Credit Dynamics and Non-performing Loans in the Czech Republic: Bayesian Approach[1]

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Abstract

The paper deals with the relationship between provided credit and non-performing loans (NPL) in the Czech Republic (CR). In the period 1994 – 2016 the CR experienced both periods of rapid credit growth and the transition to market economy followed by a strong convergence process. The aim of the paper is to investigate the effects of credit growth on the NPL dynamics. The selected method is Bayesian estimation with instrumental variables. Results demonstrate positive relationship between the credit growth and the NPL dynamics; however, estimated posterior mean values are rather small and imply that the credit growth influenced the accumulation of credit risk and the origination of the NPL in a modest way. Moreover, the effects are stronger in the CR compared to the prior value (close to zero), which is calculated based on the information obtained from the international empirical studies.

Keywords: *Bayesian estimation, credit-to-GDP gap, credit growth, non-performing loans*

JEL Classification: G21, C20, E44

Introduction

Non-performing loans (NPL) represent an ex-post indicator of credit risk materialization. The global financial crisis of 2007 and the subsequent economic downturn increased volume of the NPL in some countries.[2] In the Czech Republic

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[2] For the group of EU countries, see e.g. Aiyar et al. (2015).

(CR) there was a significant rise in the NPL observed particularly in years 2009 and 2010, see Figure 2 depicting the annual growth rates of NPL.

The rise in the NPL adversely affects credit provision through lower profitability, higher capital requirements and the increased funding costs of banks. Hence, the persistently higher level of the NPL reduces supply of credit, and the following deleveraging process constraints economic growth. In the real economy, demand for credit decreases with another adverse effects on banks. The spillover effects between real economy and the financial (banking) system, in other words the macro-financial feedback loop, are commonly studied by models of vector autoregression (VAR) or vector error correction (VEC); for the recent studies see e.g. Konstantakis, Michaelides, and Vouldis (2016) or Kjosevski and Petkovski (2016). However, this paper attempts to answer the question how credit growth influences problem loans, it does not aim to focus on the simultaneous effects of these variables.

A rapid credit growth (credit boom) increases credit-to-GDP ratio, and might be associated with financial deepening and long-run economic growth. However, an abnormal (excessive) credit growth would indicate a moral hazard problem causing subsequent loan losses. Therefore, the excessive credit growth is considered to be an important leading indicator of future problems in the financial sector, and stands in the centre of an interest of the macroprudential analysis.

A rapid credit growth does not necessarily represent excessive credit provision. This is particularly the case of converging and developing economies, where strong economic growth is accompanied by high lending dynamics. In the surveyed period 1994 – 2016, the Czech economy experienced both periods of the rapid credit growth and its transition to market economy followed by the strong convergence process. Therefore, the aim of the paper is to investigate the effects of the credit growth on the NPL dynamics in the CR in the period 1994 – 2016.

The empirical analysis is broken-down to the pre-crisis period and the period consisted of the crisis and the post-crisis time. The breakpoint is identified as the beginning of the economic downturn in CR which started at the end of 2008. It was related to the decrease in demand in the global economy in reaction to the global financial crisis of 2007. This breakpoint might represent an important change with the potential effect on the relationship between provided credit and problem loans. The novelty of this paper is two-fold: first, the paper uses the Bayesian method of estimation with a priori information obtained from international empirical studies; and second, the paper perceives the global financial crisis of 2007 as an altering event and divides the surveyed period into two subperiods (1994 – 2008Q3 and 2008Q4 – 2016).

1. Literature Review

When answering the question how the credit growth influences problem loans and the quality of loan portfolios, economic theory pays attention to the determinants of market, which stimulate higher lending dynamics. Keeton (1999) argues that the credit growth driven by banks' willingness to lend (i.e. the shift in the market supply) is conducted through reduction in lending rates and/or by easier credit standards. The common causes of this behaviour, which might increase the likelihood that borrowers will default on their loans in future, are higher market competition, euphoria in economic booms or myopic concern for the short-term reputation. Conversely, the faster credit growth driven by demand and productivity shifts might not lead to higher loan losses in the future. These changes in the lending dynamics are not related to borrowers' creditworthiness, drive lending rates upwards and tighten the credit standards. However, in the case of productivity shifts, the bank can relax its credit standards when it is presumed that borrowers will fully repay their debt due to the higher productivity of investment. Generally, both shifts in the lending dynamics, driven by either demand or productivity determinants, might ensure greater scrutiny of loan applicants, reduce the occurrence of adverse selection, and hence, decrease the probability of future loan losses.

The rapid credit growth is commonly associated with the build-up of credit risk during the economic boom, and its materialization in the downturn. The economic theory postulates that potentially NPL originate in an expansionary phase of the business cycle when banks have over-optimistic expectations about borrowers' future ability to repay their debts, and are more likely to grant loans to less creditworthy agents. A number of studies has identified a positive relationship between the credit growth and the non-performing loans ratio (NPLR), see e.g. Salas and Saurina (2002), Jiménez and Saurina (2006), Espinoza and Prasad (2010), Festić, Kavkler and Repina (2011) or Castro (2013).

On the other hand, some studies show a negative relationship between credit growth and NPLR (e.g. Guy and Lowe, 2011; Ćurak, Pepur and Poposki, 2013; or Beaton, Myrvoda and Thompson, 2016). According to Vithessonthi (2016), normal credit growth associated with standard banking operations may reduce NPLR. The author investigates the relationship based on the evidence from Japan in the period 1993 – 2013. The identified time-varying relationship for Japanese economy revealed that the credit growth was positively related to the problem loans prior to the onset of the crisis of 2007, and negatively afterwards. Lowering of interest rates in order to stimulate the economic growth may represent the potential risk for banking systems, as it is an incentive for banks to rise credit supply. However, the empirical evidence from Japan, which represents an economy facing prolonged deflationary pressures, underscores that the credit growth does not necessarily lead to the higher volumes of the NPL.

