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INTERDEPENDENCE BETWEEN MACROECONOMIC AND FINANCIAL STABILITY INDICATORS: MACRO-FEEDBACK EFFECT

Abstract:

Standard stress tests consider only first round effect from macroeconomic variables to financial stability indicators. However, the occurred shocks in banking sector reflect on macroeconomic indicators throughout different transmission mechanisms, such as expectations of economic agents, expected responses of banking sector to increased credit risk and etc. This creates the necessity of expansion and improvement of existing types of models, which will also include second round (macro-feedback) effects. The study explores the dynamic relationship between macroeconomic variables and indicators of financial stability, proving the relevance of considering second-round effects for better policy analysis. This paper develops a macro stress testing model incorporating feedback effects between financial system and the real economy. The study uses VAR approach to analyze various interactions between indicators through Impulse Response Functions (IRFs) and conducts different stress scenarios on exogenous variables. According to empirical results for the case of Georgia, there is significant relationship between real and financial variables, proving the countercyclical nature of NPLs with respect to different estimates of GDP gap. The signs of the impacts are robust with respect to different estimates of GDP gap. However, the magnitude of the effect of change in NPLs on GDP gap and vice versa varies with different estimate of GDP gap. In addition, using historical decomposition of GDP gap, the study shows that the effects of financial variables on variables of real economy differ from each other depending on the observed time interval (pre-crisis or post-crisis). The transmission of the impact goes though “credit crunch”. The model proves the fact that change in NPL ratio strongly impacts credit growth represented as change in Credit to GDP ratio. At the same time, change in Credit to GDP ratio explain significant part of output gap forecast error and has significant contribution to business cycle fluctuations, strengthening the impact of NPLs and financial stability as a whole on the real economy. The estimated model can be used for generating different scenarios and shocks for improving systemic risk analysis (effect of banking sector’s solvency on real economy) and for providing better policy recommendations.

Keywords:

Stress testing, Macro feedback effects, Solvency risk, Non-performing loans, Hodrick-Prescott filter, Kalman filter, Band Pass filter, GDP gap, Macro-financial linkages, Business fluctuations, VAR

JEL Classification: E37, E44, G17

1. Introduction

The cases of economic and financial crises throughout last decades have brought sharp interest towards the relationship between real and financial sectors. According to classical dichotomy, nominal variables are incapable of affecting real variables, meaning that shocks occurred in financial sector should not influence real sector. However, the international financial crisis of 2007-2008 has proved that financial stability is a key concept for understanding economic sustainability. Financial imbalances can lead to potentially harmful macroeconomic outcomes. Ignoring this concept may lead to misleading policy recommendations and decisions by policymakers. Lately, a growing body of literature has emerged regarding conduction of macro-prudential studies considering relationships between financial and real variables. In particular, the main object of interest for conductors of monetary policy is the relationship between macroeconomic variables and financial stability indicators, such as credit risk. Implementation of Financial Sector Assessment Program – FSAP and Basel II and Basel III standards promoted the development of risk stress analysis. Stress tests are widely used for analysis of conditions of banking sector. Sustainability of bank is dependent on systemic and idiosyncratic risk factors, creating the necessity of investigation of credit risk and its decomposition. According to different studies, business cycles can influence banks' balance sheets immediately or with some delay (Marcucci and Quagliariello, 2008). At the same time, a small attention is paid to the potential feedback from financial instability to real economy, which can strengthen cyclical fluctuations, especially during the recession.

Standard stress tests consider only first round effect from macroeconomic variables to financial stability indicators. Such assumption is realistic for explanation of the short run outcomes. However, in the medium and long run periods, the occurred shocks in banking sector reflect on macroeconomic indicators throughout different transmission mechanisms, such as expectations of economic agents, expected responses of banking sector to increased credit risk and etc. This creates the necessity of expansion and improvement of existing types of models, which will also include second round (macro-feedback) effects.

Despite the fact that financial stability has been an important aspect of interest, due to interdependence and various interactions between elements within financial sector and with real economy, there is no precise definition of financial stability among academics and policymakers. According to European Central Bank, financial stability is a state when there is no accumulation of systemic risk, which itself is described as a risk of inability of financial system to provide its services affecting economic growth and welfare. Such systemic risk can arise when there is arrangement of financial imbalances during boom of financial cycle, shocks to economy and financial system itself and contagion effects between markets (ECB, 2017). Briefly speaking, financial system can be considered as stable if there is no excess volatility or crisis in financial and banking sectors. According to Crockett (2000) there are two dimensions of financial stability: micro and macro-prudential. The main difference between them is objectives and concept of transmission mechanisms affecting economic outcomes. The main objective of micro-prudential framework is the limitation of the probability of a failure of individual institution, while the main goal of macro-prudential dimension is to lessen the cost of economy from financial stress.

The first round effect can be shown by the following pattern as an impact of business cycle on the banking system. At the beginning of the expansionary phase, firms' profits increase, asset prices rise and customers' expectations become optimistic. Such expansion in aggregate demand is followed by a significant growth in bank lending and economy's overall liability. During this boom, banks may underestimate their risk portfolio and lower their criteria for lending, causing the decline in borrowers' creditworthiness and an increase in the amount of non-performing loans in the future. Once exogenous shocks occur, clients' profitability worsens and negative expectations arise, causing the decline in asset prices and further decline of clients' financial wealth. Furthermore, the fall in liquidity and investment causes the rise of unemployment, which reduces governmental tax revenues, investor/consumer confidence and most importantly households' income and their ability to pay back their debts. A further accumulation of non-performing assets (loans) continues and the number of defaulted firms increases, causing losses in banks' balance sheets.

The feedback from banking sector to real economy begins once banks make response to these exogenous shocks. During those shocks, banks' profitability and capital adequacy decline. In response to recession, banks may react by shrinking credit supply for restoring minimum capital ratios (credit crunch), especially when they have thin capital buffers above the minimum capital requirement. In this case, it is more profitable for banks to reduce lending, rather than increase capital due to the fact that it is more costly during recessions. At the same time, firms need funding for financing their investment projects. If banks' credits are not easily substitutable by other sources of financing, firms will not have sufficient financial resources. This decline in credit supply might cause an increase in demand for external financing, making it cost more due to additional costs connected with the search for new financing sources. Those additional costs decline net return of investments, reducing the demand for investment as a result. This strengthens the effects of the downturn in economy even further.

Based on the above discussion, the strength of feedback effect depends on the degree of substitutability of loans and bonds, the adequacy of bank capital buffers regarding minimum capital requirement and the role of banks in firms' financial resources (Marcucci and Quagliariello, 2008). Therefore, the inclusion of macro-feedback in the model implies consideration of both effects including feedback loops and might change the evaluation of risks as a whole. Given some particular shocks, models with feedback effect tend to show higher aggregate loss of banking sector compared to models without feedback effect (Kida, 2008). Such shocks could be high GDP gap and/or nominal devaluation of domestic currency. Such shocks have particularly high impact in countries with highly dollarized economy. This creates the necessity of investigating this relationship in case of developing countries like Georgia. One of the most interesting cases might be the potential effect of de-dollarization policy on financial stability and its macro-feedback.

The study's goal is the estimation of the dynamic model, which will consider the relationships between financial and real sectors. The main aim of the study is the acknowledgement of the necessity of including macro-feedback effects in standard models and proving the advantage of the expended model compared to the standard stress-testing models. The framework used in the research strengthens macro-financial analysis by empirical analysis on the example of small open economy country. The model might be used by the conductors of monetary policy and banking sectors supervisors for the estimation of the credit risk with its macro-feedback effects. The study allows investigating important empirical macro-financial linkages. For example, it is possible to estimate the sensitivity of GDP gap with respect to changes in financial variables and use it for evaluation of financial cycle. This procedure helps to extract business and credit cycles for enhancing of risk analysis and compares results regarding calculation of gaps using Hodrick-Preskott, Band Pass and Kalman filters. At the same time, the model can be used for generating different scenarios and shocks for improving systemic risk analysis (effect of banking sector's solvency on real economy) and for providing better policy recommendations. Based on above mentioned framework, using impulse response functions and historical shock decomposition, the study analyzes the impact of real economy on financial sector and vice versa.

2. Literature Review

Even though the importance of the relationship between real and financial sectors has been acknowledged among scholars, the literature regarding macro-feedback effects is limited. Despite limited number of studies, the topic is characterized by variety of theoretical and empirical frameworks implemented by researchers for integrating effects from financial sector to the real economy. Goodhart, Sunirand and Tsomocos (2006) develop two-period general model to analyze possible feedback effects between financial and real sectors (macro-feedback effect) and then extend it to an infinite-horizon time framework applying UK time series data. At the same time, the paper analyzes inter-bank contagion; relationship between commercial banks, considering the fact that exposure to risk spreads extensively due to existence of inter-bank loans market. According to study's assumptions, banks solve profit maximization problem by choosing the levels of consumer credit supply, consumer deposits and by trading on inter-bank loans market. The study allows banks to default in deposit and inter-bank markets, along with violation of minimum capital requirement regulations. The authors include the macro-feedback effect using credit crunch transmission channel. As mentioned above, during credit crunch, banks lessen lending in order to increase the capital ratio, causing a decrease in GDP and further enhancing the probability of default of the households.

According to model's simulations, the downward trend of inter-bank rate causes increase of borrowing by representative commercial banks, which on the other hand increases credit supply to households through the loan market, lowering lending interest rates. At the same time, increased credit supply increases GDP in the next period. The expectation of increasing GDP makes household repay more to bank in order to decrease the level of default penalties and supply more deposits at the same time, causing reduction of deposit interest rate. Even though according to the paper's model, GDP of the next period is a positive function of only aggregate supply of credit in previous period, simulated data fits real data well. On the other hand, according to model's specification, it is more focused on inter-bank relationship rather than macro-feedback effect. In addition, the developed model is relatively complex, consisting of 56 simultaneous equations and 143 unknowns, of which 87 are exogenous parameters. This implies a high dependence of the results on calibration mechanism, creating presumption that feedback effect in this model is mostly imposed than estimated.

Based on artificial data of banking sector, Kida (2008) develops a model focusing on the transmission of banking sector solvency to the real economy, comparing different versions of the model with different types of feedback effects. According to Kida, macro-feedback effect increases influence of shocks to the system by 10 percent, while inclusion of feedback effect between interest rate and credit risks doubles the impact. In both cases, versions of models with feedback effects imply higher losses in banking sector compared to models without such effects. Similar to Goodhart, Sunirand and Tsomocos (2006), the paper relies on calibration, imposing the existence of the feedback effect into the framework. In addition, the framework implements feedback effect through credit crunch, including equation positively connecting output growth to credit growth only, which is not well suited for complete macroeconomic forecasting and running different scenarios.

Based on structural VAR analysis, Marcucci and Quagliariello (2008) examine the feedback effect through bank capital transmission channel, following the idea of Bernanke and Lown (1991) regarding bank's scarcity of equity capital as the main source of impact on its lending ability. The authors estimate the effect of business cycle on bank's portfolio riskiness (measured by default rate) in order to test the transmission mechanism of the feedback effect on the real economy and vice versa. In addition, the paper examines the feedback effect on sectoral level, considering the response of corporate and household sectors to different macroeconomic shocks. For testing the feedback effect, along with baseline variables such as default rate of borrowers, inflation rate, interbank interest rate, real exchange rate and output gap, the study uses proxies for bank disposable capital (the ratio of negative free capital to supervisory capital) and credit supply such as spread (the difference between average short-term interest rate on loans and the interest rate paid by the most solvent borrowers).

According to study, the default rate and therefore bank's portfolio riskiness seem to be cyclical, implying that default rate declines during economic expansion and increases in times of economic recession. Based in impulse response function, this effect lasts approximately for 4 quarters. At the same time, based on variance decomposition, the study suggests that 16% in the forecast error of default rate is explained by the output gap, while default rate explains 8% of forecast error of output gap. At the same time, the study suggests the robustness of results for different measures of output gap, estimated by model of central bank, simple trend and Hodrick-Prescott filter. On sectoral level, effects vary significantly. In particular, in corporate level, output gap explains 5% in the forecast error of default rate, while in household sector the corresponding measure equals to 9%. At the same time, 8% of forecast error in output gap is attributed to default rate in corporate sector and only 1% in household sector. After the inclusion of proxy variables for feedback effect, on aggregate level, 8% of the forecast error in default rate is explained by the output gap, while 2% of the forecast error in output gap is linked to the default rate. On the other hand, spread seems to explain approximately 12% of the forecast error in output gap, suggesting existence of feedback effect happening in the first two quarters according to impulse response function.

