Uncovering the Dynamic Relationship Between Credit and Economic Growth in Romania

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Abstract. *The present paper provides a comprehensive analysis of the relationship between credit and economic growth in Romania, after 30 years of financial sector development. The aim is to provide empirical evidence related to (i) the role of the banking sector in fostering economic growth and the causality direction between the financial and real sector, (ii) the relationship between consumption/investment and certain categories of loans and (iii) the identification of loan supply shocks and their role in explaining dynamics associated with other macroeconomic variables. Using a Time-Varying Parameter Vector Autoregressive model with stochastic volatility (TVP-VAR), structurally identified using sign restrictions, we study the effects of a credit supply shock and an aggregate demand shock in order to assess the links between the financial sector and the real economy. Potential policy solutions to ensure a sustainable contribution of the financial sector to economic growth relate to the strong relationship identified between investment and loans granted to non-financial corporations.*

Key words: *credit; economic growth; TVP-VAR; financial intermediation; Bayesian estimation.*

Introduction

Over the last decades and in the context of globalization, the relationship between economic development and financial intermediation has becoming increasingly tighter, as highlighted in Figure 1, which plots data extracted from the World Bank data base for over 150 countries or regions from all around the world. When comparing statistical information from 1995 with data from 2015, the statistical significance of the correlation between economic development and financial intermediation surges while the slope coefficient almost doubles in absolute size.

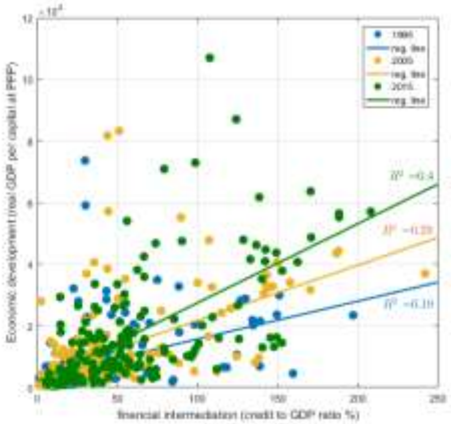

Figure 1. *The relationship between economic development and financial intermediation*
(*World Bank Database*)
Note: economic development is measured as real GDP per capita in USD at PPP while financial intermediation is defined as private sector credit to GDP ratio.

However, during episodes of turmoil such as the recent Global Financial Crisis, the financial sector can potentially become a source of systemic risk amplification through contagion effects or through a severe contraction in the supply of credit and, as a result, significantly affect the real economy.

It is, therefore, only natural that the relationship between economic development and financial intermediation was widely investigated over time in empirical literature as well as policy analysis, and has achieved increasing importance in the context of a globalization process conducted in a post-crisis period.

Two schools of thought with completely different perspectives have defined the main approaches on this matter. Firstly, renowned economists such as Schumpeter (1911), Goldsmith (1969), McKinnon (1973) and Shaw (1973) supported the idea that financial intermediation plays an important role for the long-run economic growth. On the other hand, Robinson (1952) believed that good economic growth perspectives lead to the development of a sound financial system. Another theory that sharply contradicts Schumpeter's assumptions had been founded by Lucas (1988), stating that economists "badly over-stress" the role financial factors play in economic growth.

An increasing importance has also been ascribed to the credit supply shocks subject. For instance, Bijsterbosch and Falagiarda (2014) studied the role of credit supply shocks in euro area countries during the recent pre-crisis, bust, and post-crisis periods. In this regard, the authors modelled a Time–Varying Parameter Vector Autoregressive model (TVP-VAR) with stochastic volatility as described by Primiceri (2005), for each country, identifying the structural shocks by imposing sign restrictions on impulse response functions based on the theoretical model computed used by Gerali et al. (2010). The conclusions of the paper show both that credit supply shocks have had a key role in business cycle fluctuations in the analyzed countries and that their effects on the economy have generally increased since the recent crisis. An interesting aspect highlighted by this paper is that credit supply shocks contributed differently to output growth depending on the business cycle phase.

Analyzing the relationship between the financial sector and the real economy in Romania warrants a thorough understanding of the significant structural changes the Romanian economy has experienced over the last three decades. The transition from a planned to an open market economy in the beginning of the 90's prompted a wide economic reform in which the development of the financial sector served as one of the key elements for a successful transition. Other important milestones were the capital account liberalization process, the EU accession which triggered high capital inflows in the run up to the Global Financial Crisis, the period of economic rebalancing following the crisis and the renewed economic growth period accompanied by an upturn in the financial cycle.

