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Measuring Credit Gaps: A Restricted Hodrick–Prescott Filter Approach

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Abbreviations and Acronyms

BCBS	Basel Committee on Banking Supervision
BIS	Bank for International Settlements
CBA	Central Bank of the Republic of Armenia
CBR	Central Bank of the Russian Federation
CCyB	countercyclical capital buffer
CJSC	closed joint-stock company
EFSD	Eurasian Fund for Stabilization and Development
GDP	gross domestic product
KR	Kyrgyz Republic
NBKR	National Bank of the Kyrgyz Republic
NBRB	National Bank of the Republic of Belarus
NBRK	National Bank of the Republic of Kazakhstan
NBT	National Bank of Tajikistan
OJSC	open joint-stock company
OLS	ordinary least squares
p. p.	percentage point
RA	Republic of Armenia
RB	Republic of Belarus
RF	Russian Federation
RK	Republic of Kazakhstan
RT	Republic of Tajikistan

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Introduction

The analysis of credit activity trends across different countries raises important questions as to whether the current phase of credit growth can be viewed as expansionary, and which stage of the credit cycle the respective economies are at. The answers to these questions are crucial for monetary and macroprudential authorities, as the timely identification of a phase of excessive credit growth makes it possible to implement proactive remedial measures, mitigating accumulated systemic risks and preventing credit booms that could undermine macrofinancial stability.

Empirical studies suggest that there is a strong correlation between periods of surging credit and subsequent financial crises. In particular, papers by Kaminsky et al. (1998), Kaminsky and Reinhart (1999), Borio and Lowe (2002a), Borio and Lowe (2002b), Alessi and Detken (2011), Jorda et al. (2011), Gourinchas and Obstfeld (2012), Mendoza and Terrones (2012), and Schularick and Taylor (2012) conclusively support the idea that indicators of excessive credit growth help detect early signs of mounting vulnerabilities in the financial system. These studies, which cover a substantial period of history and many countries at various stages of economic development, reveal a strong empirical correlation between extended periods of excessive lending and subsequent banking crises, currency shocks, and deep recessions.

One of the best-known and most widely used early warning indicators is the credit gap, which is defined as the difference between the actual credit-to-GDP ratio and its estimated long-term trend. The credit gap, as defined by Borio and Lowe (2002a) and subsequently formalised in the Basel III framework, serves to identify phases of abnormal credit expansion and quantify the extent to which the financial system deviates from its sustainable equilibrium. It therefore serves as a key analytical tool for identifying the current phase of the credit cycle — expansion or contraction — and for designing a sound macroprudential policy.

Empirical assessments by Borio and Drehmann (2009) and by Drehmann et al. (2010) have played a key role in establishing the credit gap as a vital tool for macroprudential surveillance. Their analysis revealed that, in terms of accuracy and reliability of early warning signals, the credit gap outperforms other potential indicators, such as GDP growth rates, inflation, asset price trends, and macroeconomic imbalances. Its effectiveness was particularly evident in the retrospective assessment of the 2008 global financial crisis: in most of the affected countries, the credit gap had reached abnormally high levels several years prior to the crisis, suggesting that it can identify hidden risks even in a seemingly stable macroeconomic environment.

The function of the credit gap expanded dramatically with the adoption of the new international regulatory framework for bank capital — the Basel III Accord. One of the key new features of this Accord was the introduction of a macroprudential component, which aimed to incentivise banks to build up an additional capital buffer during periods of economic growth to withstand shocks during economic downturns. In this context, the credit gap was formally recognised as a key indicator of the credit cycle phase, guiding the setting of the countercyclical capital buffer add-on used by regulators in their decision-making processes (BCBS, 2010).

Despite its widespread appreciation and acceptance by regulators, the method recommended by the Bank for International Settlements (BIS) for measuring the credit gap — based on the one-sided Hodrick—Prescott filter (HP filter) with a smoothing parameter $\lambda = 400{,}000$ for quarterly data (Hodrick and Prescott, 1997; BCBS, 2010) — has been heavily criticised by the academic community and practitioners alike. This criticism focuses on several key aspects: the statistical properties of the filter itself; its dependence on assumptions regarding the cycle length and the selection of the smoothing parameter; and the practical challenges of applying it in real time (Edge and Meisenzahl, 2011; Drehmann and Tsatsaronis, 2014; Bezborodova and Novopoltsev, 2017; Deryugina and Ponomarenko, 2017; Hamilton, 2018).

The issues raised by researchers regarding credit gap estimation demonstrate a clear shift away from blindly following the standard method of measuring the credit gap, towards its more flexible and meaningful employment. This shift is driven by growing awareness of the limitations of the methodology and the need to adapt it to the unique characteristics of national economies (Galán, 2019; Msiska et al., 2025). Rather than treating the credit gap as a 'universal truth', regulators are increasingly using it as one among many elements of comprehensive risk analysis.

This Working Paper reviews approaches to measuring the credit gap in EFSD member states (Armenia, Belarus, Kazakhstan, Kyrgyzstan, Russia, and Tajikistan) based on univariate HP filters and discusses the key methodological aspects that improve the accuracy and reliability of the resulting estimates.

The paper adopts the approach recommended by the BIS as its basic methodology. This involves measuring the credit gap using the one-sided HP filter. However, given the recognised limitations of this approach, we also estimate the credit gap using the two-sided HP filter. Comparing the results enables us to identify differences in growth of the trend components and assess the effect that the choice of filters has on the credit gap estimate.

The results of this analysis have important practical implications. The two-sided HP filter uses all available information, including future observations, to provide a more accurate retrospective assessment of the trend component. However, when new data are received, the trend for the entire time series is revised. As a result, trend (and thus credit gap) estimates for prior periods — including $t - 1$ and $t - 2$ — can change substantially. Such retrospective adjustments could be inconsistent with earlier decisions made by the regulators. For example, an updated estimate might show that the credit gap has exceeded the threshold for activating the countercyclical capital buffer (CCyB) in a given past period. By contrast, the one-sided HP filter ensures that the trend component calculated at time t remains unchanged in the future, thereby guaranteeing the consistency and reproducibility of regulatory decisions in real time.

As its main contribution, this paper proposes a modified approach to measuring the credit gap, combining the strengths of the one- and two-sided HP filters. In particular, we propose using the one-sided HP filter with a trend component that is subject to linear constraints based on expert assessment of the two-sided HP filter. A criterion based on bootstrap replications has been developed to help decide whether such restrictions are necessary: if the difference between the one- and two-sided HP filter estimates is statistically significant, restrictions are introduced into the one-sided model during periods of deviation.

In addition, the 'end-point' problem is solved by forecasting the credit-to-GDP ratio at least two quarters ahead. The paper proposes using the ARIMA(p, d, q) model supplemented with the procedure of bootstrapping residuals to generate such a forecast. For filtering purposes, the median value from the distribution of bootstrap realisations is used as the point forecast, which improves the robustness of the estimation compared to using the mean value.

To enhance the practical relevance of the work, we propose an algorithm for measuring the credit gap comprising six consecutive steps, from preparing the data and determining the optimal value of parameter λ to applying restricted one- and two-sided HP filters. Evidence-based analysis demonstrates that the our approach produces more balanced and robust estimates of the credit gap for different countries.

Thus, this paper proposes an approach that aims to improve the stability, interpretability, and operational applicability of the credit gap in real time, which is particularly relevant for countries with relatively short and volatile time series — typical of many developing economies.

This Working Paper has the following structure. Section 1 offers a literature review focusing on the research topic. Section 2 discusses the methodology and features of the one- and two-sided HP filters, as well as the approach used to determine the optimal value of smoothing parameter λ. Section 3 provides a detailed, step-by-step algorithm for measuring the credit gap, illustrated with examples based on real data. Section 4 presents the credit gap estimation results for the six countries under review. The Conclusion summarises the key findings and recommendations.

1. Literature Review

Over the past two decades, the credit gap has evolved from an academic concept into a key element of modern macroprudential policy. Its inclusion in the recommendations of the Basel Committee on Banking Supervision (BCBS, 2010) as a key CCyB activation benchmark has given it regulatory status and led to its widespread practical application. However, both the need to measure the credit gap and the methodology for calculating it remain subjects of active discussion in academic literature.

