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Measuring Credit Gaps for Macroprudential Policy Guidance: An Application to Georgia

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Measuring Credit Gaps for Macroprudential Policy Guidance: An Application to Georgia[1]

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Abstract

According to international experience, episodes of rapid credit growth are often associated with increasing vulnerabilities within the financial system. It is of vital importance to identify risky credit expansions early enough so that macroprudential policy can respond and ensure overall financial stability. For this purpose, a reliable policy guide is essential to detect the build-up of systemic risks and to design optimal macroprudential policy responses. The Basel Committee on Banking Supervision recommends using the credit-to-GDP gap obtained from a one-sided Hodrick-Prescott (HP) filter as a common reference guide for setting the countercyclical capital buffer – a recently introduced macroprudential policy tool for addressing financial stability risks. This paper proposes two alternative approaches to credit-to-GDP gap estimation in order to enrich the analytical toolkit of the macroprudential policy framework. By addressing the shortcomings of the Basel credit-to-GDP gap, the proposed approaches offer more insightful and informationally efficient early warning indicators of financial stress. These indicators can complement the Basel credit-to-GDP gap in guiding more informed macroprudential policy decisions.

JEL Codes: E32, E58, G01, C32

Keywords: Credit Cycle; Credit Gap; Countercyclical Capital Buffer; Macroprudential Policy; Financial Stability

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I. Introduction

International experience shows that the periods of excessive credit growth are often associated with build-up of system-wide risks. When these risks crystalize, the financial system undergoes severe stress with a surge in defaulting borrowers and cutback in credit supply. As the liquidity evaporates and asset valuations drop, the shock is also transmitted to the real economy resulting in reduced investment and consumption expenditure. This, in turn, can lead to additional credit losses and turn the initial stress into a full-blown financial crisis. In order to avoid these adverse consequences of the financial stress, it is vital to identify the build-up of systemic vulnerabilities in a timely manner and to address them with well-designed macroprudential policy tools. Assessing whether credit growth is excessive remains a challenge, as there is no single widely agreed indicator for measuring the credit cycle position. For this purpose, policymakers need to monitor combinations of indicators and apply judgement. Nonetheless, it is highly desirable to have a common reference guide to anchor judgement and facilitate policy communication. One of the widely used such guides is the credit-to-GDP gap - a deviation of the credit-to-GDP ratio from its estimated trend.

In December 2010, as a part of the Basel III reform, the Basel Committee on Banking Supervision (BCBS) introduced a new macroprudential policy tool - countercyclical capital buffer (CCyB). The CCyB is built gradually during the expansion phase of the credit cycle when system-wide vulnerabilities are accumulating and it is released promptly once the risks materialize. The tool was designed to ensure that the banking system has enough capital to absorb losses during the financial stress without compromising its solvency and overall financial stability. This way, the flow of credit to the economy can be maintained at all times. As a positive side benefit, the CCyB can help moderate the expansion phase of the credit cycle. However, this is not the primary objective of the buffer. In making and communicating the CCyB decisions, the BCBS also recommends using the credit-to-GDP gap as a common reference guide.

The credit-to-GDP gap was selected by the BCBS as a guide for steering the CCyB because of its satisfactory performance as an early warning indicator (EWI) for banking crises. In addition, it is based on widely available data and it is simple to interpret and communicate. However, this simplicity comes at a cost of various pitfalls, which have been actively discussed in the literature since its introduction. Research has identified both conceptual and methodological issues of the Basel credit-to-GDP gap, which is estimated using a univariate Hodrick-Prescott (HP) filter. It has been argued that the gap is not a suitable guide given the objective of the countercyclical buffer because this indicator is not based on an equilibrium notion of credit. It also suffers from additional methodological problems such as trend stability and parameter calibration.

The purpose of this paper is to enrich the analytical toolkit of the macroprudential policy framework by proposing two alternative approaches to assessing the credit cycle. The proposed approaches are specially tailored for a small open economy context with partially dollarized financial system such as the case of Georgia. They also address the shortcomings of the Basel credit-to-GDP gap. The first approach is based on a semi-structural macroeconomic model. It takes into account macro-financial interactions as well as financial deepening and financial dollarization. The other approach utilizes a simple atheoretical construct based on an empirically documented observation that financial variables exhibit coincident cycles. Within this approach, credit cycles are identified by extracting signals from the co-movements of selected financial variables. The proposed approaches can complement the Basel credit-to-GDP gap in guiding the CCyB decisions. Therefore, they can contribute to coherent macroprudential policy and overall financial stability.

The alternative approaches to credit cycle assessment introduced in this paper demonstrated a significantly improved performance in terms of both stability and efficiency as compared to the Basel credit-to-GDP guide. However, they still inherit data-related limitations. The small size of the data sample, with only a single episode of the pronounced financial stress[1] in Georgia, makes it impossible to evaluate the early warning properties of the proposed indicators using standard receiver operating characteristic (ROC) procedures. Instead, the behavior of the obtained indicators are explored before and during this single episode of the financial stress.

The rest of the paper is organized as follows: First, major advantages and limitations of the Basel credit-to-GDP guide are reviewed and alternative estimation methodologies are examined. Next, the two alternative approaches to the real credit gap assessment are discussed and the corresponding estimation results are presented. Afterwards, the outcomes of the proposed two approaches are

[1] 2008-2009 Global Financial Crisis.

benchmarked against the Basel credit-to-GDP guide. Concluding remarks summarize the main findings of the paper.

II. A short review of the merits and limitations of the Basel credit-to-GDP guide

The type of cycle that is relevant to the CCyB instrument is the financial cycle. It refers to the self-reinforcing interactions between perceptions of value and risk, risk-taking, and financing constraints (Borio, 2012). The buildup of the financial cycle starts with increased risk-taking accompanied by rapid credit expansion, which drive up asset prices and collateral valuations. This allows for more borrowing until the point when the risk perceptions reverse and the whole process goes in the opposite direction. Financial cycles tend to exhibit larger amplitude and length compared to the fluctuations in real economy known as business cycles (Drehmann & Tsatsaronis, 2014). Ideally, the CCyB decisions should be based on a reference guide that can identify risky financial cycle expansions with high precision and easily interpretable manner. The credit-to-GDP gap introduced in Basel III is argued to be one such reference guide.

The Basel credit-to-GDP gap is obtained as the difference between the credit-to-GDP ratio and its trend. The latter is based on the one-sided HP filter with the smoothing factor $\lambda = 400{,}000$ (BCBS, 2010). The ratio utilizes a broad definition of credit to capture all sources of private sector debt. The choice of the credit-to-GDP guide by the BCBS among a wide array of candidate indicators was motivated by its decent statistical performance as an early warning indicator (EWI) of banking crises. Based on the data of a large panel of jurisdictions over several decades, Basel Credit-to-GDP gap has emitted stable signals early enough for the policy to respond (Drehmann & Tsatsaronis, 2014). In addition, being expressed as a share of GDP, this indicator is normalized by the size of the economy and it is not influenced by noisy fluctuations of credit demand originating from the business cycle. The data requirements for the calculation of the credit-to-GDP ratio are modest. The data on nominal GDP and private sector credit are easily available in almost all jurisdictions. In the end, simplicity and ease of communication of a single indicator are additional merits of the Basel credit-to-GDP gap.

A major conceptual limitation of the Basel credit-to-GDP gap discussed in the literature is that it is not based on an equilibrium notion of credit to the economy (Baba et al, 2020). Since the gap is obtained by using a univariate statistical filter (HP), it has no capacity to distinguish between sustainable credit growth and cyclical risky credit expansions. Consequently, the HP filter decomposition of the credit-to-GDP ratio into a trend and gap components is rather mechanical. For this reason, during prolonged credit expansions, the early warning performance of the Basel credit-to-GDP gap deteriorates (Wolken, 2013). The longer the expansion, the more of the credit growth is mechanically attributed to the trend component by the HP filter. As a result, the Basel credit-to-GDP gap shrinks while the vulnerabilities might be still building up. This issue has additional important implications for implementing the Basel credit-to-GDP gap in emerging and developing countries, which are undergoing financial deepening. In these countries, credit booms may be a consequence of structural changes introduced to promote financial intermediation and increase credit availability (World Bank, 2010). When this healthy process of financial deepening generates higher-than-historical credit growth, this may be interpreted as a risky credit expansion by the mechanical use of the Basel credit-to-GDP gap. To summarize, the absence of equilibrium notions embedded in the Basel credit-to-GDP gap makes it susceptible to erroneous signals in the cases of protracted risky credit expansions and healthy financial deepening episodes.

