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CREDIT-TO-GDP GAP COMPUTATION UNDER MULTIVARIATE HP FILTER METHODOLOGY: THE CASE OF NORTH MACEDONIA

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Abstract
Unsustainable credit growth can signal systemic financial stress, potentially leading to crises and real-sector losses. The key gauges of over heatedness in the credit markets are the build-up of the credit-to-GDP ratio and its deviation from its long-term trend, the credit-to-GDP gap. When calculating the latter, the major methodological challenge is to develop a model capable of executing the most reliable trend-cycle decomposition. This study employs a multivariate Hodrick-Prescott (MVHP) approach that incorporates economic information in the trend extraction process. Our MVHP estimates suggest that the cyclical credit gap is relatively small in North Macedonia. This means that credit is generally growing close to its trend rate. The two-sided HP filter yields consistent results for the credit-to-GDP gap, while the one-sided version behaves unreliably, especially post-GFC. Given weak theoretical foundations, any gap measure should be viewed as a proxy.

Keywords: early warning indicators, excessive credit growth, financial stability, credit-to-GDP gap, multivariate HP filter, countercyclical capital buffer

JEL classification: E37; E44; E61; G01; G17; G21

INTRODUCTION

Credit booms sow the seeds of crisis (Minsky 1972; Kindleberger 1978). This happens since, when expansion is too fast, lending is driven by fierce competition that invokes reduced risk awareness and places emphasis on excessive credit growth that often results in a level of indebtedness that may exceed the equilibrium defined by underlying macroeconomic fundamentals (Kocsis and Salary 2018). Consequently, leading to a build-up of financial vulnerabilities, which if materialised into a financial crisis can cause recessions twice as costly as normal business cycles downturns (Jordà,Schularick and Taylor2011; Schularick and Taylor 2012). Therefore, is crucial for macro prudential authorities to identify and measure “excessive” credit as precisely and timely as possible, in order to take pre-emptive measures to prevent them, or at least significantly mitigate the economic consequences of such crisis.

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In the empirical literature, there is consensus that the credit-to-GDP ratio serves as a reliable base indicator for gauging the sustainable level of lending activity (Basel Committee on Banking Supervision [BCBS] 2010; Drehmann et al. 2010). Determining the sustainable level of lending is of essential interest for policy makers, since it plays a critical role in the growth of an economy, with lower than equilibrium levels of indebtness resulting in lower growth, while higher levels increasing the risk for financial instabilities. Therefore, the estimation of the equilibrium time-path of credit-to-GDP is of vital importance, serving as a mean for measuring credit-to-GDP gap, which is the deviation from aforementioned equilibrium level. The credit-to-GDP gapthus represents a prime indicator for financial systemic risk, with positive gap values highlighting potential hazards, while negative values indicating slack in the credit markets.

Due to its relatively good statistical accuracy, its stability and interpretability (Drehmann and Tsatsaronis 2014), the credit-to-GDP gap has had a wide adoption as an early warning indicator (Jokipii, Nyffeler, and Riederer 2021) making it an integral part of macro prudential policy (BCBS, 2010). However, despite this there is an ongoing debate on the best measure for the calculation of the credit-to-GDP gap. While a significant number of authors support the stance that the most suitable filtering method is the univariate HP approach, this opinion is not shared by others (Jokipii, Nyffeler, and Riederer 2021). Their critiques mainly focus on two issues: the normalization critique and the HP filter approach of determining the long-run trend component.

Of the two, the voices on the latter have been more vocal, with the end-point bias being the biggest issue for the macro prudential policy makers (Škrinjarić 2020). Moreover, the trend-cycle decomposition in the HP univariate approach is based solely on the time series of the target variable, thus it completes it disregarding any possible exogenous effects, which might affect it (Kocsis and Sallay 2018). These limitations are tackled by the usage of the multivariate approach, which gives us the opportunity to model the linkages between credit gaps and other macroeconomic variables (Baba et al. 2020), thus enabling us to better understand the drivers of the unobserved credit gaps in terms of measurable macroeconomic variables (Andrle 2013). Moreover, the multivariate filter (MVF) approach significantly reduces both the endpoint bias and phase shift, as well as provides trend values that follow the actual data less closely, thus reflecting more stable structural fundamentals. Consequently, providing a more realistic picture of the credit cycle, which can be particularly useful in assisting regulatory activity. The better real-time performance of the multivariate HP filter in comparison to the univariate are documented in the papers of Hosszú, Körmendi, and Mérő (2015) and Borio, Disyatat, and Juselius(2014).

That being said it is important to note that the comparison of different filtering methods is not the focus of the paper. Instead, the primary goal of this study is to develop and offer an optimal application of the multivariate HP method for the case of North Macedonia, which suffers from the common challenges of a transition economy such as short time series, possible structural breaks and limited number of available explanatory variables. Hence, the modelling framework can be of particular interest for researchers in transition economies investigating similar challenges related to trend-cycle decomposition.

The remainder of paper is structured as follows: Section 2 summarises the literature; Section 3 describes the underlying data set and introduces the theoretical background of the Bayesian Model Averaging (BMA) as an application of Bayesian inference to the problems of model selection; Section 4 presents the methodological procedure; Section 5 discusses the resulting filter design, while Section 6 concludes. Further technical details are presented in the Appendix.

1. LITERATURE REVIEW

The international literature has consistently demonstrated the credit-to-GDP gap's early warning properties and has highlighted its status as the single best early warning indicator (EWI) (Jokipii, Nyffeler, and Riederer 2021). This since, the credit-to-GDP gap despite performing well in terms of statistical accuracy fares well on the additional criteria of EWI by providing signals early enough for policy measures to take effect, having stability of indication as well as being easily interpretable (Drehmann and Tsatsaronis 2014). These characteristics made it the best leading indicator of banking crises, both in terms of its performance for a group of countries (Alessi and Detken 2011; Borio and Drehmann 2009; Drehmann et al. 2011) as well as on individual country level (e.g., Denmark: Harmsen 2010; Germany: Deutsche Bundesbank 2012; Portugal: Bonfim and Monteiro 2013; United Kingdom: Giese et al. 2014). Therefore, the Basel Committee for Banking Supervision (BCBS) singled out the credit-to-GDP gap indicator as a useful guide for making countercyclical capital buffer (CCyB) decisions (BCBS 2010).

