NON-PERFORMING LOANS AND CREDIT DYNAMICS IN THE CZECH REPUBLIC: SECTORAL DIFFERENCES

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Abstract

The global financial crisis highlighted the evident unpreparedness of economists to properly identify, monitor and evaluate systemic credit risks. While the Czech banking sector demonstrated relatively high resistance towards financial pressures during the crisis, the systemic credit risk monitoring still remains underresearched. We address this research gap by analysing the components of the most frequently used credit risk indicator – the non-performing loans ratio (NPLR). We contribute to the existing literature by dismantling the NPLR components – the non-performing loans and client loans and analyse them through various economic sectors. For the purpose of the analysis, we construct a large factor-augmented VAR model (FAVAR) of the Czech economy which is not limited to number of variables used as in standard VAR models. We find that there are some striking differences among sectors in their response to lending rate innovations. Our evidence shows that the sectoral differences cannot be disregarded or even neglected in financial stability analysis.

Key words: credit risk, lending rates, non-performing loans, sectoral analysis, Czech Republic

JEL Code: C3, G21

Introduction

The global financial crisis has revealed the evident unpreparedness of policy makers to properly understand, monitor and forecast the credit risk accumulation and associated risk of financial instability. It became widely accepted fact that maintaining financial stability is a crucial condition for both price stability and stability of economic output and welfare. Nowadays, the most commonly used proxy indicator for the level of credit risk materialization in the banking sectors is the level of non-performing loans[1] (NPLs) often with respect to the total loans granted in the form of non-performing loans ratio (NPLR, see Buncic and Melecky, 2013 and Castro,

[1] Nonperforming loans are nonstandard, doubtful and loss-making loans as defined by Decree No. 163/2014 Coll., https://www.cnb.cz/miranda2/export/sites/www.cnb.cz/en/legislation/decrees/decree_163_2014.pdf

2013 among others). As the NPLR increase, banks are forced to create higher loan loss provisions and to increase asset quality (BSBC, 2015).

The effect of macroeconomic indicators on non-performing loans is fairly well examined, for the literature overview and meta-analysis of macroeconomic drivers of non-performing loans see Machacek, Melecky and Sulganova (2017). Most of the identified studies however, are focused on aggregate level or bank level, but only a few perform analysis at a sectoral level (Boss et al., 2009, Beaton et al., 2016 and Holub et al., 2015 to our knowledge). Boss et al. (2009) study the relation between macroeconomic variables and probabilities of default for the main Austrian corporate sectors and find that the size and sometimes even the sign of variables' effect on credit risk may significantly differ across the sectors of economy. Beaton et al. (2016) assesses the determinants of NPLs with a special focus on deterioration in asset quality. They notice that the deterioration of asset quality leads to declining credit, with wide variations in the impact by sector. Holub et al. (2015) apply the macroprudential policy perspective and assess whether the sector concentration of the portfolio of loans could indicate a need for additional capital requirements. They conclude that supervisors should evaluate whether sector concentration risk is correctly measured, assessed and incorporated into capital requirements in the bank's internal capital adequacy assessment process.