Another shortcoming of the Basel credit-to-GDP guide is related to the instability in its trend. This is caused by the well-known end-point bias problem, which is inherent in the HP filter (Bruchez, 2003). In particular, the last point of the sample has an exaggerated impact on the estimate of the underlying trend. Thus, as new data becomes available, the estimated trend series experience sizable revisions near the end of the sample. In order to avoid these revisions, the Basel Committee recommends using a one-sided HP filter for estimating the credit-to-GDP trend. Within the one-sided approach, the HP filter is run recursively. Thus, it generates a backward-looking estimate of the underlying trend series in real time.[2] Under the one-sided filter, trend revisions are avoided when new data becomes available. This makes the estimated credit-to-GDP gaps easy to communicate.

[2] An alternative approach to the filtering exercise is the two-sided filter, which generates an ex-post estimate of the underlying trend series by utilizing both past and future data.

However, the end-point bias is still there. Within the one-sided approach, previous trend estimates are never confronted with new data and the end-point bias contaminates the whole sample. Even though the most recent estimate of the credit-to-GDP trend and, by extension, the gap are based only on the past information[3] regardless of the filtering approach, it can be claimed that the one-sided filter is informationally inefficient. Arguably, not only the most recent estimate, but also the previous values of the gap carry valuable information for the policymaker. By examining the most recent and previous values of the gap together, the velocity of the credit cycle build-up or deflation can be revealed. Therefore, it is informationally inefficient not to update those previous estimates as new data arrives. Moreover, this might lead to systematic errors in the indicator, which will be revealed too late.

Lastly, the Basel credit-to-GDP gap makes an implicit assumption on the length of the credit cycle. The smoothing factor $\lambda = 400{,}000$ is based on the credit cycle length of about 30 years (Baba et al, 2020). This is around four times larger than the average business cycle. Although it is widely agreed, that credit cycles are longer and of higher amplitude than business cycles, there is no consensus on the exact specification of the relationship. Moreover, it is argued that the length of the credit cycle varies by country-specific factors. Rünstler and Vlekke (2016) estimate the average duration of the credit cycle of 15 years for the US and five largest European economies. This estimate is half of the credit cycle length assumed by the Basel credit-to-GDP guide. Credit cycles can be even shorter for developing countries. Thus, the implicit assumption on the credit cycle length in the HP filter may be rather strong and unrealistic.

Given the conceptual and methodological shortcomings of the Basel credit-to-GDP gap, there has been a variety of alternative approaches to credit gap estimation proposed in the literature. These approaches can be grouped into two main categories: statistical and structural models. Statistical approaches attempt to extract the cyclical component of credit from the data by frequency-based decomposition. For this purpose, both univariate and multivariate statistical filters have been utilized. Bandpass methods are commonly used univariate statistical approaches (Baxter and King, 1999; Christiano and Fitzgerald, 2003). Even though these methods are more flexible comparted to the HP filter, they still require assumptions in terms of the credit cycle length. Therefore, they do

[3] Unless some prediction of the future credit-to-GDP ratios are used. In this case, however, an additional source of uncertainty is introduced.

not offer any significant improvement over the HP filter. A multivariate statistical model has been proposed by Durbin and Koopman (2012), which jointly estimates the trend and cyclical components of GDP, credit and house prices. This approach takes advantage of the multidimensional data to extract the cyclical component of credit and estimate the length of the credit cycle based on the co-movements of selected variables. As the multivariate statistical filters do not take into account structural relationships, they may pick up noisy and anomalous signals leading to estimation errors. Lastly, structural approaches can be used to model relationships between macroeconomic and financial variables explicitly. In structural models, equilibrium level of credit is defined in general equilibrium settings. These models also make it possible to capture the factors that determine the equilibrium level of credit (Galán and Mencia, 2018; Baba et al, 2020). Even though the structural models provide much more insight into the credit dynamics, they are generally less flexible and more data-intensive compared to the statistical approaches.

In this paper, the proposed alternative approaches to credit cycle assessment provide an optimal mix of the valuable insights offered by semi-structural models and the flexibility of the statistical methods. In addition, they are suited to the country-specific characteristics of a small open economy with partially dollarized financial system.

III. The semi-structural model for estimating the real credit gap

Methodology

In order to identify credit cycles, a standard semi-structural macroeconomic model has been augmented by the real credit block. Within this model, relationships between the macroeconomic variables are governed by the standard equations for output gap (IS curve), inflation (Phillips curve), policy interest rate (Taylor rule), real interest rate (Fisher equation), and real exchange rate (UIP). By imposing a structure and specifying the nature of interactions between the real economy and the financial sector, this approach allows for a better identification of credit cycles. The core of the model is based on the forward-looking small open economy model operated by the National Bank of Georgia (NBG, 2016). Therefore, the specification of the basic equations, the monetary policy regime and the parametrization are suited to the specific characteristics of the Georgian economy. The real credit block is built into the model in the spirit of Baba et al (2020) with several major modifications to account for the key characteristics of the Georgian financial sector. In particular, the credit block takes into account financial dollarization and financial deepening.

Within the semi-structural approach, the stock of real credit to the private sector [4] (c_t) is decomposed into the trend and gap components (see equation III.1). The real credit gap ($\hat{c}_t$) describes the cyclical movements in the credit stock. It is modelled as a stationary process, which exhibits some degree of persistence since it takes time for borrowers to adjust their portfolios. The real credit gap is affected by the lagged value of the output gap ($\hat{y}_{t-1}$), the real interest rate gap ($\hat{r}_t$) and the valuation effect caused by exchange rate movements ($\widehat{ds}_t$). The rest of the factors are combined in the residual term ($\epsilon_t^{\hat{c}}$) (see equation III.2).

$$c_t = \bar{c}_t + \hat{c}_t \tag{III.1}$$

$$\hat{c}_t = \theta^c \hat{c}_{t-1} + \theta^y \hat{y}_{t-1} - \theta^r \hat{r}_t + \theta^s \widehat{ds}_t + \epsilon_t^{\hat{c}} \tag{III.2}$$

$$\hat{y}_t = \{standard\ output\ gap\ determinants\} - \beta^s \widehat{ds}_t + \beta^c \epsilon_t^{\hat{c}} + \epsilon_t^{\hat{y}} \tag{III.3}$$

[4] As suggested by the BCBS, this paper utilizes a broad definition of nominal credit to capture all sources of private debt including domestically issued corporate bonds. In order to be able to identify the trend and gap components, credit has to be present in real terms. Real credit to the private sector is obtained by adjusting the nominal credit for inflation. The adjustment is made using GDP deflator.

The cyclical movements in the real economy, which are summarized in the output gap term of the real credit gap equation, influence the credit stock with a time delay. The real interest rate gap term accounts for credit conditions, which have an immediate impact on lending and borrowing decisions. In the end, as a significant portion of the financial liabilities are denominated in a foreign currency in Georgia, exchange rate movements have an immediate valuation effect on the local currency value of the credit stock. In turn, the liability revaluations affect the debt-servicing capacity as well as consumption and investment decisions of the borrowers. The size of the impact is determined by the credit dollarization ratio and the portion of unhedged foreign currency borrowers.[5] The valuation effect term is defined as the excess depreciation of the Georgian Lari against the US dollar over what is implied by the trend movements in the corresponding real exchange rate and inflation differential.[6] The excess depreciation term has built-in persistence to capture the post-depreciation portfolio adjustment process among the unhedged foreign currency borrowers. The excess depreciation term also participates in the output gap equation to capture income effects (see equation III.3). As depreciation increases the local currency service cost of the dollarized debt, the borrowers are left with less income to spend on consumption or investment.

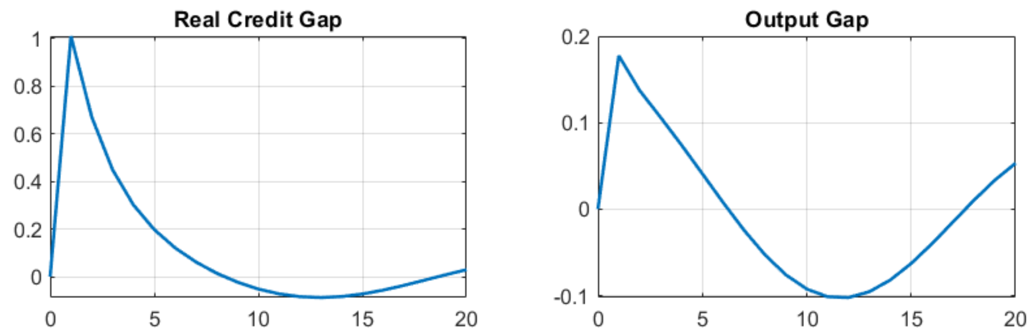
Interactions between the business and credit cycles modelled in the semi-structural approach are consistent with the literature and empirical observations on macro-financial linkages. Innovations in the cyclical component of the real credit are directly transmitted to the real economy. This linkage is captured by placing the residual term of real credit gap in the output gap equation. The dynamic response of the output gap to the one standard deviation shock to the real credit gap is depicted in Figure III.1. As the figure shows, the business cycle responds immediately to the cyclical impulses originating from the financial sector. The size of the response is calibrated to be less then one-to-one since not all of the new borrowings create value in the economy. Conversely, the financial cycle responds to the business cycle innovations with a time delay (see Figure III.2). As the impulse response shows, the reaction of the cyclical component of the credit attains its maximum value after three quarters of the initial shock. This is because the adjustment in the financial leverage takes time. In particular, when, for instance, the real sector experiences a positive demand shock, borrowers need to demonstrate a persistent improvement in their creditworthiness, before they can apply for

[5] The credit dollarization ratio, which is defined as the share of private foreign currency credit in total private credit, was around 56% in Georgia during 2020. As for the hedging, the anecdotal evidence suggests that the vast majority of the foreign currency borrowers in Georgia have a sizable currency mismatch between assets and liabilities.