The concept of a credit gap has a strong historical and theoretical basis. It is largely based on studies by Minsky (1972), Kindleberger (1978), and Minsky (1986) which describe cycles of financial distress, starting with a relatively safe period and moving into a phase of 'lending mania', where borrowers and lenders alike tend to ignore risks, before ending in collapse. The paper by Bernanke et al. (1998) on the 'financial accelerator' is an important step towards formalising the concept of how fluctuations in financial markets can amplify economic cycles.

Follow-up studies confirmed the importance of monitoring credit activity. In particular, Kaminsky and Reinhart (1999) and Kaminsky et al. (1998) showed that indicators related to credit growth and asset prices are the most reliable precursors of banking crises. In their extensive analysis of historical data for 14 economies between 1870 and 2008, Schularick and Taylor (2012) show that most severe banking crises are preceded by a rapid increase in credit to the private sector — in other words, a credit boom is a key precursor to future financial turmoil.

Borio and Lowe (2002a, 2002b) proposed an empirical embodiment of the credit gap idea, providing strong evidence of a systematic link between excessive credit growth, particularly when it is not aligned with GDP growth, and subsequent banking crises. Their approach, which involves filtering the credit-to-GDP trend, has helped quantify the extent to which credit activity has deviated from the 'norm'.

The papers by Borio and Drehmann (2009), Drehmann et al. (2010), Alessi and Detken (2011), and Borio and Tsatsaronis (2014) have reinforced the position of the credit gap as a key tool for monitoring credit cycle phases and evaluating accumulated imbalances. Using a large historical dataset, Borio and Drehmann (2009) and Alessi and Detken (2011) argue that prolonged deviations in credit and asset prices from their trend serve as an effective warning indicator of banking crises. Monitoring of global liquidity and credit gaps is the key to early warning of financial shocks.

Drehmann et al. (2010) addressed key aspects of CCyB formation, focusing on the choice of input variables determining capital accumulation and release during different credit cycle phases. The study concludes that, when considering individual banks, bank-specific variables can play a role; however, analyses of the entire banking system should be based on aggregate indicators that reflect the state of the entire financial sector. Notably, the credit gap is considered the most informative indicator of the buffer accumulation phase: it accurately reflects phases of excessive lending and facilitates the introduction of additional bank capital requirements in a timely manner.

Borio and Tsatsaronis (2014) summarise the key issues and criticisms surrounding the use of the credit gap as an indicator for CCyB formation. The authors explain that the purpose of the buffer is to minimise losses resulting from credit cycles, rather than to stabilise economic growth. It is found that the credit gap is better at identifying both the accumulation and the release of systemic stress in the banking sector than other methods. Using data from OECD countries, the authors confirm that the credit gap has a high predictive power when it comes to the timely detection of crisis build-up.

Although the importance of using the credit gap as an early indicator of imbalances or crises has been empirically validated, the methodology for calculating the credit gap recommended by the BIS and underpinning the Basel III framework has been criticised. This criticism focuses on three key areas: the statistical properties of the one-sided HP filter; its dependence on assumptions about the cycle length and the choice of the smoothing parameter[1]; and the practical problems associated with its real-time application.

For example, Hamilton (2018) critically notes that the HP filter is not a statistically valid tool for decomposing a time series into the trend and the cycle components, as it is purely a mathematical optimisation procedure. As a result, the filter may produce artificial fluctuations in trend estimates that do not accurately reflect genuine underlying economic processes. To defend the credit gap estimation method recommended in BCBS (2010), Drehmann and Yetman (2020) conducted a comparative analysis using data from 41 countries. They compared the results of the HP filter with those of the alternative, linear regression-based approach proposed by Hamilton (2018). Their study concluded that the one-sided HP filter, despite its limitations, remains the most informative and practical tool for macroprudential regulatory purposes, outperforming other methods.

Another important limitation of the HP filter — which researchers have repeatedly emphasised, and which is particularly relevant for developing economies with short time series — is the problem of the start and the end points (Hamilton, 2018). As the one-sided HP filter only uses past and current data to estimate the trend at the end of the time series, its estimates at this point are extremely sensitive to the arrival of new observations. Consequently, real-time estimates of the credit gap are subject to constant revisions as data updates are incorporated, which makes it significantly more difficult to interpret and apply them reliably in real-time macroprudential decision-making (Deryugina et al., 2020; Hosszú et al., 2015).

Given the criticism of the HP filter, a number of researchers have proposed alternative approaches to measuring the credit gap, in particular, models that explain credit-to-GDP through their relationship with fundamental macroeconomic variables. This approach involves estimating a regression model in which the dependent variable is the observed level of credit, and the explanatory variables are the long-term fundamental determinants (e.g. potential GDP, real interest rates, property prices). The residuals of this regression are interpreted as an estimate of the credit gap — the difference between actual credit and its ‘natural’ level, which is determined by the structure of the economy.

In particular, Galán and Mencia (2018) use a vector error correction model, with real credit to the private sector as the dependent variable and real GDP, the long-term real interest rate, and the real price of residential property as the explanatory variables. Similarly, Lang and Welz (2017) estimated a regression model for the credit gap in the household sector, using the real volume of credit to households as the dependent variable and potential output, potential

[1] According to BCBS (2010), it is recommended that the smoothing parameter $\lambda = 400{,}000$ be used.

output per capita (as a proxy for institutional quality), the real interest rate, and demographics as explanatory variables. It should be noted that the structural approach to measuring the credit gap also has significant limitations. In particular, regression residuals can be sensitive to model specification, sample length, and parameter estimation algorithms, leading to credit gap estimates that are neither robust nor reliable.

The most significant limitation of the HP filter is making assumptions about the length of the credit cycle. The BIS recommends using smoothing parameter $\lambda = 400{,}000$ for quarterly data, assuming that the average credit cycle length is around 30 years (BCBS, 2010; Galán, 2019). However, empirical studies show that this assumption is not always true. Although different studies provide different estimates, they all agree that the cycle is much shorter. For example, analyses of data from Spain showed an average cycle length of 15–17 years (Bedayo et al., 2018; Galán, 2019), from South Africa of 11 years (Msiska et al., 2025), and from 40 European countries of 5–8 years for credit to return to equilibrium (Baba et al., 2020).

Bezborodova and Novopoltsev (2017) also find that the length of the credit cycle varies across the countries under review. Using frequency analysis, the researchers found that, like the business cycle, the length of the credit cycle in Belarus is around 40 quarters. Based on their analysis of the definition of cycle length and filtering approaches, the authors suggested using the two-sided HP filter and smoothing parameter $\lambda = 1{,}600$ to estimate the credit gap.

Therefore, one of the main criticisms (BCBS, 2010) is that using the HP filter with an overly large smoothing parameter renders it too inert. As a result, the credit gap remains negative after a crisis hits and lending drops sharply, which can mislead regulators into thinking that there are no risks when there may well be (Galán, 2019). This limitation is directly related to the practical relevance of the indicator. If the regulator relies on the assumption that the gap will return to zero within 20–30 years, it will lead to an underestimation of the need to introduce CCyB for many years following the crisis. In addition, there is a problem of reliability of the estimates, which depends on the length of the time series. Short time series do not allow for stable and robust trend estimation, further exacerbating problems with end points and the interpretation of results.

One of the most important yet frequently overlooked methodological issues in measuring the credit gap is the indicator's reliance on the quality and consistency of the input macroeconomic data, primarily the time series of credit supply and nominal GDP. Both of these components are subject to frequent, and sometimes substantial, real-time data revisions, which directly affect the estimated gap, particularly with regard to recent observations used by regulators for real-time decision-making (Edge and Meisenzahl, 2011). Due to the inherent uncertainty of macroeconomic data, recent literature emphasises the importance of integrating estimation procedures and accounting for potential errors arising from revisions to the input data (Galvão and Mitchell, 2023).

The practical application of the credit gap in regulatory policy is also evolving. Regulators seek to conduct in-depth analyses based on both the numerical value of the credit gap and a set of supporting indicators which describe the state of the economy and financial sector. This problem was particularly acute during and after the COVID-19 pandemic. For example, in South Africa, the preliminary estimate of the decline in GDP was around 50% year-on-year in Q2 2020. This resulted in a steep increase in the credit-to-GDP ratio, despite the volume of credit remaining virtually unchanged. Consequently, the credit gap indicated a false surge in credit expansion while the real sector was actually collapsing (Msiska et al., 2025). Such distortions can mislead regulators, causing them to make erroneous decisions — for instance, enforcing overly stringent macroprudential regulations at a time when the economy needs support. In this regard, the Bank of England recommends that the credit gap be used not as a trigger, but rather as part of a broader risk assessment framework supplemented by assessments based on alternative sources and expert judgement (Bank of England, 2015).