However, despite its broad acceptance, a large part of the empirical literature has important critiques of the BIS credit-to-GDP gap approach. The first critique is related to the normalization (the division of credit by nominal GDP), which is problematic, since the estimation is made in real time while subsequent statistical revisions of any of the two variables, can considerably affect the gap's quarterly signal (Edge and Meisenzahl 2011). This issue is documented by Canova (1998) and Pedersen (2001), who argue that the addition of new or revised data could change the movement of the long-term trend captured in the HP optimization process, thus creating a difference in the decisions and policy implications, between one period and the other (Alessandri et al. 2015; Farrell 2016; Watson 2007). Secondly, from a data perspective it is important to note that the credit-to-GDP in itself lacks sectoral detail, since it's constructed using a broad credit aggregate. This might conceal imbalances that arise in narrower segments, like the residential mortgage market, potentially leading to broader consequences. Disregarding these developments in specific sectors could also complicate the identification of suitable policy responses for policymakers. Therefore, some studies suggest the presence of a credit gap when employing a more specific credit measure than the BIS credit gap (Kocsis and Salay 2018).

The second corpus of critiques, which is more broadly noted, is in terms of the HP filter approach in estimating the long-run trend component. In this regard, the end-point could be the biggest issue for the macro prudential policy makers (Škrinjarić 2022). This since the end-point of the sample has a strong influence on the estimated underlying trend. In this regard it's important to note that although the BIS credit-to-GDP gap method of calculation using a one-sided (real time) HP filter, partially mitigates the problem arising from two-sided filters which use artificially generated forecast values, it still is affected by the end-point problem (Baba et al. 2020). Another important issue in the HP estimation technique is the sensitivity of the filter to the length of the time series (ECB 2019; Baba et al. 2020; Jokipii, Nyffeler, and Riederer 2021). In this regard, Baba et al. (2020) documents a large difference on the timing and size of the positive credit gaps before the global financial crisis (GFC) depending on the length of time series used. Thirdly, studies have shown that the credit-to-GDP gap is shown to underestimates the cyclical systemic risks. More specifically, after a prolonged boom-bust cycle the BCG may fail to identify cases in which credit has normalized or is starting to become excessive again (Lang and Welz 2017; Lang et al. 2019; Baba et al. 2020). Lastly, but not least is the lack of consensus in terms of the duration of the credit cycle, which in principle should guide the choice of the smoothing parameter (lambda) in the HP filter (Ravn and Uhlig 2002; Baba et al. 2020; Giese et al. 2020). In this regard, although several studies (Aikman, Haldane and Nelson 2015; Claessens, Kose and Terrones 2012; Drehmann et al. 2014) have found that credit cycles have greater amplitude and duration than economic cycles, several authors have argued that cycle duration varies greatly among countries and over time (e.g., Rünstler and Vlekke 2016; Galán 2019).

Several authors being aware of this issue have taken an alternative approach, the multivariate one. A part of this corpus, instead of the HP filter, apply the Kalman filter to the unobserved components models (Harvey 1989; Durbin and Koopman 2012), thus estimating jointly the trend and cyclical components for GDP. While one of the main advantages of the Kalman approach is that although it would spare us from arbitrarily determining the length of the cycle, by deriving it from the data, the lack of structural relationships derived from economic theory, can make it difficult to estimate as more variables are included (Giese et al. 2020). Aside the estimation technique of the trend cycle, the multivariate approach has several advantages over the univariate models. One of the main ones, being the opportunity to model explicitly the linkages between credit gaps and other macroeconomic variables (Baba et al. 2020), thus enabling us to better understand the drivers of the unobserved credit gaps in terms of measurable macroeconomic variables (Andrle 2013). Moreover, the multivariate approach provides more stable estimates of the unobserved components compared to univariate filters (Benes et al., 2010) which is important for policymakers. This is since, the univariate approach analyses solely the time series of the target variable, thus completes the trend-cycle decomposition disregarding any possible exogenous effects, while multivariate methodologies involve explanatory variables selected by criteria based on economic theory (Kocsis and Salay 2018). Lastly, according to Baba et al. (2020), the MVF estimation can be made without prior assumptions regarding the length of the credit cycle, which, as discussed before, could be highly heterogeneous across countries. However, despite these advantages it is important to note, that the MVF has two main shortcomings. First, although it considerably reduces the end-point bias versus the HP filter, it does not resolve it and second, as many other models it presupposes the validity of specific macroeconomic relationships, but these relations require an extensive validation exercises, which demonstrate the sensitivity of the results to the initial parametrization.

Overall, despite the largely documented usefulness of the credit-to-GDP gap (BCPS approach) as an early warning indicator of financial vulnerabilities, the empirical literature emphasizes two important issues, which are necessary to tackle for the formation of better EWI. Firstly, there is a need for a more granular examination of the credit-to-GDP ratio. Analysing the ratio with a narrower segmentation can enhance the identification of financial vulnerabilities and enable the development of more appropriate policy responses. Secondly, it would be beneficial to complement the univariate models by incorporating exogenous variables derived from economic theory, thus potentially helping us provide a more comprehensive picture of the situation. Both of these issues are addressed in our paper, by examining it for the case of North Macedonia.