[6] A comprehensive list of the model equations is given in Appendix A.

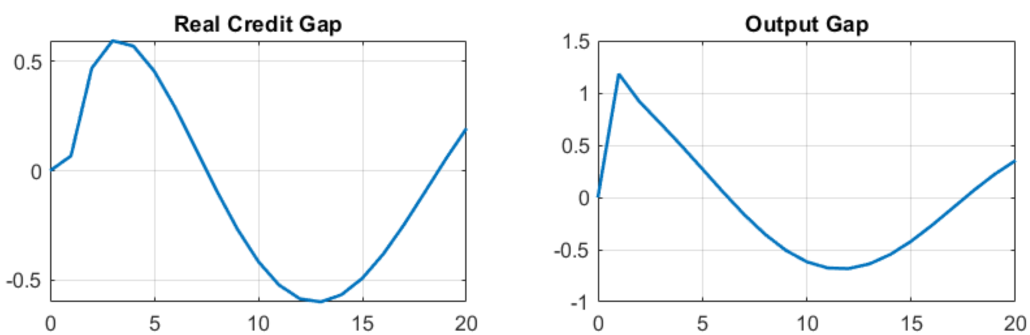
more credit. In addition, new collateral needs to be pledged by the borrowers and evaluated by the lenders. In the case of a negative demand shock, it usually takes time before the borrowers start to deleverage by restructuring or defaulting on their existing debt. The surpluses generated before the shock allow the borrowers to continue servicing their debt for a while. Lastly, the real credit gap has no direct impact on inflation, which allows for a cyclical credit expansion with muted inflationary pressures as discussed by Borio (2012).

Figure III.1. *Impulse response analysis in the semi-structural model: one standard deviation shock to the real credit gap*



Source: Author's calculations.

Figure III.2. *Impulse response analysis in the semi-structural model: one standard deviation shock to the output gap*



Source: Author's calculations.

One more important feature of the semi-structural model is the differentiation between financial deepening and cyclical risky credit expansions. Financial deepening can be defined as an increased availability of financial services as financial markets become more advanced and sophisticated. In transition economies, such as Georgia, financial deepening may occur at an accelerated pace. As countries undergo financial liberalization, capital flows in and credit availability improves. Under these conditions, credit tends to increase at higher-than-historical rates. Simple statistical techniques of credit gap identification cannot distinguish between these kinds of accelerated financial deepening and risky credit upswings. Therefore, those simple methods ascribe all the variation to the cycle, which leads to sizable estimation errors. There is no straightforward way to account for financial deepening process in the financial cycle identification exercise. Financial deepening episodes are country-specific and may be reflected in institutional, regulatory or technological changes that affect financial markets. In the semi-structural approach proposed in this paper, financial deepening is captured by changes in the trend growth of the economy. Usually, institutional or technological changes are system-wide and they affect both the financial sector and the real economy. Thus, financial deepening episodes are likely to be associated with increased production capacity of the economy. In the spirit of this argument, trend credit growth ($\Delta\bar{c}_t$) is linked to the deviation of trend growth of the economy from its steady state ($\Delta\bar{y}_t - \Delta\bar{y}_{ss}$) (see equation III.4). This relationship also holds for the reverse case. Factors that cause the trend growth of the economy to decelerate will also have an adverse impact on both the lenders capacity to issue debt and the borrowers' capacity to service liabilities. Therefore, in this case, trend credit growth will be revised downward.

$$\Delta\bar{c}_t = \rho^{\Delta\bar{c}}\Delta\bar{c}_{t-1} + (1-\rho^{\Delta\bar{c}})\Delta\bar{c}_{ss} + \delta(\Delta\bar{y}_t - \Delta\bar{y}_{ss}) + \epsilon_t^{\Delta\bar{c}} \qquad \text{(III.4)}$$

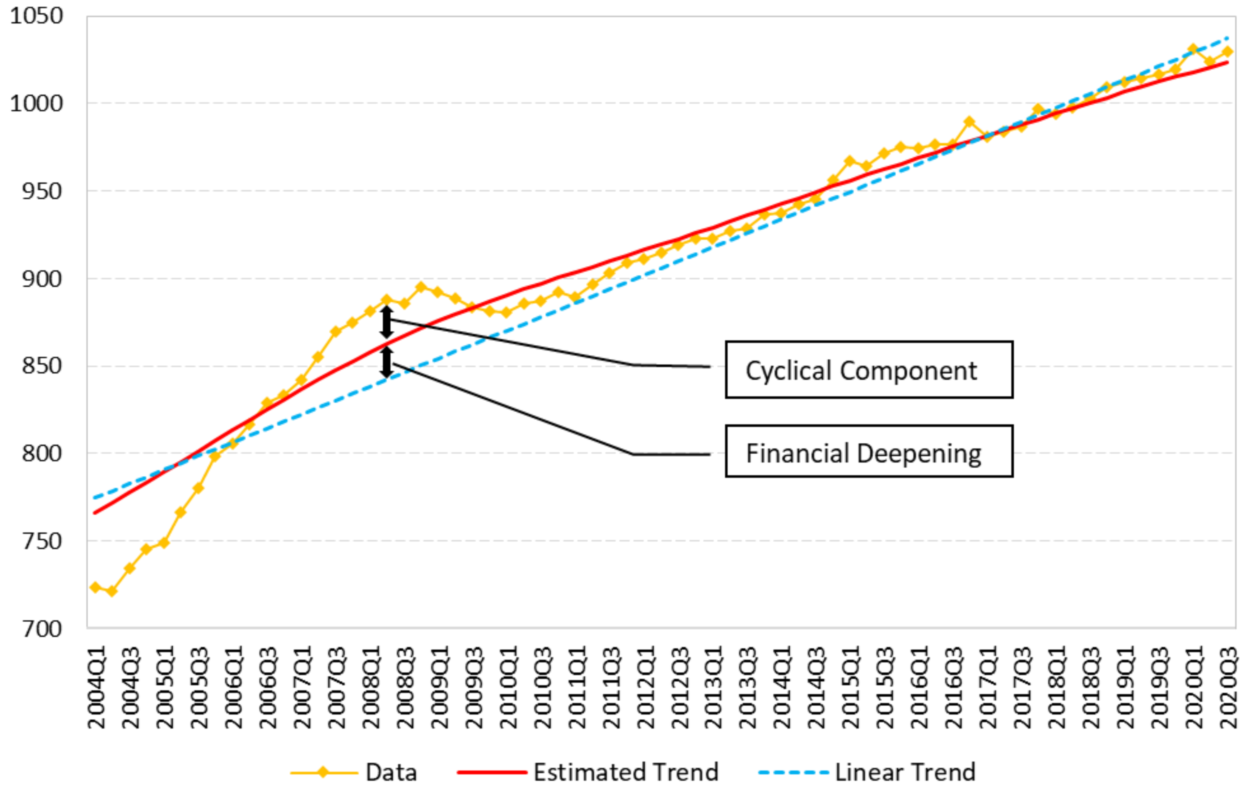
The semi-structural model proposed in this paper has been calibrated using the parameter values of the Georgian economy model operated by the NBG. As the basic equations of the two models match closely, the parameter values of the NBG model provides a good starting point. The parameters of the credit block equations have been calibrated using the values estimated by Baba et al (2020) for comparable countries. There was also an attempt to update the parameter values using the Bayesian estimation technique. However, due to the small size of the sample, the data had very little to say about the parameter values. Therefore, the posterior estimates were very close to the calibrated priors. As the sample size increases, the parameter estimation exercise can be rerun to see if there is any improvement. For now, the calibrated parameter values provide the only feasible option.