Espinoza and Prasad (2010) estimate panel data on micro and macro levels for GCC countries (Qatar, Bahrain, Saudi Arabia, Oman, Kuwait and UAE) using data from 1985 to 2008 and logit transformation of NPL ratio as indicator of financial stability. According to results from dynamic panel of 80 banks, NPL ratio is negatively dependent on economic growth as interest rates and risk aversion increases, suggesting high cumulative shock from 3 the macroeconomic shock over a 3 year horizon. On macro level, the paper uses panel VAR to estimate the feedback effect from changes in NPL ratio on various indicators of real economy. On macro level, the factors influencing accumulation of NPL remain the same. Particularly, NPL ratio is positively dependent on interest rate and negatively dependent on non-oil GDP growth. Based on one of the specifications of estimated models, one standard deviation of 2.1 percentage points amount in NPL ratio decreases credit growth by 1.5 after two years ad by 2.2 after three years, staying statistically significant for third year also. At the same time, 2 percentage point increase in the NPL ratio reduces non-oil GDP growth by 0.8 percentage point with one lag after the shock. And semi-elasticity of effect from losses in banks' balance sheets on economic activity is approximately equal to 0.4, suggesting existence of short-lived feedback effect. According to variance decomposition of forecast error, NPL shock can explain approximately 5-7 percent of the non-oil GDP growth. In addition, authors suggest non-linearity of feedback effect, implying an increase in cost after reaching particular threshold of NPL ratio.

Similar to Espinoza and Prasad, Nkusu (2011) analyzes determinants of NPL based on single equation Panel regression and studies feedback effect using Panel Vector Autoregression (PVAR) analysis focusing on 26 advanced economies based on data from 1998-2009. The paper uses significant number of macroeconomic and financial variables such as GDP growth, unemployment rate, inflation, interest rate, changes in housing and stock prices, nominal effective exchange rate (NEER), monetary policy rate and credit-to-

GDP ratio. According to the study, worsening of loan quality (higher NPL) is mainly caused by adverse shocks to macroeconomic performance, credit to private sector and asset prices, while higher NPL leads to decline in house prices, lower GDP growth and decline in credit-to-GDP ratio. Particularly, increase in housing prices by one standard deviation increases NPL by 0.3 percentage points in first period and the NPL is 1.5 percentage points higher in forth year compared to pre-shock period. 1.6 percentage points increase in inflation causes 0.3 percentage points increase in NPL in first year and cumulatively 1.6 points by the fourth year. A negative shock to GDP growth of 2.7 percentage points increases NPL by 0.4 percentage points in first year and accumulates to 1.7 by the fourth year. In addition, one standard deviation decrease in credit-to-GDP ratio increases NPL by 0.3 percentage points in the first period and by 1 percentage point by fourth year.

At the same time, one standard deviation shock of NPL decreases house prices by 1.2 percentage points in the first year and accumulates to 3.2 percentage points decline by the fourth year. The shock to NPL has adverse impact on credit-to-GDP ratio as it decreases the ratio by 4.5 percentage points in the first year, reaching 28 percentage points by the fourth period. In addition, it decreases GDP growth rate by 0.6 percentage points in the first year, which is close to the results of Espinoza and Prasad (2010), and reaches a 2.5 percentage points decline by the fourth year. According to authors, average magnitudes of NPL shocks from 0.6 to 1.7 percentage points have different strength of impact in developing and developed countries. Authors suggest that developed countries are more exposed to negative macroeconomic and financial developments due to NPL shock of such magnitude as developing countries are characterized with coincidence between systemic business cycle crises and high NPL. According to authors, the best way of avoiding adverse macroeconomic performance due to shocks to financial stability is through preventing of excessive risk-taking during economic expansion using adequate macroprudential instruments.

Using Global VAR framework with included contingent claims analysis (CCA), Gray et al. (2013) link to each other sovereign risk, banking sector risk, corporate sector risks, credit growth and real output growth. The study applies different shocks to sovereigns and banking sector of Spain and Italy. Under negative shock to banking sector, GDP of Italy declines by 0.5% and credit supply declines by 2.5% in Spain. For both countries, due to negative shocks to sovereign risk, real output and credit decline significantly. On the other hand, due to positive shocks to banking sector, GDP of Spain increases by 0.9%, while credit supply increases by 2.7%. The paper uses different measures of forward-looking risk indicators such as fair-value spreads, expected default rate and loss given default. Such measures consider non-linearity of changes in bank credit spreads and assets, equity capital and default probabilities. However, such measures represent market price based indicators rather than accounting measures, making it complicated to identify the source of distraction. In addition, in countries with limited or no market price data, usage of such indicators might not be reasonable due to sensitivity of such indicators to short-run expectation changes that might not be linked to changes in fundamentals.

Similar to Nkusu, Klein (2013) investigates determinants of NPL and its effect on macroeconomic performance in countries of Central, Eastern and South-Eastern Europe (CESEE) in 1998-2011 time period. According to the study, high rate of NPLs in the CESEE regions is mostly due to macroeconomic factors rather than banks' specific factors. In order to estimate the factors that affect NPL in 16 countries, the study uses various panel data estimation techniques based on each country's banking sector data. The analysis include different type of independent variables separated into three groups: bank-specific variables such as equity-to-assets ratio, return on equity, loans-to-assets ratio, loans growth rate; country-specific variables: inflation, Euro exchange rate, change in unemployment rate; and global variables: Euro zone's GDP growth and the measure of global risk aversion (VIX). According to estimation results, higher equity-to-asset ratio, increase in unemployment rate, higher inflation and depreciation of currency with respect to Euro increase NPL ratio in CESEE countries. Those results prove the relationship between business cycle and rigidity of banking sector. At the same time, global variables have impact on NPL ratio, as higher volatility of global risk aversion index and lower Euro zone GDP growth increase NPL ratio through higher rates on financial markets, lower revenues from export and an increase in difficulty of attracting foreign financing of banks, causing decrease in credit supply. The authors split the sample into pre and post-crisis periods. According to estimation results on separate samples, inflation and unemployment had stronger effect in pre-crisis period, while the effect of exchange rate fluctuations turned to be more significant during the post-crisis period.

In order to investigate feedback effect, Klein uses Panel VAR based on Cholesky decomposition, which mean that variables are arranged in proper order, starting from more exogenous to more endogenous variables. In particular, the used ordering is: NPL, change in credit-to-GDP ratio, unemployment rate, real GDP growth rate and change in CPI (inflation). Such ordering is based on assumption that NPL has simultaneous impacts on inflation, unemployment and GD growth, while latter variables need some time lag to affect NPL ratio. According to VAR estimation, one percentage point increase in credit-to-GDP ratio and real GDP growth causes decrease in NPL by 0.7 and 0.6 percentage point correspondingly, while increase in inflation causes increase in NPL of 0.4 percentage points. At the same time, one percentage points increase in NPL decreases credit-to-GDP ratio by 1.7 percentage points, increase in unemployment by 0.5 percentage points (in three years' time), decrease in real GDP of 1 percentage point (over two years) and decreases inflation by 0.6 percentage points in three years horizon. Using variance decomposition, the study shows that NPL explains approximately 10 percent of forecast error of other variables in 5 years horizon under baseline scenario and from 10 to 20 percent under alternative specification, which uses difference of NPL as a variable. The paper suggests strengthening of supervision for preventing sharp increase in NPL in order to avoid adverse economic shocks coming from financial sector. According to authors, such policies will help banks to avoid excessive lending, keep high lending standards and limit foreign currency lending. In addition, authors suggest to create better environment for banks' process of cleaning up their portfolio by removing taxes and regulatory obstacles.

Singh and Majumdar (2013) develop macro stress testing framework for Indian banking sector using ordinary VAR approach to test the impact of various macroeconomic shocks on banks stability and its feedback effect. The study uses growth rate of output, inflation rate, call money rate and real effective exchange rate (REER) as a variable representing the influence of the external sector on real economy and banking through trade and financial linkages. The study uses the stock of non-performing assets as a measure of financial stability in economy, as changes in stock of such assets influence the stability of the whole banking sector and have impact on the solvency of individual banks. Contemporaneously, excess of non-performing assets relatively to some limit deteriorates credit growth and reduces perspective of economic growth. At the same time, non-performing assets are considered cyclical, negatively correlated with business cycle fluctuations. The authors use slippage ratio (ratio of marginally accumulated NPLs during the year to standard advances at the beginning of the year) as a measure of default rate, reflecting the changes in non-performing assets of banks.

According to empirical results, growth rate and changes in interest rate have relatively higher impact on slippage ratio than other variables. Empirical results follow theoretical suggestion regarding cyclicity of changes in non-performing assets as economic slowdown is followed by rise in the slippage ratio. In addition contractionary monetary policy, represented by an increase in interest rate, causes deterioration of slippage ratio. Depreciation of domestic currency leads to improvement in slippage ratio after some delay. Simultaneously, increase in slippage ratio has significant negative effect on growth rate of output. In particular, based on variance decomposition, approximately 7% of the forecast error in growth rate and 19% of the forecast error in interest rate are explained by slippage ratio. Based on empirical results, authors suggest implying more coordinated policy decisions, taking into consideration second round effect of implied policies as well. An ordinary policy, like monetary tightening as a response to negative shock, might not stop inflationary expectations, but rather become the reason for financial instability and further economic downturn.

Kitamura et al. (2014) develop structural macro model implementing feedback effect through credit crunch mechanism, connecting financial and macroeconomic sectors. Negative shocks in financial sector along with credit crunch deteriorate non-banking sector balance sheet and reduce credit supply. The framework considers lending interest rate as an indicator representing negative shock and uses it for incorporating macro-feedback into the stress test. The framework is characterized with comprehensive credit risk model and allows considering dynamics of different variables like capital adequacy and net interest income not only on aggregate, but also on individual level of institutions. However, the model does not consider endogenous effects between key macroeconomic variables like response on interest rate and inflation to growth, focusing mainly on dynamics of real output as a source of macroeconomic shocks in the stress testing framework. In addition, the study uses equation-by-equation estimation with OLS and might suffer from endogeneity problem due to simultaneous causality, implying that model might not be able to generate consistent results from simulations of different scenarios.

Krznar and Mathenson (2017) develop a semi-structural general equilibrium macro model with stress-testing framework based on individual bank data of Brazil. The macro module characterizes open economy, including endogenous feedback loops between output, unemployment, inflation, interest rate, credit, foreign demand, financial conditions and real exchange rate. Stress-testing block of a macro model follows a balance sheet based approach, using panel regressions of individual bank data to estimate relationship of the solvency of banks with net income and risk-weighted assets and describe performance of individual bank in response to shocks from macro block using income and expenses. At the same time, specification of the framework provides the model with response of bank’s incomes and expenses to dynamics of capital buffer, considering Basel III standards. The link between blocks happens through credit crunch from banks’ capital to bank credit and output, considering second round effects to real economy through strengthening of banks’ deleveraging. Since level of bank capital is linked to the cost of funding and lending, banks with limited capital might increase capital adequacy, choosing to decrease the credit supply, rather than raise equity followed by further reduction of output growth. The study compares results of four model specification different from each other by inclusion of macro-feedback effect and/or income statement adjustment. The models without feedback effect, independent of inclusion of income statement response, seem to have same results for macroeconomic indicators.

According to baseline scenario, in models without income statement response, consideration of macro-feedback effect increases sensitivity of banking sector to the real economy shock. Decrease in GDP gap causes fall in the capital ratio by 0.5% in model without feedback effect. On the other hand, lower gap decreases capital ratio by 1.4% in model with second round effects, which in turn affects credit supply and decreases output approximately by 1%. Following output decline, inflation also decreases, inducing monetary easing by authorities. In addition, interest rates fall approximately by 2% in model incorporating feedback effects caused by higher decreases in output and inflation. Adaption of income statement adjustment practice lowers the negative impact in both cases (with and without feedback effect), since capital ratios are higher if banks adjust flow of income and expenses as a response of changes in capital buffer. Based on impulse response function of 1% shock to output, financial conditions, credit and capital, credit is characterized with higher sensitivity to output changes, rather than vice versa. Inclusion of macro-feedback in the model doubles the impact of a demand shock on credit because of increased capital buffers. In particular, 1% increase in output expands credit for 2 years and credit shocks have positive effect on output and capital contemporaneously. At the same time, credit responds significantly to capital only in case of including macro-feedback effect into the framework and drops by 6% due to 1% shock to capital, causing 0.6% decline in output. Worsening of financial conditions decreases net income and capital that later reduces credit and negatively affects economic activity. According to historic decomposition of the output gap, the loosening of financial conditions had important positive effect on recovery process of output after global financial crisis in 2009 until 2013 in Brazil, before an increase in foreign funding costs, which later caused worsening of financial conditions.