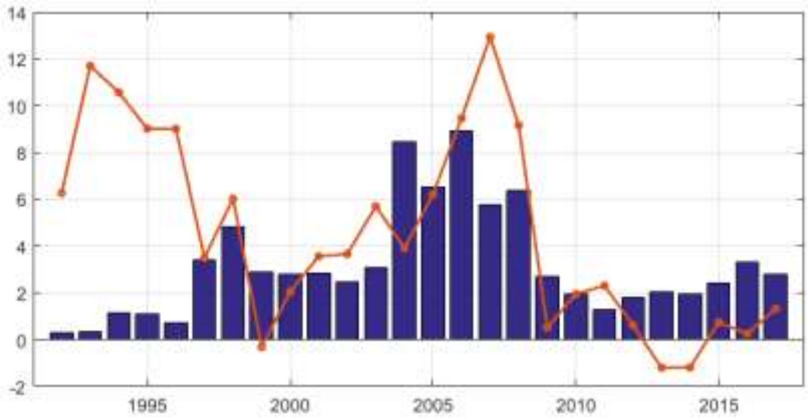

Figure 2. *FDI net inflows (% of GDP) and credit to GDP ratio growth (%)*
(World Bank, NBR)
Note: credit growth to GDP ratio is computed as the annual difference in the total credit stock divided by annualized nominal GDP, in order to create a proxy for credit flows and obtain a comparable measure to FDI flows.

In this context, financial intermediation started to expand in the second half of the 1990's, from a low level of around 15%, measured as total credit to GDP, to a peak of 39% in 2011. In the aftermath of the financial crisis, the process of disintermediation was triggered by a concomitant decline in both demand and supply of credit, while the continuous expansion of nominal GDP after 2010 has brought down the total credit to

GDP ratio to 26% in 2018. The Romanian banking sector is mostly dominated by foreign institutions, highlighted by the close relation between the flow of credit and net foreign direct investment (Figure 2). It is, therefore, only natural that overlapping the EU accession with high inflows of FDIs set the scene for an excessive credit growth episode, fueled mainly by consumption loans (the stock increased 8.6 times from 2005 to 2009, while the stock of loans granted to non-financial corporations only grew 3.6 times in the same timeframe) and adding additional pressure on the current account deficit.

The unsustainable credit growth coupled with a significant twin deficit issue overlapped with the global financial shock in 2008, which triggered capital outflows from emerging markets and led to a large depreciation of the Romanian currency. Taking into account the diminished repayment capacity of debtors, as a result of lower wages or sales, on the backdrop of higher payments on foreign currency denominated loans, the non-performing loan rates increased exponentially reaching an all-time peak in 2014 of over 20% (depending on the definition of NPLs used, NBR data). As a result, during this period of economic recovery, the banking sector accumulated one of the highest stocks of sovereign debt instruments in the EU (approximately 22% of total banking sector assets, according to European Systemic Risk Board data).

The significant losses registered after the crisis prompted restructuring measures, mergers & acquisitions and recapitalizations, together with an effort to reduce NPL ratios with positive results. Consequently, in recent years, credit activity has started to recover, geared especially towards the household sector, while further steps have been taken to consolidate the resilience of the banking sector to unanticipated shocks.

Empirical analysis

Estimating the elasticity between economic growth and credit

The first step of the analysis employs a naive approach to assess the relationship between economic growth and credit: estimating linear regressions between economic activity (real GDP, consumption and investment) and the supply of credit from the financial sector (on an aggregate and sectoral – households and non-financial corporations – basis). In terms of comparative advantage to other studies focusing on this relationship, we build a dataset using quarterly data spanning from 1995, capturing the early stages of development of the banking sector, to 2018. Macroeconomic variables are extracted from the Eurostat database, while information related to credit was requested from the National Bank of Romania. The data is transformed into quarterly growth rates for estimating the time varying elasticity coefficients and granger causality tests.

Estimating Bayesian rolling window regressions to compute time-varying elasticity coefficients

Starting from the standard regression model paradigm, we introduce Bayesian estimation as:

$$Y|X,\beta \sim N(X^T\beta, \sigma^2 I)$$
$$Y|X,\beta \propto (\sigma^2)^2 exp\left\{-\frac{1}{2\sigma^2}(Y-X\beta)^T(Y-X\beta)\right\} \tag{1}$$

In the Bayesian framework, the parameters are not point estimates but densities; therefore, we define prior distributions, choosing in this case a nature conjugate prior setting in order to obtain an analytical solution for the posterior distribution:

$$P(\beta|\sigma^2) \propto (\sigma^2)^{-\frac{k}{2}}\exp\{-\frac{1}{2\sigma^2}(\beta-\mu_0)^T\Lambda_0(\beta-\mu_0)\} \sim N(\mu_0, \sigma^2\Lambda_0)$$
$$P(\sigma^2|a,b) \sim (\sigma^2)^{-a-1} exp\left\{\frac{-b}{\sigma^2}\right\} \tag{2}$$

where μ_0 and Λ_0 are parameters from the Normal distribution for the regression coefficients in β, and a and b are shape and scale parameters defining the Inverse Gamma distribution. We draw 10,000 samples from the posterior distribution and compute the median but also plot the kernel densities in order to assess the statistical significance of the results. Moreover, to uncover changes in the time-varying relationship between the real economy and the financial sector, the elasticity coefficients are estimated on a 3-year rolling window (12 quarters).