Several papers studied the relationship between the credit growth and the problem loans in the CR. Babouček and Jančar (2005), with the help of the VAR model, investigated effects of macroeconomic shocks on the assets' quality in the period 1995 – 2004. Among others, they focus on the interaction between the NPLR and the credit growth, and results imply a weak feedback effect. Frait, Geršl and Seidler (2011) researched the credit growth using the data for a 30-year period (1980 – 2010). Authors conclude that the CR experienced the credit boom before the crisis; however, its features and quality were different compared to the experiences of other converging economies. This was because of prudent macroeconomic policies and tough monetary conditions (e.g. sustained nominal currency appreciation, which disciplined wage dynamics and constrained optimistic expectations about future). Geršl et al. (2012) analyse the effect of monetary loosening (decrease of policy rates) on the banks' risk-taking. Authors conclude that monetary loosening motivates banks to grant riskier loans, however, the lower interest rates decrease their costs during the life of loans. Havránek, Horváth and Matějů (2012) with a help of the block-restricted VAR also imply the existence of the risk-taking channel of monetary policy loosening, and show that tighter monetary conditions are associated with credit contraction, the more cautious behaviour of commercial banks and the decrease in the NPL. Konečný (2014) researches interactions between financial and real sectors using the threshold Bayesian VAR with block restrictions across the different interest rate regimes. The author concludes that the low interest rate regime weakens the incentives of agents to take on new loans because of uncertainty and lack of confidence. Further, the procyclicality of the NPL in this regime (mostly represented by the crisis environment) is lower.

Generally, financial intermediation positively affects the economic growth (e.g. Levine, Loayza and Beck, 2000, or Beck, Levine and Loayza, 2000). Financial distress, e.g. after the asset prices bubble burst, causes economic downturn, which might be deeper and/or prolonged, while the following recovery tends to be weaker. On the contrary, the recovery associated with higher lending dynamics and a quick rise in property prices is usually stronger. Therefore, the interrelations of various phases of economic and financial cycles, and the degree of financial markets development play an important role (Claessens, Kose and Terrones, 2012). Gould, Melecky and Panterov (2016) mention the rising skepticism regarding the economic benefits of financial deepening, and point out to the fast transmission of the last global financial crisis throughout the global economy. Arcand, Berkes and Panizza (2015) estimate the threshold level of financial depth (i.e. credit to private sector to GDP ratio reaches 80 – 100%) which seems to start having negative effects on the economic growth. Kasselaki and Tagkalakis (2014) conclude that the high degree of financial intermediation and the rapid credit growth are likely to be both associated with the deterioration in asset quality.

The excessive credit growth could be defined as a deviation from its equilibrium level, however, this equilibrium level is an unobserved benchmark, and its estimation is a challenging task. According to the guidelines of international and European regulatory bodies, the excessive credit growth could be identified as a positive credit-to-GDP gap (i.e. positive deviation of credit-to-GDP ratio from its long-run (HP filtered) trend, see BCBS (2010) and ESRB (2014).

This methodology is employed e.g. by Cottarelli, Dell' Ariccia and Vladkova-Hollar (2003) for the group of CESE countries. However, as the authors point out, this methodology might not be appropriate for the transition countries, and a positive deviation might capture financial deepening as well. The credit boom naturally increases the credit-to-GDP ratio and it is a robust cause of the economic growth (Kraft and Jankov, 2005). Buncic and Melecky (2014) analyse 49 high and middle-income countries, and conclude that the credit-to-GDP ratio is not the appropriate measure of the equilibrium level of credit, and the country specificities of developing economies need to be taken into account. For other studies dealing with the equilibrium/excessive credit in European countries, see e.g. Égert, Backé and Zumer (2006), Kiss, Nagy and Vonnák (2006) or Jakubík and Moinescu (2015).

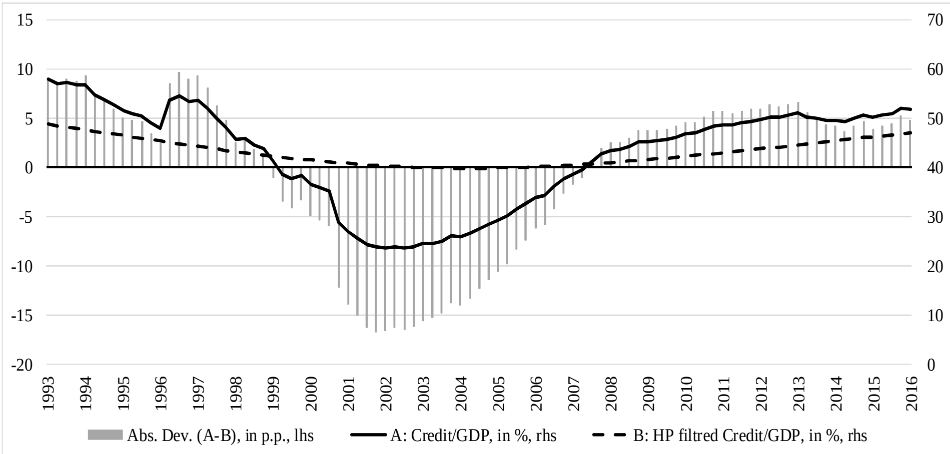
Geršl and Seidler (2011) or Frait, Geršl and Seidler (2011) investigate the credit boom in the CR, and conclude that in converging economies, where the strong credit growth is coupled with a dynamic economic growth, rapid lending might not necessarily represent the excessive credit growth. The evidence of convergence in the levels of credit across European countries is provided e.g. by Bahadir and Valev (2017), while the process is identified as particularly strong for a group of transition countries.