3. Data and Methodology

3.1 Model Specification

Necessary data for conducting the research is retrieved from the databases of the National Bank of Georgia and the National Statistics Office of Georgia. Due to inability of retriveng data for NPL before the 2002 period and for purpose of increasing the sample size and considering of short-run changes, the study uses quarterly data from 2002 to 2017. Due to the use of quarterly data, some variables like CPI, real GDP and other indicators are characterized by a seasonal pattern. For better analyzing the relationship independently of the seasonal component, the study uses the method of seasonal adjustment X-12-ARIMA developed by U.S. Census Bureau.

In order to investigate the long-run relationship between variables and predict results of different exogenous and endogenous shocks on aggregate level, study uses Vector Autoregression Model.

Specification of the Vector Autoregression Model (VAR model):

$$Y_t = A(L^i)Y_{t-1} + Z_t + D_t + E_t \quad (1)$$

$$Y_t = (NPL_t; Cr\_ratio_t; Gap_t; Ir_t; Reer_t; CPI_t) \quad (2)$$

$$Z_t = (Doll_t; Oil_t, VIX_t) \quad (3)$$

$$D_t = (d2007q4;\ d2008q3;\ d2008q4;\ d2009q3;\ d2014q4;\ d2015q2) \quad (4)$$

Where Y_t– vector of endogenous variables; Z_t – vector of exogenous variables; D_t – vector of dummy variables for considering structural breaks in time series; E_t – vector of error term; $A(L^i)$ – matrix polynomial in the lag operator; Def_t – default rate of borrower (non-performing loans will be considered during estimation of default rate); Gap_t – output gap; CPI_t – consumer price index; Ir_t – real interest rate; $Reer_t$ – real effective exchange rate; Cr_ratio_t – credit to GDP ratio; $Doll_t$ – loan dollarization; Oil_t –crude oil Brent price per barrel; VIX_t – implied volatility of the Chicago Board Options Exchange (CBOE Volatility Index) index as a proxy for global risk aversion and tight financing condition.

The vector of dummy variables consists of observations equal to 1 for time corresponding the name of variable, while other observations equal 0 otherwise. The dummy variables consider the spikes in data for NPL, GDP gap and Oil prices for pre-crisis period, crisis period and post-crisis period represented in high volatility of world oil prices, which can be considered as structural breaks, creating difficulty for investigation of relationship.

The set of explanatory variables consists of various indicators. In the period of economic growth, it is expected to have a pattern of decreasing nonperforming loans due to rising incomes and reduced financial distress (Nkusu, 2011). Therefore, the period of positive GDP gap is associated with lower NPL, while negative GDP is associated with an increase in nonperforming loans. Theoretical relationship between inflation and NPL ratio is ambiguous as inflation has effects on ability of borrowers to service debt through various channels. Increasing inflation makes debt servicing easier as a real value of loans decreases. Another way of transmission mechanism from inflation to NPL is through Phillips' curve. According to theory, higher inflation is associated with low unemployment, implying an increase in income and decrease in debt servicing burden. On the other hand, in case of sticky wages, inflation causes reduction in real income, decreasing borrower's debt servicing capacity. At the same time, increase in interest rate decreases borrower's debt servicing ability. Therefore, the expected relationship between NPLs and change in interest rate is positive. In addition, as lenders try to maximize their profits, they adjust interest rates as a response to inflation and monetary policy actions, resulting in decrease in loan servicing capacity. Similar to inflation, relationship between exchange rate fluctuations and change in NPL ratio is ambiguous. Negative shock represented by rapid appreciation of domestic currency reduces competitiveness of export-oriented companies, reducing their income and negatively affecting their debt servicing capacity. At the same time, in case of domestic currency appreciation, there is an increase in debt-servicing capacity for those who borrow in foreign currency, positively affecting amount of nonperforming loans in economy.

The fact that Georgia is highly dollarized economy has its impact on relationships between different variables. High level of dollarization makes Georgian economy vulnerable to external shocks and creates rigidity in the transmission mechanism for conducting efficient monetary policy by central bank. Initially, dollarization in Georgia was a response to the economic instability and high inflation. Despite the significant improvements in economic performance of a country compared to 90s, particularly in banking sector and in monetary policy, the country is still characterized with high levels of official and unofficial dollarization in deposits and loans. The study uses dollarization variable along with world oil price as exogenous variables in the model. Consideration of oil prices in the model is explained by its' importance for Georgian domestic currency exchange rate. Recent depreciation of GEL against the dollar between the last quarter of 2014 and the first quarter of 2015 has proved vulnerability of domestic currency to external shocks. Changes in the oil price also have a direct effect on Georgian export of re-exported cars, exported non-ferrous metals and on economy of Azerbaijan, which is one of the most important trading partners for Georgia, being largest export destination in recent years. At the same time, a decrease in oil prices caused a reduction of remittances from Russia. All those factors, caused by rapid decline in world oil price, reduced financial inflow of foreign currency, contributing to further devaluation of domestic currency. Inclusion of oil price changes in such type of relationship examination is also supported by excising literature (Carabenciov, et al., 2008).

For estimation of the model, variables should be stationary. For testing of statistical stationarity of variables, the study uses Augmented Dickey-Fuller (ADF test), Phillips-Perron (PP test) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS test) tests. Variables that turn out to be non-stationary, were replaced by differences of themselves of necessary order. The optimal lag order of the model is determined based on comparison of several measures, such as the Akaike information criterion (AIC), Bayesian information criterion (BIC) and others.

In order to examine the relationship and feedback effects between endogenous variables, the study uses impulse response functions. Contemporaneously, various exogenous shocks were conducted to estimate projections of different scenarios. This provides the study with precise length of period for which shocks affect the economy and examine expected responses of a system to policy changes. The study checks robustness of results for different measures of GDP gap, estimated by Hodrick-Prescott, Band Pass and Kalman filters. The idea of comparing is motivated by critique regarding different outcomes of cyclical indicators and inability of univariate filters (HP and BP filters) to capture influence of other variables on estimated gap.

3.2 Hodrick-Prescott Filter (HP filter)

One of the most widespread statistical tool for estimation of potential GDP is HP filter (Hodrick and Prescott, 1997). It is based on assumption that real GDP consists of cyclical and trend components. Trend component is characterized with proportional growth rate, while cyclical component shows the effect of economic shocks on real GDP.

$$Y_t = Y_t^* + Y_t^c \tag{5}$$

Where Y_t is real GDP gap at time t, Y_t^*- trend component of GDP (potential GDP) and Y_t^c is cyclical component of GDP (GDP gap).

The wide usage of this univariate filter is due to its simplicity. By restricting variation of potential GDP, HP filter minimizes the sum of squared differences between actual and potential GDP, which itself represents the gap. The mentioned restriction of variation of potential GDP explains the fluctuations in GDP during the business cycle.

$$min \sum_{t=1}^{T}(Y_t - Y_t^*)^2 + \lambda \sum_{t=1}^{T}[(Y_{t+1}^* - Y_t^*) - (Y_t^* - Y_{t-1}^*)]^2 \tag{6}$$

Where λ is smoothing parameter, defining the level of volatility of potential GDP. When λ low, potential GDP is close to actual GDP. At the same time when λ goes to infinity, trend of potential GDP becomes linear. The value of λ depends on the length of business cycle and can be studied for particular economy. However, there are problems of estimating smoothing parameters in developing countries due to lack of data on business cycle fluctuations and structural changes. Authors suggest to use λ equal to 100, 1600 and 14400 in cases of annual, quarterly and monthly data correspondingly, which is widely used in literature.

3.3 Band-Pass Filter (BP filter)

Additional univariate filter, which is widely used in economic researches is the Band Pass filter developed by Christiano and Fitzgerald (1999). According to this methodology, real GDP consists of cyclical and trend components with statistical noise elements. For decomposition of real GDP into those elements, the time period is chosen for further estimation. The fluctuations of length less than 1.5 year are assumed to be the white noise process. According to authors, it is appropriate to consider 1.5-8 years period as it is considered to be the length of the full economic cycle in literature. Hence, changes occurring during the 1.5-8 year period are considered a cyclical component of GDP. It should be mentioned, those intervals represent appropriate, but not essential framework and different time periods can be adopted in other cases according to the specification of economy.

Potential GDP is estimated the following way:

$$\widehat{y_t} = B_0 X_t + B_1 X_{t+1} + \cdots + B_{T-1-t} X_{T-1} + \widetilde{B_{T-1}} X_T + B_1 X_{t-1} + \cdots + B_{t-2} X_2 + \widetilde{B_{t-1}} X_1 \quad (7)$$

Where $B_j = \frac{\sin(jb) - \sin(ja)}{\pi j} j \geq 1$; $B_0 = \frac{b-a}{\pi}$; $a = \frac{2\pi}{p_u}$; $b = \frac{2\pi}{p_l}$; $[p_u; p_l]$ time period considered for GDP decomposition and X_t is real GDP at time t.

Despite the simplicity of univariate filters (HP and BP), there are particular drawbacks regarding the fact that those filters do not consider other variables and economic trends for estimation of potential GDP as they are not based on economic model. In addition, such filters have problem of “end-point” bias due to asymmetry at the extreme points of time series caused by lagging and forwarding of variable in time (Mohr, 2005). The problem of “end-point” bias can be partially corrected by extending sample using forecasted values before the implementation of filters. In order to make short-run projections of real GDP, study uses ARIMA (Autoregressive Integrated Moving Average) process on the whole sample from 1996. The forecasted values are used to expand the estimation sample for filters which should remove “end-point” bias for estimated values for 2017.

3.4 Kalman Filter

Estimation of GDP gap using Kalman filter follows the model developed by Tahir (2014). The paper uses typical State-Space model for extracting trend and cycle components from actual data of real GDP. Kalman filter allows estimation of unobserved components (trend and cycle) given that they appear in State-Space model as explanatory variables. Similar to above mentioned methods, real GDP is decomposed into trend and cycle components, where trend is assumed to be a random walk with drift and cyclical component is modeled to be an autoregressive variable. Typical Phillips' curve is incorporated into the unobserved components of the model for extracting GDP gap and making the whole model more consistent with real economy. According to model, inflation depends on the expectation of economic agents and cyclical fluctuations. Based on the model, inflation is dependent on the expectations of economic agents as it is partly determined by rational and adaptive expectations. The State-Space model is specified by the following way:

$$\text{Signal Equation 1: } Y_t = Y_t^{trend} + Y_t^{cycle} \quad (8)$$

$$\text{Signal Equation 2: } \pi_t = \pi_t^* \quad (9)$$

$$\text{State Equation 1: } Y_t^{trend} = Y_{t-1}^{trend} + \vartheta_{t-1} + \varepsilon_t \quad \text{where} \quad \varepsilon_t\ iid{\sim}N(0, \delta_\varepsilon^2) \quad (10)$$

$$\text{State Equation 2: } \vartheta_t = \vartheta_{t-1} + \omega_t \quad \text{where} \quad \omega_t\ iid{\sim}N(0, \delta_\omega^2) \quad (11)$$

$$\text{State Equation 3: } Y_t^{cycle} = \gamma_1 Y_{t-1}^{cycle} + \varphi_t \quad \text{where} \quad \varphi_t\ iid{\sim}N(0, \delta_\varphi^2) \quad (12)$$