Analyzing the results for the constant and slope extracted from the rolling window regressions (Figure 3), we ascertain that the relationship between real GDP and total credit growth rates relatively stable in the pre-crisis period (average coefficient of 0.045), followed by an increase after 2009 and an inversion episode between 2015 and 2017, highlighting the fact that the Romanian economy experienced a period of *creditless recovery,* when economic activity was bolstered by other measures from other policy areas such as fiscal or by a high rate of EU funds absorption. More recently, the elasticity coefficient has become positive and is increasing, on the backdrop of lower statistical significance emphasized by the widening of the interpercentile interval. In fact, when assessing the statistical relevance of the series under scrutiny, a high degree of uncertainty is associated with the post 2015 period, results confirmed by the kernel density plots. On average, regression estimates indicate that an increase in the stock of total loans by 10% leads to an expansion in real GDP of roughly 62 basis points.

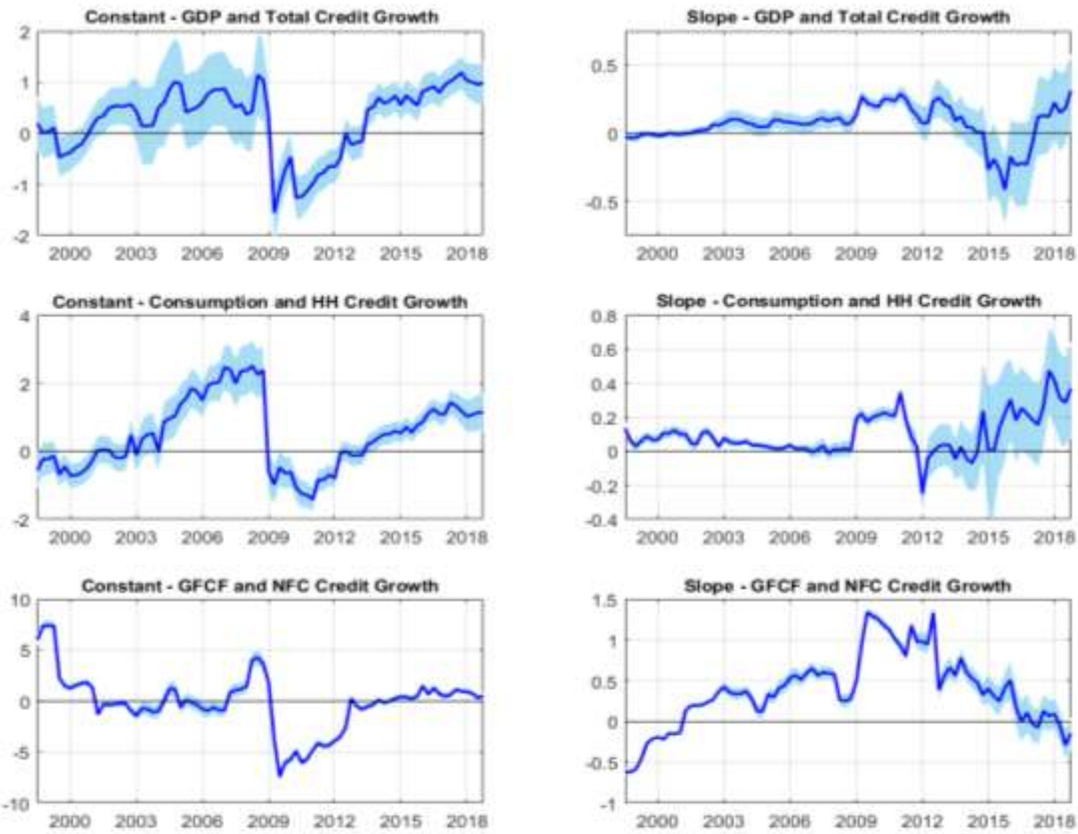

Figure 3. *Results from rolling window Bayesian regressions between economic growth and components and total and sectoral credit growth*
(own estimation)
Note: results are obtained for a rolling window of 3 years (12 quarters) using 10.000 draws of the Gibbs sampler

Extending the analysis to the subcomponents, some similarities can be identified together with significant differences. In the case of the consumption – household credit relationship, rolling-window estimates follow a similar dynamic, although the coefficient is mostly positive throughout the entire time span and increases rapidly in the post-crisis period. The conclusions radically change when analyzing the results for investment (Gross Fixed Capital Formation) and non-financial corporations credit growth: first of all, the coefficient is significantly higher than in the case of the first two cases, secondly we can identify an increase starting from 2004-2005 overlapping with the period of high capital inflows experienced by the Romanian economy and thirdly the relationship remains statistically strong throughout the entire period. The average elasticity coefficient is 0.37 while for consumption it is close to 0.1, potentially underlining the multiplicative effect of credit granted towards productive economic sectors for the real economy.