Results

Since the estimated real credit trend accounts for the financial deepening process, it exhibits pronounced acceleration and deceleration episodes (see Figure III.3). For comparison, the estimated trend is presented side by side the linear trend,[7] which is an extreme case of the HP filter when its smoothing parameter tends to infinity. As the figure shows, there was a financial deepening episode in the 2000s before the Global Financial Crisis (GFC). During this period, the country experienced major institutional changes that contributed to increased efficiency in financial intermediation. Therefore, the rapid buildup of credit during those times should not be fully ascribed to the upswing in the financial cycle. Part of that credit growth can be explained by the financial deepening. This result has an important implication for the estimated real credit gap size. For that period, the positive real credit gap turns out to be smaller in size and shorter in duration than the one estimated without accounting for the financial deepening. This can be one of the reasons why the Georgian banking sector suffered relatively smaller losses when the cycle turned during the GFC. Another episode of interest is the recent period starting from late 2014. During this period, the country experienced a series of persistent external shocks that have adversely affected the trend growth of the economy. Subsequently, the real credit trend growth has decelerated reflecting higher riskiness of the existing financial liabilities and a deteriorated debt-servicing capacity of the borrowers. This recent change in the trend gives rise to a larger size of the current real credit gap with a higher likelihood of vulnerabilities building up within the financial sector.

[7] Since the figure uses a logarithmic scale, the linear trend of the log real credit series corresponds to the exponential growth at a constant rate. Increasing (decreasing) slope of the estimated trend corresponds to acceleration (deceleration) in the trend growth.

Figure III.3. *The estimated trend of the real credit within the semi-structural model (log scale)*



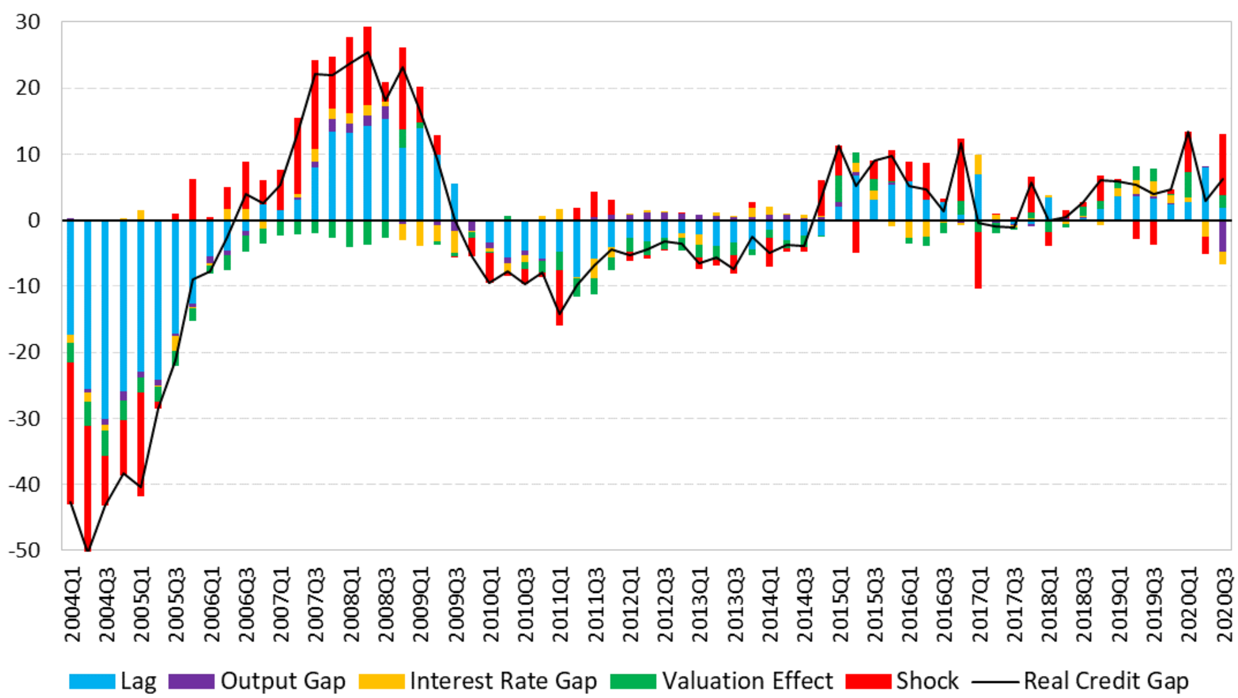
Source: Author's calculations.

The semi-structural approach permits to identify the real credit gap determinants, and therefore it provides valuable insights about the main driving forces of the credit cycle (see Figure III.4). As the figure depicts, during the upturn phase before the GFC, all of the determinants contributed to the real credit gap increase except for the valuation effect.[8] Once the cycle turned, the first component that started pulling the real credit gap down was the real interest rate gap. The negative contribution of the output gap was registered only afterwards. This result is consistent with the empirical observation that the financial conditions manifested in the real interest rate gap are the fastest to respond once the risks materialize. As for the real economy, it takes more time to respond. In the current period, the gap remains positive but of a much smaller size compared to the pre-GFC upturn phase. This indicates a lower likelihood of the buildup of vulnerabilities within the financial sector. However, a close attention should be paid to the current driving factors. In the face of several recent

[8] The contribution of the valuation effect was negative during that period because the Georgian Lari experienced appreciation against the US dollar. All else being equal, this caused the local currency value of the foreign currency debt to shrink.

episodes of the Georgian Lari depreciation against the USD, the valuation effect has persistently contributed to the widening of the gap. The financial conditions have also been accommodative until the last quarters when the interest rates surged due to the COVID-19 pandemic. Going forward, the sign and size of the future real credit gaps can be predicted by the interplay of its driving factors. In other words, the semi-structural approach allows for the translation of the views on the real credit gap determinants into the expected dynamics of the credit cycle and the likelihood of the buildup of risks within the financial sector.

Figure III.4. *The estimated real credit gap decomposition within the semi-structural model (percentage points)*



Source: Author's calculations.

IV. The multivariate filter for identifying the common financial cycle

Methodology

The identification of the common financial cycle is based on the empirical observation that financial variables (credit and property prices, in particular) exhibit coincident movements (Aikman et al, 2010). The proposed approach attempts to identify the unobserved common factor driving the financial cycle by extracting signals from the co-movements of real credit and real residential property prices.[9] Even though this approach has no theoretical foundations, it performed quite well in assessing financial stability risks for the US and China (Laxton et al, 2019). The unobserved common driver of the financial cycle is estimated using the Kalman filter. Within this filter, the model predictions are confronted with data to obtain the optimal updates of the unobserved components.

The multivariate filter approach is based on the model proposed by Laxton et al (2019). Real credit gap ($\hat{c}_t$) and real house price gap ($\hat{h}_t$) are modeled as stationary processes with some degree of persistence (see equations IV.1 and IV.2, respectively). Each of these gaps is affected by the previous period output gap ($\hat{y}_{t-1}$), the unobserved common financial cycle component (f_t) and own idiosyncratic shocks ($\epsilon_t^{\hat{c}}$ and $\epsilon_t^{\hat{h}}$, respectively). By construction, co-movements in the real credit and real house prices, which are not sourced to the real economy, are captured by the common financial cycle component.[10] The modelling of the relationship between the financial and real business cycles is based on a similar logic as discussed in the semi-structural approach. Particularly, the impact of real shocks is transmitted to the financial sector with a delay, while the common financial cycle innovations have immediate effects on the real business cycle (see equation IV.3).

$$\hat{c}_t = \rho^c \hat{c}_{t-1} + \beta \hat{y}_{t-1} + f_t + \epsilon_t^{\hat{c}} \tag{IV.1}$$

$$\hat{h}_t = \rho^h \hat{h}_{t-1} + \gamma \hat{y}_{t-1} + f_t + \epsilon_t^{\hat{h}} \tag{IV.2}$$

$$\hat{y}_t = \rho^y \hat{y}_{t-1} + \alpha f_t + \epsilon_t^{\hat{y}} \tag{IV.3}$$

[9] Real credit and real house prices are obtained by adjusting the nominal credit to the private sector and residential property price index, respectively, for inflation. The adjustment is made using GDP deflator.
[10] A comprehensive list of the model equations is given in Appendix B.

The multivariate filter proposed in this paper has a simpler structure and it is more data-driven compared to the semi-structural approach. The quality of the results obtained from the multivariate filter is strongly correlated to the signaling quality of the financial variables used in the model to identify the common financial cycle. Ideally, stock exchange valuations and the spreads on fixed income instruments would provide additional valuable input in identifying the common financial cycle. However, given the shallow capital markets in Georgia, these data are not available. Thus, the cyclical signals are extracted only from the movements in credit and residential property prices.