2. Data

The credit-to-GDP ratio and its deviation from the HP filtered long-run trend for the CR in period 1993 – 2016 is captured in Figure 1.[3] The higher values of the positive credit-to-GDP gap were evidenced in the period 1993 – 1997. The positive values were calculated from the year 2008 as well. However, as was mentioned above, the credit-to-GDP gap might not be the appropriate measure of the excessive credit growth for transition and/or converging economies. In the case of the CR, the long-run (HP filtered) trend of credit-to-GDP ratio is influenced by the occurrence of the banking crisis in the late 90s. The CR also experienced its transition to market economy and a strong convergence process in the surveyed period. Therefore, the Czech National Bank (CNB) has employed national (additional) measures to assess the position of Czech economy in the financial cycle. These measures are the expansionary credit gap and the financial cycle indicator (CNB, 2017).

Figure 1

Credit-to-GDP Gap



Note: The HP filtered trend of credit-to-GDP ratio is estimated with the suggested value of smoothing parameter (lambda) of value 400 000 (see ESRB, 2014). Abs. Dev. (A – B) denotes the absolute deviation of A (credit--to-GDP ratio) from B (HP filtered credit-to-GDP ratio).

Source: Self-elaboration based on BIS data.

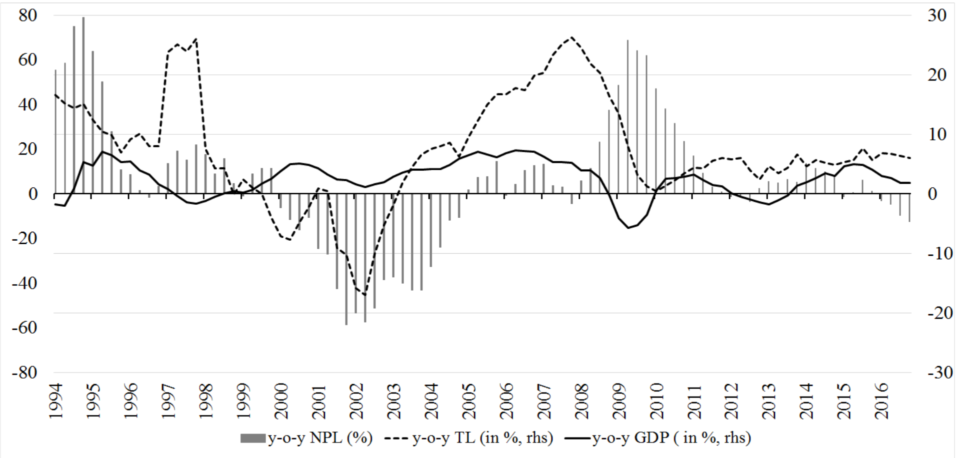
The quarterly data for the CR in the period 1993Q1 – 2016Q4 are obtained for the purposes of estimation. The NPL represent the ex-post indicator of credit risk materialization. The credit growth (CG) is calculated as an annual growth rate of total client loans provided to residents and non-residents by banks operating in the Czech banking sector. The real economic growth (REG) is calculated as an annual growth rate in GDP in constant prices. CPI deflates both the NPL and total loans. The dataset is obtained from the CNB with an exception of CPI. For a more detailed description of data, see Table A1 in Appendix. Figure 2

[3] According to ESRB (2014), when calculating the standardized credit-to-GDP gap, the credit represents a broad measure of the stock of credit to the non-financial sector (i.e. it includes loans both from banking and non-banking sectors and issued obligations). However, due to the scarcity of data for the CR, the credit is measured as total client loans provided by the banking sector. As pointed out by Hájek, Frait and Plašil (2017), the standardized credit-to-GDP gap is considered when regulatory bodies are taking decisions on the value of countercyclical capital buffer (CCyB). This macroprudential instrument is aimed at the banking sector, thus, it is reasonable to monitor stability of credit provided by the banking sector as well.

plots the real economic growth and the annual growth rate in the non-performing and the total loans. As the selected variables are transformed to the annual growth rates, the dataset covers the period 1994 – 2016.

Figure 2

Dynamics of Real GDP, Non-performing and Total Loans



Note: NPL, TL denote non-performing loans and total loans, respectively; calculated as year-over-year percentage changes (y-o-y).

Source: Self-elaboration based on CNB data**.**

Figure 2 shows that the volatility of provided credit is higher than the volatility in economic activity. There were four economic downturns while the severest one was caused by the global economic recession, which affected the Czech economy at the end of 2008. The credit dynamics reached two peaks in the periods 1997 – 1998 and 2007 – 2008 when the annual growth rate in total loans was higher than 25%. The highest decrease in the provided credit (approximately –16%) was observed in 2002. This significant decline in granted loans was associated with the adverse effects of the banking crisis, which hit the Czech banking sector before the millennium. From 2008 – 2010, there was a strong decrease in provided credit related to the economic slowdown. In the last few years, the credit growth has been relatively stable and has reached values roughly about 5%. Regarding the dynamics of the NPL, there were two periods of credit risk materialization. These periods of the high positive annual growth rate in the volume of the NPL are 1994 – 1995 and 2008 – 2010. In the first period, a significant amount of problems loans was in the form of quasi-loans, which were granted in the socialist period. The second period of the materialization of credit risk was caused by the strong economic downturn related to the global financial crisis of 2007. In contrast, in the period 2000 – 2004 the annual growth rate in the NPL was negative because the banks' balance sheets were being "cleaned up" (i.e. a significant amount of problem loans was written off from banks' books and transferred to the Czech Consolidation Agency).[4] For a more detailed description of macroeconomic and credit conditions in the CR, and the resolution of the NPL, see e.g. Matoušek and Sergi (2005) or Frait, Geršl and Seidler (2011).