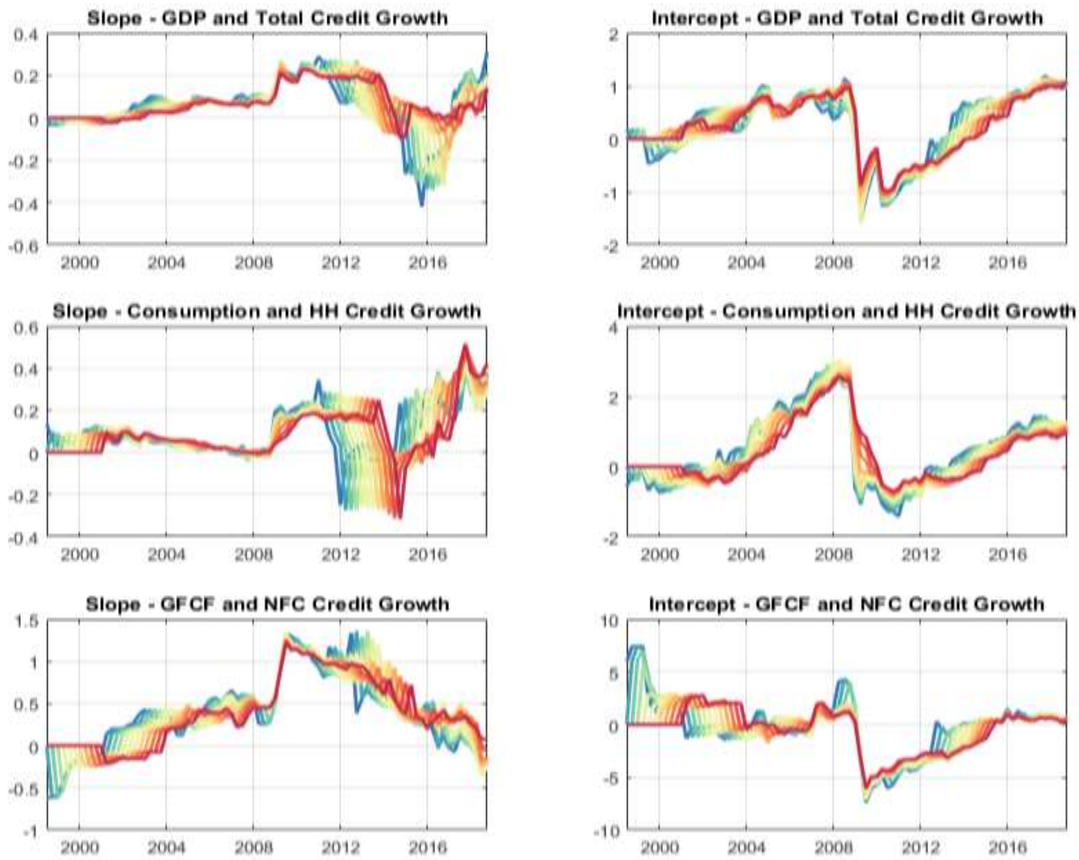

Figure 4. *Bayesian regression estimation results using recursive rolling windows between 12 – 24 quarters (own estimation)*
Note: colors range from dark blue (12 quarters) to dark red (24 quarters)

In order to ensure that the results are not distorted by the choice related to the size of the rolling window (12 quarters), we iteratively re-estimate the models using rolling windows from 12 to 24 quarters. Analyzing the results from Figure 4, we can ascertain that while some changes occur in the dynamics of the series, especially in the period following the Global Financial Crisis, the overall conclusions formulated in the previous section remain largely unchanged.

Additionally, we compute Grange Causality tests between the variables analyzed in first part of the section, using automatic lag selection based on the Bayesian Information Criterion (BIC). The main conclusion we can draw from this exercise is that credit towards non-financial corporations can contribute to an overall increase in investment while consumption and household credit have a synergic relationship.

Robustness check – estimating a time-varying parameter regression using the Variational Bayes (VBKF) method

As an alternative to rolling window regressions, a time-varying parameter model can be estimated by defining a law of motion for the regression coefficients. In practice, TVP models are estimated using Bayesian methods, due to their complexity and parametrization. However, their flexibility in approximating a large variety of non-linear behavior can outweigh the computational costs associated with the Markov chain Monte Carlo (MCMC) estimation methods.