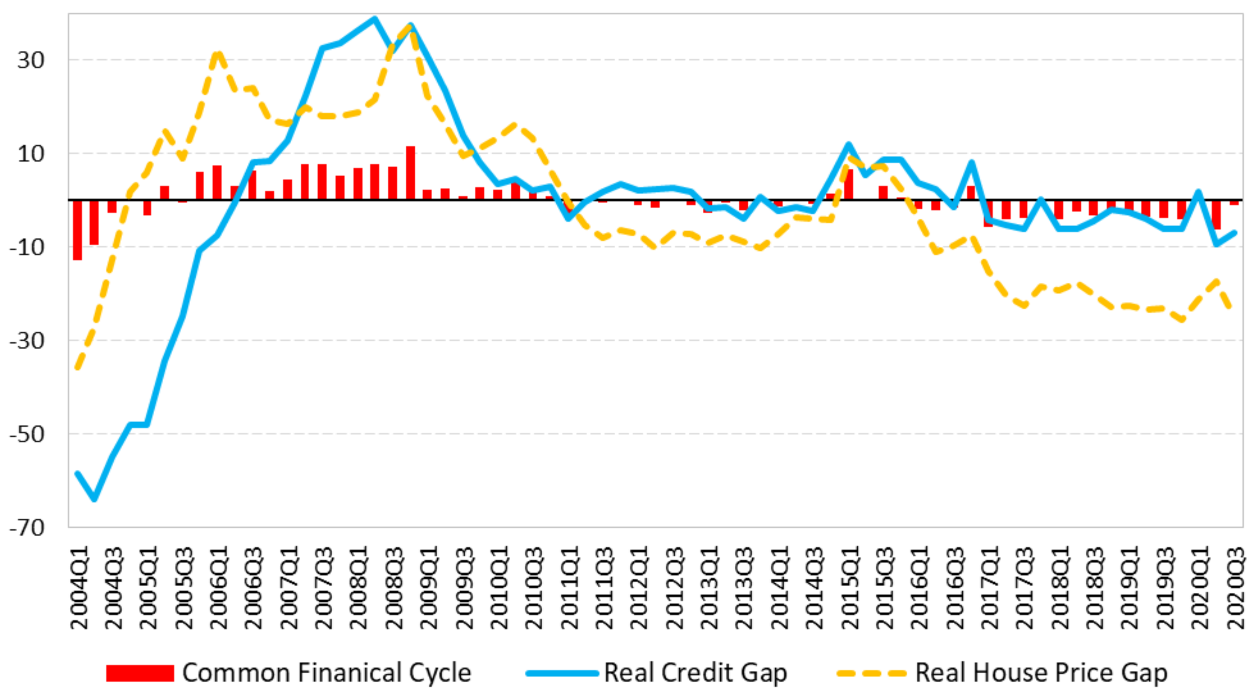
Results

The unobserved common financial cycle component estimated within the multivariate filter indicates the phase and magnitude of the financial cycle (see Figure IV.1). During the buildup phase before the GFC, this cycle indicator was persistently positive and increasing in value. However, it did not jump to the negative territory after the risks crystalized. This is because the adjustment was not fast and large enough. The estimated real credit and real house price gaps remained positive for several quarters after the initial shock. Subsequently, real house prices dropped below the estimated trend, while the real credit closely followed its sustainable trajectory. The smaller-than-expected post-crisis adjustment in real credit indicates that the financial sector was not hit hard even though the real estate prices dropped significantly. This finding can be explained by the fact that in 2008, apart from the GFC, Georgia also suffered from the August war.[11] Afterwards, the country received international financial aid, part of which was injected as capital in the commercial banks. Therefore, the capital injection alleviated the stress and allowed the financial sector to continue providing credit to the economy. In recent years, starting from 2017, the estimated common financial cycle indicator has been persistently negative, which suggests that the country is still undergoing the financial cycle downturn. While the real credit remains relatively close to its sustainable level, real house prices have been well below the trend.[12] This discrepancy may partly be explained by the possible

[11] The war took place in August 2008 when Russian troops illicitly crossed the Russo-Georgian state border. The loss to public and private infrastructure caused by the war amounted to billions of US dollars.
[12] The underlying assumption about the real house price trend is that in the long term it should grow at a rate of gross real income growth in the economy.

measurement error in the house price index used in the paper.[13] However, the possible measurement error cannot be so large to affect the model estimates in a significant way. There is a more intuitive explanation of the persistently below-the-trend real house prices in recent years. In particular, house prices are usually advertised in US dollars in Georgia. During the local currency depreciation episodes, the advertised prices in USD do not adjust immediately and remain rigid for some time. This leads to reduced affordability of houses and the corresponding slack in demand, which constrain house prices to grow as normal. On the other hand, the local currency depreciation is more promptly transmitted to the general price level in the domestic economy. As a result, the depreciation episodes are associated with below-the-trend growth in real house prices. Overall, the results of the multivariate filter collectively indicate that currently there are no signs of the financial cycle buildup.

Figure IV.1. *The estimated common financial cycle within the semi-structural model (percentage points)*



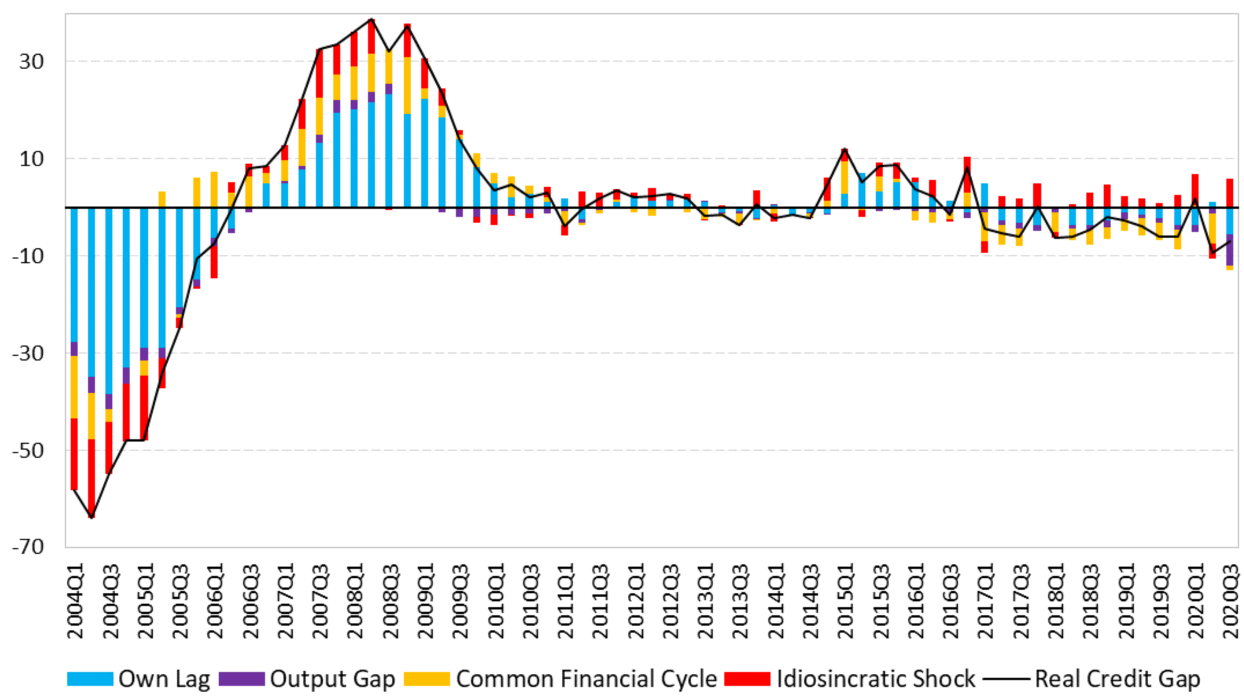
Source: Author's calculations.

The multivariate filter approach allows for decomposition of the obtained real credit gap into its determinants (see Figure IV.2). As the figure shows, the buildup of the credit cycle before the 2008

[13] The index is based on the advertised prices of the residential real estate collected from the domestic advertising webpages. The advertised prices may be a biased proxy of transaction prices, for which consistent data series are not available.

crisis was predominantly driven by the common financial cycle component, which can be interpreted as a financial conditions indicator. The positive values of the component correspond to easy and accommodative financial conditions manifested in low interest rates and stretched valuations. The contribution of the real business cycle captured by the output gap component was relatively smaller and delayed. By construction, the output gap component of the real credit gap only picks up income effects, which work with a delay. The optimistic expectations that accompany the buildup phase of the credit cycle are captured by the common financial cycle component. In the recent period, the real credit gap has remained negative driven by tight financial conditions manifested in the negative sign of the common financial cycle component. The main reason behind this tightness is the suggested depressed valuation of the real estate as discussed above. Currently, the real credit gap dropped even more as the impact of the COVID-19 pandemic was transmitted through both the financial conditions and the real economy channels. Overall, according to the current negative value of the real credit gap estimated by the multivariate filter approach, there is no indication of the financial cycle buildup.

Figure IV.2. *The estimated real credit gap decomposition within the multivariate filter (percentage points)*



Source: Author's calculations.

