left\{-\frac{1}{2}tr\left[\sum_{i=1}^{2}\left(\mathbf{Y}_i-\mathbf{X}_i\mathbf{\Pi}_i\right)'\mathbf{\Sigma}_i^{-1}\left(\mathbf{Y}_i-\mathbf{X}_i\mathbf{\Pi}_i\right)\right]\right\}=$$

$$=\left|\mathbf{\Sigma}_1\right|^{-\frac{n_1}{2}}\left|\mathbf{\Sigma}_2\right|^{-\frac{n_2}{2}}$$

$$\exp\left\{-\frac{1}{2}\sum_{i=1}^{2}\left(\boldsymbol{\pi}_i-\boldsymbol{\pi}_i^{OLS}\right)'\left(\mathbf{\Sigma}_i^{-1}\otimes\mathbf{X}_i'\mathbf{X}_i\right)\left(\boldsymbol{\pi}_i-\boldsymbol{\pi}_i^{OLS}\right)-\frac{1}{2}tr\left[\sum_{i=1}^{2}\mathbf{\Sigma}_i^{-1}\left(\mathbf{Y}_i-\mathbf{X}_i\mathbf{\Pi}_i^{OLS}\right)'\left(\mathbf{Y}_i-\mathbf{X}_i\mathbf{\Pi}_i^{OLS}\right)\right]\right\}=$$

$$=N\left(\boldsymbol{\pi}_i \mid \boldsymbol{\pi}_i^{OLS},\mathbf{\Sigma}_i\otimes\left(\mathbf{X}_i'\mathbf{X}_i\right)^{-1}\right)\times W\left(\mathbf{\Sigma}_i \mid \left(\mathbf{Y}_i-\mathbf{X}_i\mathbf{\Pi}_i^{OLS}\right)'\left(\mathbf{Y}_i-\mathbf{X}_i\mathbf{\Pi}_i^{OLS}\right),n_i-1+pk-1\right)$$

where $n_1=\sum_{t=1}^{T-k}\mathbf{I}_{\left\{y_i^{thr}\right\}}$ and $n_2=T-k-n_1$ are parameters dependent on the threshold value r.

For the estimation of the autoregressive coefficients and the residual variance-covariance matrix, we employ the Gibbs sampler:

1) AR coefficients:

$$\boldsymbol{\pi}_i \mid \boldsymbol{\Sigma}_i, r, d, \mathbf{Y} \approx N\left(\boldsymbol{\pi}_i^{post}, \left(\left(\mathbf{V}_i^{prior}\right)^{-1} + \boldsymbol{\Sigma}_i^{-1} \otimes \mathbf{X}_i^{'}\mathbf{X}_i\right)^{-1}\right)$$

where

$$\boldsymbol{\pi}_i^{post} = \left(\left(\mathbf{V}_i^{prior}\right)^{-1} + \boldsymbol{\Sigma}_i^{-1} \otimes \mathbf{X}_i^{'}\mathbf{X}_i\right)^{-1} \left(\left(\mathbf{V}_i^{prior}\right)^{-1} \boldsymbol{\pi}_i^{prior} + \left(\boldsymbol{\Sigma}_i^{-1} \otimes \mathbf{X}_i^{'}\mathbf{X}_i\right)\boldsymbol{\pi}_i^{OLS}\right)^{-1}$$

2) Residual variance matrix

$$\boldsymbol{\Sigma}_i^{-1} \Big| \boldsymbol{\pi}_i, \mathbf{Y}, r, d \approx W\left(\left[\left(\mathbf{Y}_i - \mathbf{X}_i\boldsymbol{\Pi}_i^{OLS}\right)^{\prime}\left(\mathbf{Y}_i - \mathbf{X}_i\boldsymbol{\Pi}_i^{OLS}\right) + \left(\boldsymbol{\Pi}_i - \boldsymbol{\Pi}_i^{OLS}\right)^{\prime} \mathbf{X}_i^{'}\mathbf{X}_i\left(\boldsymbol{\Pi}_i - \boldsymbol{\Pi}_i^{OLS}\right)\right]^{-1}, n_i\right)$$

3) Threshold value

For the estimation of the conditional posterior probability of the threshold *r,* we employ the Metropolis-Hastings algorithm following Chen and Lee (1995):