Table 1 shows the correlation coefficients of the pairs of selected variables. The selected period is broken-down into two sub-periods with the breakpoint of the fourth quarter of 2008. In the period 1994 – 2016, all correlations between selected variables are statistically significant at the 5% level. There are positive correlations between the CG and the NPL (0.39) and the CG and the REG (0.19). The correlation coefficient between the NPL and the REG is negative with the value of –0.29. In the pre-crisis period, both correlations between the CG and the NPL, and the CG and the REG are stronger and statistically significant. However, the correlation coefficient between the NPL and the REG is –0.01 and is not statistically significant. In the period from the end of 2008 up to now, there has been one statistically significant correlation between the NPL and the REG (–0.59) which is stronger compared to the one for the whole period.

T a b l e 1

Correlation Matrix in Selected Period and Sub-Periods

1994 Q1 – 2016 Q4				**1994 Q1 – 2008 Q3**				**2008 Q4 – 2016 Q4**			
	NPL	**CG**	**REG**		**NPL**	**CG**	**REG**		**NPL**	**CG**	**REG**
NPL	1			**NPL**	1			**NPL**	1		
CG	0.39 *(0.00)*	1		**CG**	0.47 *(0.00)*	1		**CG**	–0.003 *(0.98)*	1	
REG	–0.29 *(0.00)*	0.19 *(0.06)*	1	**REG**	–0.01 *(0.96)*	0.29 *(0.02)*	1	**REG**	–0.59 *(0.00)*	0.04 *(0.82)*	1

Note: NPL denotes annual growth rate in volume of non-performing loans. CG is credit growth and REG is real economic growth. The numbers in brackets are p-values.

Source: Author's calculations.

3. Methodology

The NPL show some persistence and are commonly modelled as a dynamic process. Therefore, the dynamic form of model specification is used, i.e. the lagged value of the dependent variable is included in the right-hand side of the

[4] One needs to be aware of the structural changes in the Czech economy and its financial system, which took place mainly at the beginning of the surveyed period. Therefore, the empirical analysis was conducted also in the shorter period 2002 – 2016 which was not influenced by turbulent times of the transition to market economy, the banking crisis, the changes in methodology, etc. Estimated results are similar to those for the period 1994 – 2016 with the exception of the parameter of the credit growth which is statistically non-significant. We favor the usage of the whole dataset that enables us to divide the period 1994 – 2016 into two sub-periods.

model equation. This inclusion controls for inertial and seasonal components, which are not captured by other explanatory variables. Further, it helps to limit serial correlation in the residual component (Gambera, 2000). The chosen dynamic model specification is defined in the equation (1):

$$NPL_t = \alpha NPL_{t-1} + \beta_1 CG_t - \beta_2 REG_t + \varepsilon_t \tag{1}$$

where the NPL is the annual growth rate in the volume of non-performing loans and the NPL_{t-1} is its lagged value. The CG and the REG denote the credit growth and real economic growth, respectively. Parameters β_1 and β_2 capture the contemporaneous effects of the credit and real economic growth on the NPL dynamics, respectively. The credit growth is included in the analysis because it may add to the accumulation of the credit risk, particularly if it is excessive or if it is associated with the higher willingness of banks to grant riskier loans. The real economic growth is considered as the important determinant of problem loans as it affects the financial condition of agents and their ability to repay debts.

The NPLR was investigated as an indicator of aggregate credit risk as well. However, due to the different time lags with which the changes in explanatory variables influence the nominator and the denominator of this ratio, the preferred form of explained variable is an annual growth rate in the volume of the NPL. We favour this transformation of data as its interpretation is more intuitive.

For the purposes of econometrical estimation, the idiosyncratic component of the model equation ε_t is perceived to be a residuum with a process described by the following equation:

$$\varepsilon_t = \mu \varepsilon_{t-1} + \omega_t \tag{2}$$

where

μ – autoregressive parameter,
ω_t – *i.i.d.* shock with the distribution $N(0, \sigma_\epsilon)$.

Due to a potential endogeneity of changes in credit provision and economic activity given the dynamics of NPL, the model is estimated with the help of instrumental variables, as defined in the equation (3):

$$CG_t = \sigma CG_{t-1} + \vartheta_t \tag{3}$$

where

σ – autoregressive parameter,
ϑ_t – *i.i.d.* shock with the distribution $N(0, \sigma_\vartheta)$.

The economic growth is instrumented in the suggested way as well. The Bayesian estimation method of instrumental variables (see e.g. Lubik and Schorfheide, 2007) enables us to take into account a potential endogeneity of economic and credit growths vis-à-vis the NPL. Moreover, this method uses a priori information obtained from the published international studies which helps to improve the identification of estimated parameters beyond the scope of information gained from empirical data of economy. To create a priori assumptions about the probability distribution of regression parameters 9 relevant empirical studies with dynamic specification are used (see Table A2 in Appendix). These studies contain estimated parameters, and respective standard errors (s.e.) or t-statistics of selected variables. The median of published parameters reflects the centering of probability distribution. The average value of s.e. is calculated as the median of respective s.e. of parameters' estimates. This value captures dispersion of probability distribution. The final average values of parameters and standard errors represent a priori assumptions regarding the parameters of the model equation (1) see the last two rows in Table 2.

