▪ Journal of Competitiveness

Credit cycle fluctuations measurement in the context of pandemic shock

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Abstract

This paper proposes and to empirically tests an alternative method of measuring credit cycle fluctuations with a "nominalized" state of the population used as a denominator to the sum of the credit in the economy. It is a response to the often-quoted disadvantage of the baseline approach that estimates the credit gap with HP-filtered credit-to-GDP time, which distorts information on the state of the credit cycle in periods of significant declines in nominal GDP. The COVID-19 pandemic caused an economic shock that created ideal conditions for another practical manifestation of this weakness almost on a global scale. In the proposed alternative method, the cyclical component from the adjusted credit per capita time series is obtained through HP filter, i.e., similarly as in the baseline approach. Although the "credit per capita" approach is not completely new in this research subject, we use some important innovative features, such as quarterly state of population and its "nominalisation" with the use of a GDP deflator. Our empirical results show that the proposed credit per capita approach proved to be more appropriate compared to the baseline credit-to-GDP approach, at least in periods of large swings in economic activity. This feature of the proposed innovative approach can be valuable in the sense of eliminating false signals to countercyclical regulation and assessment of a country´s competitiveness to enhance the credibility and validity of the findings, adding value to the overall research outcome using data reliability validation.

Keywords: *credit cycle, credit gaps, GDP deflator, HP filter*

JEL Classification: E44, G01, E32, E44, E51, G28

Article history: Received: May 2023; Accepted: May 2024; Published: June 2024

1 INTRODUCTION

Questions related to the optimal methodology for measuring the credit cycle came to the forefront of the professional public's interest in the period after the global financial crisis and the debt crisis in the Eurozone (Bräuning et al., 2023). The goal of economists and also financial market supervisors in this area is to identify a suitable indicator of credit market overheating, which is usually followed by a period of bubble deflation, financial instability, and economic recession. Measuring fluctuations in the credit cycle also has other practical applications in the fields of monetary policy, banking supervision and to some extent also in the field of competitiveness, as recent research has shown that credit booms tend to lead to external imbalances and ultimately to a decline in competitiveness, at least in the short term.

This article is based on the latest knowledge in the field of measuring credit cycle fluctuations. It identifies the strengths and weaknesses of the currently most widely used method of measuring fluctuations in the credit cycle, which is the credit gap estimation obtained by application of the Hodrick-Prescott filter (hereinafter referred to as the HP filter) on quarterly time series. This methodology is recommended by the Basel Committee on Banking Supervision, so we will refer to it as the benchmark or baseline approach. The empirical output of the article is an estimation of the credit-to-GDP gap in ten E.U. countries (namely Slovakia, Czechia, Germany, Estonia, Finland, Hungary, Poland, Portugal, Romania and Slovenia) in the period from 2003 to 2021, using the recommended baseline approach as well as an alternative method that uses the nominalized state of the population as a weight for the state of loans instead of nominal GDP. Although for some countries of the sample, data on credit gap obtained from the baseline approach are regularly published by BIS, we needed to calculate the outputs of both approaches from the same data sample (in terms of credit definition and time span) in order to obtain comparable results.

The proposed alternative method is innovative due to two aspects. First, data on population are typically only available annually, which disadvantages the "credit per capita" approach in comparison with the baseline approach, as both credit and GDP data are available on a quarterly basis for most countries. We solve this problem by "nominalizing" annual population data with the quarterly inflation index so we obtain quarterly extrapolations of the "nominalized" population. This feature is important in order to preserve "early warning" ability of the credit gap measure. Second, we use quarterly data for GDP deflator as a representative inflation index, instead of the more commonly used consumer inflation index (CPI / HICP). We prefer the GDP deflator in order to account for inflation of the whole economy and not in the consumer sector only, as is the case with CPI.

When evaluating alternative methods of measuring credit cycle fluctuations (or credit gap estimation), empirical literature focuses primarily on the ability of the compared methods to predict financial instability. However, that was not the purpose of this article. The main goal of this paper is a comparison of credit gap estimates as calculated by the baseline "credit to GDP" approach and proposed alternative "credit per capita" approach. The comparison will be made in longer term as well as in shorter periods of economic shocks. Therefore, in the empirical part of the paper, special emphasis is placed on the output of both mentioned methods of measuring the credit gap during the period of the Covid-19 pandemic (Lau and Gozgor, 2023, Pan et al., 2021), which was perhaps the most significant shock in developed economies in the post-war period. The ultimate goal is to choose one approach that can provide more reliable estimates of credit gap, regardless of the state of the economy.

2 THEORETICAL BACKGROUND

Although the connection between credit booms and subsequent credit crunches, often accompanied by steep recessions, has been well documented (e.g., Alessi & Detken, 2009, De Jong & Sakarya, 2016, Reinhart & Rogoff, 2011, Taylor & Schularick, 2009), the topic of credit cycle returned to scrutiny by economists and policymakers again after the 2008-2009 global financial crisis. Different approaches to defining a credit cycle can be found in the literature (see Nyffeler et al., (2020), Poloni & Sbrana, 2016, Yamada, 2020, 2022).

The definition of a credit cycle (Audretsch & Feldman, 1996) should be the starting point before we dig deeper into more specific aspects of credit cycle measurement. Flamini et al. (2019) provide a relatively technical definition, according to which a credit cycle is a deviation of the ratio of the total credit (or debt) outstanding in the economy to GDP from the long-term trend. Stein (2021) defines a credit cycle more generally through its consequences by emphasizing two sets of stylized facts on the basis of repeated empirical observations. Alessi and Detken (2018) link credit cycle fluctuations to excessive risk taking, which is reflected in the extension of loans to more risky borrowers. Drehman and Yetman (2018) state that phases of excessive credit growth in the economy are an integral part of the financial cycle in the context of a credit cycle. However, they also admit that the definition of "excessive credit growth" is missing. Altman (2020) defines "benign credit cycles" as periods when at least three market conditions are incentivizing major growth in the supply and demand for credit.

To the best of our knowledge, there is no generally accepted definition of a credit cycle in the academic and practical approaches. The available literature mainly focuses on the analysis of empirical data in the sense of the deviation of the development of the total credit from a certain equilibrium state or the long-term trend within the credit cycle issue.