V. Cross-comparison of the Credit-to-GDP gaps obtained from the proposed approaches

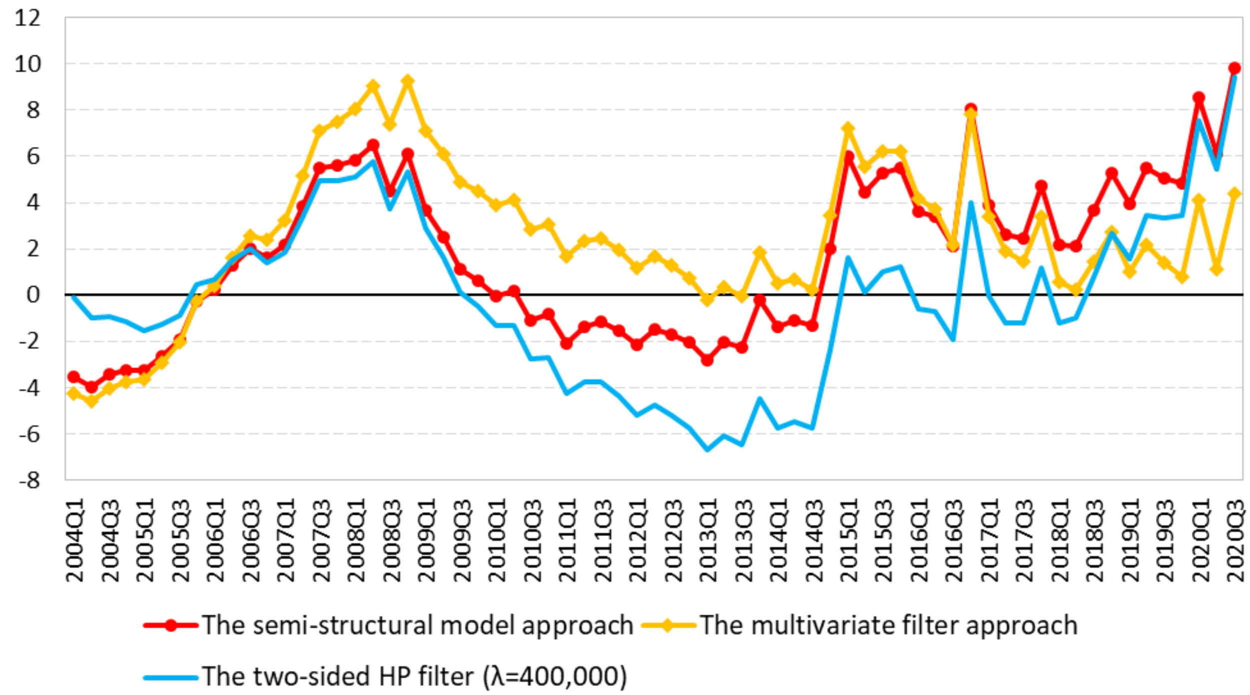
In order to make meaningful comparisons between the results of the proposed approaches and the Basel credit-to-GDP guide, they need to be presented in similar terms. For this purpose, the credit-to-GDP trend is constructed for each of the proposed approaches as the ratio of the real credit trend to the annualized output trend. This way of building a new trend variable is valid here because in each of the approaches the real credit trend and the output trend are interlinked. Next, the corresponding credit-to-GDP gaps are computed as the difference between the credit-to-GDP ratio and its model-consistent trend. The obtained credit-to-GDP gaps exhibit a different cyclical behavior as opposed to the corresponding real credit gaps. This is because the credit-to-GDP gap, essentially, measures the excess debt burden of the economy, while the real credit gap measures the size of excess real debt. In terms of identifying risky credit expansions, credit-to-GDP gap is more informative as it takes into account the capacity of the economy to service the existing debt.

Figure V.1 depicts the alternative estimates of credit-to-GDP gap obtained from the semi-structural model, the multivariate filter and the two-sided HP filter with the smoothing parameter suggested by the BCBS[14]. By construction, all of the estimates are based on ex-post analysis and therefore they utilize the data of the whole sample. The figure shows clearly that during the GFC episode, the HP filter-based indicator, when compared to the proposed measures of the credit-to-GDP gap, underestimated the peak and overestimated the trough of the credit cycle. Therefore, using solely the HP filter measure of the credit-to-GDP gap for macroprudential policy guidance would lead to sizable policy errors with corresponding welfare costs. The credit-to-GDP gaps obtained from the semi-structural approach and the multivariate filter are less susceptible to such errors because they both are based on an equilibrium notion of credit. They utilize the imposed structure of the macro-financial interactions to identify the deviations from the equilibrium. In addition, at the end of 2014, when the Georgian economy faced a substantial external shock, the proposed credit-to-GDP gaps became positive promptly indicating increased vulnerability of the financial sector. The HP gap also responded to this shock. However, as it was overstating the previous trough, it took much longer to show alarming signs. Moreover, its signals were vague and inconsistent. Thus, the proposed

[14] Since the proposed two estimates of the credit-to-GDP gap are based on a two-sided filtering approach, they are compared to the two-sided HP filter counterpart.

measures of the credit-to-GDP gap demonstrate better early warning performance compared to the two-sided HP filter.

Figure V.1. *The alternative estimates of the credit-to-GDP gap (percentage points)*



Source: Author's calculations.

In the current period, as the local currency depreciated and the economic activity dropped due to the COVID-19 pandemic, all of the credit-to-GDP gaps surged indicating a possible buildup of systemic vulnerabilities in the face of increased uncertainty. However, the increase in the multivariate filter-based indicator was relatively moderate. This is because the latter is based on the notion of the common financial cycle, which incorporates the cyclical co-movements of the real credit and real house prices. As the real house prices are currently estimated to remain below the trend, the multivariate filter suggests that the systemic risks are relatively subdued.

Another aspect in which the proposed credit-to-GDP guides outperformed the HP filter-based counterpart is the trend stability. Since both the semi-structural model and the multivariate filter exploit an imposed structure of macro-financial interactions, they are less susceptible to end-point bias as opposed to the mechanical and purely data-driven HP filter. This property allows for utilization of the whole sample data without significant revisions[15] in the previously estimated trend series as new data arrives. As Table V.1 displays, the credit-to-GDP trend estimated within the semi-structural model demonstrated a marked improvement in trend stability over the HP filter (26% less root mean squared revision). The multivariate filter also outperformed the HP filter in this regard (17.6% less root mean squared revision). Because of the significantly smaller revisions compared to the two-sided HP filter, the two-sided credit-to-GDP gaps obtained from the semi-structural model and the multivariate filter are easier to communicate as macroprudential policy guides. This permits to exploit their informational advantage and regularly update the whole series with new data in order to identify the current slope of the credit cycle in an informationally efficient manner. By contrast, the one-sided Basel credit-to-GDP guide incorporates the new data only in the most recently estimated value of the gap in order to avoid sizable revisions in previous values.

Table V.1. *Comparison of the trend stability across the alternative estimation approaches*

Estimation Approach	The Semi-Structural Model	The Multivariate Filter	The HP Filter
Root Mean Squared Revision (percentage points)	1.7091	1.9034	2.3087
Improvement over the HP Filter	26.0%	17.6%	---

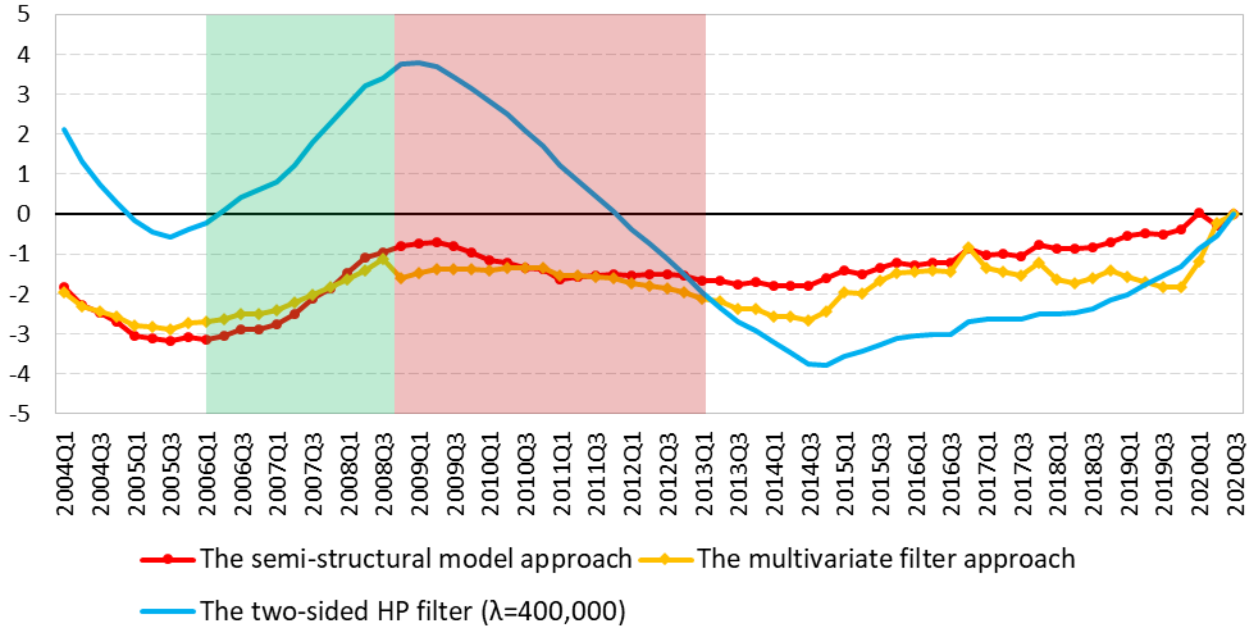
Source: Author's calculations.