Table 2

A Priori Assumptions about Probability Distribution of Regression Parameters

	Study	**NPLR $_{t-x}$**		**CG $_{t-x}$**		**EG $_{t-x}$**	
		EC	**s. e.**	**EC**	**s. e.**	**EC**	**s. e.**
1	Salas and Saurina (2002)	0.525	0.071	0.003	0.002	–0.115	0.015
2	Jiménez and Saurina (2006)	0.552	0.089	0.004	0.001	–0.140	0.020
3	Espinoza and Prasad (2010)	0.865	0.059	0.104	0.055	–1.950	1.140
4	Guy and Lowe (2011)	0.796	0.068	–0.022	0.018	–0.150	0.020
5	Castro (2013)	0.956	0.109	0.024	0.005	–0.026	0.010
6	Ćurak et al. (2013)	0.103	0.050	–0.001	0.005	–0.170	0.077
7	Alhassan et al. (2014)	0.298	0.097	0.004	0.002	–1.030	0.490
8	Kasselaki and Tagkalakis (2014)	0.847	0.063	–0.001	0.009	–0.132	0.073
9	Beaton et al. (2016)	0.825	0.012	–0.002	0.001	–0.004	0.004
	Median	**0.838**		**0.002**		**–0.135**	
	Standard error		**0.063**		**0.008**		**0.066**

Note: If the study includes several models (estimations), the median of published parameters and the median of respective standard errors are calculated for the individual study. The final values of the median and standard error (in bold) are calculated as the median of published parameters and standard errors from all selected studies. EC denotes estimated coefficient. The NPLR is non-performing loans ratio, the CG is credit growth and the EG is economic growth.

Source: Self-elaboration.

Table 2 shows that the majority of selected studies capture the medium or the high persistence of the NPLR. On the contrary, the weak persistence is estimated in studies by Ćurak, Pepur and Poposki (2013), and Alhassan, Kyereboah-Coleman and Andoch (2014). These studies cover the similar surveyed period, the former one 2003 – 2010, and the latter one 2005 – 2010. The estimated coefficients of effects of the credit growth are rather small (close to zero), while 5 studies report positive values and 4 studies capture negative values, i.e. there is no prevalence of either a positive nor negative relationship between the credit growth and the NPLR. In the case of economic growth, the differences among reported values are bigger; however, all selected studies demonstrate a negative relationship, which is in line with the theory. Studies by Espinoza and Prasad (2010), and Alhassan, Kyereboah-Coleman and Andoch (2014) in particular imply the stronger effect of the economic growth on the NPLR compared to other analyses.

The type of distribution of parameters CG and REG is normal. An a priori assumption about the parameter of the lagged value of explained variable is specified by the beta distribution. The model equation models the stationary process and the respective parameter should reach positive values lower than 1. Similarly, other autoregressive parameters from the auxiliary equations (2) and (3) have the beta distribution. The moderate serial correlation of the residual component is assumed. In the case of an a priori assumption about the standard errors of shocks from the model and auxiliary equations, the inverse gamma distribution is selected (see e.g. Melecky, 2012).

The combination of the likelihood function of the examined model with defined a priori assumptions about the probability distribution of parameters determines *posterior probability density*. Based on the a priori distribution $p(\theta)$, where θ is the vector containing model parameters, the posterior density is proportional to the multiplication of likelihood function $L(\theta / Y)$ and a priori distribution $p(\theta)$ (West and Harrison, 1997):

$$p(\theta / Y) \propto L(\theta / Y)\, p(\theta) \tag{4}$$

The posterior probability density of parameters from equations (1), (2) and (3) is a function of parameters θ, and it is maximized by the Monte-Carlo (Markov Chain Monte-Carlo, MCMC) optimization algorithm of numeric optimization available in the software platform *Dynare* which runs on the top of the software *Matlab*.

4. Discussion of Empirical Results

Table 3 reports parameters' priors (i.e. type, centering and dispersion of probability density) and the results of basic Bayesian estimation in the selected period and its sub-periods. Moreover, Figure 3 graphically describes the prior and posterior probability densities of selected parameters. The prior distribution is marked with a grey colour and the posterior with a black one. The dashed vertical line shows the posterior mode, i.e. the most likely value of the posterior probability density. The scaling factor is set to the value 0.65, and leads to the ratio of acceptance (of random samples within two chains generated for the purposes of calculations), which ranges from 31% to 36% for all estimated periods. The overall explanatory power of the model is satisfactory as the model's estimates accurately copy actual data. Convergence diagnostic of the basic estimation for the period 1994 – 2016 is plotted in Figure A1 in Appendix.[5]

Table 3

A Priori Assumptions and Results of Basic Estimation

Parameters	Prior distribution	Posterior mean	Posterior 90% Bayesian confidence interval
1994 Q1 – 2016 Q4			
a_npl(1)	B(0.84; 0.06)	0.88	[0.8332; 0.9328]
a_cg	N(0.002; 0.10)[6]	0.18	[0.0535; 0.3016]
a_reg	N(0.14; 0.07)	0.17	[0.0653; 0.2820]
r_cg(1)	B(0.60; 0.10)	0.85	[0.7995; 0.9013]
r_reg(1)	B(0.60; 0.10)	0.84	[0.7786; 0.8911]
p_npl(1)	B(0.20; 0.10)	0.29	[0.1545; 0.4245]
1994 Q1 – 2008 Q3			
a_npl(1)	B(0.84; 0.06)	0.88	[0.8210; 0.9323]
a_cg	N(0.002; 0.10)	0.17	[0.0458; 0.3045]
a_reg	N(0.14; 0.07)	0.15	[0.0385; 0.2602]
r_cg(1)	B(0.60; 0.10)	0.84	[0.7765; 0.8978]
r_reg(1)	B(0.60; 0.10)	0.81	[0.7485; 0.3667]
p_npl(1)	B(0.20; 0.10)	0.23	[0.0961; 0.0179]
2008 Q4 – 2016 Q4			
a_npl(1)	B(0.84; 0.06)	0.89	[0.8263; 0.9449]
a_cg	N(0.002; 0.10)	0.05	[–0.1150; 0.2196]
a_reg	N(0.14; 0.07)	0.17	[0.0663; 0.2891]
r_cg(1)	B(0.60; 0.10)	0.61	[0.5027; 0.7155]
r_reg(1)	B(0.60; 0.10)	0.75	[0.6517; 0.8451]
p_npl(1)	B(0.20; 0.10)	0.29	[0.1296; 0.4617]

Note: B(a; b) and N(a; b) denote beta and normal distribution where 'a' and 'b' determine location and scale parameters, respectively. Results in shaded areas are statistically non-significant at the 10% level.