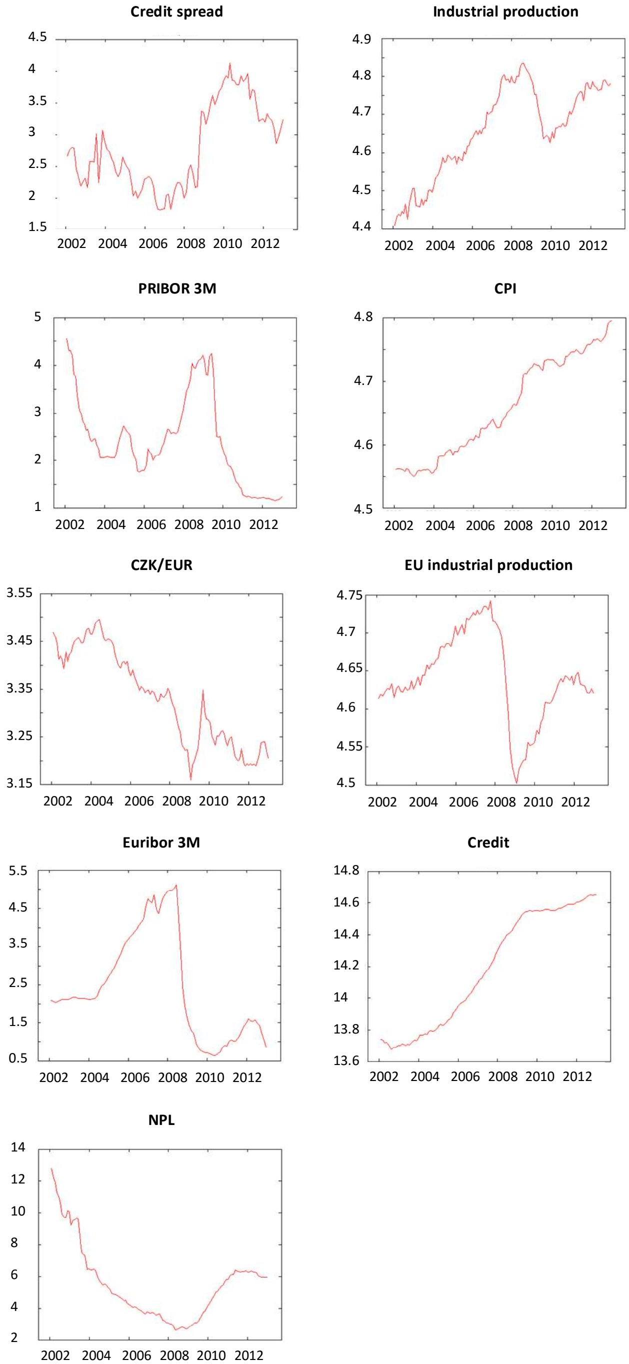
$$p\left(r \mid \boldsymbol{\Pi}_1, \boldsymbol{\Pi}_2, \boldsymbol{\Sigma}_1, \boldsymbol{\Sigma}_2, d, \mathbf{Y}\right) \propto \left|\boldsymbol{\Sigma}_1\right|^{-\frac{n_1}{2}} \left|\boldsymbol{\Sigma}_2\right|^{-\frac{n_2}{2}} \exp\left\{-\frac{1}{2} tr\left[\sum_{i=1}^{2}\left(\mathbf{Y}_i - \mathbf{X}_i\boldsymbol{\Pi}_i\right)^{'}\boldsymbol{\Sigma}_i^{-1}\left(\mathbf{Y}_i - \mathbf{X}_i\boldsymbol{\Pi}_i\right)\right]\right\} \times pr(r)$$

4) Delay parameter

The conditional posterior follows a multinomial distribution with probability

$$p\left(d \mid \boldsymbol{\Pi}_1, \boldsymbol{\Pi}_2, \boldsymbol{\Sigma}_1, \boldsymbol{\Sigma}_2, d, \mathbf{Y}\right) = \frac{L\left(\boldsymbol{\Pi}_1, \boldsymbol{\Pi}_2, \boldsymbol{\Sigma}_1, \boldsymbol{\Sigma}_2, r, d \mid \mathbf{Y}\right)}{\sum_{d=1}^{d_0} L\left(\boldsymbol{\Pi}_1, \boldsymbol{\Pi}_2, \boldsymbol{\Sigma}_1, \boldsymbol{\Sigma}_2, r, d \mid \mathbf{Y}\right)}.$$

Figure 1A Plots of Model Variables



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