In addition to demonstrating a greater trend stability, the semi-structural model and the multivariate filter exhibit revisions that are not affected by the credit cycle. By contrast, the two-sided HP filter revisions are highly correlated to the credit cycle (see Figure V.2). As the figure shows, the two-sided HP filter revisions were increasingly positive during the expansion phase before the GFC (the shaded green area in the figure). Once the cycle turned, the revisions started to decrease and continued so throughout the deflation phase of the cycle (the red shaded area in the figure). This strong and positive correlation between the revisions and credit cycle implies that the two-sided HP filtered credit-to-GDP gaps are highly susceptible to type one errors (understating risky credit expansions in real time), which have a greater welfare cost compared to type two errors (overstating

[15] In this paper, revisions are defined as the difference between the two-sided and one-sided estimates of the same unobserved variable. In essence, revisions show in which direction and by how much real time (one-sided) estimates are adjusted ex-post when they are confronted with new data.

risky credit expansions in real time). By comparison, the gap revisions of the semi-structural model and the multivariate filter are smaller and persistently negative, which makes them more susceptible to type two errors with lower welfare costs.

Figure V.2. Revisions in the alternative estimates of the credit-to-GDP gap (percentage points)



Source: Author's calculations.

To summarize, the proposed alternative credit-to-GDP gap measures can complement the Basel credit-to-GDP gap in guiding macroprudential policy decisions. As these indicators are based on an equilibrium notion of credit and they take into account the macro-financial interactions, they are less susceptible to trend revisions and more informationally efficient. Thus, including these indicators in the analytical toolkit of the macroprudential policy framework will address the shortcomings of the Basel credit-to-GDP gap. They will also provide valuable insights into the credit cycle dynamics by explicitly identifying its driving factors.

VI. Concluding Remarks

The two alternative approaches to credit-to-GDP gap estimation introduced in this paper are designed to enrich the analytical toolkit of the macroprudential policy framework. They can complement the Basel credit-to-GDP gap in guiding the countercyclical capital buffer decisions, which aim to protect the financial sector from losses during the financial stress. The proposed approaches to credit cycle assessment provide an optimal mix of the valuable insights offered by structural models and flexibility of the statistical methods. In addition, they are suited to the country-specific characteristics of a small open economy with a partially dollarized financial system.

As compared to the Basel credit-to-GDP gap, the proposed indicators of the credit cycle emit more reliable early warning signals of the financial stress since they are capable of distinguishing cyclical risky upswings from healthy financial deepening episodes. In addition, they provide valuable insights into the credit cycle dynamics by explicitly identifying its driving factors. The proposed approaches are more informationally efficient and less susceptible to trend revisions. These improvements are achieved by incorporating the equilibrium notions of credit and accounting for relevant macro-financial linkages.

In the current period, the proposed credit-to-GDP gaps indicate the buildup of vulnerabilities in the financial system in the face of increased uncertainty and weak economic activity caused by the COVID-19 pandemic. However, the signals from the semi-structural approach are more alarming compared to the multivariate filter approach. This is because the former takes into account the deterioration in debt-servicing capacity of the economy caused by slower trend growth, while the latter suggests that systemic risks are relatively subdued as real house prices are currently estimated to remain below the trend. In combination, the two approaches offer a more comprehensive image of the current credit cycle dynamics and the likelihood of vulnerabilities building up within the financial sector.

Appendix A. The semi-structural model equations

Real Credit Block

Real Credit Level (100 · log):

$$c_t = \bar{c}_t + \hat{c}_t$$

Real Credit Gap (pp):

$$\hat{c}_t = \theta^{-}\hat{c}_{t-1} + \theta^{y}\hat{y}_{t-1} - \theta^{r}\hat{r}_t + \theta^{s}\widehat{ds}_t + \epsilon_t^{\hat{c}}$$

Real Credit Trend (100 · log):

$$\bar{c}_t = \bar{c}_{t-1} + \frac{1}{4}\Delta\bar{c}_t + \epsilon_t^{\bar{c}}$$

Real Credit Trend Growth (%, Q/Q @ar):

$$\Delta\bar{c}_t = \rho^{\Delta\bar{c}}\Delta\bar{c}_{t-1} + (1-\rho^{\Delta\bar{c}})\Delta\bar{c}_{ss} + \delta(\Delta\bar{y}_t - \Delta\bar{y}_{ss}) + \epsilon_t^{\Delta\bar{c}}$$

Real Output Block

Real Output (100 · log):

$$y_t = \bar{y}_t + \hat{y}_t$$

Real Output Gap (pp):

$$\hat{y}_t = \beta^{-}\hat{y}_{t-1} + \beta^{+}\hat{y}_{t+1} - \beta^{r}\hat{r}_t + \beta^{*}\hat{y}^{*} - \beta^{z}\hat{z}_{t-1} - \beta^{s}\widehat{ds}_t + \beta^{c}\epsilon_t^{\hat{c}} + \epsilon_t^{\hat{y}}$$

Real Output Trend (100 · log):

$$\bar{y}_t = \bar{y}_{t-1} + \frac{1}{4}\Delta\bar{y}_t + \epsilon_t^{\bar{y}}$$

Real Output Trend Growth (%, Q/Q @ar):

$$\Delta\bar{y}_t = \rho^{\Delta\bar{y}}\Delta\bar{y}_{t-1} + (1-\rho^{\Delta\bar{y}})\Delta\bar{y}_{ss} + \epsilon_t^{\Delta\bar{y}}$$

Inflation Block

Headline Inflation (%, Q/Q @ar)

$$\pi_t = \lambda^e \pi_t^e + \lambda^- \pi_{t-1} + \lambda^y \hat{y}_t - \lambda^z (\hat{z}_t - \hat{z}_{t-1}) + \lambda^s \widehat{ds}_t + \epsilon_t^\pi$$

One-Quarter Ahead Headline Inflation Expectation (%, Q/Q @ar):

$$\pi_t^e = \psi^\pi E_t\{\pi_{t+1}\} + (1 - \psi^\pi)\pi_{t-1} + \epsilon_t^{\pi^e}$$

Four-Quarters Ahead Headline Inflation Expectation (%, Y/Y):

$$\pi_t^{e4} = \frac{1}{4}(\pi_t^e + E_t\{\pi_{t+1}^e\} + E_t\{\pi_{t+2}^e\} + E_t\{\pi_{t+3}^e\})$$

Inflation Target (%, Q/Q @ar):

$$\pi_t^T = \rho^{\pi^T} \pi_{t-1}^T + \left(1 - \rho^{\pi^T}\right)\pi_{ss}^T + \epsilon_t^{\pi^T}$$

Four-Quarters Ahead Expected Inflation Target (%, Y/Y):

$$\pi_t^{T4} = \frac{1}{4}(E_t\{\pi_{t+1}^T\} + E_t\{\pi_{t+2}^T\} + E_t\{\pi_{t+3}^T\} + E_t\{\pi_{t+4}^T\})$$

Interest Rates Block

Policy interest Rate (%):

$$i_t = \gamma^- i_{t-1} + (1 - \gamma^-)\left[\bar{r}_t^f + E_t\{\pi_{t+1}^T\} + \gamma^{\pi^T}(\pi_t^{e4} - \pi_t^{T4}) + \gamma^y \hat{y}_t\right] + \epsilon_t^i$$

YTM on One-Year GEO Treasury Bonds (%):

$$i_t^{1Y} = \frac{1}{4}(i_{t-1} + i_t + E_t\{i_{t+1}\} + E_t\{i_{t+2}\}) + TP_t$$

One-Year Term Premium (%):

$$TP_t = \rho^{TP} TP_{t-1} + (1 - \rho^{TP}) TP_{ss} + \epsilon_t^{TP}$$

Risk-free Real Interest Rate (%):

$$r_t^f = i_t + \pi_t^e$$

Risk-free Real Interest Rate Trend (%):

$$\bar{r}_t^f = \rho^{\bar{r}} \bar{r}_{t-1}^f + (1 - \rho^{\bar{r}})\bar{r}_{ss}^f + \epsilon_t^{\bar{r}^f}$$

Market Real Interest Rate (%):

$$r_t = \frac{1}{4}\left(r_{t-1}^{f} + r_t^{f} + E_t\{r_{t+1}^{f}\} + E_t\{r_{t+2}^{f}\}\right) + TP_t$$