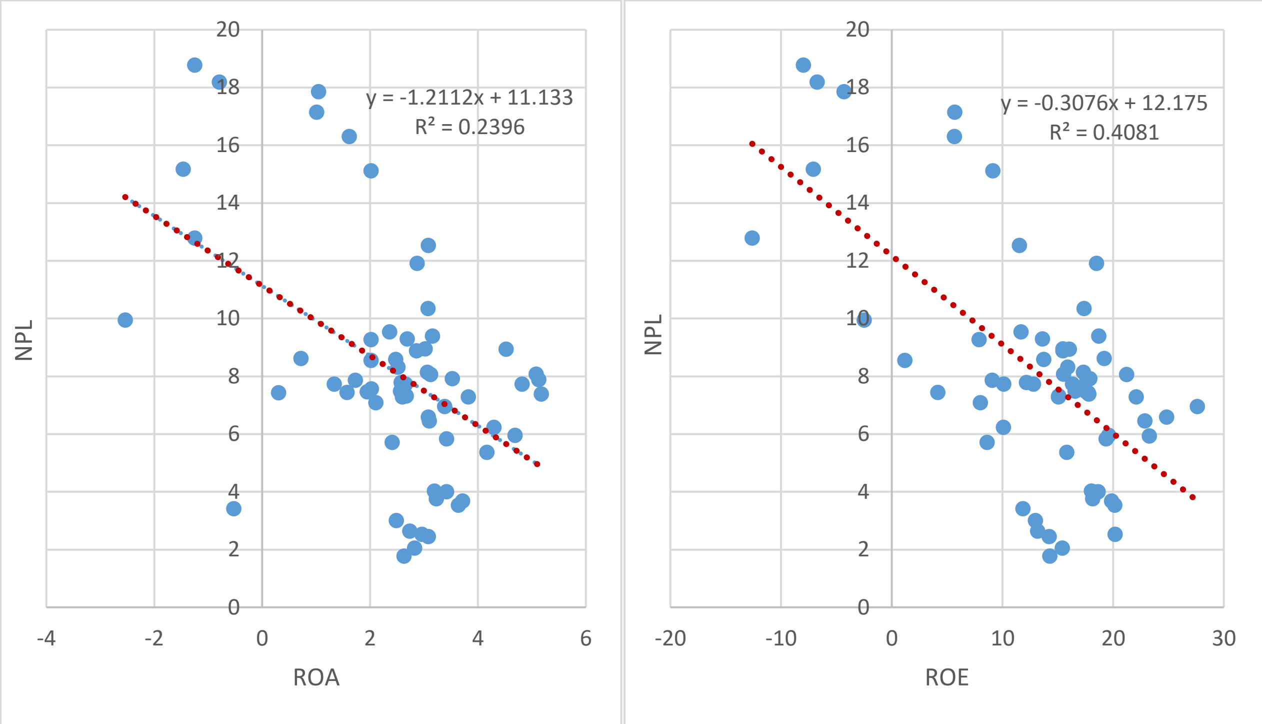
$$\text{State Equation 4: } \pi_t^* = \gamma_2 \pi_{t-1} + \gamma_3 \pi_{t-1}^* + \gamma_4 Y_{t-1}^{cycle} + \theta_t \quad \text{where} \quad \theta_t\ iid{\sim}N(0, \delta_\theta^2) \quad (13)$$

Where Y_t is real GDP (log of real GDP), Y_t^{trend} is trend component of real GDP (potential GDP), Y_t^{cycle} is cyclical component of real GDP (GDP gap), which is assumed to be AR(1) process, π_t is CPI inflation, π_t^* is target inflation and ϑ_t is drift component of real GDP trend, which is assumed to be a constant. Parameters are estimated by recursive procedures with evaluation of Likelihood function using the methodology of Kalman filter.

4. Stylized Facts

Formation of NPL depends on various factors on different level of accumulation. Those factors might be bank-specific or factors that have impact on economy on country and global levels. According to figure 1, banks that are more profitable seem to have less amount of Nonperforming Loans, reflecting the quality of bank management. NPL ratio is negatively correlated with banks' return on asset (ROA) and banks' return on equity (ROE), which can be considered as indicators of banks' profitability. In both cases correlation coefficient equals approximately to -0.64. It should be mentioned that there is an opposite causality as well, as higher NPLs destabilize profitability of banks' through higher provisioning.

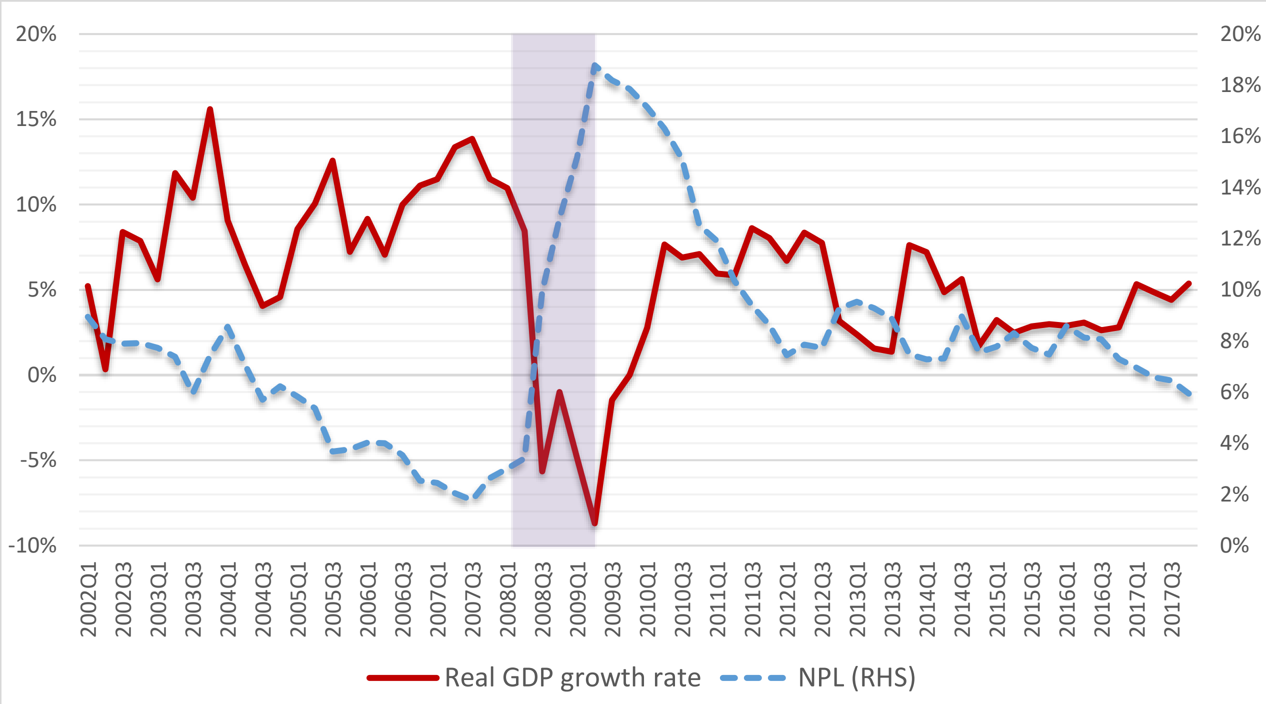
Figure 1: NPL and Bank Profitability, 2002-2017



Source: NBG

The pre-crisis period is characterized with decreasing trend in NPL until the third quarter of 2007 reaching its historical minimum of 1.8%. The sharp increase in NPL ratio started in the second quarter of 2008 and lasted for one year, reaching maximum value of 18.8% in the second quarter of 2009. Such a rapid increase was followed by a gradual decrease for next three years until the beginning of 2012, reaching 7.8%. As a result, since the beginning of 2016 there seems to be a decreasing trend. However, the average NPL (7.8%) after the crisis (since 2012) still exceeds the corresponding average indicator of the pre-crisis period (5.3%). Throughout the whole period, NPL dynamics seem to act in a countercyclical nature, as increase in real GDP growth rate is associated with decrease in NPL ratio, while negative growth rate is associated with increase in NPL as suggested by theory (Figure 2). The correlation coefficient between corresponding indicators proves the negative association and equals to -0.65.

Figure 2: Dynamics of Real GDP Growth Rate (y-o-y) and NPL

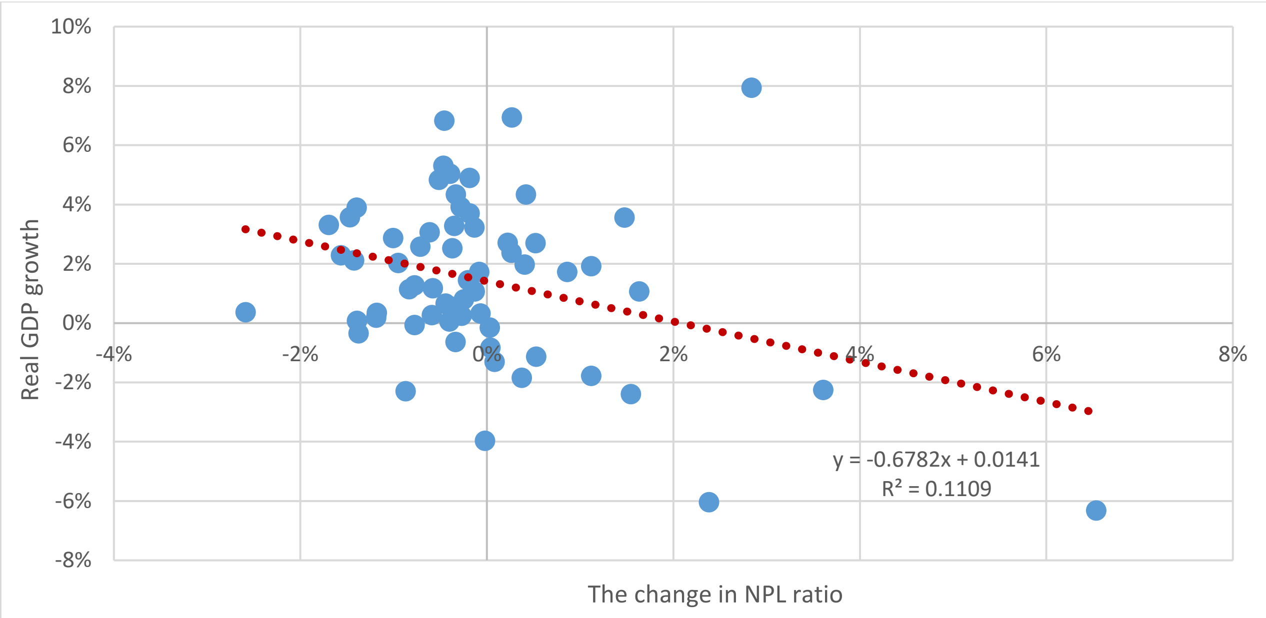


Source: NBG, Geostat

Scatter plot in figure 3 shows once again the fact that there is a negative relationship between real GDP growth ate and change in NPL. Simple linear trend suggests the effect of changes in NPL on real GDP growth ate to be equal similar to correlation coefficient of -0.65, implying that one percent change in NPL decreases real GDP growth by 0.67 percent. However, this simple estimate cannot be considered as a measure of a feedback effect as the estimation process does not consider all the necessary transmission mechanisms and other variables that affect real GDP growth. Thus, the estimate represents basic empirical prove of negative association between variables in case of Georgian economy, which the paper is studying more precisely.

Figure A1 in Appendix shows the dynamics of GDP gap and ratio of nonperforming loans. On the whole time span, there seems to be negative relationship. This pattern especially appears to hold during extreme cases, such as global financial crisis. In pre-crisis period, when NPL was slowly decreasing, GDP gap was characterized by small fluctuations approximately around 2%. The trend of positive GDP gap appeared in the beginning of 2005 until the third quarter of 2007 when it started to decrease and turned negative in the third quarter of 2008. The rapid decrease in GDP gap happened in second quarter of 2008. In particular, GDP gap decreased form 8% (5.8% for Kalman filter and 4.3% for BP filter) to -6.7% in one year (-6.3% for BP filter and -3.5% for Kalman filter). During the whole time span, the NPL was following the cyclical path. NPL achieved its maximal value of 18.8% at the extreme points of negative GDP gap in the middle of 2009.