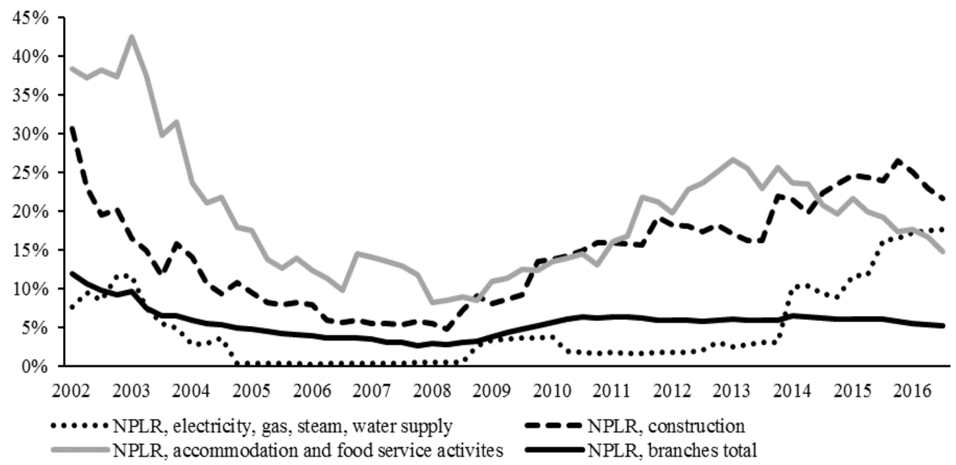
In this paper, we present novel evidence on the matter. We argue that the aggregate NPLR may be an ill-advised indicator for policy makers as it may be easily under- or over-valuated in many cases due to: (i) different development of its core components - the non-performing loans (numerator) and client loans (denominator) and (ii) divergent development across various sectors of the economy. We support our arguments by empirical evidence using Czech macroeconomic and bank-specific data. While the Czech banking sector demonstrated relatively high resistance towards financial pressures during the global financial crisis, the credit risk monitoring still remains underresearched. Our approach aims to improve credit risk monitoring by emphasizing the need for in-depth sectoral analysis of the NPLR indicator. Conclusions, presented in this paper, are applicable to other economies as well.

The remainder of the paper is organized as follows. Section 1 provides stylized facts regarding the development of the NPLR dynamics and its components in the Czech Republic. Section 2 outlines theoretical underpinnings of the applied framework and describes the employed data. Section 3 discusses the empirical results and performs a sensitivity analysis. The last section concludes.

1 Stylized facts

Dynamics of the NPLR differs across the sectors of economy. Figure 1 presents an illustrative example containing evolution of the NPLR in three sectors with the highest values of NPLR in 2016 compared with an aggregate level of this indicator. It is evident that the variability of the aggregate NPLR and its levels lags far behind the variability of the selected sectors. NPLRs were generally decreasing from 2002 up to the global financial crisis. The strongest consolidation can be found in accommodation, food service activities and construction sectors. NPLRs in these sectors increased significantly response to the global financial crisis and construction sector became one with the highest values of NPLR in 2014. In construction sector, which currently employs approximately 400,000 people, high NPLR may result in an unpleasant unemployment increase. Yet another interesting fact is the obvious change in trend development of NPLR in electricity, gas, steam and water supply sector starting from 2013. This previously stable sector became the source of significant credit risk materialization. In general, judging from this simple graphical analysis, we can conclude that the aggregate NPLR indicator is not able to capture the key changes in the sectoral loans dynamics and should be submitted to further analysis.

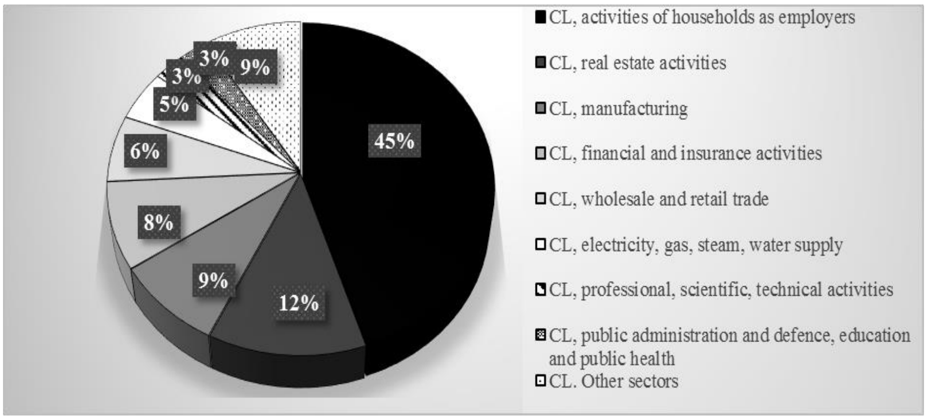
Fig 1: Sectors with the highest NPLR vs aggregate NPLR (2002:Q1 – 2016:Q3)



Source: Czech National Bank (CNB) database, 2016

To see what lies behind the high values of the NPLR, let us focus on its individual components. Formally written, the NPLR is a ratio of the volume of non-performing loans (NPLs) and the volume of loans granted to clients (CLs). Figure 2 provides information regarding the distribution of client loans across the sectors of the Czech economy in 2016. About 45% of all loans granted result from activities of households acting as employers, followed by real estate (12%), manufacturing (9%) and financial and insurance activities (8%) sectors.