Therefore, the credit gap is more than just a quantitative indicator; it is an integral element of a system designed for early detection of macro-financial imbalances. Modern research increasingly emphasises the need to adapt the unified methodology set out in the BIS recommendations flexibly, depending on national specifics such as the structure of the financial system, the duration of credit cycles, and the quality and robustness of macroeconomic statistics. This approach reduces distortions associated with the 'end-point' problem, data revisions, and mismatches between the assumed and the actual cycle lengths, resulting in more stable, robust, and economically interpretable estimates.

2. Hodrick—Prescott Filter

There are two versions of the HP filter: one-sided and two-sided (Wolf et al., 2020). Since elements of the two-sided version form the basis of the one-sided filter, it is reasonable to start exploring the HP filter with the former version.

Two-Sided HP Filter

Let y_t stand for the time series under study (credit-to-GDP ratio). Our hypothesis is that y_t can be decomposed into g_t (the trend component, or the trend) and c_t (the cycle component).

$$y_t = g_t + c_t. \tag{1}$$

Hodrick and Prescott (1997) propose that g_t should be obtained by solving the following optimisation problem:

$$\min_{\{g_t\}_{t=1}^{T}} \left[\sum_{t=1}^{T} (y_t - g_t)^2 + \lambda \sum_{t=2}^{T-1} \left[(g_{t+1} - g_t) - (g_t - g_{t-1}) \right]^2 \right]. \tag{2}$$

The algorithm for estimating g_t based on minimising (2) is detailed in Annex A.

The solution to optimisation problem (2) in matrix form is as follows:

$$\hat{g} = (I + \lambda F)^{-1} y, \tag{3}$$

where $y, \hat{g}$ are vectors of size $(T \times 1)$,
I, F are matrices of size $(T \times T)$.

Determination of the Optimal Value of Parameter λ for the HP Filter

In the HP filter, parameter λ is important as it determines the balance between smoothing the trend (g_t) and the accuracy of its fit to the input data:

- with $\lambda \to \infty$ the filter produces a strictly linear trend (g_t),
- with $\lambda \to 0$ component g_t will exactly replicate the dynamics of y_t.

Since the optimal value of λ depends on the nature of the data and the problem to be solved, it is important to find methods for determining it. For example, Hodrick and Prescott (1997) recommend to use a standardised value of $\lambda = 1{,}600$ for quarterly data.

One approach to optimising λ is based on time series spectral density analysis (Pedersen, 2001). Annex B provides a brief explanation of the spectral density function.

In practice, however, it is common to use a sample periodogram (see Annex B for details) estimated for different frequencies w_j $(j = 1, 2, \ldots, T)$ instead of the spectral density function. For example, with $j = 1$, it is assumed that there is one complete cycle[2] in the time series over entire period T, then the value of frequency w_j is a relatively small number. If $j = 2$, then two complete cycles are observed for entire period T, etc. Based on this, we can infer that (Hamilton, 1994):

$$\frac{T}{j} = \frac{2\pi}{w_j} \Rightarrow w_j = \frac{2\pi j}{T}. \tag{4}$$

The values of w_j calculated in this way are used in the formula for sample periodogram $\hat{s}_Y(w)$ from Annex B. The higher the estimated value of the periodogram, the more important the periodic fluctuations corresponding to this frequency w_j are for explaining the volatility of the input series.

To avoid an overly large effect of the trend component on the variance, it is suggested that the effect of the trend be eliminated before starting the analysis of the sample periodogram of the indicator in question (Hamilton, 1994). In practice, the following procedure is used for this purpose:

$$x_t = (log(y_t) - log\,(y_{t-4})) \times 100. \tag{5}$$

Pedersen (2001) suggests using the power transfer function (Annex B) to construct a criterion for calculating the optimal value of λ. To this end, the power transfer functions of the ideal and the HP filters are compared[3].

The power transfer function for an ideal low- and high-frequency band-pass filter can be presented as follows (Pedersen, 2001):

$$H^*_{lp} = \begin{cases} 1, & \text{if } |w| < w_l \\ 0, & \text{if } |w| \geq w_l \end{cases}, \tag{6}$$

$$H^*_{hp} = \begin{cases} 0, & \text{if } |w| < w_h \\ 1, & \text{if } |w| \geq w_h \end{cases}, \tag{7}$$

where H^*_{lp}, H^*_{hp} are the power transfer functions for the low- and the high-frequency band-pass filter, respectively (an illustration of the power transfer function is presented in Figure 1).

It should be noted that the difference between the ideal filter and the optimal filter is that the latter is merely an approximation of the former. This is due to the fact that it is impossible to construct a perfect filter using finite time series data. The HP filter is one such approximation of the ideal filter.

Let us present the power transfer function of the HP filter as follows (King and Rebelo, 1993):

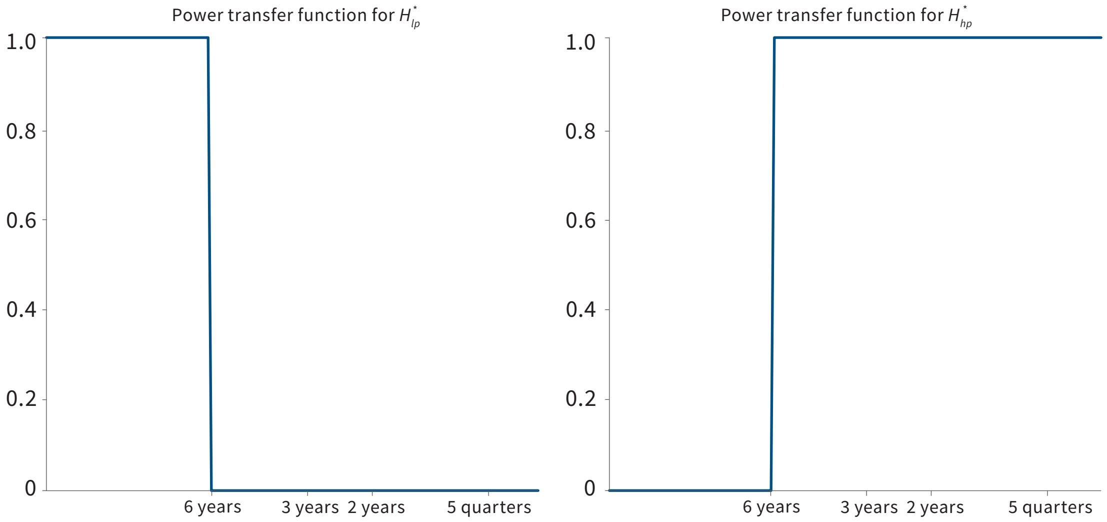
$$H_{HP}(w) = \left| \frac{4\lambda(1-cos(w))^2}{1+4\lambda(1-cos(w))^2} \right|^2. \tag{8}$$

[2] In this case, *one complete cycle* of a time series is assumed to be a period of time during which the time series passes through all the phases of its periodic component and returns to its initial state (or a state close to it).

[3] Detailed information on the power transfer functions of the ideal filter and the HP filter can be found in King and Rebelo (1993).

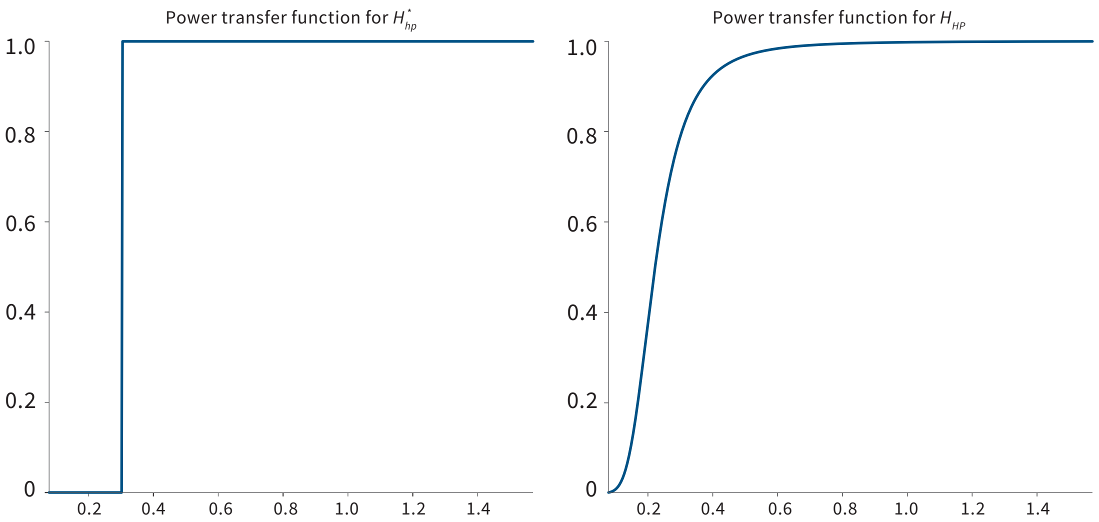
Figure 2 shows illustrative examples of the power transfer functions for the ideal high-pass filter and the HP filter. It should be noted that the HP filter is a high-pass filter; therefore, the transfer function is also compared with that of the ideal high-pass filter.