However, it can be concluded that credit cycle (analogously to the economic cycle) means the alternation of different phases of growth dynamics of aggregate credit in the economy: the phase of growth (or acceleration of growth) of aggregate credit is usually followed by a decrease or slowdown in the growth of aggregate credit relative to economic activity, or another reference variable. In practice, credit cycle has a different intensity in different countries and in different periods: from mild cycles, which are not much reflected in the real economy, to 'roller coaster' type cycles (or boom and bust cycles), when rapid growth of credit, replaced by its sharp contraction, translates into more significant fluctuations in economic activity.

Quite surprisingly, researchers have not paid much attention to direct connections between credit cycles and competitiveness. A potential relationship between a credit cycle and / or credit bubbles on one hand and competitiveness on the other hand only received some attention at the time of the investigation into the causes of the debt crisis of the Eurozone periphery. It is fair to say that the search for a direct relationship between credit cycle and competitiveness was not the primary motive of the cited research. It was rather a side effect (Basmar et al., 2022, Campbell et al., 2020, Ćehajić & Košak, 2021, and Iqbal et al., 2023).

In response to the common claim that the crisis was caused primarily by a loss of competitiveness of the Eurozone periphery, Wyplosz (2013) argues that the main cause of the crisis was excessive spending in affected countries. This excessive spending had different causes in different countries including unsustainable credit growth (namely in Ireland and Spain). The decline in competitiveness was rather a consequence of excessive spending. Wyplosz (2013) described the causality as follows: the credit bubble fueled growth and an external deficit while exogenous demand shock (fueled by unsustainable growth of credit) led to growth of relative unit labor cost and therefore a decline in competitiveness. The hypothesis that a credit bubble can first create an external imbalance and then lead to a decline of competitiveness was later supported by empirical evidence provided by Unger (2017) and Comunale (2022).

The benchmark method of measuring fluctuations of the credit cycle

The Hodrick – Prescott filter is a commonly used statistical method for estimating the cyclical component of time series of economic variables (most often the production gap). The basic element of the HP-filter is the assertion that a time series of any economic variable Y_t is the sum of the trend component g_t and the cyclical component c_t.

In practical applications of the HP filter, the value of parameter λ is crucial for obtaining reasonable results, as this parameter is used to find balance between two conflicting goals: a) to minimize changes of the g_t trend component and b) to minimize the differences between Y_t and estimated values of the c_t.

The value of the parameter λ is determined arbitrarily. In the case of quarterly GDP growth data, Hodrick and Prescott suggest a value of $\lambda = 1600$ as the standard deviation of cyclical fluctuations of real GDP is approximately forty times the standard deviation of the potential growth of the economy. Then: $\lambda = (5/0.125)^2 = 1600$.) . This value is also most often used in practice for the analysis of quarterly real GDP data.

However, in the case of an analysis of financial and/or credit cycles, such a value of λ (=1600) may not be satisfactory, as credit and economic cycles may show different characteristics, especially with regard to the average length of individual cycles. In this context, Borio (2014) mentioned the much lower frequency of peaks in the financial cycle compared to the economic cycle as one of the stylized facts of financial cycle research. To adjust the parameter λ, it is possible to use the procedure of Ravn and Uhlig (2002), according to which it is appropriate to adjust the parameter λ by the fourth power - changing the data frequency ratio observation (e.g., if the frequency of data changes from quarterly to monthly, the frequency ratio of observations is three times the original value, and then the parameter λ should be adjusted according to this rule as follows: 34 * 1600 = 129,600. Conversely, in the case of a change from quarterly to annual observations, in the frequency ratio of quarterly observations, the proposed modification of the parameter λ is as follows: (1/4)4*16 = 6.25.).

Based on this rule, Drehman et al. (2010) proposed quarterly data on the credit cycle, as well as an empirical estimation of the average length of the credit cycle in developed economies being three to four times the usual length of the economic cycle (financial crises caused by excessive debt growth occur in advanced economies on average every 20 to 25 years), and set up values of parameter λ as shown in Table no. 1.

Tab. 1 – Indicator of aggregates. Source: Drehman et al. (2010)

Length of credit cycle (in years)	**Multiplication of the economic cycle**	**λ**	**λ (approximation)**
4 - 8	1	1 600	1 600
8 - 16	2	25 600	25 000
12 - 24	3	129 600	125 000
16 - 32	4	409 600	400 000

The HP filter is an often used method of estimating the trend and cyclical component of a time series of economic quantities due to its simplicity and low input data requirements. This calculation also has certain shortcomings associated with the arbitrary determination of the size of parameter λ. This approach is also criticized for defining a purely statistical method using the λ parameter, i.e., cannot capture structural changes in the analyzed time series. Another significant shortcoming is that it mostly produces skewed estimations at the ends of the data sample, due to the setting of the HP filter as a symmetric filter, using a condition based on the sum of individual production gaps being close to zero. The size of the output gap at the end of the monitored period is then adjusted to this condition and can lead to distortion. A precise estimation of the size of the cyclical component of observed time series can thus be obtained only after several quarters.

A natural feature of the HP filter (similar to other estimation techniques of trend and cyclical components of economic variables) is also that the result can be significantly influenced by the length of the investigated time series. Hamilton (2018) lists several serious shortcomings of the HP filter: (1) the product of the HP filter is a time series with spurious dynamic relations that do not have a fundamental basis in the underlying time series; (2) the problematic outputs of the HP filter at the end of the sample (‘end-point problem’); and (3) its practical application is usually contrary to a strictly statistical approach in terms of the size of the used parameter λ.

Grant and Chan (2017) proposed the use of the HP filter when calculating the credit-to-GDP gap. The motivation for their research was the hypothesis that if the ratio of private sector loans to GDP (along with other investigated variables) moves sufficiently above the trend level, then financial imbalances arise, which signals the risk of an upcoming financial crisis. Hall and Thomson (2021) understands the credit gap as a rough measure using financial leverage in the economy, which provides an indication of the loss of absorption capacity of new loans in the financial system. In further research, the credit gap, together with asset prices (mainly real estate), have been shown to be indicators with promising potential for predicting financial crises Lang et al. (2019).