In this context, we apply an optimization algorithm proposed by Korobilis and Koop (2018) which combines Kalman filter updates for time-varying coefficients and volatilities with trivial posterior updates of all other model parameters, namely the Variational Bayes Kalman Filter (VBKF). The TVP regression model with stochastic volatility is defined as follows:

$$\begin{aligned} y_t &= x_t\beta_t + \sigma_t\varepsilon_t \\ \beta_t &= \beta_{t-1} + \eta_t \end{aligned} \tag{3}$$

Where $\varepsilon_t \sim N(0,1)$ and $\eta_t \sim N(0, Q_t)$, with Q_t a diagonal matrix, are independent. The model implies a conditional prior on the coefficients defined as $\beta_t|\beta_{t-1}, Q_t \sim N(\beta_{t-1}, Q_t)$ while the elements of Q follow a Gamma distribution $q_{i,t}^{-1} \sim Gamma(c, d)$. The algorithm involves updating the state-space matrices via the modified Kalman Filter until the absolute incremental change between the parameters drops below a certain error threshold. After obtaining the posterior mean of the time-varying regression model, we compare the estimated series to the rolling window regression from the first subsection.

Figure 5 plots the results obtained from the TVP regression model estimated using the VBKF methodology and the rolling window regression estimates. The robustness check demonstrates the fact that the coefficient levels and dynamics are very similar between the two radically different methodologies and simultaneously validates the choice for the rolling window of 12 quarters. Moreover, on average the difference between the estimated elasticity coefficients for all three model setups (economic growth-total credit, consumptions-household credit and investment-non-financial corporations' credit) is negligible. To summarize, the TVP regression model confirms the results and conclusions drawn in the first section of the analysis.

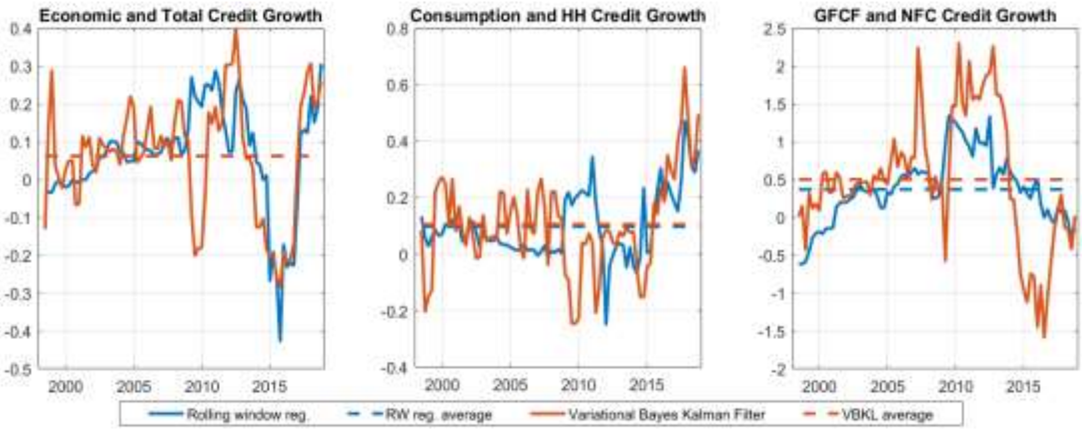

Figure 5. *Results from VBKF model compared with rolling window Bayesian regressions (own estimation)*

A structural TVP-VAR model to identify credit supply shocks and their role in explaining economic growth

Model setup

This section details a time-varying parameters VAR model with stochastic volatility. The identification of the credit shocks is done using sign restrictions. The numerical computation and optimization procedures were done in Matlab 2017b, using the Bayesian Estimation, Analysis and Regression (BEAR) Toolbox.
The further detailed model, as expressed in formula (4) is a vector autoregressive model (VAR) that allows for time variation both in its coefficients and in the residual covariance matrix:

$$y_t = A_{1,t}y_{t-1} + A_{2,t}y_{t-2} + \cdots + A_{p,t}y_{t-p} + Cx_t + \varepsilon_t \tag{4}$$

with

$$\varepsilon_t \sim N(0, \Sigma_t). \tag{5}$$

The posterior does not admit analytical posteriors; therefore, we resort to the Gibbs sampling algorithm to recover the results of the estimation.

In this paper, the TVP–VAR model with stochastic volatility and sign restrictions is used to identify the role played by credit supply shocks over the main macroeconomic variables in Romania. We include variables related to aggregate economic activity (the real GDP year-on-year growth rate), a measure of price dynamics (the HICP year-on-year rate), the exchange rate year-on-year growth rate, a short term interest rate (the 3-months reference rate in the Romanian money market or ROBOR 3M) and the yearly growth rate of the total stock of loans granted to households and non-financial corporations. In this regard, we build a dataset using quarterly data spanning from 2002 to 2018, capturing different stages of the financial and business cycles. As mentioned in the previous sub-section, the macroeconomic variables are extracted from the Eurostat database, while information related to credit was requested from the National Bank of Romania.