Figure 3: Real GDP growth and the change in NPLs, 2002-2017

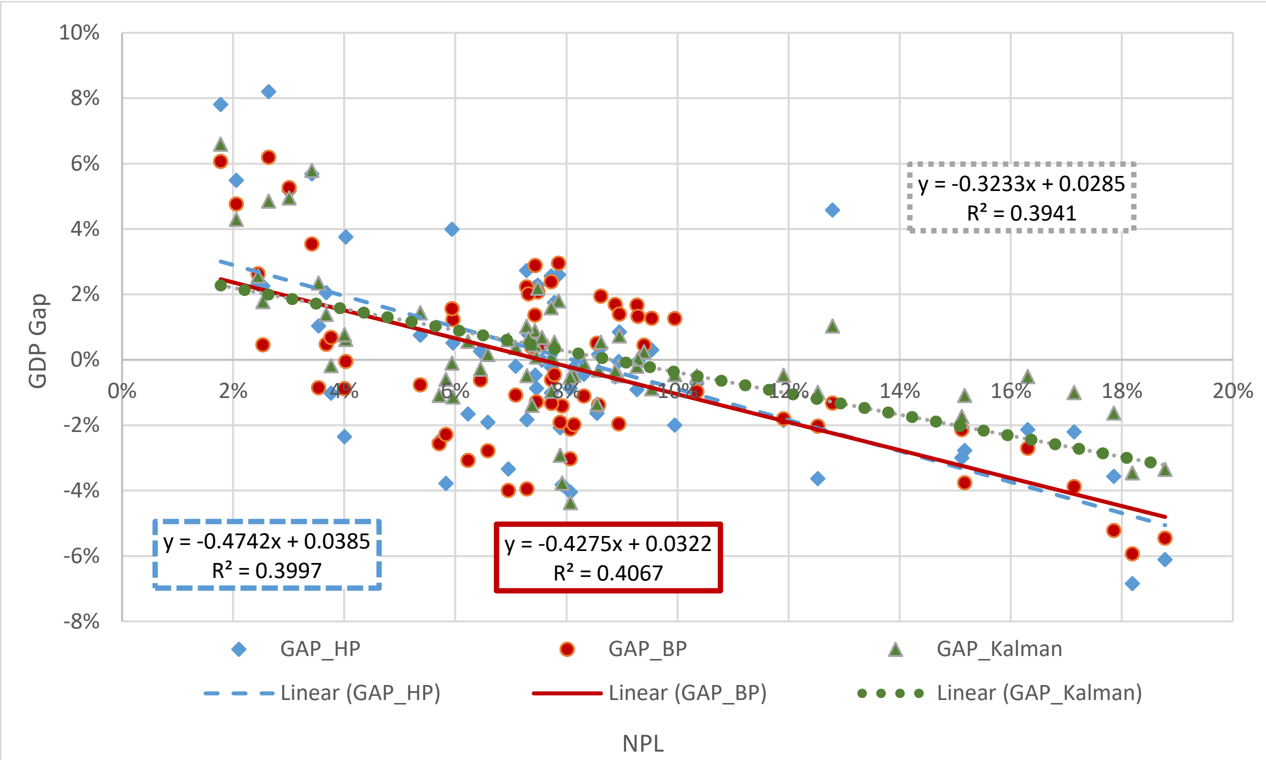


Source: NBG, Geostat

It should be mentioned that according to actual data there seems to be no lagged effect in extreme cases, as increase in GDP gap simultaneously is followed by decrease in NPL and vice versa. At the same time, the scatter plots on figure 4 prove the idea of countercyclical nature of NPL, as it is negatively correlated with different estimates of GDP gap. According to estimation, NPL has the strongest relationship with GDP Gap estimated by Hodrick-Prescott filter. The linear trend parameter equals to -0.47, while correlation coefficient equals to -0.7. GDP gap estimated by Band Pass filter also shows negative relationship, with parameter equal to -0.42 and correlation coefficient equal to -0.68. Similarly, estimate of GDP gap by Kalman filter also has significantly high negative relationship, as the slope of trend equals to -0.32 and correlation coefficient equals to -0.63.

The main transmission mechanism through which growing NPLs can affect real economy is the credit growth channel (credit crunch). Banks that suffer from high level of non-performing loans, which alters their profitability, may react by shrinking credit supply for restoring minimum capital ratios. Lower credit growth not only affects real economy through more difficult ability of receiving additional financial sources for investment and production, it also affects the quality of loan portfolios later. Increase in NPLs along with depreciation of domestic currency can reduce credit growth.

Figure 4: GDP Gap and NPL, 2002-2017



Source: NBG, Geostat, author's calculations

According to empirical data, there seems to be only small negative association between changes in NPLs and credit growth (correlation coefficient equals to -0.23). However, despite the fact that dynamics might not represent the fact that changes in variables are in close relationship, according to IMF report (2016), for the case of Georgia, 1 percentage change in NPL ratio reduces credit growth by 0.2 percent with 2-quarter lag. In addition, similar change in exchange rate of domestic currency with respect to US dollar reduces credit growth by 0.5 percent after 1 quarter. Credit to GDP ratio and its gap in particular are considered as one of the most important indicators for decision making regarding counter-cyclical buffer instrument. Therefore, consideration of this indicator should improve the explanatory capacity of the GDP gap in the model.

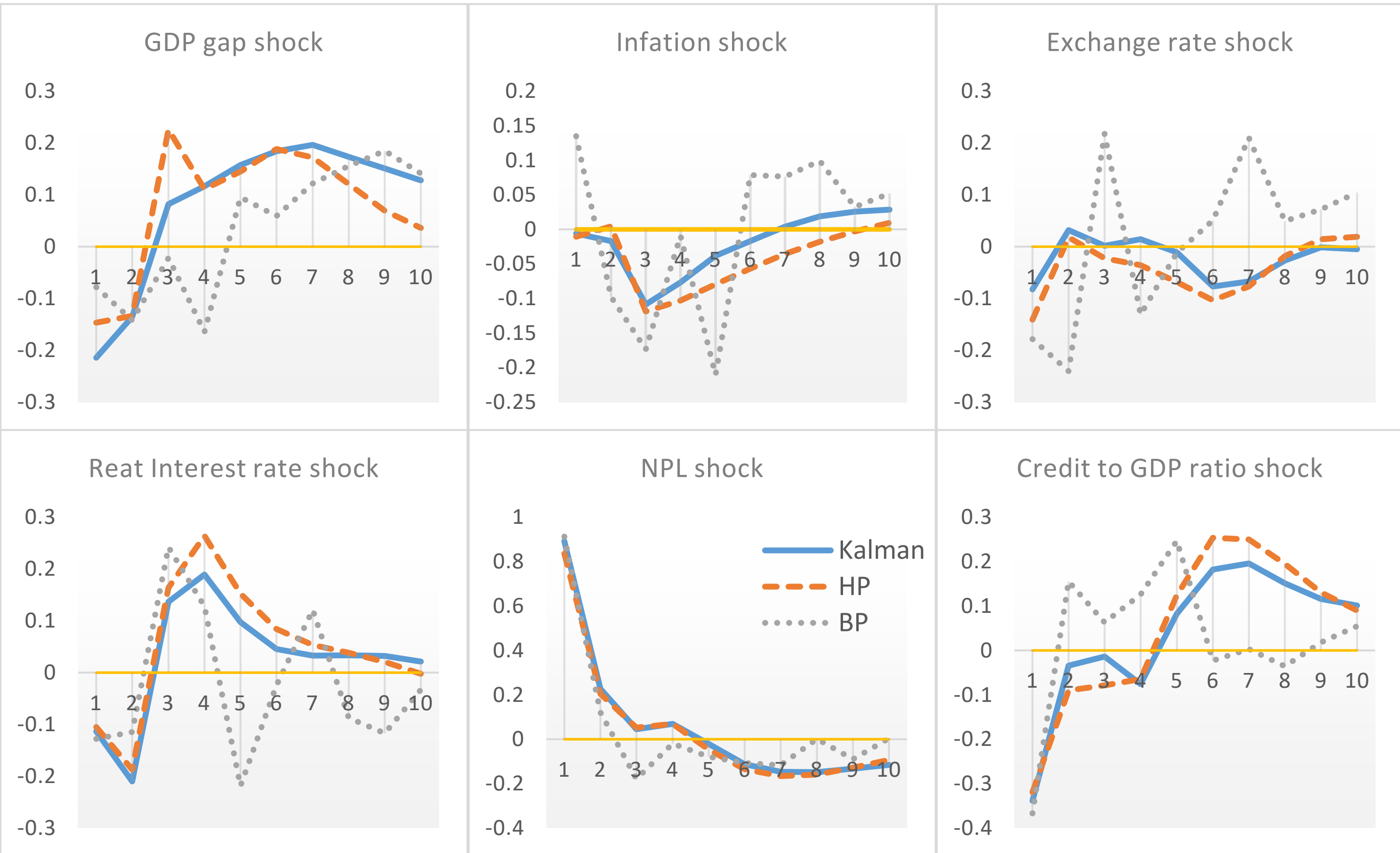
5. Results and Analysis

The first step of analysis is the testing of variables for existence of unit root. According to various unit root tests at 5% significance level, most of variables are integrated processes of order 1. In most cases, KPSS test has different suggestion regarding an order of integration of variable compared to ADF and PP tests, but the final decision regarding the stationarity was taken considering the nature and definition of variable. In addition, following the example of other studies on this subject (Espinoza and Prasad, 2010; Gray et al., 2013; Kida, 2008; Nkusu, 2011) the paper bases its analysis on the results of the ADF test.

For choosing a proper lag length of the VAR model, the study uses various criteria for optimization of the optimal lag order. In two cases, AIC (Akaike information criterion) suggests to include 2 lags, while it suggests to use 4 lags for model based on BP filter, which is economically reasonable due to the usage of seasonally adjusted quarterly data (A3 in Appendix). Data suggests to use logarithmic specification of variables in the model. All estimated models satisfy basic assumptions and models are stable according to inverse roots of characteristic polynomial (A4 Appendix).

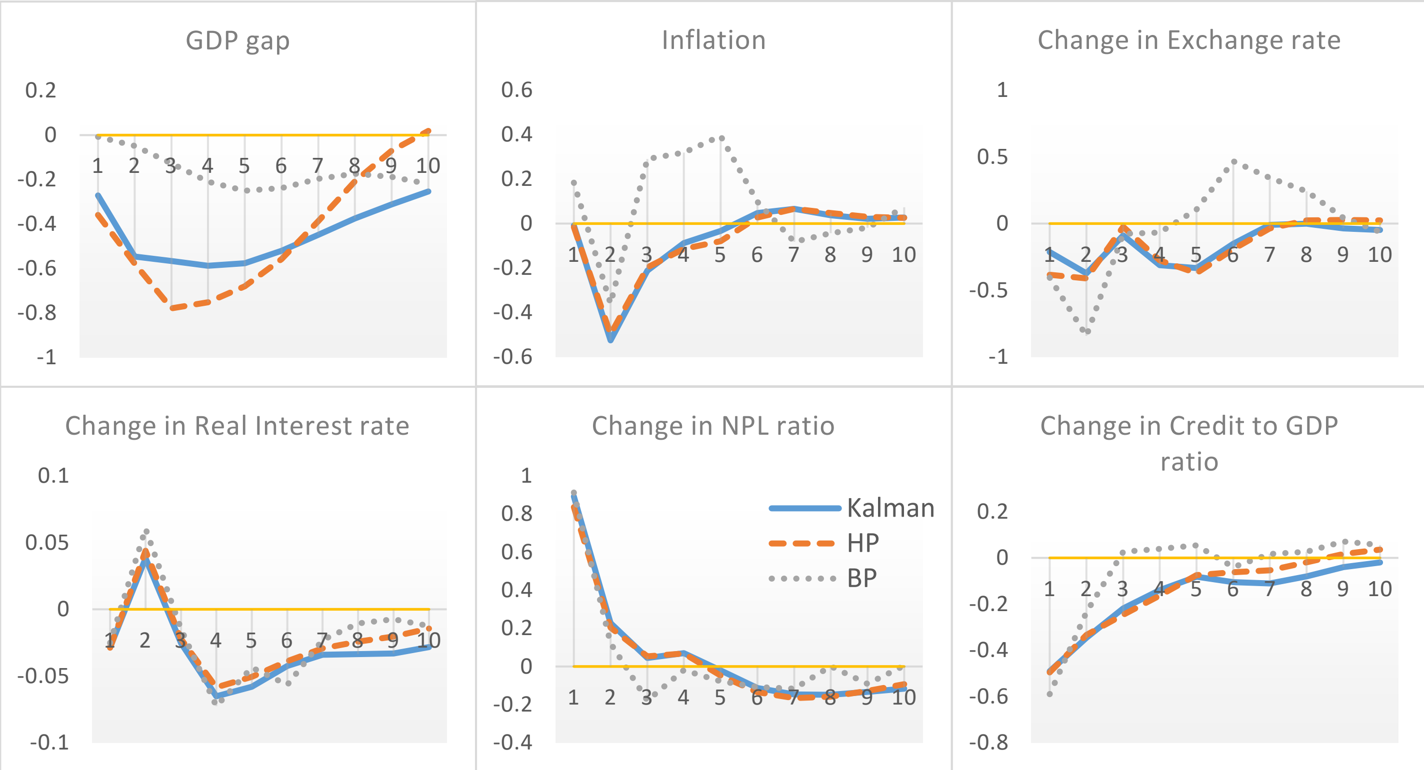
For better analyzing of dynamic relationship between variables in a model, the study uses generalized impulse response functions. In contrast to standard impulse response analysis, generalized impulse response analysis does not depend on the ordering of the variables in the VAR (Pesaran & Shin, 1998).