Source: Author's calculations in Matlab.

The results confirm the high persistence of NPL dynamics in all selected periods. The parameter of the lagged value of the dependent variable (*a_npl(1)*) reaches values 0.88 and 0.89 at the 10% level of statistical significance. In Figure 3 we can observe the shift of posterior distribution to the right (compared to the prior distribution), i.e. the significant influence of information gained from empirical data for the CR. As noted in literature, the NPL show persistence because they are not immediately written-off from banks' books (Salas and Saurina, 2002, or Jimenéz and Saurina, 2006). Espinoza and Prasad (2010) associate

[5] The rest of graphical outputs of all estimations is available upon request due to the limited extent of the paper.

[6] The median of published coefficients of credit growth and the median of respective standard errors are close to zero (see Table 2). Therefore, to prevent that the prior will be too tight, the dispersion of prior distribution is determined by standard error with the value of 0.1.

materialization of credit risk and loan losses with the time lag in reaction to the business cycle, what implicates the persistent accumulation of the NPL.

The parameter *a_cg* captures effects of the credit growth on the NPL dynamics. The estimated parameters are similar for the whole period (0.18) and the pre-crisis period (0.17). The interpretation is as follows: if the credit growth increases by 1%, the annual growth in the volume of the NPL will rise by 0.18% and 0.17%, respectively. These results imply the positive relationship between the credit growth and the NPL dynamics in the CR in the above mentioned periods. From the graphical representation of the distribution of the parameter *a_cg* in Figure 3, we can observe a significant shift of the posterior distribution to the right. It captures the stronger effect of the credit growth on the NPL dynamics compared to the prior information obtained from the selected empirical studies (i.e. compared to the prior value which is close to zero). In the period after the year 2008, the estimated parameter *a_cg* is smaller (0.05); however, it is statistically non-significant at the 10% level.

The influence of the business cycle on credit risk materialization and the accumulation of the NPL is captured by the values of the parameter *a_reg*. The estimated parameters are robust throughout all selected periods and reach values –0.17 and –0.15 (in the pre-crisis sub-sample).[7] These results emphasize the negative relationship between real economic growth and problem loans as is assumed by theory and commonly confirmed by empirical literature. Figure 3 depicts small adjustment of posterior distribution compared to the prior one. The prior value (median) calculated based on the published parameters in international studies is –0.14, thus, the effect of the REG is similar to the effect estimated for the CR.

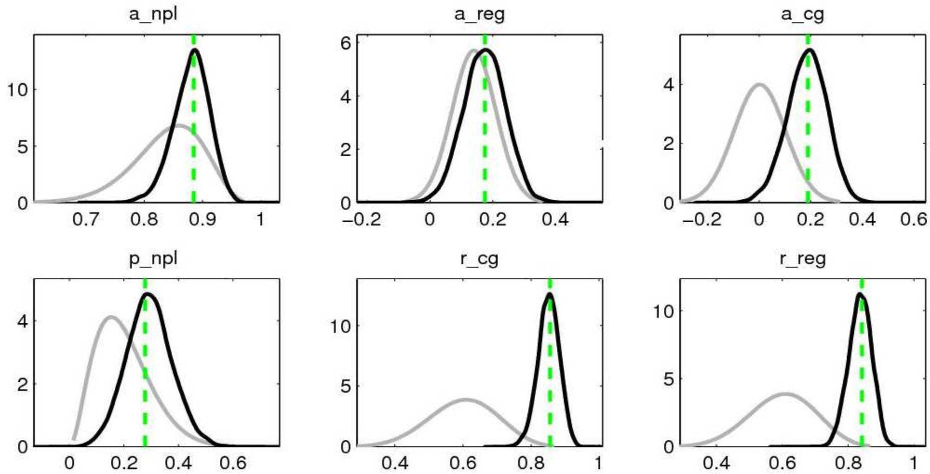
Autoregressive parameters of credit growth *r_cg(1)* and the real economic growth *r_reg(1)* reach high values, i.e. these variables show high persistence as well. In the case of credit growth, the estimated values are 0.85 in the whole period and 0.84 in the pre-crisis sub-sample. For the period after the end of 2008, the value of the parameter decreases and reaches 0.61. All results suggest that the dynamics of credit provision depends on its previous values. In the times of credit boom, banks are more prone to grant loans to clients with a weaker credit history what might lead to higher loan losses in the future. If these losses are not adequately covered by loan loss provisions they deplete banks' capital, and constrain banks' ability and willingness to lend. In the case of real economic growth, the estimated posterior mean values of autoregressive parameters are similar to

[7] The relationship between the NPL dynamics and real economic growth is a priori modeled as the negative one (based on the negative prior value obtained from the empirical studies); see the Table 2 and the model equation (1).

the results of the credit growth. The economic growth also shows high persistence with a modest decrease in the crisis and the post-crisis period when the estimated value of the parameter *r_reg(1)* is 0.75. The high persistence of both credit and economic growth could be observed in Figure 3 where the posterior distributions of estimated autoregressive parameters shift to the right compared to the assumed prior distribution. The autoregressive parameter of idiosyncratic component (*p_npl(1)*) of the model equation reaches stable values as follows: 0.29 in the whole period and the period of 2008 – 2016, and 0.23 in the pre-crisis period. These results implicate a modest serial correlation in residuals. All discussed results of autoregressive parameters are statistically significant at the 10% level.