Fig 2: Client loans distribution across the sectors of economy (2016:Q3)

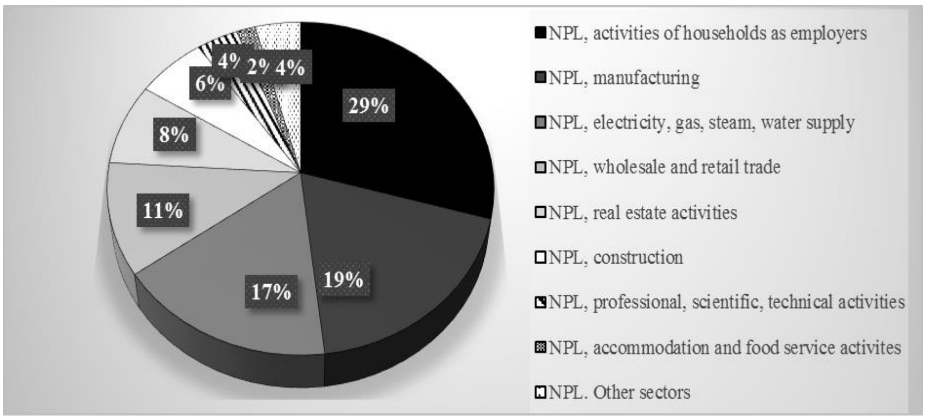


Source: own calculations based on CNB data, 2016

Note: To keep the graph clear, we present only 8 sectors with the largest share on total client loans. The rest is summarized in category other sectors.

Figure 3 (similarly to Figure 2) provides information about the distribution of non-performing loans across the sectors of the Czech economy in 2016. About 29% of all non-performing loans are stemming from the activities of households as employers sector, followed by manufacturing (19%), electricity, gas, steam, water supply (17%) and wholesale and retail trade (11%). As apparent from this brief graphical analysis, even relatively small sectors with respect to loans granted could significantly contribute to the total level of NPLs.

Fig. 3: Non-performing loans distribution across the sectors of economy (2016:Q3)



Source: own calculations based on CNB data, 2016

Note: In order to keep the graph clear, we present only 8 sectors with the largest share on total non-performing loans. The rest is summarized in category other sectors.

2 Methodology and data

We aim to determine how the changes in lending rates are transmitted to the two components of the NPLR and how these effects vary among economic sectors. To utilize the full information set available to us, we use a factor-augmented VAR (FAVAR) model introduced in Bernanke et al. (2005). The basic idea of the FAVAR model rests on incorporating a large amount of data series into a small number of factors which are then used for the estimation of a VAR model. We specify an $M \times 1$ vector of macroeconomic time series Y_t and a $K \times 1$ vector of unobserved factors F_t. We assume that the joint dynamics of F_t', Y_t' is given by the following equation:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \varepsilon_t , \qquad (1)$$

where $\Phi(L)$ is a lag polynomial and ε_t is an error term with a zero mean and a covariance matrix Q. Equation (2) describes a standard VAR model which represents a reduced form of a linear rational-expectations model including both observed and unobserved variables. Due to the unobserved variables, the model is impossible to estimate. To get around this fact, we assume that additional informational time series (X_t) are linked to the unobservable factors (F_t) and the observable factors (Y_t) by:

$$X_t' = \Lambda^f F_t' + \Lambda^y Y_t' + e_t' , \qquad (2)$$

where Λ^f and Λ^y are matrices of factor loadings and e_t' is a serially uncorrelated error term with a zero mean (innovation shock). Equation (2) captures the idea that both vectors (Y_t) and (F_t) are pervasive forces that might drive the common dynamics of (X_t). We use a two-step principal components approach, which is a nonparametric way of estimating the space spanned by the common components $C_t' = (F_t', Y_t')$ in equation (2).