2. DATA

Explanatory variables involved in our filter design consist of various financial and real economic indicators as well as business and consumer survey data. Finance related variables reflect the behaviour of financial institutions, thus supply side symptoms of emerging systemic risk can be tracked through them. Real economic variables capture effects related to the business cycle. Coupled with business and consumer surveys, these indicators excel at depicting economic effects linked to risk-taking behaviour on the demand side, hence may prove to be good proxies while modelling the cyclical properties of lending. Indicators included in the exercise enter the equations with contemporary and lagged values (lagged by one period primarily). Inclusion of lags incorporates the role of adaptive expectations into the model.

To ensure the appropriateness of subsequent analysis, all time series variables were tested for stationarity using both the KPSS and ADF unit root tests. Prior to regression analysis, all variables were demeaned. This transformation facilitates estimation of the cyclical component by eliminating the constant term from the regression equation, thereby simplifying interpretation and focusing on deviations from the mean. The list of variables as well as the applied transformations are summarized in Table 1 in the Appendix. The overall data set covers the period 2008q3-2020q3[2]. The data is gathered from the National bank of the Republic of North Macedonia, State Statistical Office and European Commission Survey. The main indicator - credit to GDP is calculated as a ratio between the nominal stock of credits and the four-quarter moving sum of nominal GDP.

The interpretation of the coefficients should be performed in light of the fact that the applied methodology explains the cycle with the chosen macroeconomic fundamentals. State-space modelling with the application of the Kalman filter enables the model to estimate both the trend-cycle decomposition and the coefficients of the explanatory variables simultaneously. Another aspect of the interpretation that is worth to behighlighted is that the connection shown in the model results represents correlation and not causality.

Thus, the model depicts the strength and direction of the connection between the cyclical component and the explanatory variables, but does not give an answer to whether the variables cause the cycle development or vice versa.

[2] The sample captures the initial downturn associated with the COVID-19 pandemic. This analysis may be further extended in future studies as the post-pandemic landscape becomes more stable and comprehensible.

Moreover, the candidate variables resonate with the sector-specific developments. The employed sectoral perspective ultimately is supposed to make the process of identification of adequate policy responses less complicated.

Due to the vast number of explanatory variables, we established a criteria to narrow the scope of models that are considered plausible. Namely, we employed the Bayesian Model Averaging (BMA) technique in order to address the fact that inference using a regression model is typically conducted without accounting for variable selection carried out prior to estimating the model. Ignoring the uncertainty associated with variable selection may yield misleading inference. BMA approaches the variable selection problem by averaging quantities of interest over all possible models. BMA estimates the unknown quantities of interest under each competing model (with different sets of explanatory variables), and then computes the weighted average of the quantities.

The BMA approach starts by considering all possible combinations of the available variables, yielding an initial set of certain number of models, reduced by the use of Occam's window. The models encompassed by the Occam's window were used to calculate the BMA estimates of the regression coefficients. Within this setup, the two-sided HP filtered sectoral credit gap served as a dependent variable. The posterior probability of being an indicative variable, given by certain probability was the primary consideration. To this end, posterior probability of 100 per cent resulting from the use of the Occam's window approximation indicates that all the models that were plausible a posteriori contained the corresponding variable. The finally selected variables had posterior probability of over 20 per cent, but also coefficient signs that we would expect on the basis of economic theory.

As we discussed previously in the paper, in order to grasp the idiosyncrasies of the different subsystems of the economy, which may be driven by different factors, segmentation is necessary. In line with this reasoning, we follow the approach of Kocsis and Salay (2018) and Hosszú, Körmendi and Mérő (2015) by dividing the total loans outstanding into two separate segments: household loans and corporate loans. To this end, since the results are greatly dependent on the definition of the underlying data as well as the corresponding driving factor we employ distinct sets of explanatory variables for each segment, which we will further elaborate in the subsequent section.

Consequently, the *household segment* model considers six explanatory variables.

-A change in unemployment rate reflects the demand side, but it is also an indicator of the risk cost development of the household lending. The unemployment rate influences the credit gap through both demand and supply channels. Higher unemployment dampens credit demand by reducing household income, while simultaneously increasing default risk, prompting lenders to raise risk premiums. A positive coefficient is expected, as rising unemployment lowers the sustainable level of lending, while actual credit may adjust more slowly, widening the gap between actual and trend credit levels.

-Changes in average financial system leverage capture credit supply dynamics and signal potential overheating. A positive coefficient is expected, as rising leverage reduces the sustainable level of lending by increasing default risk and prompting tighter credit conditions. To this end, the positive coefficient reflects a lag in credit adjustment, where actual lending remains elevated relative to the declining sustainable level.

-Changes in household loan interest rates capture credit constraints in this key lending segment. A positive coefficient is expected, as higher rates curb sustainable lending by discouraging borrowing and mitigating default risk. Due to gradual adjustment, actual credit levels diverge from the sustainable trend.

-Changes in the banking sector's return on equity (ROAE) reflect supply-side lending conditions. A negative coefficient is expected, as higher profitability strengthens capital buffers and supports increased sustainable lending. However, actual credit may adjust slowly due to regulatory or risk management delays, causing credit growth to lag behind the rising sustainable level.

-The survey indicator on households' financial situation for next 12 months reflects their capacity to sustain debt. A negative coefficient is expected, as improved financial outlook raises the sustainable lending level. However, due to cautious lending practices and regulatory constraints, actual credit adjusts slowly, causing credit growth to lag behind the rising sustainable level.

-The survey indicator of the general economic situation for next 12 months captures household demand and financial expectations. A negative coefficient is expected, as a positive outlook raises sustainable lending. However, slow credit adjustment due to lender risk management causes credit growth to lag behind the rising sustainable level.

The *corporate segment* model considers the following nine indicators:

-The change of the corporate loans' interest rates directly follows the credit constrains in the corporate lending. In this role a positive coefficient is expected. Namely, higher rates signal tighter credit conditions, reducing loan demand and borrowing capacity. A positive coefficient suggests that as interest rates rise, actual borrowing diverges further from the sustainable level.