Figure 1. Illustrative Example of Power Transfer Function for Ideal Band-Pass Filter



Note: The abscissa axis shows the cycle length.
Source: developed by the authors.

Figure 2. Illustrative Example of Power Transfer Function for Ideal High-Pass and HP Filters



Note: The abscissa axis shows the indicator equal to frequency (*w*).
Source: developed by the authors.

As smoothing parameter λ increases, the transfer function shifts to the left, cutting off less and less low-frequency[4] information. In other words, as the value of parameter λ increases, the importance of low-frequency information also increases, resulting in a smoother trend.

[4] According to the example in Figure 1, *low-frequency information* is assumed to be information that recurs at least once every 6 years (Pedersen, 2001).

Having identified the basic building blocks needed to estimate the optimal value of λ, we can now consider the logic of the loss function to determine smoothing parameter λ.

According to Pedersen (2001), the main goal of the optimal filter theory is to design filters that minimise distortionary effects.

Let us denote the power transfer function of the ideal high-pass filter as $H^*(w)$, where $w \in W = (w_1, w_2, \ldots, w_n)$, $w_1 = 0$, and $w_n = 2\pi$. Let the power transfer function of the approximating filter be $H_{HP}(w)$. The spectral representation of the true and distorted cycle components for $w \in W$ will then be as follows (Annex B):

$$H^*(w)2s_x(w) \text{ and } H_{HP}(w)2s_x(w).$$

According to Pedersen (2001), the distortionary effect occurs due to the differences in the transfer function of the ideal and the distortionary filters. Based on this argument, the distortionary effect of filter (Q) is the sum of the absolute values of the difference between the cycle component of the ideal and the approximating filters, which are weighted by the spectrum of the input time series ($2s_x(w)$) and grid width $\Delta w = w_i - w_{i-1}$. The above can be summarised as follows:

$$Q = \sum_{w \in W} | H^*(w) - H_{HP}(w) | 2s_x(w) \Delta w. \tag{9}$$

To normalise the sum of weights, the spectrum of the input time series is divided by its variance (Hamilton, 1994):

$$v(w) = \frac{2s_x(w)\Delta w}{\sum_{w \in W} 2s_x(w)\Delta w}. \tag{10}$$

Then we can present the minimisation of the distortionary effect of filter (Q) as follows:

$$\underset{\lambda}{arg\min}(Q) = \sum_{w \in W} | H^*(w) - H_{HP}(w) | v(w). \tag{11}$$

By applying function (11) to the actual data, we can calculate the optimal values of smoothing parameter λ for different periodicity.

One-Sided HP Filter

The main difference between the one- and two-sided HP filters is their respective methods of trend identification (g_t). In the one-sided version, this component is determined sequentially for each point in time t based on the data available at that time, whereas the two-sided filter uses the entire time series (time period T).

It should be noted that g_t can be estimated using either optimisation problem (2) or the Kalman filter. The results obtained from both approaches will be consistent (Meyer-Gohde, 2010).

Restricted HP Filter

The restricted Hodrick—Prescott filter (hereinafter referred to as the RHP filter) enables restrictions to be imposed on trends, which makes it possible to incorporate expert judgement (Jönsson, 2010). In Appendix A, the details for deriving the analytical formula for the HP filter with constraints are presented. The formula is as follows:

$$\hat{g}_{HPR} = \hat{g}_{HP} + AR(R^{T}AR)^{-1}(\tau - R^{T}\hat{g}_{HP}), \tag{12}$$

where $\hat{g}_{HPR}$, $\hat{g}_{HP}$ are the trend components calculated using the HP filter with and without restrictions, respectively. Formula (12) can also be used for the one-sided HP filter. The main difference in this case is that the restrictions will not apply to the entire period in question, but only to a specific date.

Solving the End-Point Problem in the HP Filter

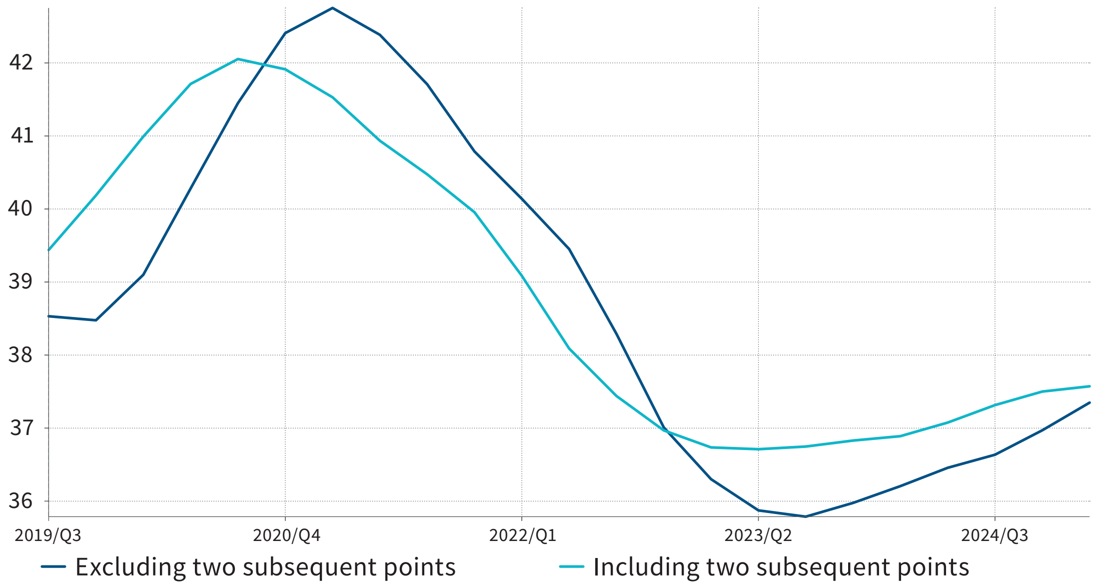
It should be noted that the two-sided HP filter is suboptimal at the end points in the time series (Baxter and King, 1995; Apel, et al., 1996; St-Amant and van Norden, 1997). Therefore, the question of how to solve the end-point problem and obtain the optimal values of the cycle component at time *t* using the two-sided HP filter remains relevant (unless otherwise stated, we will refer to the two-sided HP filter throughout this Section).

Building on the work of Mise et al. (2005), we propose solving the end-point problem by augmenting the input time series with forecast values for periods $t + 1$ and $t + 2$. Then it is assumed that the HP filter values at time *t*, estimated given the forecast, will be relatively close to the optimal values. To test this on actual data, a predictive model should first be selected. Annex C explains why the ARIMA model was selected for forecasting input time series y_t and demonstrates that the trend and cycle components of series y_t can be simulated as the ARIMA(p, d, q) process corresponding to y_t.

Having selected the ARIMA model, we conducted the following experiment. The credit-to-GDP time series was divided into two parts in a 70/30 ratio, with 70% of the input series used to estimate the model and the remaining 30% used for testing. To illustrate this, we can look at the credit-to-GDP time series for the Republic of Belarus between Q2 2005 and Q3 2025. Based on the 70/30 ratio, the first part includes data between Q2 2005 and Q2 2019 and the second part includes data between Q3 2019 and Q3 2025. The gist of the experiment is as follows: first, we take the series from Q2 2005 to Q3 2019 and calculate the trend using the HP filter. Then, we save the resulting trend value at the end point. Next, we calculate the trend for the period between Q2 2005 and Q1 2020, retaining the resulting value for Q3 2019. Thus, the optimal value of the HP filter is found at point *t*, since information from periods $t + 1$ and $t + 2$ has already been taken into account. Following this logic, the calculation is performed iteratively until the period from Q2 2005 to Q1 2025 is reached. For this period, two trend values are produced: one excluding Q2 and Q3 2025, and one including them. This generates two series of trend values for the period from Q3 2019 to Q1 2025 (23 observations): excluding and including two subsequent points (Figure 3).