The HP filter is now an established tool for measuring credit cycle, a tool for credit cycle analysis recommended by Repullo and Saurina (2011), while the size and sign of the credit gap are recommended as indicators for the performance of countercyclical regulation of the financial market. According to this recommendation, the credit gap is calculated as the difference between the actual share (status) of credit and nominal GDP and its trend value calculation using the HP filter (with a setting of parameter λ = 400,000). According to the recommendation of the Basel Committee on Banking Supervision (BIS, 2010), credit gap should be able to capture the current state of the credit cycle, while the prognostic ability of this indicator consists in the ability to signal an upcoming extremely adverse occurrence (in the case of an extremely high positive value of the credit gap) correctly. The Basel Committee acknowledges that this 'benchmark' definition of the credit gap may not always work correctly in all countries, so individual jurisdictions' specific conditions and knowledge must be considered. In this context, Flamini et al. (2019) note that estimating the credit-to-GDP gap with use of the HP filter should not be perceived as a trivial task, particularly in developing economies where financial deepening is typically underway and available credit time series tend to be short and/or subject to important structural breaks.

Using the HP filter to measure the size of the credit gap can be considered as a mainstream approach, although criticism of this approach can also be found. Some authors list three reasons why estimation of cyclical gap in real time may differ from final estimation for the general use of the HP filter when measuring cycles of economic variables: (1) the source data used for the cyclical gap of observed variable calculation may be revised over time; (2) a change in originally estimated trend value may be caused by new values of monitored recent variable data when they become available over time; (3) incoming data may cause a revision of used time series model of observed variable (in our case credit-to-GDP value) to estimate trend and cyclical component (Hall & Thomson, 2023, Tercioglu, 2021). In the case of credit gap estimation, the risk of significant inaccuracies in HP filter outputs is largely reduced by the high value of the used parameter (λ = 400,000).

Some authors list, in addition to general issues associated with the application of the HP filter, several potential weaknesses of the 'benchmark' credit gap measurement method:

- Excessive credit vs. financial deepening, when periods with credit growth significantly exceeding GDP growth may reflect 'healthy' growth of financial deepening and not necessarily excessive and risky credit growth. Thus, the estimation of credit gap may signal a growing imbalance in the economy erroneously.

- Countercyclicality, when the credit-to-GDP ratio can develop countercyclically with respect to GDP growth (Repullo & Saurina, 2011). In case of a GDP decrease as a result of a negative shock, the level of loans usually decreases more slowly due to the inertia of the static variable (opposite to the nominal GDP – dynamic variable). This leads to an increase in the value of the credit-to-GDP ratio, and thus naturally also leads to an increase in the value of the credit gap. The positive value of the credit gap can thus be a consequence of not only credit expansion, but also a consequence of a decline in economic activity. In this context, Nyffeler et al. (2020) suggest that signals emerging from a thus-calculated credit gap should be interpreted with caution. This risk association with the application of the HP filter estimation of a credit gap is one of the main motivations for writing this article, since in the empirical part, special attention is focused on changes in the credit gap in the period of the Covid pandemic shock, when there was the sharpest decline in both nominal and real GDP in advanced economies in the period after World War II (Prabheesh et al., 2023, Sukha, 2017, and Liu et al., 2021).

- Periods of strong credit expansion (credit booms) in the past – the recommended benchmark method for estimation of the credit gap shows excessive inertia in countries with strong fluctuations in the credit cycle. In other words, the peak of the credit cycle is captured with a lag, and conversely, the credit gap remains deep in negative territory even after credit aggregates have returned to their 'normal' levels. However, this does not mean, that in times of excessive credit expansion, the credit gap estimate fails to signal a growing imbalance.

- Lack of information on individual sectors – since the credit gap is calculated from a broad credit aggregate, it may not capture growing imbalances in narrower credit segments (e.g., the mortgage loan market or loans from non-financial corporations), which, however, have potential to spread to other segments of the financial market as well as the entire economy (Faias & Torres-Martínez, 2017, Kadiric & Korus, 2019), Tiwary & Paul, 2023).

Despite the listed shortcomings of the HP filter (either in general or directly in relation to credit gap estimation), this approach has its advantages in credit gap estimation. The general benefits of the HP filter include the previously mentioned simple application and low input data requirements. In the specific application of the HP filter to the time series of loan to nominal GDP ratio, relatively quickly available quarterly data is an advantage of this assessment. For example, with an alternative procedure where the credit gap would be calculated from the share of loans to total population (which could theoretically eliminate the risk of the pro-cyclicality of the benchmark method, since the population of the country is normally a much more stable base than nominal GDP), we encounter a problem with the availability of data. Quarterly population figures are not published in most jurisdictions. In contrast, the first estimate of nominal GDP is already available several weeks after the end of the relevant quarter.

Among other statistical methods of credit gap estimation, each has its own advantages and disadvantages. Drehman and Yetman (2018), based on empirical research on the example of data from 42 countries in the period from 1970 to 2017, concluded that none of the five tested alternative credit gap estimation approaches outperformed the benchmark (baseline) credit gap estimation approach through the application of the HP filter to the ratio of the state of loans to nominal GDP.

In literature, it is also possible to come across an opposite solution to the discrepancy between nominal values of the state of loans and real values of population size. Jordá et al. (2017) and Richter et al. (2020), instead of nominalizing the population, revised the state of loans more closely to economic reality, and thus the underlying time series was the share of the state of loans in real terms per inhabitant (real credit per capita).

The nominalization of the population by multiplying it by the inflation index for the purpose of estimating the credit gap was used, for example, by Drehman and Yetman (2018), although they also used the Consumer Price Index (CPI) as a measure of inflation. In this article, a broader indicator of GDP deflator was used instead of CPI, as the state of loans includes not only those for households but also for non-financial corporations. In other words, we use a GDP deflator to account for inflation of the whole economy and not in the consumer sector only, as is the case with CPI. In this context, using the GDP deflator has several advantages over the CPI. The GDP deflator measures not only the change in the price of a fixed basket of goods but also the change in the prices of all goods and services, while the weight of individual items is automatically adjusted. The change in the price of production inputs or investment goods is usually captured in the CPI only indirectly, or with a delay, but for the business sector, it is an important determinant of the need for investment and/or operating loans.

3 RESEARCH GOALS AND METHODOLOGY

This paper proposes and empirically tests an alternative method of measuring credit cycle fluctuations with the nominalized state of the population used as the denominator of the amount of loans in the economy.