Figure 5: First-round effects – Response of Change in NPL ratio to corresponding one percentage shock



Source: author's calculations

Figure 6: Second-round effects – Response of corresponding variables to one percentage shock to change in NPL ratio

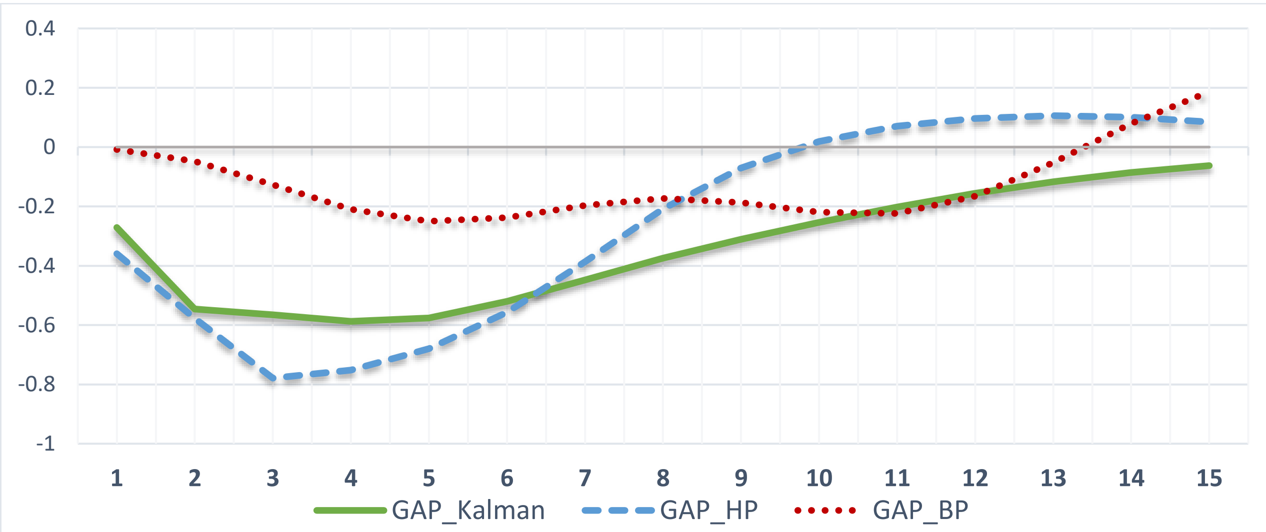


Source: author's calculations

Figure 5 and 6 show first and second round effects between macroeconomic and financial variables for the model estimated using different filters. According to model, one percent shock to GDP gap (positive change) leads to decrease in NPL in the first period by 0.21 percent for case of model based on Kalman filter. The effect is similar in direction, but has lower impact as it decreases by 0.14 and 0.07 percent for HP and BP filters correspondingly. The NPL reaches long-run equilibrium after 10-12 quarters since the initial shock. At the same time, all other variables seem to have moderate impact (statistically significant impact on during particular time periods) on change in NPL as 0 falls into confidence bounds of ± 2 S.E. in most periods of the whole time span. In particular, in case of Georgia, increase in inflation causes decrease of NPL in the first 3 quarter by 0.11 percent for the case of Kalman filter. The corresponding impact equals to -0.11 and -0.17 percent for cases of HP and BP correspondingly. The impulse response function shows statistically insignificant impacts during other time periods. The impact of exchange rate fluctuations on changes in NPL is ambiguous as the magnitude of positive or negative effects are dependent on the time passed time since the initial one percentage shock to change in exchange rate. However, in cases of HP and Kalman filters, impacts fluctuate close to zero, converging to equilibrium value faster compared to the case of BP filter. At the same time, positive change in NPL causes depreciation in real effective exchange rate by 0.21 percent in the first quarter. In cases of HP and BP filters, initial response is higher and equals to -0.38 and -0.4 correspondingly. Despite fast converging to 0 effect after 3 quarters, there is rapid depreciation by 0.34 percent in 5th quarter followed by small appreciation for the next 2 quarters. Increase in NPLs does not affect inflation in first quarter and decreases it by 0.52 percent after the second quarter for the model based on Kalman filter. The similar result holds for HP filter. However, initial shock to change in NPL increases inflation by 0.18 percent in case of GDP gap estimated by BP filter. The effect stabilizes after 6 quarters since the initial shock. In addition, an increase in NPLs reduces Credit to GDP by 0.49 percent in the first quarter and the negative effect is slowly converges to 0 effect after 10 time periods (even though it becomes statistically insignificant after 5 time periods) for models based on HP and Kalman filters. Initial response of change in credit to GDP ratio is higher and equals to -0.59 in case of BP filter, converging to zero faster compared to other specifications.

The necessity of checking the robustness of model results with respect to different estimates of GDP gap following the critique that univariate filters are incapable of estimating unbiased values. Figure 7 shows responses to generalized one percentage shock to changes in NPL ratio in models with different estimate of GDP gap. According to different models, the model based on HP filter shows highest decline in GDP gap for the first 5 quarters since the shock to NPL. The negative effect reaches its maximum for HP filter estimate in third quarter and equals to -0.78 percent. However, the impact is characterized with higher volatility compared to other estimates as it changes from negative to positive after 9 quarters since the initial shock and takes more time to converge to zero compared to the case of Kalman filter. Simultaneously, the maximal negative effect for Kalman estimate is achieved in 4th quarter and equals to 0.58 percent. The impact is less volatile and it slowly converges to equilibrium after the shock. In the case of BP filter, impact is less volatile and statistically equals to zero as the confidence bounds include zero value during the whole time span.

Figure 7: Response of GDP Gap to one percentage change in NPL



Source: author's calculations

In case of model based on Kalman filter, it takes less time to achieve equilibrium compared to other models. In particular, it takes 16 quarters for to fully reach zero value (even though the impact becomes statistically insignificant (equal to zero) after the 6th period, while it takes 20 quarters for model based on BP filter to achieve zero value. At the same time values of effects also vary between different specifications. In the first period after the shock, model based on HP filter suggests decrease in GDP gap by -0.36 percent, while impact equals to -0.27 for the model based on Kalman filter. Since the model based on Kalman filter turned out to be more stable and statistically significant, all the discussion followed below are based on the model using Kalman filter.

Figure 8 shows variance decomposition of forecast error conducted using the Cholesky decomposition. According to results, forecast error in GDP gap is mostly explained by itself with decreasing trend. However, the share of change in NPLs increases as it was explaining 6.74% of forecast error in GDP gap in 2 quarter and reaches value of 17.9% in 10th quarter. It should be mentioned that the pattern of increasing share in total error also characterizes Credit to GDP ratio from 2.5% in second quarter to 6.4% in 10th quarter. At the same time, error in GDP gap explains 5.8% of forecast error in NPL changes in first quarter and reaches value of 19.4% in 10th quarter. In addition, as it seems from the figure, share of exchange rate fluctuations, inflation and interest rate changes is approximately unchanged on the whole time span. In addition, forecast error in changes in NPLs explains approximately 17% of forecast error in Credit to GDP ratio and 14.6% in forecast error of inflation on average. Despite significant explaining capacity of changes in NPLs, it does not explain fluctuations in exchange rate as its share on average equals approximately to 4% and 9% in forecast error in change of real interest rate.

It should be mentioned that results are different for other specification of variables. In particular, forecast error in NPLs change does not explain forecast error of GDP gap estimated by BP filter (only 1% on average). However, explaining power of forecast error in change of NPL ratio is significantly high for inflation and credit to GDP, reaching 15% on average in both cases. It should be mentioned that instruments that represent indirect way of transmission mechanism from change in NPL ratio to real economy have significant explaining power in the variables of real economy.

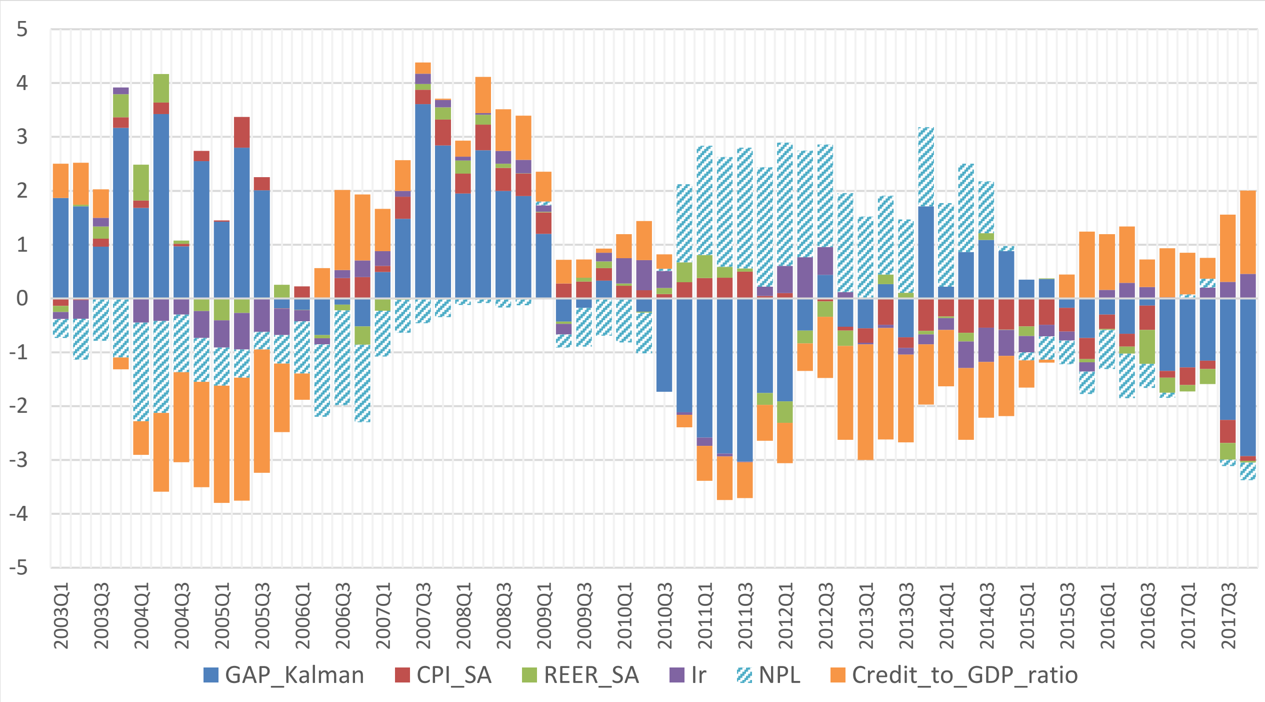
In particular, forecast error in credit to GDP ratio explain on average 32% of forecast error in change of interest rate and 15% in forecast error in GDP gap. On the contrary, in model with HP filter, forecast error in NPL change explains on average 13% of forecast error in GDP gap, reaching value of 15.9% in 8th quarter, while on the opposite, error in GDP gap explains on average 14% of forecast error in NPLs change, reaching 15.8% in 9th quarter. In the last case, error in NPLs significantly explains forecast error in changes of real interest rate and inflation, reaching average values of 8% and 13% correspondingly. More detailed results for other specifications are represented in A2 of Appendix.

Figure 8: Variance Decomposition of forecast error

Source: author's calculations

Using historical decomposition based on decomposition method of generalized impulses, the study allows to breakdown cyclical fluctuations by the shocks coming from other variables in the framework. According to figure 9, shocks to changes in Credit to GDP ratio had significant share in business cycle fluctuations during the whole time span and its contribution increased significantly compared to pre-crisis period. Since the crisis, the leading position in explaining GDP gap is held by itself as a lagged value and share of changes in NPL ratio. It should be mentioned that its share significantly increased in post-crisis period compared to pre-crisis period. The same patterns seems to hold in case of the model based on HP filter. In addition, changes in NPL ratio seem not to explain GDP gap under the case of BP filter. However, in all three cases credit to GDP ratio shock has significant share of contribution to GDP gap changes, following cyclical fluctuations. Compared to other models, once the Kalman filter is implemented, the explanatory capacity of shocks to change in NPL significantly improves. As suggested by figure A3, during the pre-crisis period shocks to NPLs change were contributing towards decreasing the gap as the contribution was negative. However, since the crisis the magnitude and share in overall contribution has increased along with the direction of the contribution. In addition, there seems to be declining trend of contribution since the end of 2014 following the rapid depreciation of GEL.