In the next step, instead of the actual values in $t + 1$ and $t + 2$, we use the forecast values for these points and estimate the value of the trend component in period *t*. If the trend estimated using the forecast points is closer to the trend based on the actual data, we can conclude that the optimal value of the HP filter in period *t* is best calculated using the forecast values in $t + 1$ and $t + 2$.

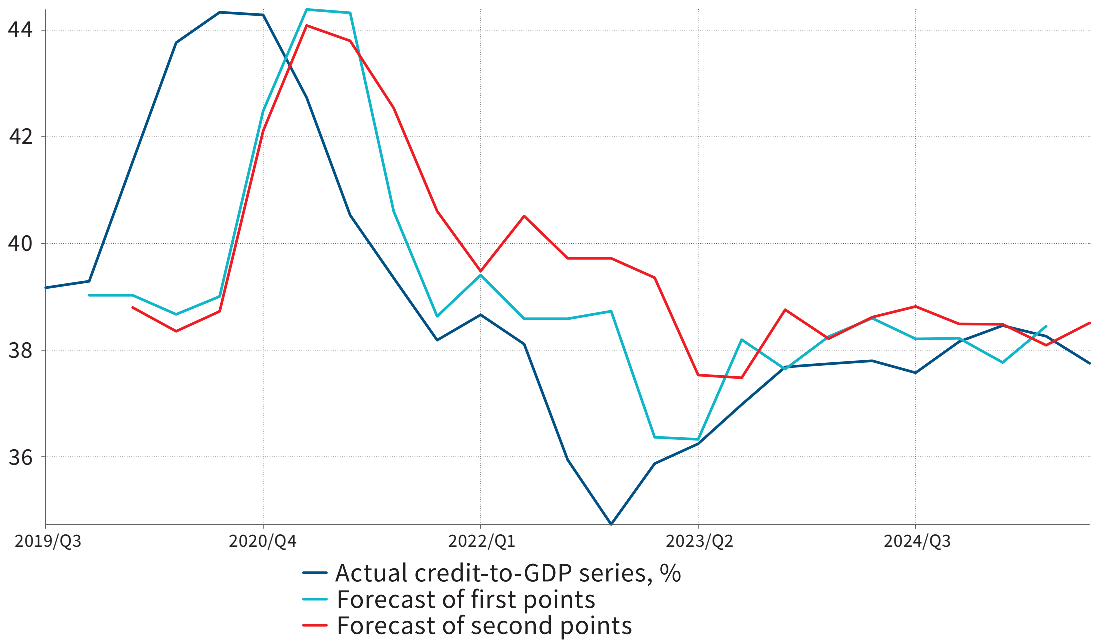
Figure 3. Trend Component of Credit-to-GDP Series Excluding and Including Two Subsequent Points



Source: authors' estimates.

As mentioned above, the ARIMA(p, d, q) model should be applied to predict two subsequent points. We use the pmdarima Python library to find the optimal ARIMA model. To improve the accuracy of forecasts, we also run the bootstrap replication algorithm on the selected ARIMA(p, d, q) models. The ARIMA(p, d, q) model with bootstrap replications provides an interval of predictions, from which we select the median value as the point forecast. Figure 4 shows the evolution of actual and forecasted loan-to-GDP values over the period from Q4 2019 to Q3 2025.

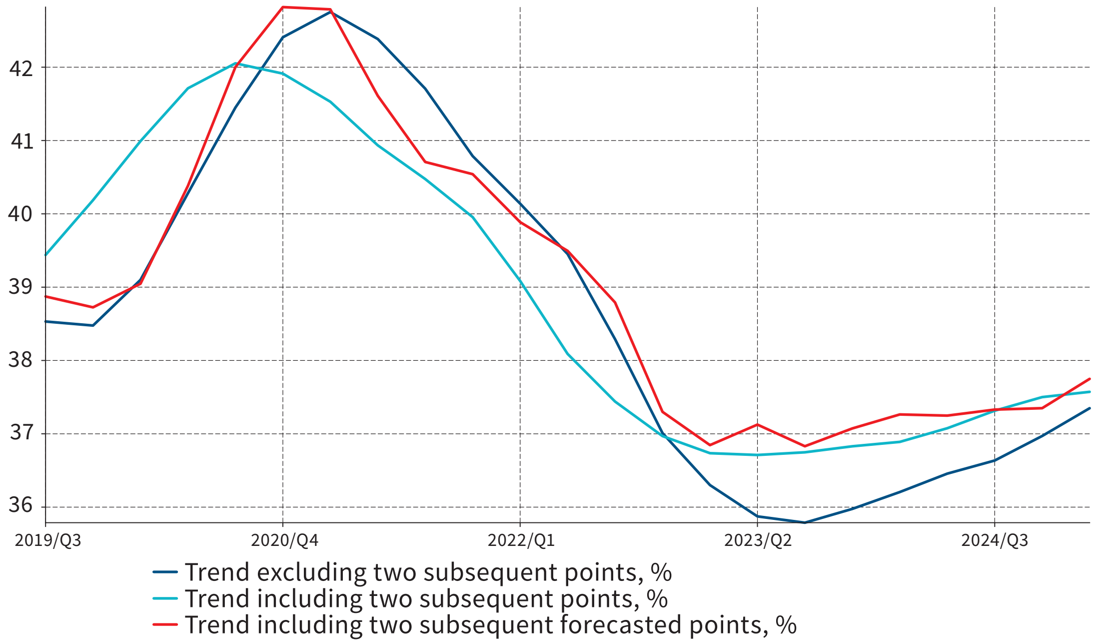
Figure 4. Recursive Forecasts of Two Subsequent Points of Credit-to-GDP, %



Source: authors' estimates.

Following the methodology described above, we estimate the value of the HP filter in period *t* taking into account the forecast points (Figure 5). We refer to the resulting values as adjusted values. As Figure 5 shows, using the forecast points enables us to get trend component values close to the optimal ones in several cases. This is most clearly seen in the period from 2023 to 2025. The success of this approach depends heavily on the forecast accuracy of the selected ARIMA model. For instance, during the period of elevated growth in the credit-to-GDP ratio between 2020 and 2021, the forecast accuracy decreased significantly, producing HP filter estimates that were closer to the suboptimal trajectory. It should be noted that, while our proposed approach does not solve the HP filter end-point problem completely, it can provide additional information when experts estimate the trend and cycle components in period *t*.

Figure 5. Trend Component of Credit-to-GDP Series Including Two Subsequent Forecasted Points



Source: authors' estimates.

3. Proposed Algorithm for Credit Gap Estimation

The proposed credit gap estimation algorithm comprises six consecutive steps:

1. Preparation of statistical data.
2. Software preparation.
3. Determination of optimal smoothing parameter (λ) for the HP filter.
4. Preliminary credit gap estimation using the one- and two-sided HP filters without restrictions and comparative analysis of the results.
5. Credit gap estimation using the restricted two-sided HP filter.
6. Credit gap estimation using the restricted one-sided HP-filter.

We will now take a closer look at each step.

1. Preparation of statistical data

We analysed time series of credit (end-of-period monthly data, see Table 1) and GDP at current prices (quarterly data) for six countries.

Table 1. Input Credit Data

Country	Credit indicator	Period	Source
Armenia	Loans granted by commercial banks and credit organisations to economic sectors, total in local and foreign currencies	January 2003–June 2025	CBA
Belarus	Commercial banks' claims on the economy, total in local and foreign currencies	July 2004–June 2025	NBRB
Kazakhstan	Credit to the economy from second-tier banks, total in local and foreign currencies	January 2003–June 2025	NBRK
Kyrgyzstan	Commercial banks' credit to the economy, total in local and foreign currencies	January 2004–June 2025	NBKR
Russia	Commercial banks' claims on economic sectors, total in local and foreign currencies	January 2001–June 2025	CBR
Tajikistan	Credit to the private sector provided by the NBT and commercial banks, total in local and foreign currencies	April 2001–June 2025	NBT

It is important to note that the proposed methodology is flexible: the researcher can expand the list of analysed series by, for example, disaggregating the indicators in Table 1 by economic sector or currency.