Within the framework of fulfilling the main goal, we set three sub-goals. The first partial goal is to, based on published international research, identify key advantages and disadvantages of the current benchmark approach to measuring credit cycle fluctuations. The second partial goal is to propose a new original approach to credit gap estimation that should eliminate at least some of the key shortcomings of the benchmark approach. The third partial goal is the estimation of the credit gap for selected countries with the use of the benchmark method as well as the proposed innovative approach based on the time series of credit per capita. The ultimate research goal is to choose one of the two approaches that can provide more reliable estimates of the credit gap, regardless of the state of the economic cycle or occurrence of exogenous shocks.

Within the empirical part of the research, i.e., when dealing with the second partial goal and the ultimate research goal, we used the HP filter to obtain results both for the benchmark method and the proposed innovative approach. While the benchmark method uses a quarterly credit-to-GDP time series as the input of the HP filter, in the proposed alternative approach, we use quarterly credit per capita data. In order to obtain consistent input data, the population size needs to be nominalized before the use of the HP filter.

Using both methods, the credit gap estimations were calculated from quarterly data for 10 E.U. countries: Germany, the Czech Republic, Estonia, Finland, Hungary, Poland, Portugal, Romania, Slovenia, and Slovakia. We consider the sample representative, as it contains countries with different characteristics: a) so-called core E.U .countries (Finland and Germany); b) Portugal as a proxy for the so-called euro area periphery; c) new E.U. member states inside the euro area (Estonia, Slovakia, and Slovenia); and d) new E.U. member states outside the euro area (Hungary, Poland, and Romania). Obviously, the sample contains bias towards an over-proportional representation of new E.U. member states. The bias is intentional, as new E.U. member states have been undergoing more dynamic changes and, at the same time, especially in prominent research, they are often put aside, so policies and regulations are often simply adopted from more advanced economies.

The observed baseline period was the period from the 1st quarter of 2003 to the 4th quarter of 2021. For some countries, data for the entire observed period was not available due to unavailable data on the balance of loans. Therefore, time series of underlying data for a shorter period were used to estimate the credit gap. Time series were available for Poland and Slovenia beginning in the first quarter of 2004, for Romania beginning in the fourth quarter of 2004, for Slovakia beginning in the first quarter of 2006, and for Estonia beginning in the first quarter of 2008. The data source for nominal GDP was the Eurostat database. Data for the state of loans were taken from the ECB's database from items on the balance sheet of the banking sector (ECB's Monetary Financial Institutions balance sheet statistics). The state of loans in the economy was calculated in a given quarter as the sum of loans from the domestic banking sector to households and the corporate sector, i.e., non-financial corporations. The state of household loans represented the sum of consumer loans (credit for consumption), loans for the purchase of real estate, and other loans (other lending, which refers to loans other than for consumption and house purchase, and includes loans granted to households for business, debt consolidation, educational purposes, etc.).

4 RESULTS AND DISCUSSION

Insights gleaned from the literature, the recommended approach for the HP filter to the loan share of nominal GDP involves calculating a smoothed measure of nominal GDP by summing the values of nominal GDP across the last four quarters in the denominator. To mitigate one-time exceptional variations in inflation and assume a relatively constant population size during regular time (Alessandri & Mumtaz, 2017), a similar smoothing technique was employed for the nominalized population time series. This entailed using an average of GDP deflator values over four quarters to derive the deflator value for nominalizing the population in a given quarter. Subsequently, the loan time series was divided by this smoothed, nominalized measure of the population and input into the HP filter with a smoothing parameter (λ).

In response to the risk of procyclicality of the benchmark method of estimating the credit gap at a time of sharper decline in economic activity, the credit gap was subsequently estimated in an alternative way: time series of ratio of loans to number of inhabitants. This was used as an input into the HP filter (λ = 400,000) instead of the ratio of loans to GDP as per the benchmark method. The reason for this substitution is that a country's population typically shows no signs of cyclicality. Therefore, we formulate a hypothesis that use of a non-cyclical denominator for credit outstanding (such as population size) can provide more reliable estimates of credit gap, regardless of the state of the economic cycle or occurrence of exogenous shocks. The number of inhabitants for individual years of the covered time frame was obtained for individual countries from the Eurostat database. To obtain quarterly time series of the loan-to-population ratio, we faced two obstacles:

a) Data size of population is available in the database only with an annual frequency, always on January 1st.

b) Discrepancy between numerator and denominator of a fraction, when state of loans is a nominal value, while the number of inhabitants is a real value.

These obstacles were eliminated using a) the simplifying assumption of a constant state of population throughout the year, i.e., 1 January values were recorded in other quarters as well, and b) by transforming data on the size of the population into a nominal value through indexation by the GDP deflator. Quarterly values of the GDP deflator (2005 = 100) for individual countries were again obtained from the Eurostat database. Nominalization of the state of population makes perfect sense to us: the base of the state of loans in nominal terms is automatically adjusted for change in the inflation rate. In other words, in times of rapidly rising prices, it is logical that loans used to finance consumption and investments also grow faster, and vice versa in the case of a drop in price level.

The technique utilized by Drehman and Yetman (2018) for estimating the credit gap involved nominalizing the population by multiplying it with the inflation index. While Drehman and Yetman used the CPI as their inflation metric, this study opts for a broader indicator in the form of the GDP deflator. By considering loans from both households and non-financial corporations, the GDP deflator is a more comprehensive measure of inflation across the entire economy, as opposed to the CPI which predominantly reflects consumer sector inflation. The choice of using the GDP deflator over the CPI in this context offers several advantages, including:

- GDP deflator does not measure the change in price of a fixed basket of goods only, but the price change of all goods and services, while the weight of individual items is automatically adjusted.

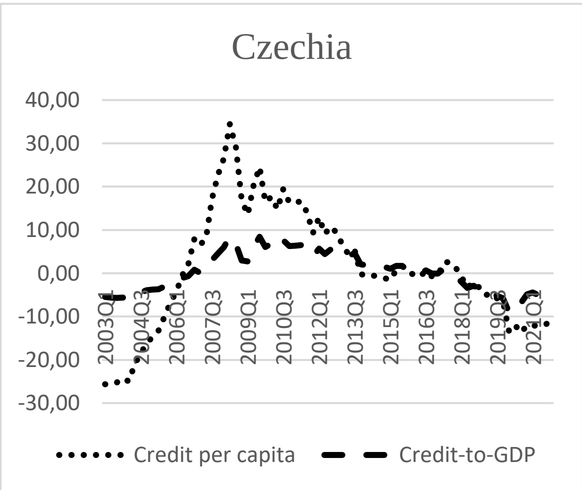
- A change in the price of production inputs or investment goods is usually captured in the CPI only indirectly, or with a delay, but for the business sector it is an important determinant of the need for investment and/or operating loans.