-The retail trade confidence indicator, reflecting SME expectations on future economic conditions such as sales and market outlook, serves as a proxy for the sector's economic environment. A negative coefficient is expected, as positive sentiment supports a higher sustainable level of corporate lending. However, due to cautious risk management and regulatory constraints, actual credit adjusts gradually, causing lending to lag behind the sustainable trend.

-Similarly, the services confidence indicator reflects the economic outlook for the SME sector. A negative coefficient is expected, as improved expectations support higher sustainable lending. However, actual credit may respond with a delay due to risk management practices and regulatory constraints, causing lending to lag behind the sustainable level.

-The Economic Sentiment Indicator (ESI) captures overall economic optimism among businesses and consumers. A negative coefficient is expected, as improved sentiment raises the sustainable level of lending. However, actual credit may adjust slowly due to lender caution resulting in lending that falls short of the improved outlook.

-The construction industry confidence indicator is a composite survey index reflecting the growth expectations and risk assessment of the businesses in the construction sector. As construction investments pay-off in the long run, this indicator channels in assessment of long-term risks. A negative coefficient is expected for similar reasons as in the case of the above sentiment indicator.

-The industrial confidence indicator is also a composite survey-based index that reflects the expectations and assessments of businesses within the industrial sector. This indicator is designed to capture the mood of industrial sector businesses regarding future economic conditions, growth potential, and overall market performance. Also here, a negative coefficient is expected. The negative coefficient reflects actual lending lagging behind its sustainable potential.

-The ratio of actual to potential production reflects production intensity and credit demand in the corporate sector. A positive coefficient is expected, as higher utilization signals overheating and potential credit overextension. Actual credit may lag the adjustment to a lower sustainable level, leading to a divergence captured by the positive coefficient.

- Industrial production trends provide a short-term proxy for economic activity and GDP growth. Rapid growth may signal overheating, increasing the risk of economic downturns and defaults. As it serves a very similar role as the capacity utilization indicator, also here a positive coefficient is expected.

-As industrial production index plays a very similar role as the indicator mentioned above, here as well, a positive coefficient is expected. Rapid industrial production growth signals potential economic overheating and credit overextension. When production slows, defaults rise, asset prices fall, and financial instability follows, harming long-term economic health. As credit levels may not immediately adjust to the lower sustainable trend, the expected positive coefficient reflects borrowing deviating from the sustainable level.

3. METHODOLOGY

The methodology used in this paper closely follows the approach developed by Kocsis and Salay (2018). In the following paragraphs we offer a brief summary of the adopted methodology.

However, before diving into the multivariate Hodrick-Prescott approach it's important to explain the segmentation aspect of the model, which is one of the more challenging moments in the building process of models tackling financial stability (Kocsis and Salay 2018). That being said, this feature is even more important in the case of loans outstanding, since a narrower definitions of loans may also be a good bank crisis indicator (Detken et al. 2014). Namely, it may be the case that systemic risk build-up does not happen in the same way in different credit markets i.e. a large portion of risks may be concentrated only in a narrower segment, which may be concealed by performing the analysis based on aggregate data. Moreover, this is important in order to grasp the idiosyncrasies of the different subsystems of the economy, which may be driven by different factors. Following these premises, in our paper, we follow the approach of Kocsis and Salay (2018) and Hosszú, Körmendi, and Mérő (2015) by dividing the total loans outstanding into two separate segments: Households and Corporate. Aside the before mentioned aspects, the division of the loans outstanding into these categories is necessary, because development in lending in the two sectors may be very different and it may already entail serious consequences if lending to one of these sectors is inadequate (Hosszú, Körmendi, and Mérő 2015). That being said, this division is also the most granular segmentation level given the data constraint of the available variables used in the two segments. Finally it's important to mention that the split in the modelling process is done in a way that it remains additive. Hence, the separation of household and corporate loans results in two sub models with two segment-level multivariate HP trends.

We choose the multivariate Hodrick-Prescott method over the univariate HP filter estimation, which is recommended by the Basel Committee on Banking Supervision as the most appropriate for the credit-to-GDP trend decomposition, due to two reasons. First, the multivariate filtering enables us to explain the trend in the development of the credit-to-GDP gap while taking into account the changes in the economic environment. The aforementioned aspect is especially important, since it enriches the filtering framework in comparison to the univariate method, whose main advantage is the relatively low data requirement, but which emanates the fact that the univariate method depends solely on the time series of the credit-to-GDP ratio. Second, the univariate method suffers from a phase shift of the trend compared to the observed data as documented in the paper of Kocsis and Salay (2018). More precisely, the authors argue that the estimation output of this method gives the impression that the trend series follows the time path of the actual data with a notable delay. It's important to note, that the phase shift aspect is a well-known attribute of the HP trend (Gyomai and Nilsson 2011; Kocsis and Salay 2018), and is worth counterweighting if one looks for means of enhancing the model efficiency. The multivariate approach is able to significantly reduce the phase shift effect (Kocsis and Salay 2018) and thus increase the model efficiency.

State-space trend cycle model

We cast the model into a state-space form. The approach is similar to the one taken by Kocsis and Salay (2018) and Borio, Disyatat, and Juselius (2014). First, the trend is modelled based on the trend smoothing component taken from HP filter function, rather than modelling it as a random walk. This modelling approach has the advantage that knowledge about the cycle length, either as an observed factor or as an expert opinion, can be accounted for with the smoothing parameter (Kocsis and Salay 2018). In this paper, we follow the empirical literature by filtering the credit-to-GDP ratio with a smoothing parameter (λ) which takes the value of 400,000 (see. European Systemic Risk Board 2014a; Kocsis and Salay 2018). This is equivalent to assuming a credit cycle about four times longer than the business cycle (Ravn and Uhlig 2002; Drehmann and Tsatsaronis 2014; Kocsis and Salay 2018).