Market Real Interest Rate Trend (%):

$$\bar{r}_t = \rho^{\bar{r}}\bar{r}_{t-1} + (1-\rho^{\bar{r}})\left(\bar{r}_{ss}^{f} + TP_{ss}\right) + \epsilon_t^{\bar{r}}$$

Market Real Interest Rate Gap (pp):

$$\hat{r}_t = r_t - \bar{r}_t$$

Exchange Rates Block

Real Effective Exchange Rate Index (100 · log, increase = real appreciation):

$$z_t = \bar{z}_t + \hat{z}_t$$

Real Effective Exchange Rate Trend (100 · log, increase = real appreciation):

$$\bar{z}_t = \bar{z}_{t-1} + \frac{1}{4}\Delta\bar{z}_t + \epsilon_t^{\bar{z}}$$

Real Effective Exchange Rate Trend Appreciation (%, Q/Q @ar):

$$\Delta\bar{z}_t = \rho^{\Delta\bar{z}}\Delta\bar{z}_{t-1} + (1-\rho^{\Delta\bar{z}})\Delta\bar{z}_{ss} + \epsilon_t^{\Delta\bar{z}}$$

Real Effective Exchange Rate Gap (pp):

$$\hat{z}_t = \kappa^{uz}\widehat{uz}_t + \epsilon_t^{\hat{z}}$$

USD/GEL Real Exchange Rate Index (100 · log, increase = real appreciation):

$$uz_t = \overline{uz}_t + \widehat{uz}_t$$

USD/GEL Real Exchange Rate Trend (100 · log, increase = real appreciation):

$$\overline{uz}_t = \overline{uz}_{t-1} + \frac{1}{4}\Delta\overline{uz}_t + \epsilon_t^{\overline{uz}}$$

USD/GEL Real Exchange Rate Trend Appreciation (%, Q/Q @ar):

$$\Delta\overline{uz}_t = \rho^{\Delta\overline{uz}}\Delta\overline{uz}_{t-1} + (1-\rho^{\Delta\overline{uz}})\Delta\overline{uz}_{ss} + \epsilon_t^{\Delta\overline{uz}}$$

USD/GEL Real Exchange Rate Gap (pp):

$$\widehat{uz}_t = \widehat{uz}_t^{e} + \frac{1}{4}(\hat{r}_t - \hat{r}_t^{*} - \widehat{SP}_t) + \epsilon_t^{\widehat{uz}}$$

One-Quarter Ahead USD/GEL Real Exchange Rate Gap Expectation (pp):

$$\widehat{uz}_t^e = \psi^{\widehat{uz}} E_t\{\widehat{uz}_{t+1}\} + \left(1 - \psi^{\widehat{uz}}\right)\widehat{uz}_{t-1} + \epsilon_t^{\widehat{uz}^e}$$

Sovereign Risk Premium (%):

$$SP_t = \rho^{SP} SP_{t-1} + (1 - \rho^{SP})\overline{SP}_t + \epsilon_t^{SP}$$

Sovereign Risk Premium Trend (%):

$$\overline{SP}_t = E_t\{\Delta\overline{uz}_{t+1}\} + (\bar{r}_t - \bar{r}_t^*) + \epsilon_t^{\overline{SP}}$$

Sovereign Risk Premium Gap (pp):

$$\widehat{SP}_t = SP_t - \overline{SP}_t$$

GEL/USD Nominal Exchange Rate Change (%, Q/Q, increase = GEL depreciation):

$$ds_t = \epsilon_t^{ds}$$

Valuation Effect (%):

$$\widehat{ds}_t = \rho^{\widehat{ds}}\widehat{ds}_{t-1} + \left(1 - \rho^{\widehat{ds}}\right)[ds_t - (\pi_t^T - \pi_{ss}^* - \Delta\overline{uz}_t)]$$

External Sector Block

Foreign Demand Gap (pp):

$$\hat{y}_t^* = \rho^{\hat{y}^*}\hat{y}_{t-1}^* + \epsilon_t^{\hat{y}^*}$$

US One-year-ahead Inflation Expectation (%, Y/Y):

$$\pi_t^{e*} = \rho^{\pi^{e*}}\pi_{t-1}^{e*} + \left(1 - \rho^{\pi^{e*}}\right)\pi_{ss}^* + \epsilon_t^{\pi^{e*}}$$

YTM on One-Year US Treasury Bonds (%):

$$i_t^{1Y*} = \rho^{i^{1Y*}} i_{t-1}^{1Y*} + \left(1 - \rho^{i^{1Y*}}\right)(\bar{r}_t^* + \pi_{ss}^*) + \epsilon_t^{i^{1Y*}}$$

US Market Real Interest Rate (%):

$$r_t^* = i_t^{1Y*} + \pi_t^{e*}$$

US Market Real Interest Rate Trend (%):

$$\bar{r}_t^* = \rho^{\bar{r}^*}\bar{r}_{t-1}^* + (1 - \rho^{\bar{r}^*})\bar{r}_{ss}^* + \epsilon_t^{\bar{r}^*}$$

US Market Real Interest Rate Gap (pp):

$$\hat{r}_t^* = r_t^* - \bar{r}_t^*$$

Appendix B. The multivariate filter equations

Real Credit Block

Real Credit Level (100 · log):

$$c_t = \bar{c}_t + \hat{c}_t$$

Real Credit Trend (100 · log):

$$\bar{c}_t = \bar{c}_{t-1} + \frac{1}{4}\Delta\bar{c}_t + \epsilon_t^{\bar{c}}$$

Real Credit Trend Growth (%, Q/Q @ar):

$$\Delta\bar{c}_t = \rho^{\Delta\bar{c}}\Delta\bar{c}_{t-1} + (1 - \rho^{\Delta\bar{c}})\Delta\bar{c}_{ss} + \epsilon_t^{\Delta\bar{c}}$$

Real Credit Gap (pp):

$$\hat{c}_t = \rho^{c}\hat{c}_{t-1} + \beta\hat{y}_{t-1} + f_t + \epsilon_t^{\hat{c}}$$

Common Financial Cycle Component (pp):

$$f_t = \rho^{f} f_{t-1} + \epsilon_t^{f}$$

Real House Price Block

Real House Price Index (100 · log):

$$h_t = \bar{h}_t + \hat{h}_t$$

Real House Price Trend (100 · log):

$$\bar{h}_t = \bar{h}_{t-1} + \frac{1}{4}\Delta\bar{h}_t + \epsilon_t^{\bar{h}}$$

Real House Price Trend Growth (%, Q/Q @ar):

$$\Delta\bar{h}_t = \rho^{\Delta\bar{h}}\Delta\bar{h}_{t-1} + \left(1 - \rho^{\Delta\bar{h}}\right)\Delta\bar{h}_{ss} + \epsilon_t^{\Delta\bar{h}}$$

Real House Price Gap (pp):

$$\hat{h}_t = \rho^{h}\hat{h}_{t-1} + \gamma\hat{y}_{t-1} + f_t + \epsilon_t^{\hat{h}}$$

Real Output Block

Real Output Level ($100 \cdot \log$):

$$y_t = \bar{y}_t + \hat{y}_t$$

Real Output Trend ($100 \cdot \log$):

$$\bar{y}_t = \bar{y}_{t-1} + \frac{1}{4}\Delta\bar{y}_t + \epsilon_t^{\bar{y}}$$

Real Output Trend Growth (%, Q/Q @ar):

$$\Delta\bar{y}_t = \rho^{\Delta\bar{y}}\Delta\bar{y}_{t-1} + (1 - \rho^{\Delta\bar{y}})\Delta\bar{y}_{ss} + \epsilon_t^{\Delta\bar{y}}$$

Real Credit Gap (pp):

$$\hat{y}_t = \rho^y\hat{y}_{t-1} + \alpha f_t + \epsilon_t^{\hat{y}}$$

Appendix C. Data Sources

Variable	Source
Domestic Credit to Private Sector in Georgia	National Bank of Georgia
Foreign Demand Gap for Georgia	National Bank of Georgia (FPAS)
GEL/USD Exchange Rate	National Bank of Georgia
Real Effective Exchange Rate Index in Georgia	National Bank of Georgia
Real Estate Price Index in Georgia	National Bank of Georgia
The National Bank of Georgia Policy Rate	National Bank of Georgia
USD/GEL Real Exchange Rate Index	National Bank of Georgia
YTM on One Year Georgian Treasury Bonds	National Bank of Georgia
Consumer Price Index in Georgia	National Statistics Office of Georgia
Gross Domestic Product in Georgia	National Statistics Office of Georgia
JPMorgan EMBI Global Georgia Sovereign Spread	Bloomberg
US One-year-ahead Inflation Expectations	Federal Reserve Bank of St. Louis
YTM on One Year US Treasury Bonds	Federal Reserve Bank of St. Louis

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