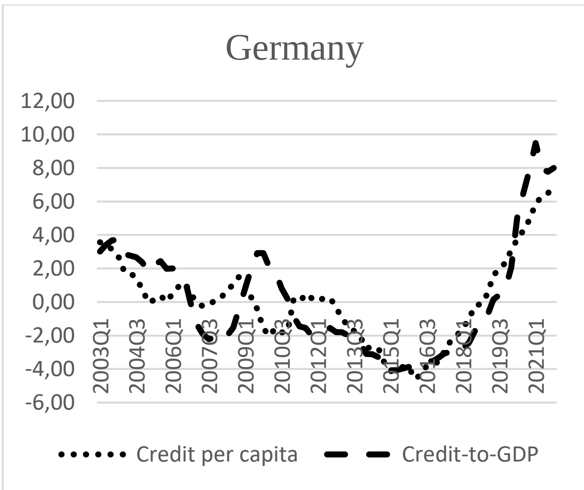
- Within the CPI, household costs associated with housing (input rent, energy, water, and sewage) have a significant weight, i.e., items that are irrelevant for the business sector (e.g., due to the fact that energy and water prices for households are regulated in several E.U. countries), or they enter the prices of the business sector only indirectly.

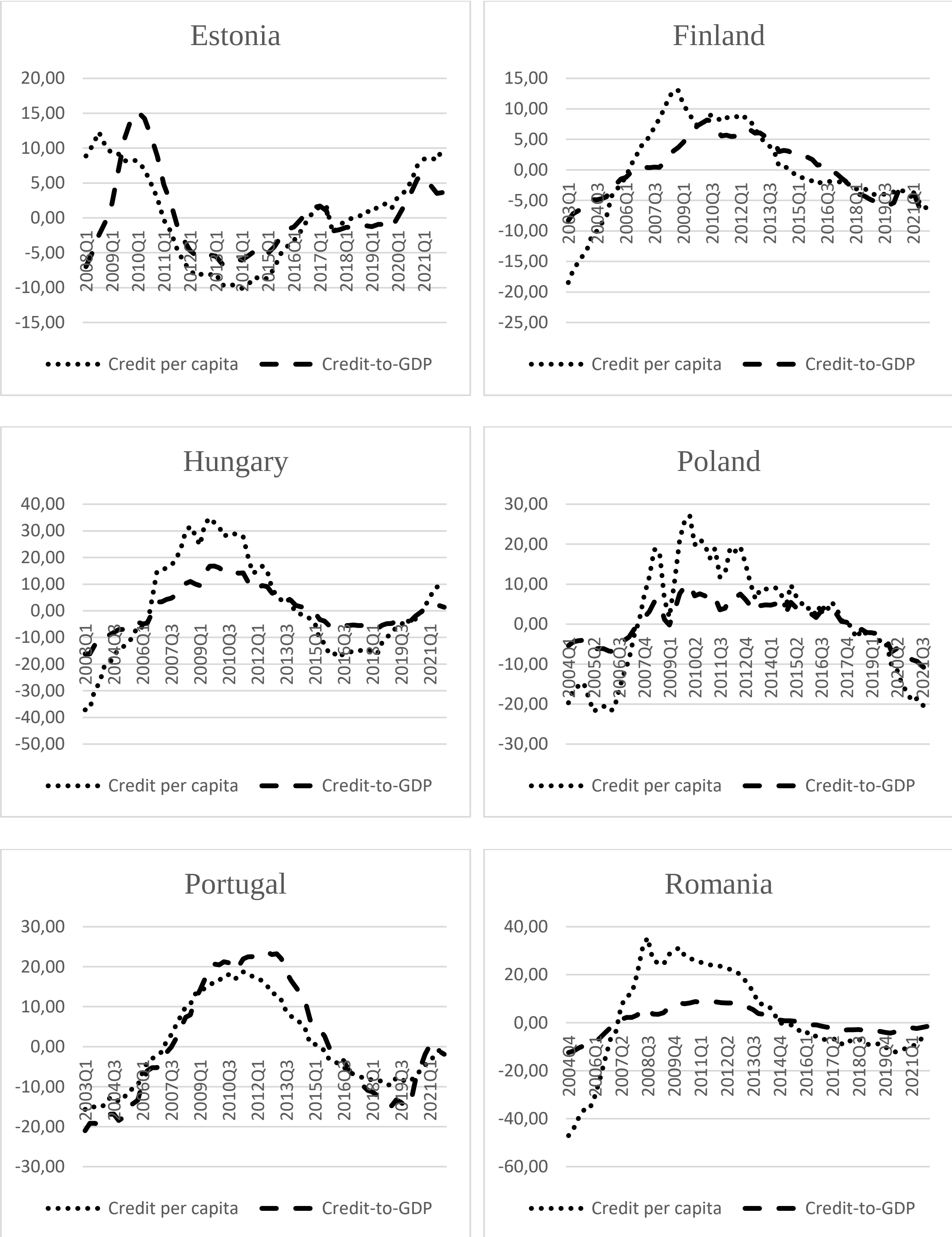
- GDP deflator is an overall broader indicator of inflationary pressures in the economy.

The recommended procedure for applying the HP filter to the share of loans to nominal GDP is that, in the denominator, GDP is calculated as the sum of nominal GDP for the last four quarters. Due to the need to eliminate one-time extraordinary fluctuations in inflation (we assume a relatively stable population size in peacetime), an analogous smoothing of the time series of nominalized population was ensured so that the deflator value used in the nominalization of population in a given quarter (Q_t) (i.e., when indexing the real of the population by inflation) was calculated as a moving average of the GDP deflator values for four quarters: Q_t, Q_{t-1}, Q_{t-2} a Q_{t-3}. The time series of loans was then divided by a nominalized and smoothed proxy of the population and then used as an input into the HP filter (λ = 400,000).