Second, in our approach the credit aggregate is not explained by regressors, but instead the credit cycle component, because from a regulatory point of view there is much more information in understanding and modelling the cycle (Kocsis and Salay 2018). However, it is important to note that in comparison to Kocsis and Salay (2018) who follow several criteria (hard and soft) to narrow the scope of models, we instead use the Bayesian Model Averaging (BMA)as variable selection technique. The BMA, as already stressed, accounts for the uncertainty in variable selection by averaging over the best models (see Harrell 2001). On the other hand, the traditional model building strategies can result in biased estimates and overly narrow confidence intervals, among other problems due to the stepwise variable selection process.

It is also important to highlight that the employed methodology provides robust trend estimates in a sense that they do not change notably as the model is re-estimated in future periods. Moreover, effects of included variables should be relatively balanced, meaning deviation from the univariate HP trend values must not be heavily dominated by only one or a few variables. Please refer to the Appendix for more details on the quantitative evaluation of the selected models (Robustness check and Relative importance of explanatory variables).

Below we show the mathematical formulation of the applied methodology. We start with the observation equation, the dependent variable is split into latent components. In our case this means splitting the credit-to-GDP series into unobservable trend (τ_t) and cycle (μ_t) component:

$$\left(\frac{Credit}{GDP}\right)t = \tau_t + \mu_t \qquad (1)$$

The state equation represents the assumed dynamics of these latent components (state variables). Thus, two equations are needed, one for the trend and one for the cycle. The trend equation encompassesthe following three mathematical expressions:

$$\tau_t = 2 * \tau_{t-1} - \tau_{t-2} + \varepsilon_{1,t} \qquad (2)$$

$$\mu_t = \varepsilon_{2,t} \qquad (3)$$

$$\frac{Var(\varepsilon_{1,t})}{Var(\varepsilon_{2,t})} = \frac{1}{\lambda} \qquad (4)$$

The cycle component that is represented solely by the error term $\varepsilon_{2,t}$ in the univariate HP filter, for our (multivariate HP filter) case is estimated through the regression function (5):

$$\mu_t = \varepsilon_{2,t} + \sum_{i=1}^{N} \beta_i X_{it} \qquad (5)$$

whereX_{it} is the value of the variable explaining the cycle component at time t, while β_i is its ceteris paribus effect on μ_i due to a unit change.

Namely, in the presented variant of the multivariate HP filter the explanatory variables enter the state equation of the cycle component. Hence, in this formulation, the trend and cycle dynamics affect each other (through the observation equation and the link between residual variances), so the explanatory variables of the cycle are implicitly affecting the trend as well (Kocsis and Salay 2018).

4. RESULTS AND DISCUSSION

This section presents the segment level models and provides an overview on aggregate results. To this end, the finally selected corporate model places more focus on the production aspect of the corporate segment, gaining additional information from the Economic sentiment indicator and the Assessment of current production capacity in industry as explanatory variables. The finally selected household model on the other hand, uses Average return on equity of the banking sector and Financial system leverage. Financial Stability Indicators (FSIs) are aggregate measures of the current financial health and soundness of the financial institutions in a country and of their corporate and household counterparties.

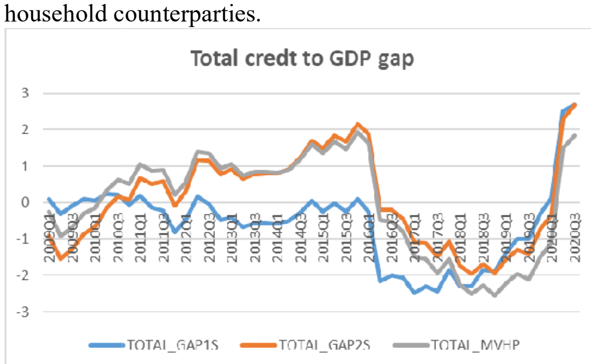

Figure 1. Total credit to GDP gap.

The aggregate credit-to-GDP gap is given by the simple sum of the two segment level sub-models (Figure 1).The results show that the total credit gap estimated with the MVHP filter has on average similar volatility and similar cycle-length to two-sided HP gap.Additionally, we discard the results obtained by the one-sided HP filter as it displays illogical behaviour (it fails to capture the growth momentum in lending after the Global Financial Crisis (GFC)).

In general, when interpreting the results derived from purely mechanical transformations of the original data such as the Hodrick-Prescott filter (Hodrick and Prescott 1997), it makes sense to be circumspect about a problem that is an intrinsic part of the HP filter specification, i.e. about the instability of trend estimations at the end of the data sample. The trend values of the last sample periods can change significantly when the sample is extended with the arrival of new data. The trend also changes if past data are revised ex post.

The multivariate credit-to-GDP gap (Figure 1), shows signs of slightly excessive credit growth from mid-2010 up until 2016q1. In 2016q2 the credit to gdp gap plunges into negative territory and stays there until 2020q1. The closing of the negative gap in the most recent period is slower in the case of the multivariate approach compared to the two-sided HP filter gap simply due to the fact that the multivariate trend is more stable and less exposed to the movements and level of the credit-to-GDP itself[3]. In other words, the effect of the explanatory variables enables the multivariate trend to calibrate the signal of an overheated credit cycle to the macroeconomic environment.

Moreover, corporate credits account for most of the total credit-to-GDP ratio's deviation from its long-term trend (please refer to Figure 2).

[3]In the most recent period which coincides with the immediate aftermath of the Covid-19 outbreak, the credit-to-GDP gap is again slightly above the optimal level, but primarily due to the sharp fall in economic activity during the lockdown.