All time series must undergo preparation before the credit gap is estimated. This includes the following steps:

- **Anomaly detection and adjustment:** analysing the series for outliers and deciding whether to eliminate or smooth them.
- **Elimination of the seasonal component:** adjustment of series for statistically detected seasonality.
- **Conversion to quarterly frequency:** converting monthly credit data to quarterly averages.
- **Calculation of the resulting indicator:** calculation of the ratio of average quarterly credit to total GDP for the previous four quarters (a moving annual sum). This relative indicator is used for subsequent credit gap estimation.

2. Software preparation

The following software was used to conduct this study:

- for seasonal adjustment of time series → JDemetra+;
- for the selection of optimal smoothing parameter (λ) for the HP filter → MATLAB;
- for trends and credit gap estimation → Python.

This list of software is not exhaustive. Researchers can also use other software products (e.g. Eviews, R, etc.).

3. Determination of the optimal smoothing parameter

As noted above, the standard value of smoothing parameter λ in the HP filter is 1,600 for quarterly data (Hodrick and Prescott, 1997). However, for credit cycle analysis, the Basel Committee on Banking Supervision (BCBS, 2010) recommends using the one-sided HP filter with a higher value of parameter $\lambda = 400{,}000$[5].

This discrepancy shows that there is no single value of parameter λ that is suitable for analysing heterogeneous time series. This study examines the credit-to-GDP ratio for different countries, which are characterised by varying depths of historical data and different economic development trajectories. These features may result in credit cycles of different durations and amplitudes, implying the need to adapt the smoothing parameter for each case. The use of a single parameter for all countries may lead to incorrect estimation of the trend component and, as a consequence, to a distorted estimate of the credit gap.

In this regard, this paper uses an algorithm to select unique optimal smoothing parameter λ for each time series. The methodology is based on spectral density analysis and follows the approach proposed by Pedersen (2001) (the theoretical justification is presented in Section 2).

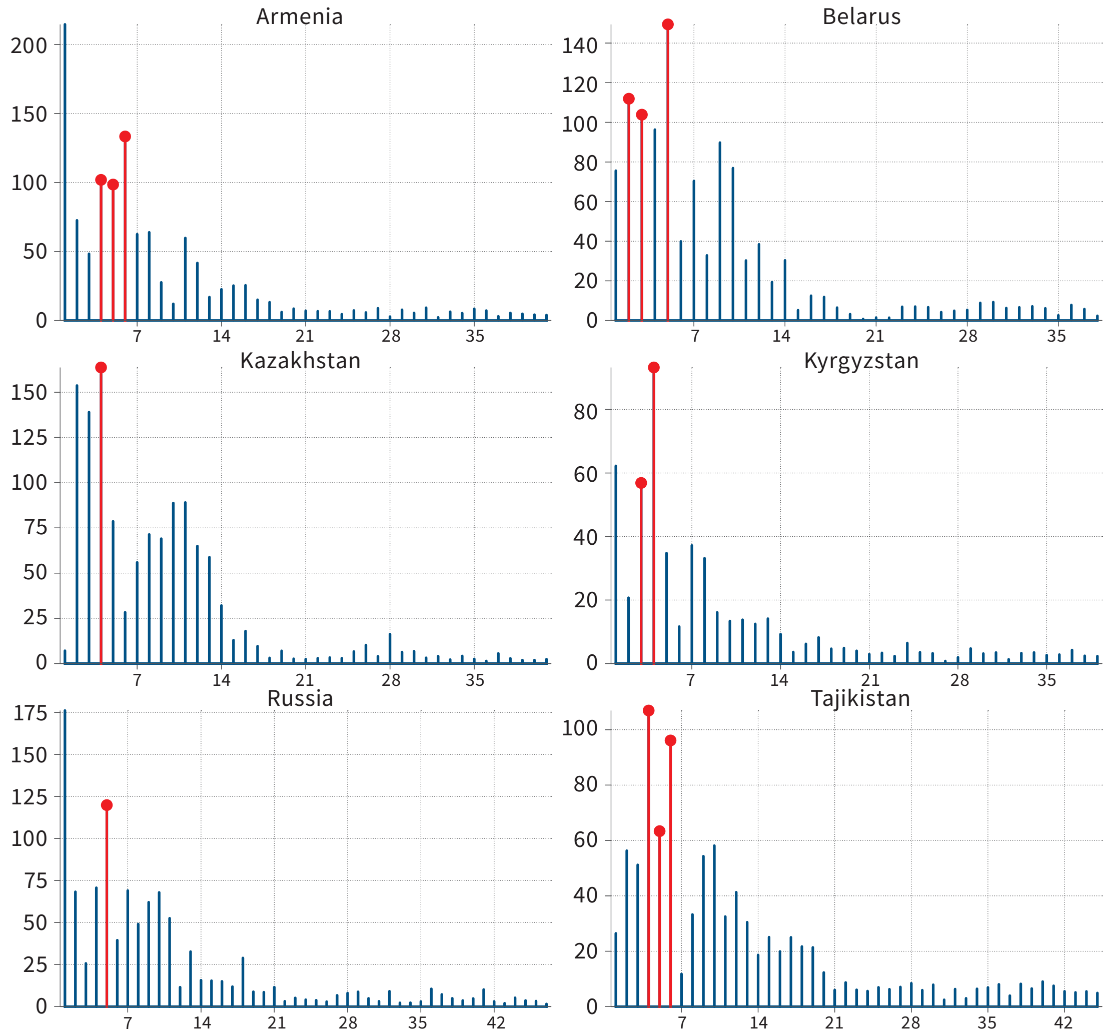
[5] BCBS (2010) does not provide a direct justification for choosing the specific value for parameter $\lambda = 400{,}000$. However, based on the work of Ravn and Uhlig (2001), it can be assumed that the authors of BCBS (2010) intended to account for low-frequency fluctuations in 40–60-year time series.

The first step in implementing this approach is to produce sample periodograms of the credit-to-GDP time series for all countries under consideration. Figure 6 presents a visualisation of the periodograms.

Then, based on the analysis of the periodograms (Figure 6) and using formula (4), we can determine the period for each analysed time series, in which the cycle amplitude reaches its peak.

Example. *Let us examine the credit-to-GDP time series for Russia. The maximum amplitude of its cycle is observed at the frequency corresponding to j = 5. With a series length of T = 98 quarters, this means that the cycle length is T/j = 98/5 = 19.6 quarters, or approximately 5 years.*

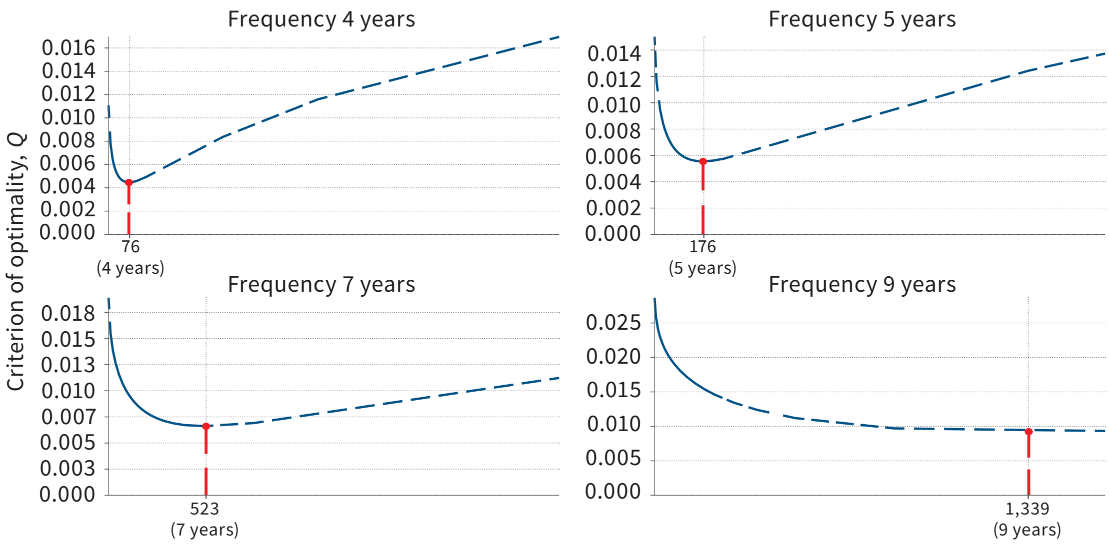
Figure 6. Sample Periodograms for Analysed Credit-to-GDP Time Series



Source: authors' estimates.