Compared to other papers that use the same approach, we included in the model solely the short term interest rate, as the spreads between the loan interest rates and the short term interest rate are available starting 2007, significantly reducing the dataset. We also use the short-term interest rate as a proxy for the credit cost, considering the strong correlation we identified between the two variables (on the 2007–2018 dataset).

The structural shocks identification methodology is based on sign restrictions, as described in Table 1, which allows us to avoid the usual recursive assumptions on the contemporaneous effects between endogenous variables. Our assumptions closely follow the traditional identification schemes used in empirical literature such as Gambetti and Musso (2012) - we allow for an aggregate demand shock, which drives real GDP and inflation upwards while also having an expansionary impact on credit, while an expansionary credit supply shock has a positive impact on real GDP and credit. We do not impose a restriction on the short-term interest rate considering that, in general, loan supply shocks drive credit spreads lower while the short-term interest rate, used as a monetary policy instrument, should increase to counteract an increase in inflation and economic activity.

Table 1. *Sign restrictions imposed in the TVP-VAR model (own estimation)*

	Responses to an expansionary shock				
Shock	Real GDP	Inflation rate	Exchange rate	Short-term rate	Credit
Aggregate demand	+	+		+	+
Credit supply	+	?		?	+

Estimation results

At first, we estimated a suite of constant parameter models, aiming to observe the suitability of the model to the analyzed data. The obtained results indicate a good fit of the chosen model, for all the series. Furthermore, in order assess the robustness of the results we use various prior calibration methods offered by the BEAR toolbox such as the Minnesota prior, the Inverse Wishart prior or the Dummy prior defined by Banbura et al. (2010).

We identified two shocks: a credit supply shock and an aggregate demand shock. Credit supply shocks can be associated with a set of events (for instance unexpected changes in bank capital available for loans, changes in bank funding, changes in the risk perception of potential borrowers by bank management or changes in the degree of competition in the banking sector).

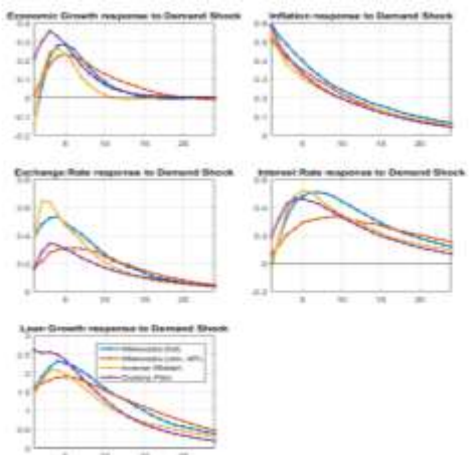

Figure 6. *Impulse response functions to an aggregate demand shock obtained from BVAR with sign restrictions using multiple methods for the calibration of priors (own estimation)*

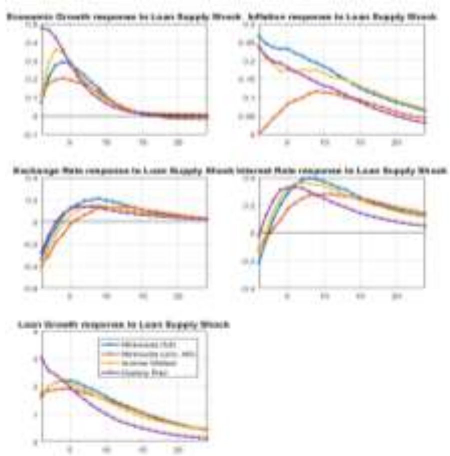

Figure 7. *Impulse response functions to credit supply shock obtained from BVAR with sign restrictions using multiple methods for the calibration of priors (own estimation)*

Figure 6 details the responses to a positive one standard deviation aggregate demand shock. Two of the four calibration methods indicate a negative effect at first in the economic growth case. For all the other analyzed variables, these methods indicate positive reactions with longer durations than in the case of the economic growth. The most significant positive response is the one of the loan growth to an aggregate demand shock, with a peak in the first 5 periods, indicating an important effect of the real economy on the financial system. Therefore, we can ascertain that the demand shock identified in the structural model is in accordance to mainstream literature and brings further evidence to support the model's robustness.