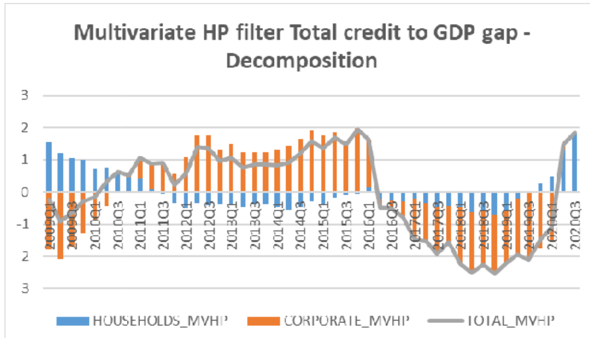

Figure 1. Multivariate HP filter (MVHP) -- Total credit to GDP gap - Decomposition

The corporate credit-to-GDP ratio (Figure 2) shows cyclical movements similar to those observed in the overall credit aggregate. The main reason for this phenomenon is that household credits tend to follow the economic cycle more closely, resulting in a relatively stable credit-to-GDP ratio. Put differently, our estimates point out that the cyclical movements are a more distinctive factuality for corporate loans. On the other hand, household credits as a share of GDP, with brief periods of exceptions, display a trajectory to a large extent consistent with long-term fundamentals.

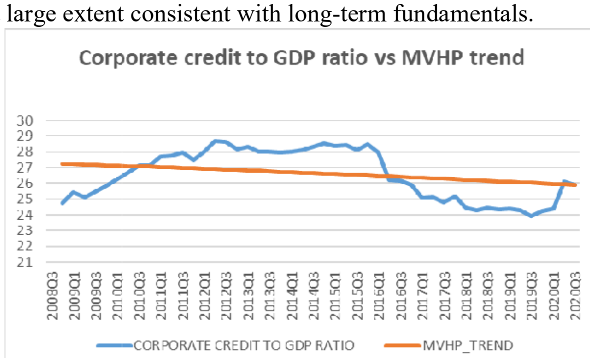

Figure 2. Corporate credit to GDP ratio vs MVHP trend

The growth of nominal GDP has weighed on corporate credit-to-GDP ratio in a prolonged period (Figure 3) starting from 2016 q2. However, since 2019 q4 the credit-to-GDP gap has shown incipient signs of closing, especially in 2020 q2 during the great lockdown, when nominal GDP registered a sharp decline.

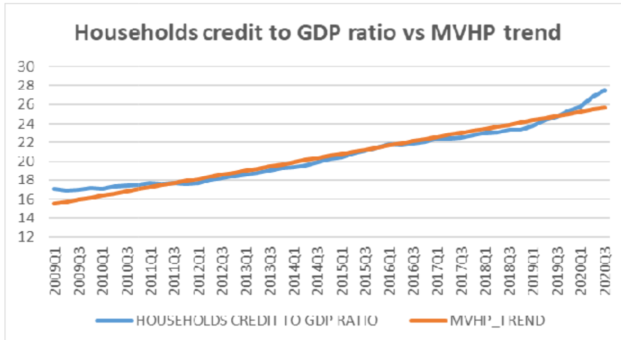

Figure 3. Households credit to GDP ratio vs MVHP trend

On the other hand, household credit-to-GDP ratio stayed rather flat between 2009 q1 and 2011q4 (Figure 4). More visible growth momentum of household credit occurred in the period between 2012q2 and 2020q3. Household credit-to-GDP ratio rose to 27.5 per cent as off end-2020 q3, from 24.8 per cent a year earlier (again, due to the fierce downward correction of nominal GDP during the lockdown).

The historical development of the segments' credit-to-GDP ratio is deeply impacted by the post-transition macroeconomic environment. As the 00s were characterised by high nominal interest rates, household lending in particular, started to build up only after the end of the decade (more visibly from 2012). As a result, the observed households credit-to-GDP ratio starts from a low level, with its coursebeing defined by financial deepening and unbroken growth until the pandemics in 2020. Consequently, one of the biggest challenges in evaluatinga trend-cycle decomposition model is to decide from which point of time should the credit growth be identified as excessive.

4.1. Methodological considerations on the multivariate credit gap

This paper applies a multivariate HP filtering approach to estimate the credit gap by incorporating macro-financial information into the trend-cycle decomposition. Explanatory variables were selected through Bayesian Model Averaging (BMA), using the cyclical component of the univariate two-sided HP filter as the dependent variable. We therefore frame our multivariate approach not as an independent validation of the univariate gap, but as a robustness check and extension. Our goal is to assess how much additional cyclical signal can be extracted by incorporating multiple macro-financial indicators, relative to the standard univariate measure. Put differently, we use the univariate HP-filtered credit gap as our baseline benchmark. The univariate HP filter is widely used in both academic and policy settings due to its simplicity and intuitive interpretation of the credit cycle. Starting from this benchmark allow us to anchor our analysis on a familiar and transparent measure of cyclical fluctuations in credit. To this end, the BMA procedure identifies variables with robust explanatory power across model specifications, offering an empirically grounded alternative to relying on conventional significance tests.

A similar reasoning was adopted by (Hosszú, Körmendi, and Mérő 2015), which argued that standard errors are not a reliable basis for assessing the importance of explanatory variables in this type of filtering framework. Due to the latent and smoothed nature of the trend component, inference based on standard coefficient significance can be misleading. To address this, (Hosszú, Körmendi, and Mérő 2015) introduced an economic significance threshold, requiring that the inclusion of a variable shifts the estimated trend by at least two percentage points across its observed range. This criterion ensures that variables have a meaningful influence on the estimated cycle, even if statistical significance cannot be established in the usual sense.

Consequently, the BMA framework used in this paper plays a similar role. By evaluating explanatory variables across a large number of model combinations, BMA effectively screens out weak or unstable relationships, retaining only those with consistent explanatory value. It offers a more flexible and probabilistically coherent way to impose a relevance threshold, thereby addressing the same concern—how to meaningfully include information in a filter when conventional significance testing falls short.