Figure 9: Historical Decomposition of GDP gap

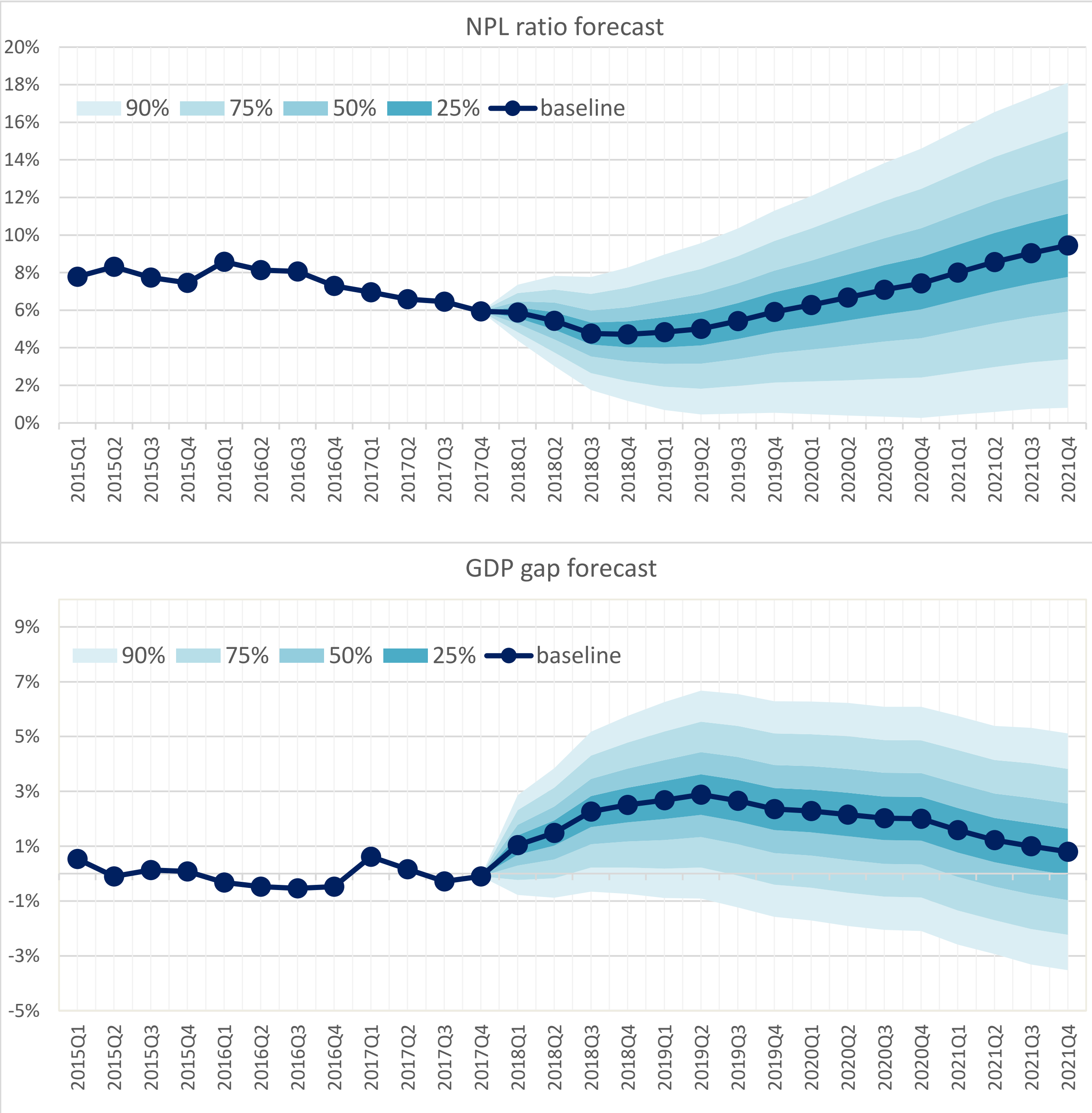


Source: author's calculations

The estimated framework can be used to implement different types of scenarios. For example, consider baseline scenario, under which, projections of exogenous variables such as world oil prices are retrieved from the Economy Forecast Agency (EFA), VIX projections are estimated using ARIMA forecasting and dollarization level is assumed to follow slowly decreasing path of -0.79% average growth rate which was observed since the implementation of governmental de-dollarization program. Based on stochastic estimation of the model given exogenous data, results are shown on figure 10 and A4 of the Appendix. The model suggests, that given those exogenous scenarios, NPL ratio is expected to decrease from 5.8% in 2018Q1 till 4.6% in 2018Q3 and then start increasing for the rest of the estimation range.

At the same time, according to estimation, GDP gap will be positive on the whole forecasting range. It increases from 1.1% in 2018Q1 till 2.9% in 2019Q2 before decreasing to 0.8% in 2021Q4. In addition, model suggests that real effective exchange rate will depreciate by 1.3% in first quarter of 2018 and appreciate by 2.6% in 2018Q3. Since third quarter of 2018, projection of real effective exchange rate has a negative trend toward depreciation equal to 0.18% in 2021Q4. At the same time, according to baseline scenario, inflation has a negative trend (A4 shows increasing forecast of logarithm of CPI, which is used in order to derive quarterly inflation by using exponential and percentage difference between different time periods[1]), achieving its peak of 3.4% in second quarter of 2018 and falling to 0.65% in fourth quarter of 2021 with short-term increasing inflationary processes along the time period. Forecast value for real interest rate and credit to GDP ratio are relatively more stable compared to above mentioned variables as the average growth rate and direction of changes is the same during the whole forecasting sample.

Figure 10: Forecast of NPL ratio and GDP gap under baseline scenario



Source: author's calculations

[1] The same procedure was used in order to derive level of appreciation/depreciation of real effective exchange rate.

6. Conclusion

The study explores the dynamic relationship between macroeconomic variables and indicators of financial stability, proving the relevance of considering second-round effects for better policy analysis. The study shows that on different interval of time (pre-crisis or post-crisis) the effects of financial variables on variables of real economy differ from each other and vice versa. Based on estimated model, financial variables have higher explanatory capacity and contribution to real variables in the post-crisis period. According to different specification of models, the shocks happened in one variable have impact on other variables without much time lag. In addition it approximately takes from 8-15 quarters to achieve long-run equilibrium depending on the tool for estimation of GDP gap. Usage of different estimates of GDP gap proves the point of taking special attention regarding the estimation of potential values of variables using univariate filters, as in case of BP filters, there was no direct and in most cases insignificant effect from change in NPL ratio to real economy variables. In most cases, results based on HP filter were following results of model based on Kalman filter. However, in some extreme cases there seemed to be a tendency of overestimation of the impacts. On the contrary, Kalman filter proved to have more rigid, statistically significant short-run and long-run effects of shocks to variables. The highlighted difference between different estimates of GDP gap proves the necessity of establishing a new way for estimating latent variables. The study proves the countercyclical nature of NPLs with respect to different estimates of GDP gap. Despite not obvious and explicitly shown strong relationship between NPLs and GDP gap, there is an indirect transmission mechanism mentioned as “credit crunch”. All specifications of the model proved the fact that change in NPL ratio strongly impacts credit growth represented as change in Credit to GDP ratio. At the same time, change in Credit to GDP ratio turned out to explain significant part of GDP forecast error and has significant contribution to business cycle fluctuations, strengthening the impact of NPLs and financial stability as a whole on the real economy.

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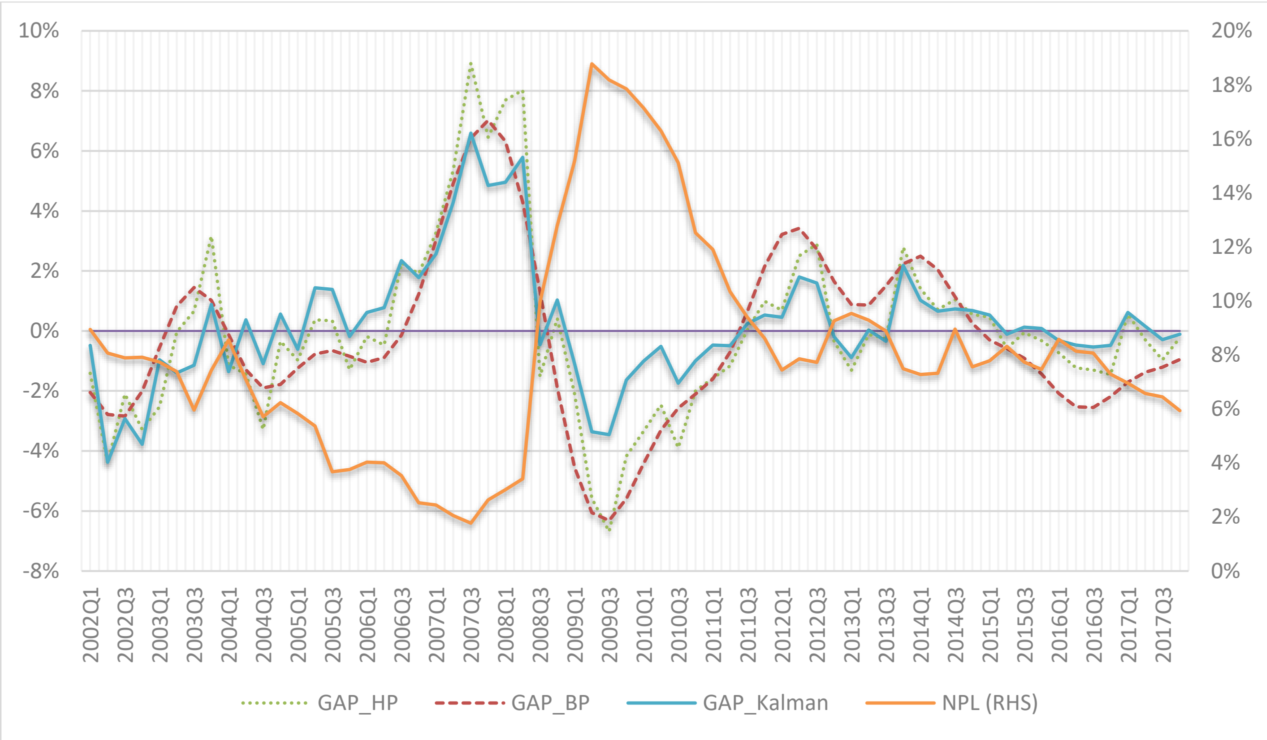
Appendix