Results of credit gap estimates are presented below in graphic form (given the large number of output data points, in our opinion, the graphical form of the presentation of results is the best choice). An estimation of the credit gap for individual countries for the entire monitored period is presented, using both described approaches: a) benchmark methodology, where the credit gap is calculated from an underlying time series of the share of loans in nominal GDP (in the figures below, the estimate of the credit gap is marked as “credit-to-GDP”) and b) an estimation of the credit gap from the share of loans to a nominalized number of inhabitants (the thus obtained estimate of the credit gap is marked as “credit per capita” in figures). In both cases, the credit gap estimate is presented in a percentage scale.







Estonia
20,00
15,00
10,00
5,00
0,00
-5,00
-10,00
-15,00
Credit per capita
Credit-to-GDP
Finland
15,00
10,00
5,00
0,00
-5,00
-10,00
-15,00
-20,00
-25,00
Credit per capita
Credit-to-GDP
Hungary
40,00
30,00
20,00
10,00
0,00
-10,00
-20,00
-30,00
-40,00
-50,00
Credit per capita
Credit-to-GDP
Poland
30,00
20,00
10,00
0,00
-10,00
-20,00
-30,00
Credit per capita
Credit-to-GDP
Portugal
30,00
20,00
10,00
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-10,00
-20,00
-30,00
Credit per capita
Credit-to-GDP
Romania
40,00
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-40,00
-60,00
Credit per capita
Credit-to-GDP

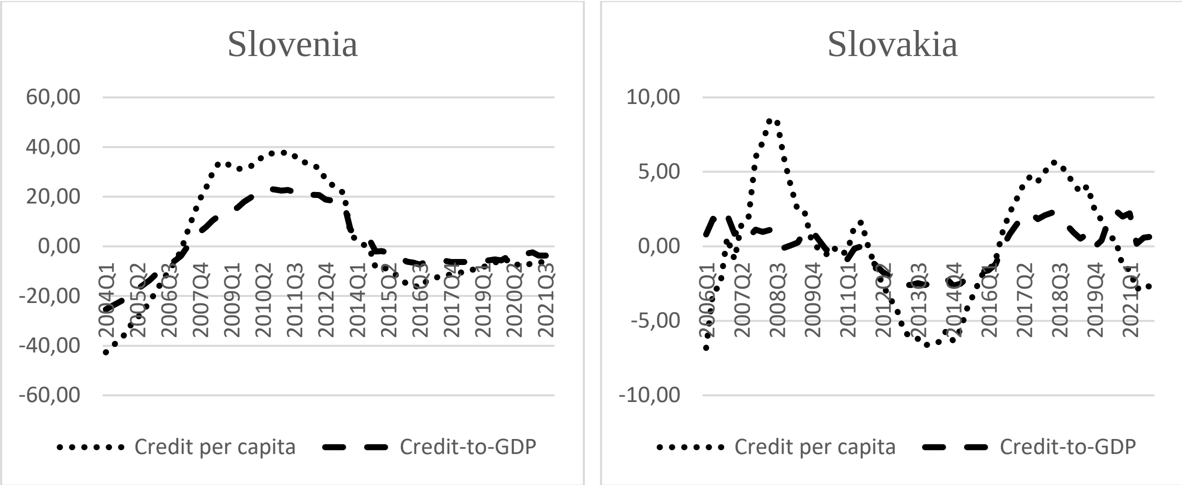


Fig. 1 – Estimated credit gap in individual countries in the monitored period (%). Source: own research

From the presented results, several conclusions emerged:

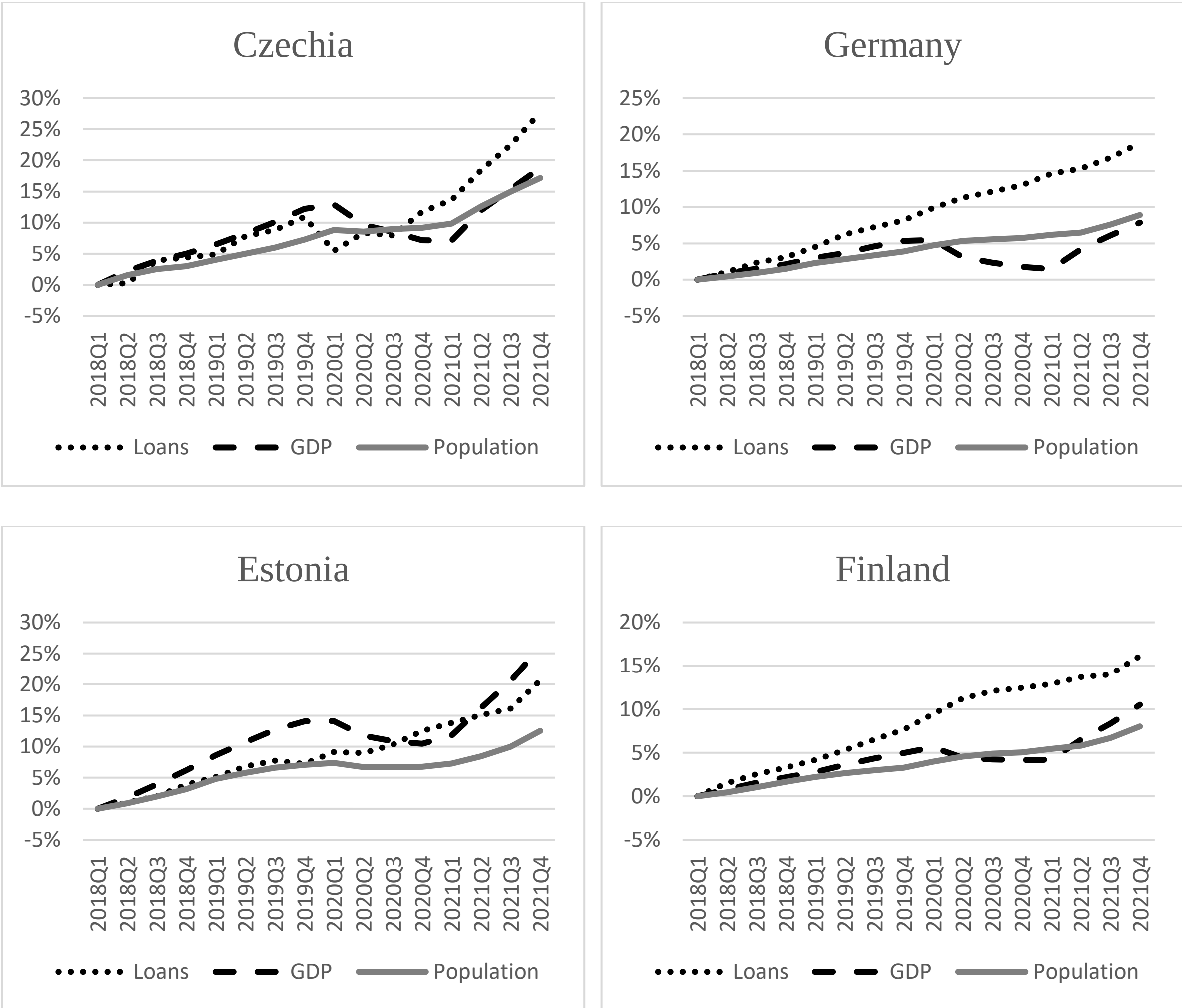
I. The results of both methods are consistent with respect to the sign and relative size of the estimated credit gap.