F i g u r e 3

Prior and Posterior Probability Densities – Basic Estimation in the Period 1994 – 2016



Source: Author's calculations in Matlab.

4.1. Analysis with Alternative Priors

The model specified in the equation (1) is estimated with the usage of alternative a priori assumptions. Concretely, the standard error of the parameters is doubled and the dispersion of the prior distribution is increased. The aim of this alternative approach to setting the priors is to employ information obtained from the empirical data of the CR to a greater extent. In other words, it increases the uncertainty of a priori assumptions and lowers the weight of this information in estimation of posterior probability density.

Table 4 reports the estimated values of parameters (the posterior mean) and the 90% Bayesian confidence interval.

T a b l e 4

A Priori Assumptions and Results of Alternative Estimation

Parameters	Prior distribution	Posterior mean	Posterior 90% Bayesian confidence interval
1994 Q1 – 2016 Q4			
a_npl(1)	B(0.84; 0.12)	0.88	[0.8106; 0.9400]
a_cg	N(0.002; 0.20)	0.32	[0.1416; 0.4726]
a_reg	N(0.14; 0.14)	0.23	[0.0349; 0.4145]
r_cg(1)	B(0.60; 0.20)	0.90	[0.8506; 0.9632]
r_reg(1)	B(0.60; 0.20)	0.89	[0.8295; 0.9503]
p_npl(1)	B(0.20; 0.20)	0.31	[0.1256; 0.4859]
1994 Q1 – 2008 Q3			
a_npl(1)	B(0.84; 0.12)	0.86	[0.7887; 0.9394]
a_cg	N(0.002; 0.20)	0.31	[0.1407; 0.4877]
a_reg	N(0.14; 0.14)	0.19	[–0.0207; 0.4223]
r_cg(1)	B(0.60; 0.20)	0.91	[0.8429; 0.9757]
r_reg(1)	B(0.60; 0.20)	0.87	[0.8021; 0.9458]
p_npl(1)	B(0.20; 0.20)	0.24	[0.0000; 0.4133]
2008 Q4 – 2016 Q4			
a_npl(1)	B(0.84; 0.12)	0.91	[0.8337; 0.9953]
a_cg	N(0.002; 0.20)	0.21	[-0.1386; 0.5203]
a_reg	N(0.14; 0.14)	0.23	[0.0373; 0.4339]
r_cg(1)	B(0.60; 0.20)	0.62	[0.4941; 0.7544]
r_reg(1)	B(0.60; 0.20)	0.84	[0.7341; 0.9533]
p_npl(1)	B(0.20; 0.20)	0.33	[0.0002; 0.5385]

Note: B(a; b) and N(a; b) denote beta and normal distribution where ‘a’ and ‘b’ determine location and scale parameters, respectively. Results in shaded areas are statistically non-significant at the 10% level.

Source: Author’s calculations in Matlab.

When compared to the basic estimation, the estimated posterior mean values for the parameter *a_npl(1)* are almost identical in all periods. These results confirm the high persistence of the NPL growth (i.e. the high dependence on its previous values). Regarding the persistence of the credit growth and the real economic growth, the posterior values of the autoregressive parameters *r_cg(1)* and *r_reg(1)* are slightly higher, and implicate a slightly higher persistence, especially in the pre-crisis period.

The results related to the effect of the credit growth on the NPL dynamics are different compared to those estimated in the basic estimation. These results prove the positive relationship between respective variables; however, the estimated parameters are higher. For the whole period, the posterior mean value of *a_cg* is 0.32, and for the pre-crisis period, it is 0.31. Both results are statistically significant at the 10% level, and suggest the stronger effect of credit growth on the NPL dynamics when using the alternative prior distribution (i.e. using the information from empirical data to a greater extent). The similar behavior (i.e. stronger effect) is estimated for the second sub-period (2008 – 2016); however, parameter is statistically non-significant at the 10% level.

In the alternative estimation, the effects of the real economic growth on the NPL dynamics are higher than the one from basic estimation. However, the increase in the estimated parameter *a_reg* is smaller than in the case of a parameter of the credit growth. The posterior mean values are as follows: 0.23 in the whole period, 0.19 in the pre-crisis period and 0.23 in the period from the end of 2008. Results are statistically significant at the 10% level, with the exception of the pre-crisis period.

Conclusions

The paper evaluates the effects of the credit growth on the NPL dynamics in the Czech Republic in the period 1994 – 2016. To investigate whether the global financial crisis of 2007 represents the change in the relationship between provision of credit and development of the NPL, the surveyed sample was broken-down into the pre-crisis period and the period covering the crisis and the post-crisis time.

Estimated parameters showed the positive relationship between the credit growth and the NPL dynamics in the Czech Republic. The results were statistically significant in the whole period (1994 – 2016) and in the pre-crisis period. In the alternative estimation, with higher weight on the information gained from empirical data the effects of the credit growth on the NPL dynamics were stronger compared to the basic estimation. Presented results are in line with the theoretical postulates of pro-cyclical credit provision, i.e. that credit risk is being accumulated during the boom phase of the economic cycle, when the lending dynamics is usually higher. The identified positive relationship associates problem loans and potential loan losses to the credit growth driven by banks' willingness to lend more and/or to the less creditworthy clients (i.e. the supply side of the market played an important role in the surveyed period).