Our vector (X_t) incorporates 160 quarterly time series representing the Czech economy and the rest of the world. They are drawn mainly from CNB, Czech statistical office and the ECB databases. The series span over the 2001:Q1 – 2016:Q1 period. The set of variables can be divided into six blocks: (i) real economy variables (gross domestic product, construction production index, retail sales, labour market indicators), (ii) fiscal variables (government debt and deficit, interest payments), (iii) prices (consumer price index, industrial producer price index, house prices, real wages), (iv) credit and interest rates, (v) financial sector variables (regulatory variables, exchange rates, market indexes, financial cycle indicator, asset prices), and (vi) open economy variables (real economy and financial sector development in Germany and Eurozone). Prior to the estimation, we transform all data series using natural logarithms and first differences to assure stationarity. A more detailed description of the data is available upon request.

We assume that the lending rate is the only observable factor in (Y_t) and we treat it as a factor that has a pervasive effect on the economy (X_t). To identify the lending rate innovations (a positive shock), we apply recursive Cholesky decomposition to the covariance matrix. For this purpose, we divide our panel of variables into two groups: slow- and fast moving variables. We assume that slow-moving variables display a lagged response to a shock, whereas fast-moving variables react contemporaneously. In the lending rate shock, identification blocks describing the real economy, fiscal variables, prices and the external environment are classed as slow-moving (in the given order). The remaining variables are classed as fast-moving.

3 Empirical results

We present the effects of a lending rate shock using impulse response functions (IRFs). To account for any uncertainty in the factor estimation, we also calculate accurate confidence intervals as in Kilian (1998).[2] The baseline model specification is based on Schwarz information criteria and employs 3 lags of explanatory variables and 3 factors. Figures 4 and 5 present the effects of a positive one standard deviation lending rate shock. For the sake of clarity and comparability of the responses across sectors, we normalize them to account for 1 percentage point (pp) increase in the lending rate.

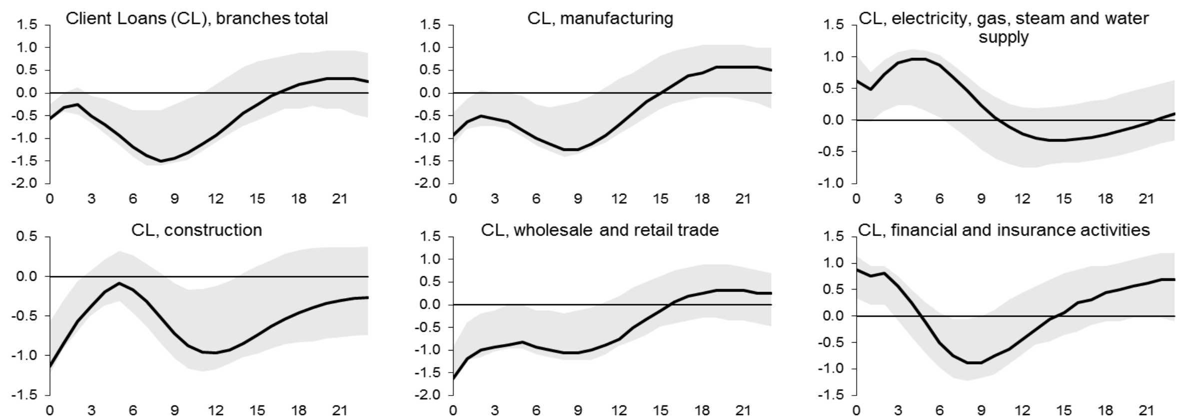
The empirical results confirm our theoretical assumption about the negative effect of increase in lending rate on the size of the granted loans in most of the sectors. Higher lending rate should also increase the cost of financing, thus making investment projects more costly. After that, some of the investment projects may not be profitable any more so the investors do not realize them, demand for client loans decrease and therefore the amount of granted client loans decrease as well. There are two notable exceptions in our sample: first exception is the financial and insurance activities sector, where the amount of loans increase at impact but drops after about four quarters. Part of the explanation may be the increased uncertainty in the post-