II. In most countries (with the exception of Germany, Estonia, and Portugal), the estimation of the credit gap from the “credit per capita” data shows a significantly wider dispersion of the resulting data (i.e., more pronounced fluctuations in the credit cycle) compared to the estimation obtained from the “credit-to-GDP” data. In the case of both methods of application defining the regulation of the banking sector, the thresholds of the credit gap would have to be set differently and would require countercyclical stabilization. This fact is due, among other things, to the fact that the presented values of the credit gap are in different units for the values obtained for credit-to-GDP data (indicated in % of GDP) and credit per capita data (indicated in % of trend, as it would be meaningless to indicate in % of the population).

III. The fluctuations of the credit cycle in the monitored period were shown to be extremely mild in Germany and Slovakia, within the selected sample of E.U. countries, as in none of the periods did the estimate of the credit gap in these countries exceed 10% of the trend value. This percent applies to the results of both credit gap estimation methods. Relatively mild fluctuations in the credit cycle were also recorded in Finland and Estonia.

IV. A significant shift (large swing) or change in the direction of the estimated credit gap, was manifested in several countries, especially in the case of the credit gap estimate from the underlying credit-to-GDP time series since the beginning of 2020, i.e., at the time of the onset of the global COVID-19 pandemic. This effect was most noticeable in the estimates for Portugal, Slovakia, Finland, Estonia, and Germany, and to some extent also in the Czech Republic. The reason for such a direction must be sought in changes in the underlying time series: during the pandemic, there was a sharp drop in nominal GDP in most advanced economies. On the contrary, the state of loans was not affected by the pandemic, or only to a limited extent. In this regard, during the pandemic, the disproportion between the outstanding amounts of loans (accumulated over a longer period of time) and the flow of nominal GDP manifested itself. In contrast, the development of the nominalized state of the population proved stable, even during the pandemic. Therefore, the proposed credit per capita approach proved to be a more stable tool when measuring credit cycle fluctuations in times of economic disruptions in the sense of eliminating false signals. Following the discussion in Section 2, this feature of the alternative approach can also be valuable for reducing false threats to competitiveness.

The development of the observed time series during the two years before and after the onset of the pandemic is shown in figure 2. We note that the data in the graph shows the development of the adjusted values of nominal GDP and population as they were used in the estimation of the credit gap, i.e., GDP for the last four quarters and population status nominalized by multiplying by the average value of the GDP deflator for the last four quarters. In summary, the effects of the pandemic on the monitored quantities were even more significant in individual quarters at the beginning of 2020.