However, estimated parameters of the credit growth were rather small and imply that the credit growth in the CR influenced the accumulation of credit risk and the origination of the NPL in a modest way; despite the fact that the CR experienced periods of the rapid credit growth (more than 25%) before the millennium and before the financial crisis of 2007. Overall, results suggest that the observed high lending dynamics was associated with the strong economic growth during the convergence process, thus, did not represent the excessive credit provision.

In the period from the end of 2008, both estimated parameters of the credit growth (i.e. in basic and alternative estimation) reached smaller values and were statistically non-significant at the 10% level. The results of correlation analysis also suggest the change in relationship between the credit growth and the NPL dynamics in the period covering crisis and post-crisis times where the correlation coefficient reached statistically non-significant value close to zero.

Further, results suggest stronger effect of the credit growth on the NPL dynamics in the CR compared to the prior information obtained from the empirical literature (mostly panel data studies) where the average effect of the credit growth on the NPLR was close to zero. This result also emphasizes the importance of country-specific studies, above all, in the case when the international experience is mixed and economies face country-specific factors.

From the point of view of the policy, the concepts designed to identify equilibrium and excessive credit growth as well as the position of economy in the financial cycle need to be further developed and applied for setting adequate prudential measures ensuring financial stability, especially in converging and developing economies.

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Appendix

Table A1

Data Overview

Variable	Characteristic	Source
Non-performing loans (NPL)	Annual growth rate in total volume of NPL, CPI deflated	CNB (ARAD and internal data in 1993 – 2002)
Real economic growth (REG)	Annual growth rate in GDP, seasonally adj., in 2010 prices	CNB (ARAD and internal data in 1993 – 1996)
Credit growth (CG)	Annual growth rate in total client loans provided to residents and non-residents, CPI deflated	CNB (ARAD)
CPI	Consumer price index (2005 = 100)	CSO and CNB (internal data in 1993 – 1995)

Note: CNB, CSO denote Czech National Bank and Czech Statistical Office, respectively.

Source: Self-elaboration.

Table A2

Selected Studies and their Characteristics

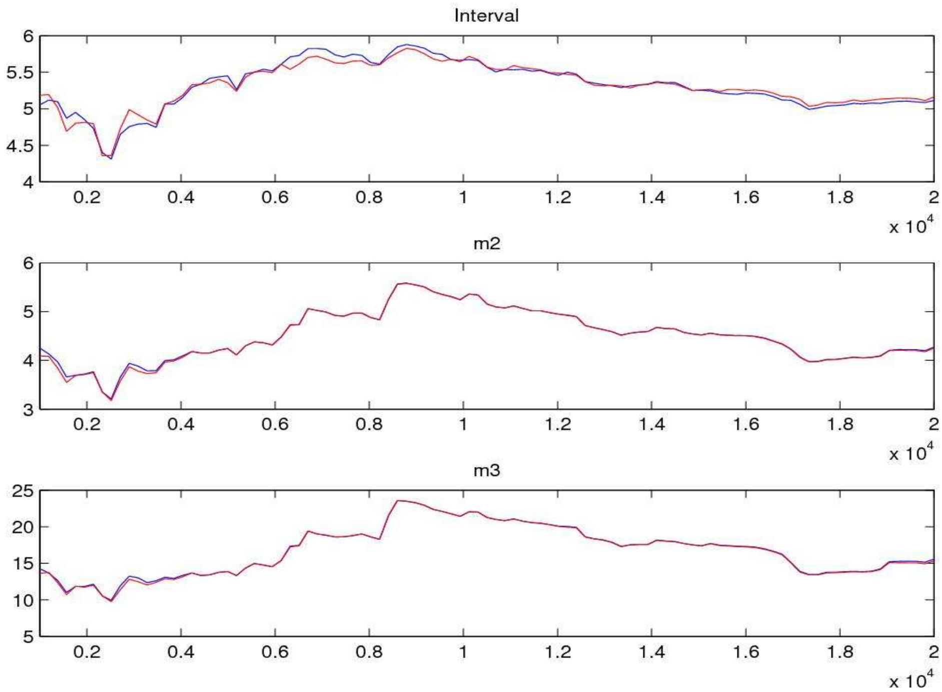
	Study	Countries	Period	Frq.	Source
1	Salas and Saurina (2002)	Spain	1985 – 1997	A	WOS
2	Jiménez and Saurina (2006)	Spain	1984 – 2002	A	WOS
3	Espinoza and Prasad (2010)	Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, UAE	1995 – 2008	A	WP
4	Guy and Lowe (2011)	Barbados	1996Q1 – 2008Q4	Q	REV
5	Castro (2013)	Greece, Ireland, Portugal, Spain, Italy	1997Q1 – 2011Q3	Q	WOS
6	Ćurak et al. (2013)	10 South-eastern countries	2003 – 2010	A	SC
7	Alhassan et al. (2014)	Ghana	2005 – 2010	A	SC
8	Kasselaki and Tagkalakis (2014)	20 OECD countries	1997 – 2009	A	SC
99	Beaton et al. (2016)	6 Eastern Caribbean Currency Union countries	1996Q1 – 2015Q4	Q	WP

Note: Two studies, which meet the required conditions of study selection, are not included in the list of employed studies as they are published in the journals classified as potential, possible, or probable predatory according to the Beall's List. Moreover, one study publishes unusually high value of standard error of estimation.

Source: Self-elaboration.

F i g u r e A1

Convergence Diagnostics – Basic Estimation (1994 – 2016)



Source: Author’s calculations in Dynare/Matlab.