Furthermore, Figure 7 illustrates the responses to a positive one standard deviation credit supply shock. All four calibration methods indicate the same-sign effects for all macroeconomic variables included in the study. The positive response of the economic growth is significant but short-lived, returning to baseline quickly, regardless of the prior calibration choice. Therefore, according to our result, the effect of a credit supply shock on the economic growth is both smaller and shorter than the effect of an aggregate demand shock on the loan growth. The impact on inflation, left unrestricted in the model, is positive but significantly lower than the effect of the demand shock. The short-term interest rate also decreases initially, as a potential consequence of a decrease in costs associated with lending, but quickly returns to positive values. In this sense, the intervention of the monetary policy authority in the sense of tightening credit conditions as a reaction to an increase in inflation and expansion of economic activity could be reflected in the dynamics of the short-term interest rate.

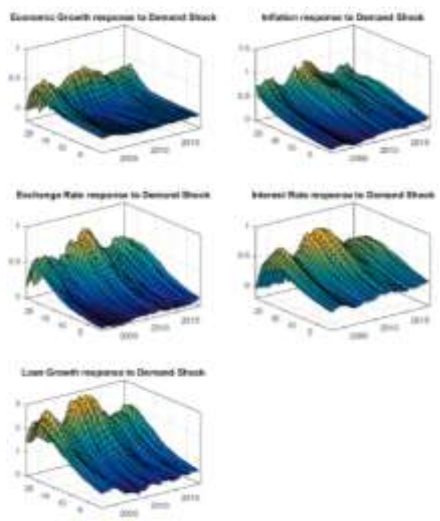

***Figure 8**. Time-varying impulse response functions to an aggregate demand shock (own estimation)*

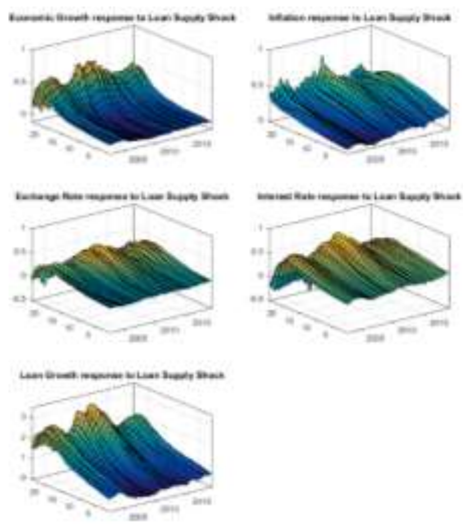

***Figure 9.** Time-varying impulse response functions to a loan supply shock (own estimation)*

Furthermore, we augment the model with time variation in the coefficients and shocks (Figure 8 and 9). Time-varying impulse response functions indicate an amplification both in the case of the aggregate demand shock effect on the loan growth and in the case of the credit supply shock on the economic growth during the crisis period. Both responses remain positive during the analyzed period. Time variation allows for uncovering important structural changes throughout the entire period under scrutiny. We can split the sample in three different subsamples: (i) the first part (until 2005) shows a heightened response but decreasing over time, (ii) the second part, between 2005 and 2010, is the period with the largest responses demand and loan supply shocks almost doubling in size compared to the previous period and (iii) the post-2010 period indicates a decreasing response in all cases. In this sense, the results are consistent with the conclusions from the first part of the study according to witch, after 2010, the link between credit and economic growth has weakened in Romania.

Finally, we analyses the historical decomposition to evaluate the impact of demand and loan supply shocks on the variables included in the model. Figure 10 details the historical decomposition of the selected variables to structural shocks. The historical decomposition decomposes actual data into a trend and the accumulated effects of the structural shocks. Therefore, it allows us to perform counterfactual exercises by providing a picture of the estimated impact of structural shocks during the analyzed period.