The next step is to calculate the optimal values of λ using the relationship between the cycle length and the smoothing parameter generated by function (11). At the same time, in order to make the right choice of the final value of parameter λ, it is recommended to analyse not only the values that strictly correspond to the calculation period (for example, 5 years for Russia), but also neighbouring values (4, 5, 7, and 9 years, see Figure 7). This enables the potential inaccuracy of periodogram estimation to be taken into account, allowing a more robust trend to be selected.

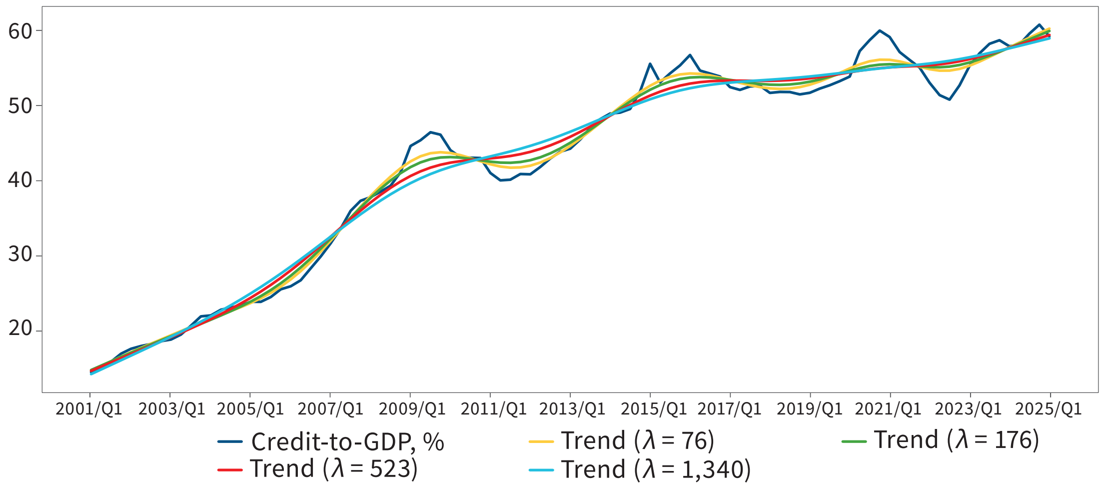
Figure 7. Determining Optimal Value of Parameter λ when Analysing Credit-to-GDP in Russia



Source: authors' estimates.

Example. *If we consider the data for Russia, comparison of the trend component obtained using different values of λ (Figure 8) shows that the value of λ = 523 (corresponding to a period of about 7 years) provides a less volatile estimate of the potential level of credit that is also consistent with the initial estimate of the cycle length (5 years).*

Figure 8. Comparison of Potential under Different Smoothing Parameters λ when Analysing Credit-to-GDP in Russia



Source: authors' estimates.

The following optimal smoothing parameters were determined based on the above procedure for all countries included in the analysis in order to identify the trend component in the credit-to-GDP series:

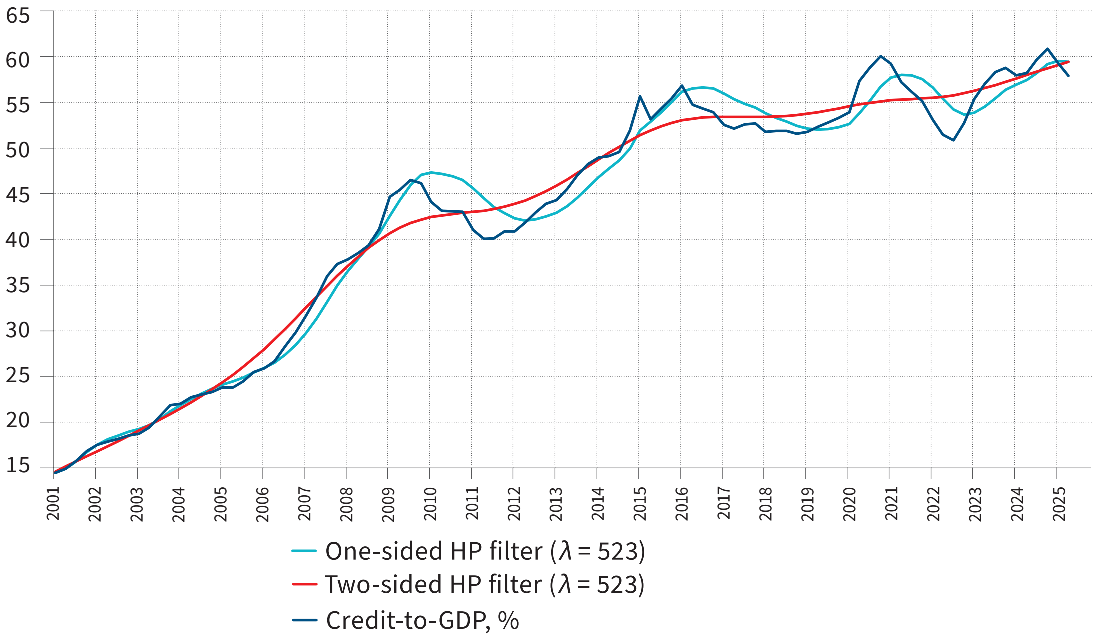
- Armenia, Belarus, Kyrgyzstan, Tajikistan: λ = 353,
- Kazakhstan: λ = 173,
- Russia: λ = 523.

4. Preliminary credit gap estimation using the one- and two-sided HP filters without restrictions and comparative analysis of the results

The key methodological difference between the two-sided and one-sided HP filters lies in their respective approaches to estimating the trend component. For each point in the historical series, the two-sided filter uses all available information, resulting in a revised trend for the entire period when new data are added. By contrast, the one-sided filter uses the information available at the time of each observation (i.e. past data only) to estimate the trend, with no subsequent retroactive adjustment.

To visualise this difference, Figure 9 presents the estimated credit-to-GDP trend in Russia, while Figure 10 shows the credit gap estimated based on both methods without imposing any restrictions.

Figure 9. Credit-to-GDP Trend in Russia Estimated Using One- and Two-Sided HP Filters without Restrictions



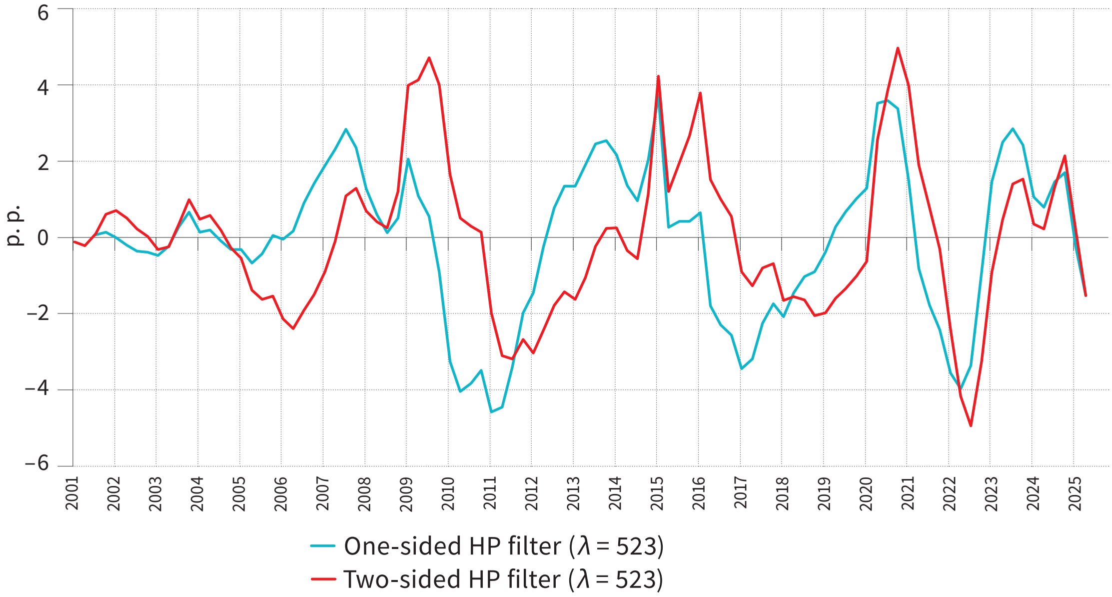
Source: authors' estimates.