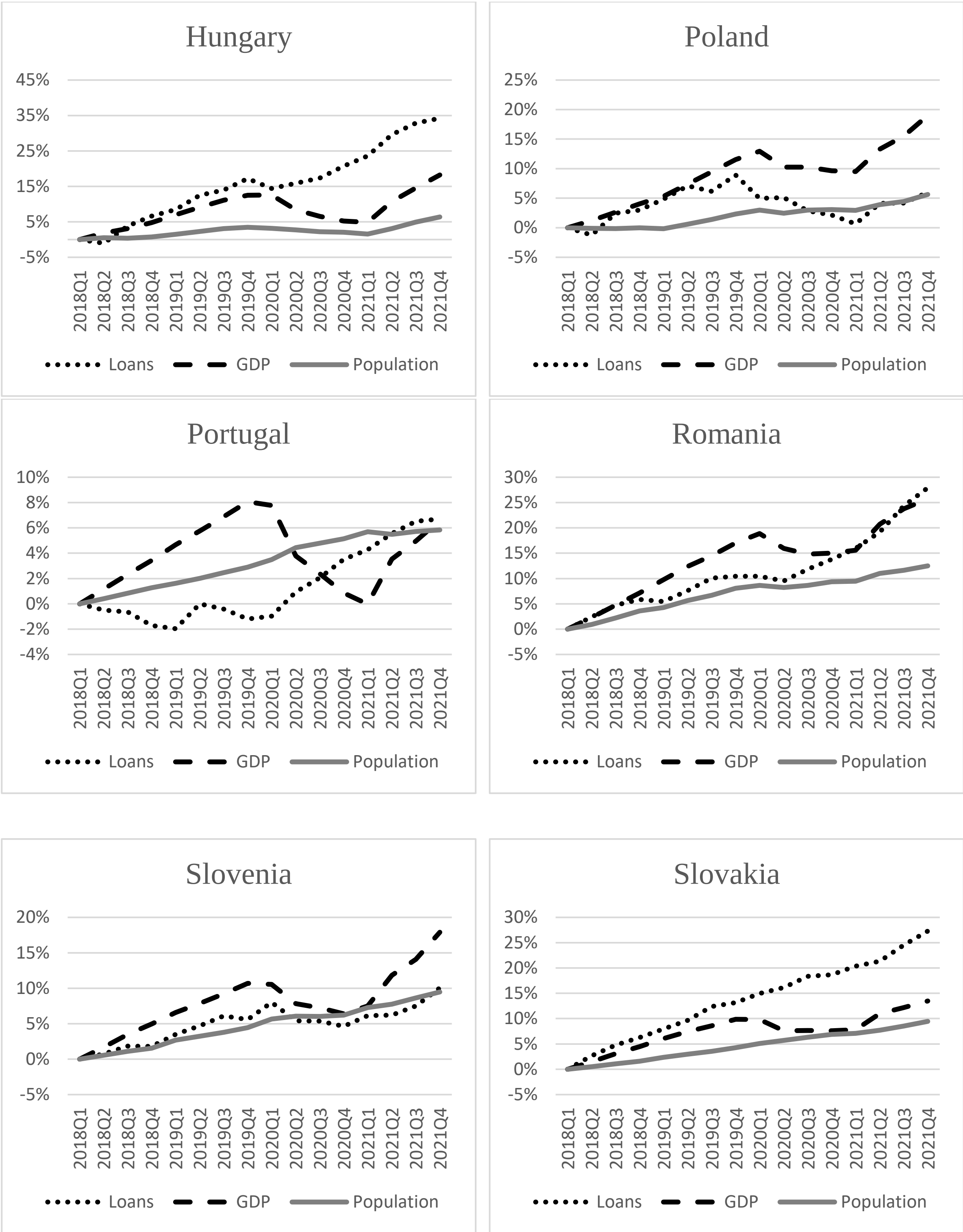


Fig. 2 – Development of the underlying time series of credit gap estimates during the global Covid-19 pandemic: nominal credit stock, nominal seasonally adjusted GDP and nominal population (percentage change compared to the 1st quarter of 2018). Source: own research

The data presented in figure 2 demonstrates that, in all countries, the pandemic had a noticeable negative impact on the sliding value of nominal GDP for four quarters, which is the underlying value for estimating the credit gap from the credit-to-GDP time series. On the contrary, in the case of the alternative weight of the state of loans – the nominalized state of the population –

the fluctuations of this time series were not observed in the monitored countries, or in the case of Hungary, Estonia, and the Czech Republic, a slight fluctuation in the growth trajectory was observed. This fluctuation was most probably caused by slower growth of the GDP deflator at that time.

The development of the time series of the loans outstanding was significantly different in the monitored countries during the pandemic. The increase in the amount of loans outstanding had grown at approximately the same level during the pandemic period as the growth during the previous immediately preceding quarters in Slovakia, Finland, Estonia, and Germany. There was a change from the downward trend of the state of loans outstanding to a growth trajectory in Portugal. The state of loans started to grow again in other states after a short-term decline at the beginning of 2020 (i.e., with the onset of the first wave of the pandemic) in Romania, Hungary, Slovenia, and the Czech Republic. In Poland, the decline in the level of loans after the onset of the pandemic was the most pronounced and the longest among the monitored countries, while the decrease in the level of loans was more pronounced in relative comparison with the decrease in nominal GDP.

5 CONCLUSION

The goal of our study was to propose and empirically test an alternative method of measuring credit cycle fluctuations with the "nominalized" state of the population used as the denominator of the amount of loans in the economy.

Through a comprehensive review of the literature, we have identified several important advantages of the current benchmark method of credit gap estimation through HP-filtering of quarterly credit-to-GDP time series. We have proposed a new original approach to credit gap estimation that should eliminate at least some of the key disadvantages of the benchmark approach. The key advantages of the benchmark approach are its ability to capture the current state of the credit cycle, its solid prognostic ability to signal upcoming adverse scenarios (especially in cases of extremely high positive values of the estimated credit gap), its simple application, low input data requirements, and relatively short delays in the availability of the necessary quarterly data.

In reaction to the benchmark's bias towards producing false "countercyclical" signals, and while fulfilling the second partial goal of the paper, we developed an innovative approach with the quarterly time series of loans divided by a nominalized and smoothed proxy of population as input into the HP filter. We substitute the benchmark credit-to-GDP approach with the credit per capita approach. The ensuing innovative feature of the proposed approach is the use of quarterly proxies of nominalized population size with the use of quarterly GDP deflator data.

We have calculated estimations of the credit gap with both methods for 10 E.U. countries for a 19-year period between the 1st quarter of 2003 and the 4th quarter of 2021. The potential countercyclicality issue of the benchmark method not surprisingly occurred at the end of the monitored period, i.e., during the pandemic, when all ten monitored countries had recorded large negative changes of nominal GDP at the beginning of 2020. The general consequence is a significant shift and/or a change in the sign of the estimated credit gap from the underlying credit-to-GDP time series. This effect, which could produce false signals for macroprudential policies, was manifested most prominently in Portugal, Slovakia, Finland, Estonia, and Germany at the time of the onset of the global COVID-19 pandemic.

In contrast, the development of the nominalized state of the population proved stable, even during the pandemic. Correspondingly, the estimated values of credit gap obtained from extrapolated credit per capita time series did not show any significant impact of the pandemic in all 10 E.U. countries. Therefore, we conclude that credit gap estimation from the credit per capita time series proved to be more appropriate compared to the recommended baseline method, at least from a short-term perspective during times of large swings of economic activity. In other words, the conducted research confirmed the hypothesis that the use of a non-cyclical denominator for credit outstanding (such as population size) can provide more reliable estimates of credit gap, regardless of the state of the economic cycle or occurrence of exogeneous shocks.

Nevertheless, it can be judged that the one-off fluctuations in the baseline credit gap estimation caused by the pandemic shock were probably not of such a scale that would require the intervention of the monetary authority in any of the monitored countries. In addition, international financial market supervisory authorities emphasize that the judgment of the specific circumstances of a particular country is an integral part of the regulatory framework when interpreting the outputs of the baseline approach to credit gap estimation at a given time. It is hard to imagine that the monetary authorities would ignore the one-sided effect of the pandemic when interpreting the output of the credit gap estimation.

The promising results of the proposed alternative approach to credit gap estimation do create opportunities for further research. First, the research sample can be extended to the whole European Union or even to a wider international scale. Second, the research sample can be extended to a longer time series when such consistent data will be available, as we used data from up to 18 years. Third, given that recent research showed that credit booms tend to lead to external imbalances and ultimately to a decline in competitiveness, it would be valuable to conduct further research to compare the tightness of relationships between the estimates of the credit gap obtained by both methods and macroeconomic indicators of competitiveness.

Acknowledgement:
This study was performed with the financial support of the following projects:
VEGA 1/0723/24 the opportunities and risks arising from the growing role of non-bank financial institutions and the acceleration of the dynamics of innovation in the financial system.
APVV-20-0338 Driving forces of economic growth and survival of firms in the sixth K-wave.
VEGA 1/0607/21 Proticyklické nástroje bankovej regulácie v podmienkach eurozóny.

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