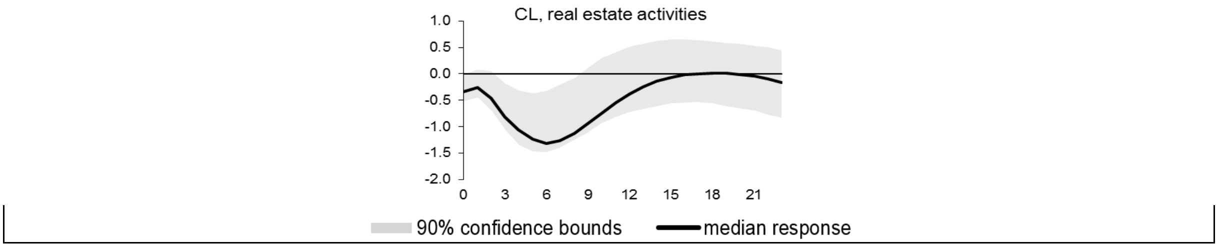
[2] Note that IRFs can be constructed for any variable in our information set. However, due to space constrains, we only report here those relevant for our analysis.

crisis period, which forms a great part of our sample. In such times, economic subjects are more likely to invest in the insurance to cover for any unforeseen loses. In addition, a state pension reform partaking since 2013 may have some impact on the results. Second exception is the electricity, gas, steam and water supply sector, where the amount of client loans conversely rise after the positive lending rate shock. This may be associated with the irreplaceability of power industry in the Czech economy and changes in electricity purchase prices associated with the uncontrolled boom in solar power plants construction.

Furthermore, economic sectors differ in terms of size and timing of their response to increased cost of financing. In the construction sector, manufacturing and wholesale and retail trade sector, the strongest reaction happens rather quickly after the shock with the maximum size of -1.13 pp, -1.26 pp and -1.64 pp respectively. Interestingly, the construction sector is hit twice. The first more eminent decrease is caused solely by increased cost of financing while the second drop is a result of decreases in other sectors of the economy (especially the real estate activities sector). This finding is important, as it shows some form of a cost multiplication effects between sectors of the economy when hit by a lending rate shock. This ‘second round effects’ are also visible in manufacturing and wholesale and retail trade sector. The strongest reaction of financial and insurance (-0.88), and real estate activities (-1.32) sectors are lagged and are more in line with the aggregate reaction of the CLs. To sum it up, increase in lending rate has different effects on the demand for credits in particular sectors of the economy and some of the sectors behave otherwise compared to the aggregate CLs.