The priors informed by BMA provide guidance in the multivariate HP filtering process, resulting in a credit gap that remains relatively aligned with the univariate benchmark. While deviations between the two series are generally modest, they tend to persist during certain phases and near the sample endpoints, reflecting the influence of additional macro-financial information. This observed similarity across different model specifications suggests that the multivariate framework enhances the trend extraction by incorporating relevant economic signals without fundamentally altering the underlying credit cycle captured by the univariate filter. Such behavior underscores the complementary role of the multivariate approach in refining, rather than replacing, traditional univariate trend measures.

The resulting credit gap is robust to moderate changes in sample length. Given the filtering framework's purpose and inherent limitations, the emphasis is placed on coherence, plausibility, and robustness rather than statistical inference in the narrow sense. Another important feature of the specification is that the explanatory variables contribute in a balanced way—no single variable dominates the estimation, and their combined influence supports the shape of the trend without introducing distortions. This balance is crucial to avoid over-reliance on individual indicators and ensures that the multivariate filter reflects a broad-based macro-financial context. In this setting, the multivariate approach offers a meaningful enhancement to conventional credit gap estimation by refining the trend in a stable and interpretable manner.

CONCLUSION

Crediting in the banking sector plays an important role in countries, which have built their financial system more on banking rather than capital markets. Regulation authorities naturally increase their efforts to curb the prolonged excessive credit growth in order to minimize the damages that might be created.

However, the credit gap should not be viewed as a purely mechanical benchmark for activation of a CCyB. While an entirely rules-based approach has attractiveness, especially when it comes to dealing with the macro-prudential policy, available indicators and thresholds of excessive credit growth might not fully capture risks due to model uncertainties and estimation errors (Slovak Republic: IMF Selected Issues 2016). It requires a broad assessment of risks from developments in credit markets, private sector leverage, property prices, and the banking sector, as well as assessment of the overall context and the possible need for pre-emptively building capital buffers.

The BCBS proposes to use a one-sided version of the HP filter, where only past and current observations are used to compute the trend at each moment of time. This allows obtaining real time estimations of the gap but limits the ability of the filter to incorporate structural changes in the trend (due to financial deepening for instance - shared specificity for many developing countries) (Galán 2019). As a result, the one-sided version of the HP filtered credit gap, in the case of North Macedonia, yields large negative values in a prolonged period after the GFC which do not reflect properly the position in the financial cycle and the cyclical risk environment.

Our MVHP estimates suggest that credit is generally growing close to its trend rate. Our sectoral estimates point out that the corporate loans display much more pronounced cyclical pattern. On the other hand, household credits as a share of GDP, with short periods of exceptions, closely follow the estimated long-run trend.Univariate specification (i.e. two-sided version of the HP filter) of the credit-to-GDP calculation method do not substantially alter the findings of this study. However, in the absence of clear theoretical foundations, any considered gap measure should be treated only as an informed guess.

Appendix

Visual representation of comparable movement of the GDP gaps of the corporate and household sectors, according to the different estimation methods.

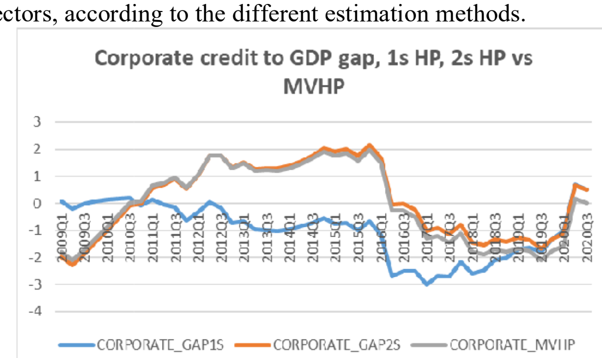

Figure 4. Corporate credit to GDP gap, One-sided HP, Two-sided HP vs MVHP filter

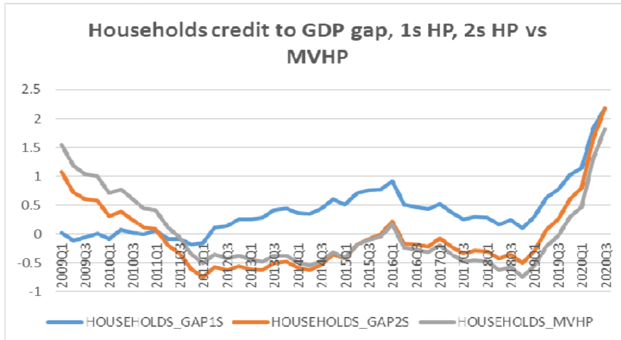

Figure 5. Households credit to GDP gap, One-sided HP, Two-sided HP vs MVHP filter

Robustness check

The out-of-sample robustness test is performed by adding four additional observations to the original time series, so that each of the sub-models are re-estimated four times as if the given observation point was the last element of the series. This is used to measure the effect on the model of adding an additional observation, thus, measuring the end-point bias.

It can be observed on Figure 3 that the corporate segment shows almost no end-point bias at all, while the household segment has weak signs of end-point bias (Figure 4). Overall, models' robustness are assessed as strong, and therefore we consider the results of the out-of-sample test reassuring.