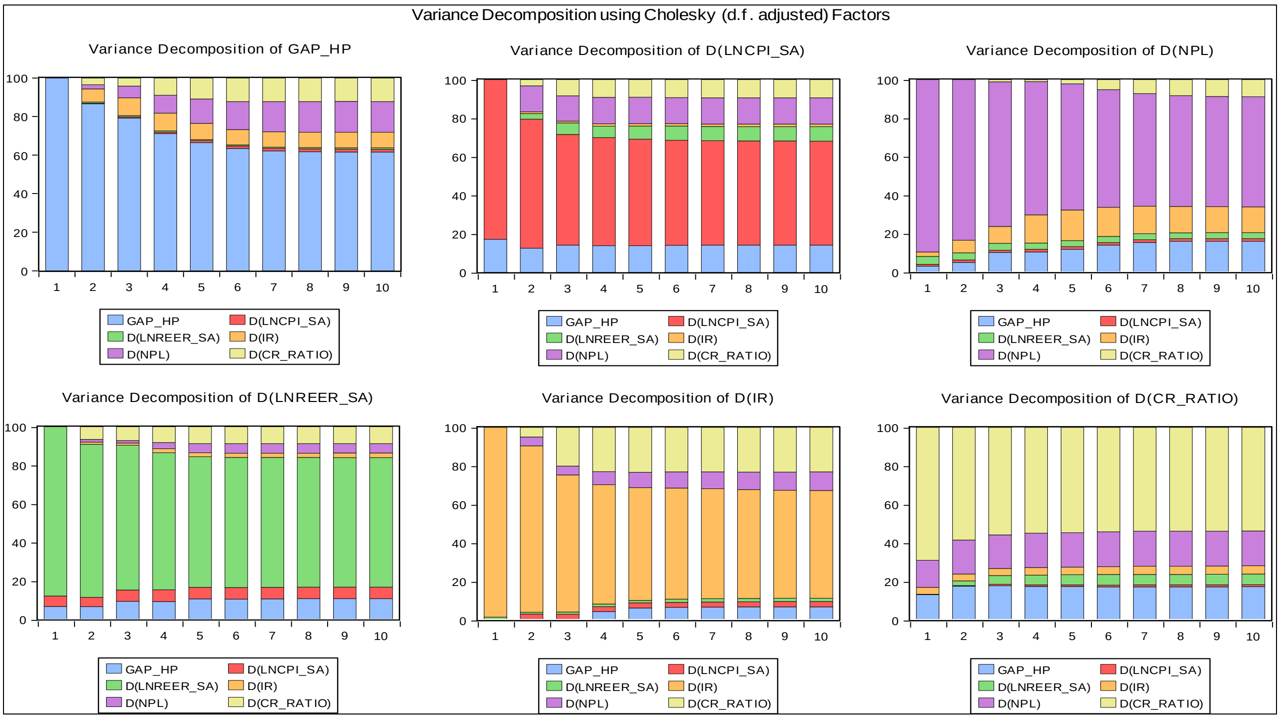
A1: Dynamics of NPL and GDP Gap



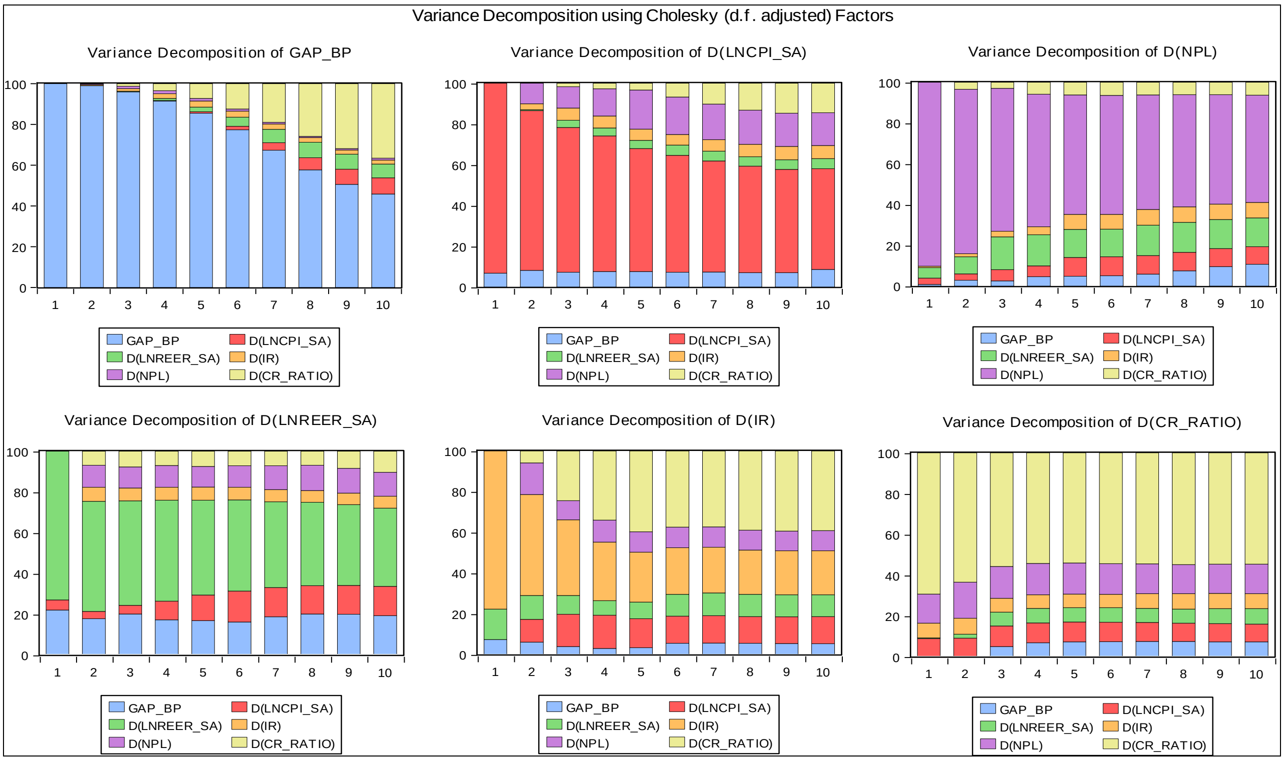
Source: NBG, Geostat, author's calculations

A2: Variance Decomposition

Model based on Hodrick-Prescott filter



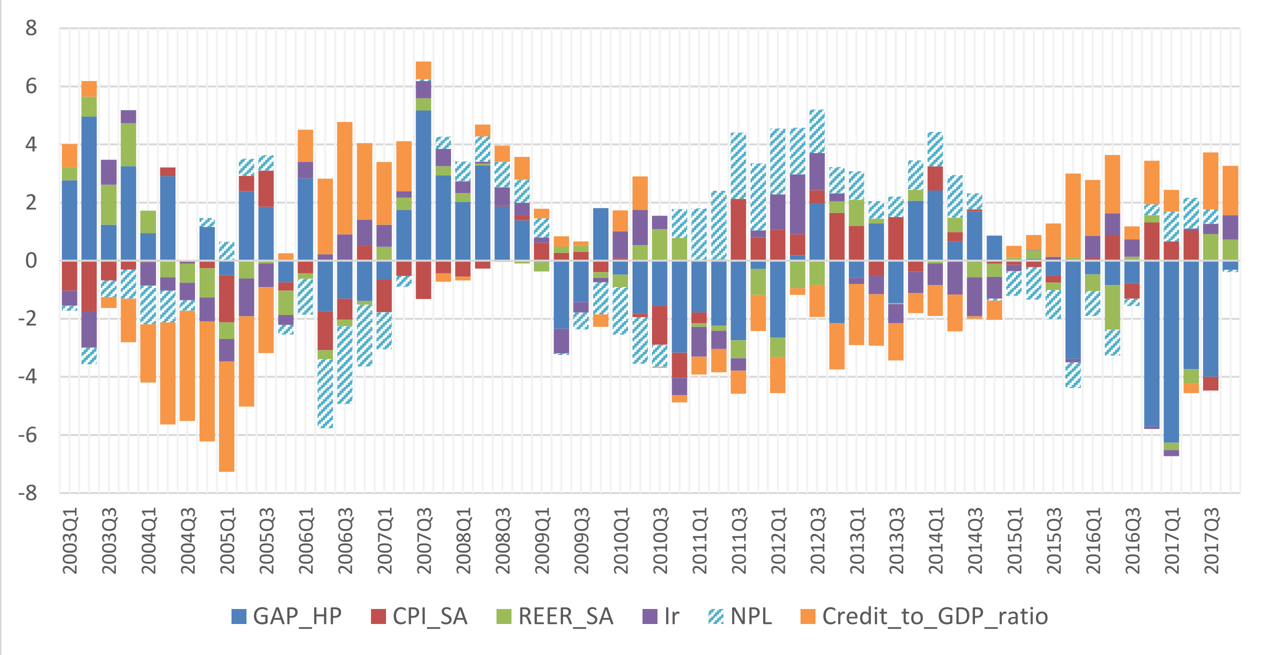
Model based on Band-Pass filter



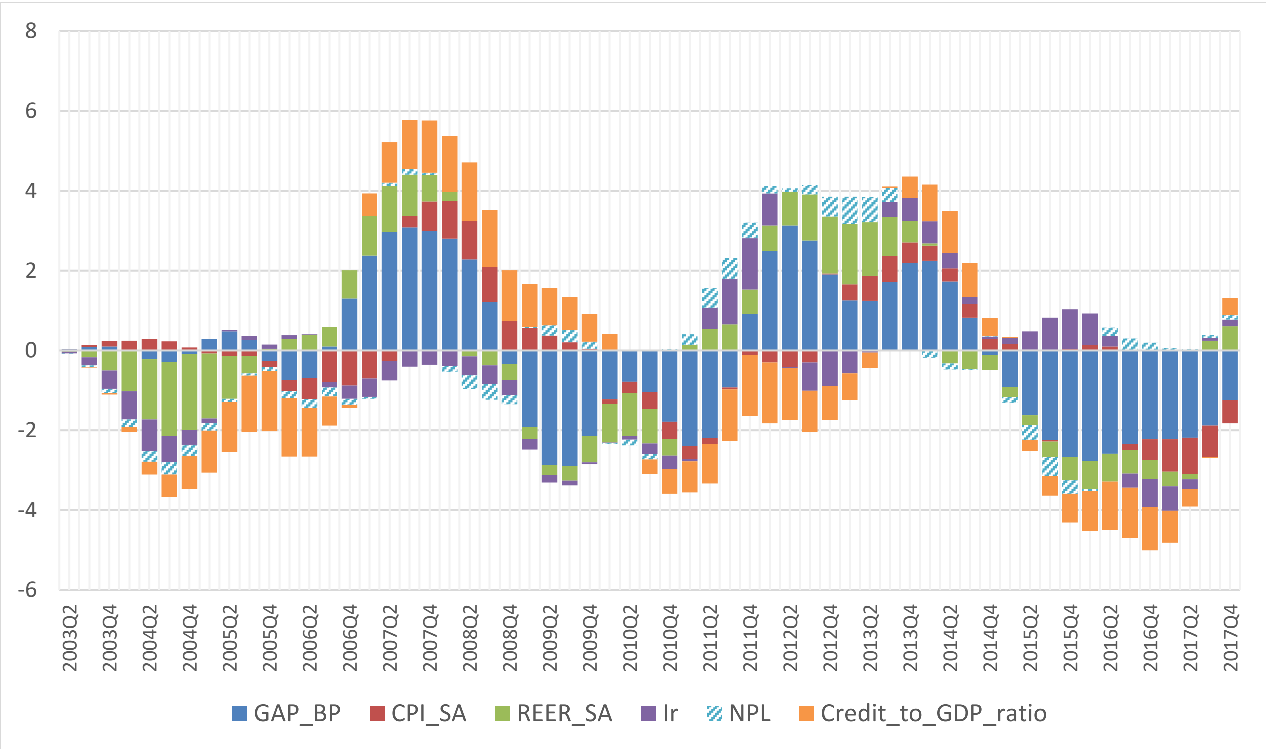
Source: author's calculations

A3: Historical Decomposition

Model based on Hodrick-Prescott filter

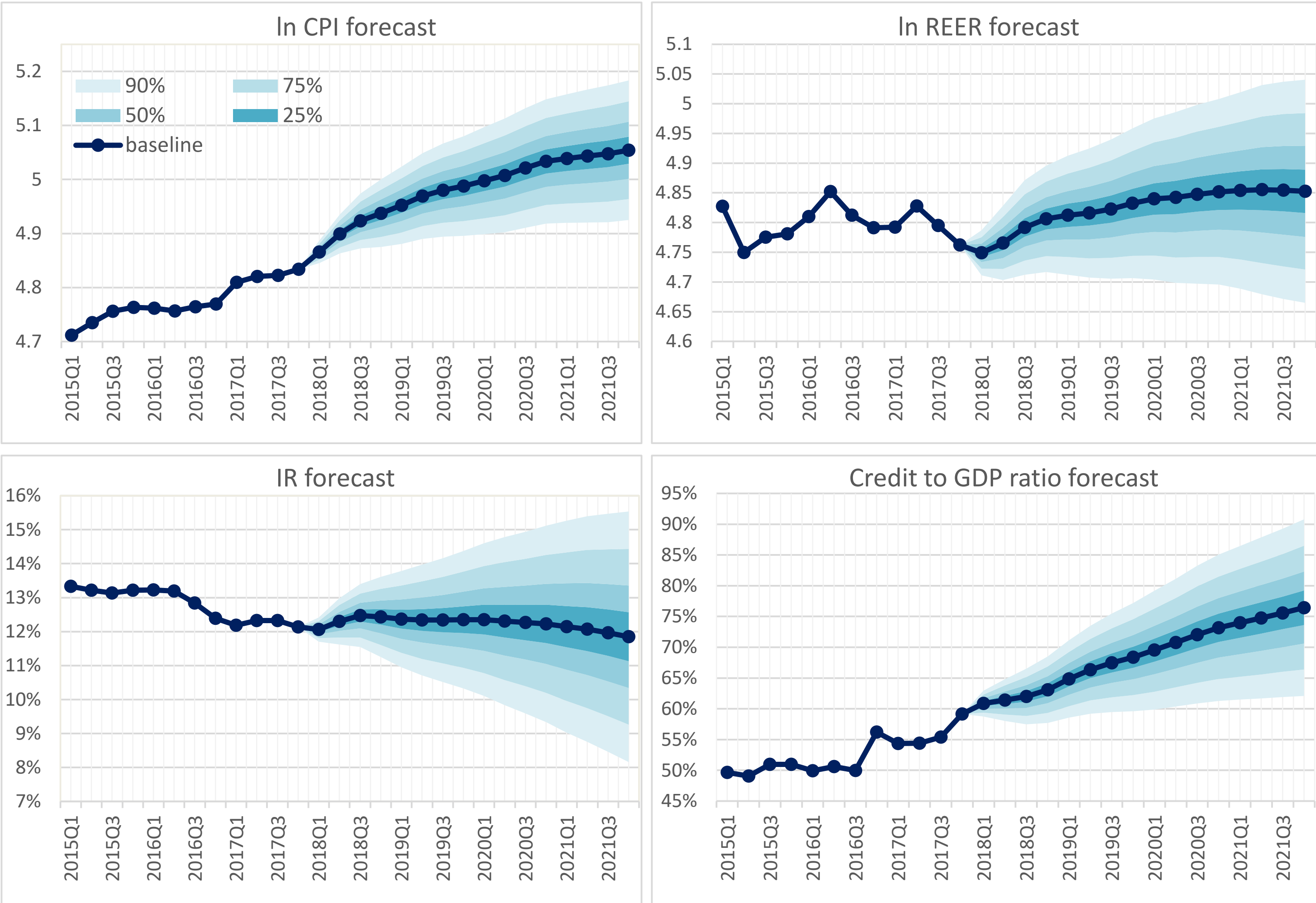


Model based on Band-Pass filter



Source: author's calculations

A4: Forecast under baseline scenario



Source: author's calculations

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