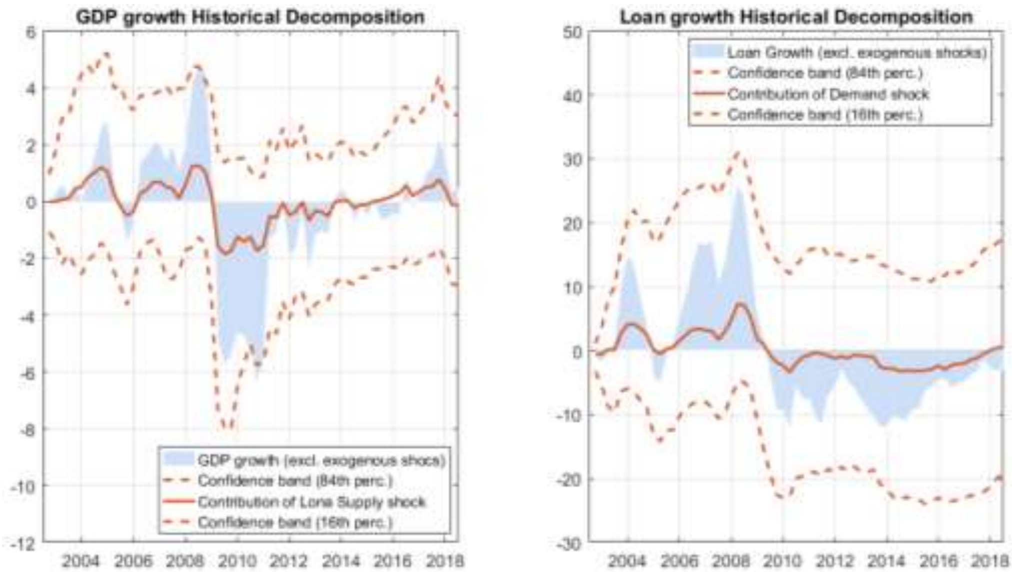

Figure 10. *Historical decomposition of selected variables to structural shocks obtained in the structural TVP-VAR model (own estimation)*

The first important aspect to mention is that both contributions had a sign change at the end of 2008. Moreover, as already indicated by the impulse response functions, the contribution of the aggregate demand shock to the credit growth variation is considerably more significant than the contribution of the loan supply shock to the GDP growth variation. In both cases, we can observe a positive peak in 2008 and a negative one in 2010, near the sign-changing moment. In terms of size, the contributions of loan supply shocks have been mostly positive in the pre-crisis period reaching a peak of around 1 percentage point in 2008, and falling to a negative impact of around 2 percentage points after the onset of the crisis. After 2011, the idea that credit supply shocks have had a rather mild contribution to economic growth is once again reinforced, with a slight upturn at the end of the analyzed period. The results are similar in the case of loan growth with the difference that, after 2010, the contribution of demand shocks was mostly negative, only reversing the trend starting from 2016.

Conclusions

The present paper provides a comprehensive analysis of the relationship between credit and economic growth in Romania, after 30 years of financial sector development, aiming to find answers to questions related to (i) the role of the banking sector in fostering economic growth and the causality direction between the financial and real sector, (ii) the relationship between consumption/investment and certain types of loans and (iii) the identification of loan supply shocks and their role in explaining dynamics associated with other macroeconomic variables included in a structural model of the Romanian economy.

The study starts with some baseline regressions, analyzing the link between economic growth and total credit on an aggregate level, building a dataset using quarterly data spanning from 1995, capturing the early stages of development of the banking sector, to 2018. We ascertain that the relationship between real GDP and total credit growth rates relatively stable in the pre-crisis period, followed by an increase after 2009 and an inversion episode between 2015 and 2017, highlighting the fact that the Romanian economy experienced a period of *creditless recovery,* when economic activity was bolstered by other measures from other policy areas such as fiscal or by a high rate of EU funds absorption. More recently, the elasticity coefficient has become positive and is increasing, on the backdrop of lower statistical significance emphasized by the widening of the interpercentile interval. In fact, when assessing the statistical relevance of the series under scrutiny, a high degree of uncertainty is associated with the post 2015 period. The TVP regression model confirms the results and conclusions drawn in this first section of the analysis.

The second part of the paper focuses on a TVP–VAR model with stochastic volatility and sign restrictions to identify the role played by credit supply shocks over the main macroeconomic variables in Romania. The model uses quarterly data spanning from 2002 to 2018, in order to capture different stages of the financial and business cycles in Romania. We identify two shocks: a credit supply shock and an aggregate demand shock. The impulse response functions indicate a significant positive response of the loan growth to an aggregate demand shock, with a peak in the first 5 periods, indicating an important effect of the real economy on the financial system. On the other hand, the response of the economic growth to a credit shock is positive but short-lived, returning to baseline quickly. Therefore, according to our results, the effect of a credit supply shock on the economic growth is both smaller and shorter than the effect of an aggregate demand shock on the loan growth. The same conclusion is highlighted by the time-varying impulse response functions and the historical decompositions. Moreover, they indicate an amplification both in the case of the aggregate demand shock effect on the loan growth and in the case of the credit supply shock on the economic growth during the crisis period.

Time variation allows for uncovering important structural changes throughout the entire period under scrutiny. We can split the sample in three different subsamples: (i) the first part (until 2005) shows a heightened response but decreasing, (ii) the second part, between 2005 and 2010, is the period with the largest responses demand and loan supply shocks almost doubling in size compared to the previous period and (iii) the post-2010 period indicates a decreasing response in all cases. In this sense, the results are consistent with the conclusions from the first part of the study according to witch, after 2010, the link between credit and economic growth has weakened.

Potential policy solutions to ensure a sustainable contribution of the financial sector to economic growth relate to the strong relationship identified between investment and loans granted to non-financial corporations. In this sense, the leading behavior of non-financial corporations' credit growth coupled with the statistically significant and high elasticity coefficient support the conclusion that credit plays an important role in driving investment, with positive repercussions of ensuring a sustainable rate of economic growth.

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