Fig. 4: Sectoral client loans IRFs

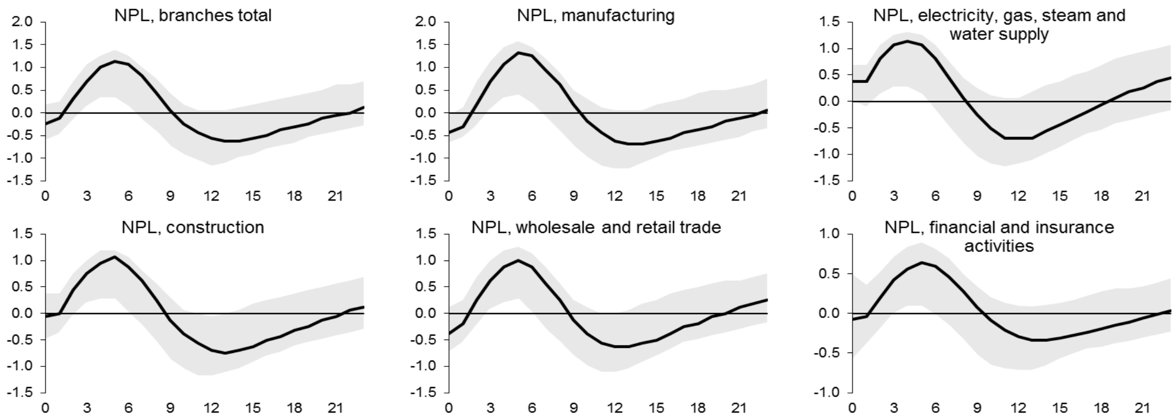


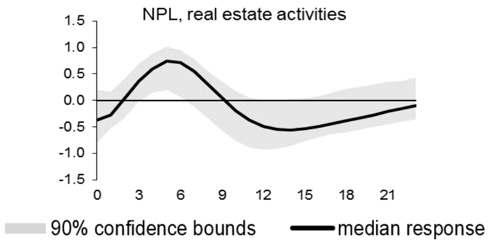


Note: The figure shows median impulse responses from FAVAR model with 3 lags with 10% and 90% confidence bands. Responses are normalized to account for 100 basis point increase in the average lending rate.

In line with the economic theory, NPLs in all sectors increase after a positive lending rate shock because of higher interest payments and the inability of economic subjects to meet the obligations. As it is apparent from Figure 5, the NPLs growth culminates mostly in the fifth quarter after the shock, with an exception of NPLs in electricity, gas steam and water supply sector, where the reaction is slightly faster. The lagged response of NPLs after the shock stems from the fact that it takes some time before the loan is re-classified as non-performing. Simply said, in the Czech Republic, the loan is classified as non-performing if the payments are delayed more than 90 days (for details see CNBs' degree no. 123/2007 Coll., as amended). In addition, the shapes of the IRFs are similar across the sectors. The main difference is in the size of the reaction. If we focus solely on peak points, the strongest reaction of NPLs to lending rate shock is in manufacturing sector (1.32 pp) and electricity, gas, steam and water supply sector (1.13 pp). On the other hand, significantly weaker reactions are typical for financial and insurance activities (0.64 pp) and real estate activities sectors (0.75 pp). Therefore, we conclude that the effects of increasing lending rate to the ability to repay the debt is not identical or even similar across all sectors of Czech economy.

Fig. 5: Sectoral non-performing loans IRFs





Note: The figure shows median impulse responses from FAVAR model with 3 lags with 10% and 90% confidence bands. Responses are normalized to account for 100 basis point increase in the average lending rate.

In order to verify our results, we perform robustness tests. Specifically, we change the number of factors and lags included in our FAVAR model (baseline models employ 3 lags of explanatory variables and 3 estimated factors). The FAVAR model with 5 and 7 factors tells the same story. Most of the IFRs from the models with 5 and 7 factors lie inside the 90% confidence interval of the FAVAR model with 3 factors. The only difference is a slightly slower reaction of the variables to the lending rate shock in the case of models with larger number of factors. Further robustness checks including an increased number of lags in the FAVAR model (3 lags) for 3, 5 and 7. The results are both qualitatively and quantitatively similar.

Conclusion

Based on the empirical findings, we conclude that the use of the aggregate NPLR as an indicator of credit risk materialization may be miss-leading for policy makers. There are two main reasons for such a claim. First, the two components of the NPLR do not always respond to lending rate shock with the same sign and second, the responses are significantly different in intensity and timing across economic sectors. The highest peak reaction of non-performing loans after the shock appears in manufacturing sector and electricity, steam, gas and water supply sector, while the most significant peak drop of client loans granted in wholesale and retail trade sector, followed by real estate activities sector.

The FAVAR model proved to be useful tool for this type of analysis. The policy makers should closely monitor individual components of NPLR on a sectoral level to reduce potential model risk as the NPLR is directly linked to both the micro- and macro-prudential policy tools (stress testing, risk weighting, provisioning and credit loss recognition).

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