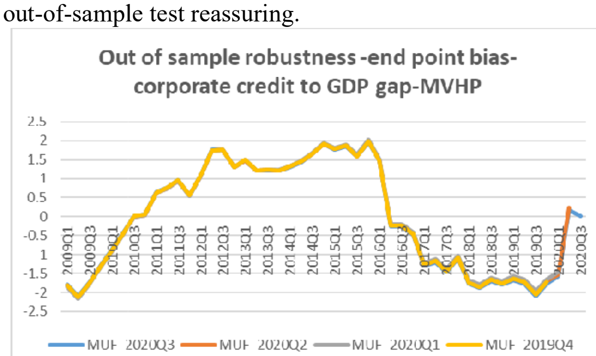

Figure 6. Out of sample robustness -end point bias-corporate credit to GDP gap-MVHP

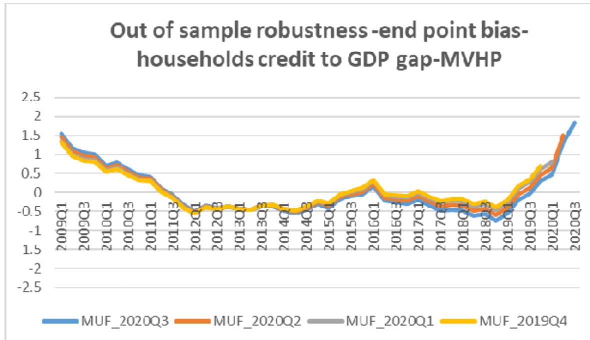

Figure 7. Out of sample robustness check -end point bias-households credit to GDP gap-MVHP

Relative importance of explanatory variables

Figure 5 and Figure 6 show the effect of each distinct explanatory variable so that sum of the values returns the difference between the multivariate and the univariate (two-sided HP filter) trend.

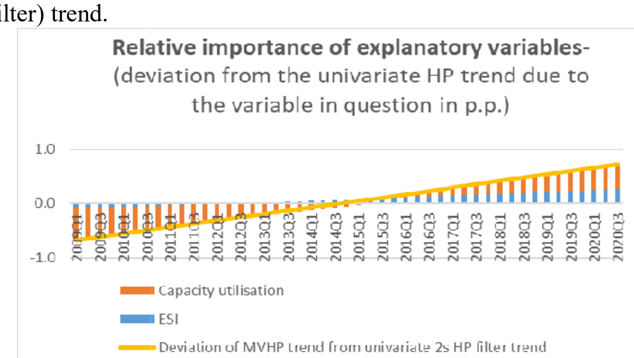

Figure 8. Relative importance of Corporate credit to GDP trend -(deviation from the univariate HP trend due to the variable in question in p.p.)

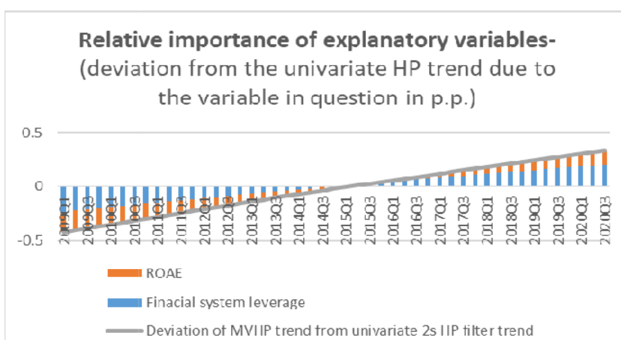

Figure 9. Relative importance of households credit to GDP trend-(deviation from the univariate HP trend due to the variable in question in p.p.)

Here (Figure 5 and Figure 6) the individual effects are highlighted, so that the relative importance, the direction and the economic intuition of the distinct effects can be observed, while the whole figure adds up to the difference between the multivariate and the univariate trends (highlighted by the straight line in the figure). The effect analysis is performed with excluding the examined variable from the model and calculating the effect of the variable as the difference between the two trends[4].

Table 1. Potential explanatory variables, unit root tests and transformations

Variable	ADF	KPSS	Transformation
unemployment rate	NS	NS	logarithmic difference
financial system leverage	S	S	logarithm
housing loans' interest rates	S	NS	logarithmic difference
average return on equity (ROAE) of the banking sector (4 quarters moving average)	NS	NS	first difference
households' financial situation over next 12 months (survey)	NS	NS	-
general economic situation for next 12 months (survey)	S	NS	-
corporate loans' interest rates	NS	NS	logarithmic difference
retail trade confidence indicator (survey)	S	S	-
services confidence indicator (survey)	S	S	-
economic sentiment indicator (ESI) (survey)	S	S	-
construction industry confidence indicator (survey)	S	S	-
industrial confidence indicator (survey)	S	S	-
assessment of current production capacity (survey)	NS	S	-
industrial production trends, past 3 months (survey)	S	S	-
industrial production index	NS	S	logarithmic difference

NS – non-stationary, S – stationary.

Table 2. Selected model for the households'credit-to-GDP gap

Explanatory variables	Coefficients for the cycle component
Financial system leverage (-1)	10.492
ROAE (quarter to quarter change) (-1)	-0.114

Note: All variables were demeaned. This is done so that estimating one additional coefficient (the intercept) is avoided. Percent changes were calculated as logarithmic differences. Negative integers in parentheses indicate lagged values. Coefficients for the cycle component are presented. *** - significant on the 1% level, **-significant on the 5% level.

Table 3. Selected model for the corporate credit-to-GDP gap

Explanatory variables	Coefficients for the cycle component
ESI(-1)	-0.031
Capacity utilisation (-1)	0.030

Note: All variables were demeaned. This is done so that estimating one additional coefficient (the intercept) is avoided. Percent changes were calculated as logarithmic differences. Negative integers in parentheses

[4] Meaning the original trend and the one calculated with the exclusion of the examined variable. For the effect analysis, the other variables enter the model with fixed coefficients, so the resulting difference shows only the real effect of the variable, omitted variable bias plays no role here.

indicate lagged values. Coefficients for the cycle component are presented. *** - significant on the 1% level, **-significant on the 5% level.

All of the coefficients in Table 2 and Table 3 are statistically insignificant at 10% significance level, presumably because of the small sample size relative to the variability in our data.However, the implemented robustness checks give the necessary and sufficient evidence for structural validity of the estimates.

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