The comparative analysis revealed the following strengths and shortcomings of each method:

One-sided HP filter:

- **Shortcoming:** Tendency to overestimate the trend during periods of credit expansion. As the filter does not anticipate future adjustments, it interprets a boom as the new normal, leading to an underestimation of the real-time credit gap and consequently delayed detection of accumulated risks.
- **Strength:** No retroactive adjustment of the trend as new data are added.

Figure 10. Credit Gap in Russia Estimated Using One- and Two-Sided HP Filters without Restrictions



Source: authors' estimates.

Two-sided HP filter:

- **Shortcoming:** Shifts in estimates at the end of the period. In an environment of active credit stimulus, such as that observed after 2023, the filter extrapolates high growth rates across the entire trend, which can result in overestimation until future developments confirm or refute the sustainability of that growth.
- **Shortcoming:** Retroactive adjustment of the trend as new data are added. The resulting credit gap may contradict conclusions reached in the past. For example, it can seem in retrospect that the CCyB should have been activated in a previous period (BCBS, 2010), whereas in reality, no decision was made.
- **Strength:** It provides the most accurate retrospective assessment of the trend trajectory and credit gap using all available information.

Figure 10 clearly shows that, for most of the analysed period, the credit gap estimates obtained by the two methods diverge significantly. The most significant divergences occur when the gap crosses zero, i.e. at the turning points of the credit cycle. Consensus periods (e.g. H2 2020) are more of an exception.

Therefore, it was concluded that a comprehensive estimate of the credit gap requires both approaches to be employed in tandem. The one-sided filter is essential for analysis from the perspective of real-time decision makers, while the two-sided filter is necessary for retrospective analysis and reconciliation of historical data.

Taking the identified features into account, the following credit gap estimation algorithm is proposed:

1. **Initial estimation:** credit gap calculation using the one- and two-sided HP filters without restrictions.
2. **Comparative analysis:** detailed comparison and interpretation of the results produced.
3. **Expert adjustment:** Based on the analysis, a decision is made as to whether the trend need adjusting. If so, the restricted HP filter can be used, taking expert judgement about the potential level of credit into account.

5. Credit gap estimation using the restricted two-sided HP filter

At this stage, the researcher imposes restrictions on the trend based on expert judgement and knowledge about the development of a particular economy over a certain period of time, which makes it possible to adjust the trend.

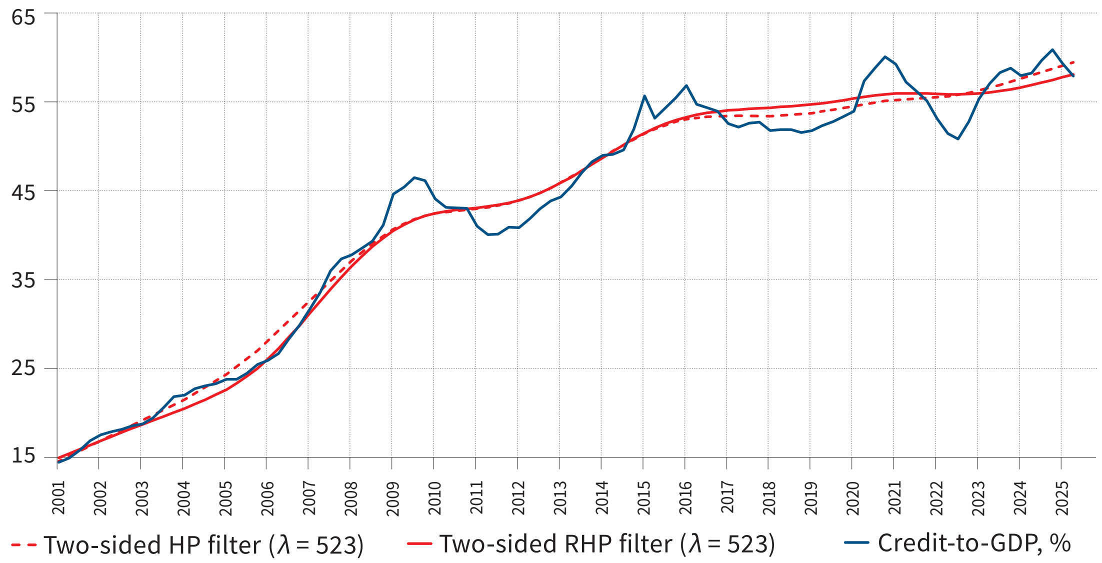
By way of example, the results of applying restrictions to a two-sided HP filter, using loan-to-GDP time series data for Russia, are presented below (Figures 11–12).

The periods requiring adjustment should be identified before applying expert judgement to the trend. When it comes to the economic analysis of the unobserved component estimates obtained using the HP filter without restrictions, the following is worth noting:

1. The negative credit gap observed between 2005 and 2007 does not accurately reflect the real economic situation, as its magnitude is comparable to that of the gap observed between 2011 and 2013 — a period characterised by severe and prolonged adjustments to bank lending following the global financial crisis. In our opinion, the credit gap from 2005 to 2007 should be slightly positive, given that credit in Russia grew at a consistently high rate during this period.
2. The negative credit gap from 2017 to 2019 should be slightly larger, as this period is characterised by a sharp contraction in credit activity, following the shocks of 2015–2016 — comparable to the period from 2011 to 2013. In addition, we believe that there is no scope for a reduction in the trend component in 2017–2019, as the average loan-to-GDP ratio for 2017–2025 remains stable.
3. The credit gap is around zero between 2023 and 2025, but then moves sharply into negative territory in Q2 2025, which does not reflect the real economic situation either. During this period, the rate of credit growth increased and inflation was high, indicating that the Russian economy was overheating. Therefore, the credit gap in this period should be revised upwards.

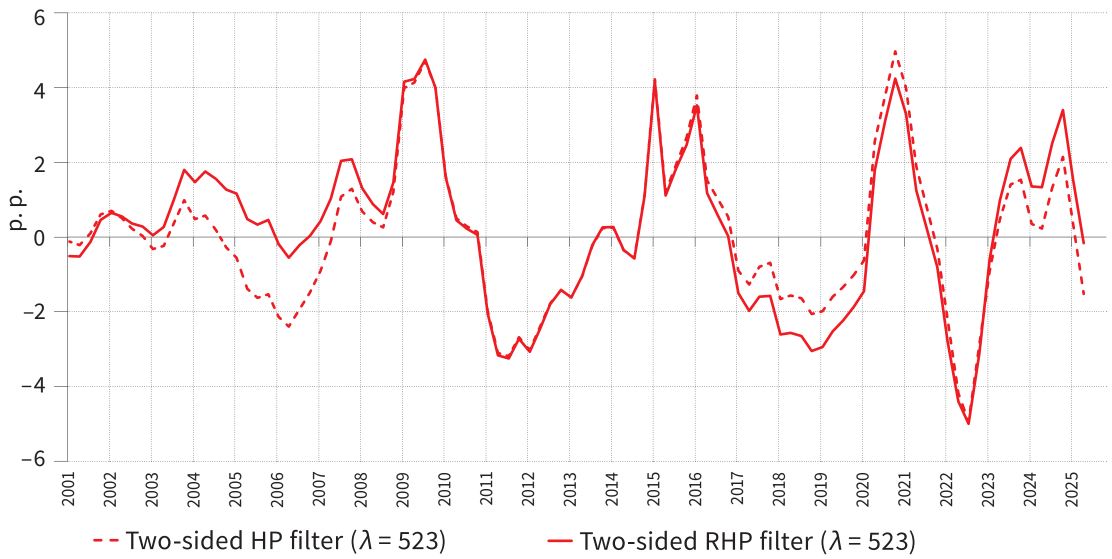
To address these issues and adjust the credit gap values, the use of the restricted HP filter — discussed in detail in Section 2 — is proposed. Expert judgement was used to adjust estimates of the unobserved components of the credit-to-GDP time series for Russia in the following periods: Q1 2004–Q4 2007, Q1 2017–Q4 2019, Q4 2023–Q2 2025 (Figures 11–12). These restrictions enabled us to adjust the trend component in designated time intervals, thereby achieving a more economically reasonable credit gap in the respective periods.

Figure 11. Credit-to-GDP Trend in Russia (two-sided HP filter and λ = 523, restricted two-sided HP filter and λ = 523)



Source: authors' estimates.

Figure 12. Credit Gap in Russia (two-sided HP filter and λ = 523, restricted two-sided HP filter and λ = 523)



Source: authors' estimates.

6. Credit gap estimation using the restricted one-sided HP filter

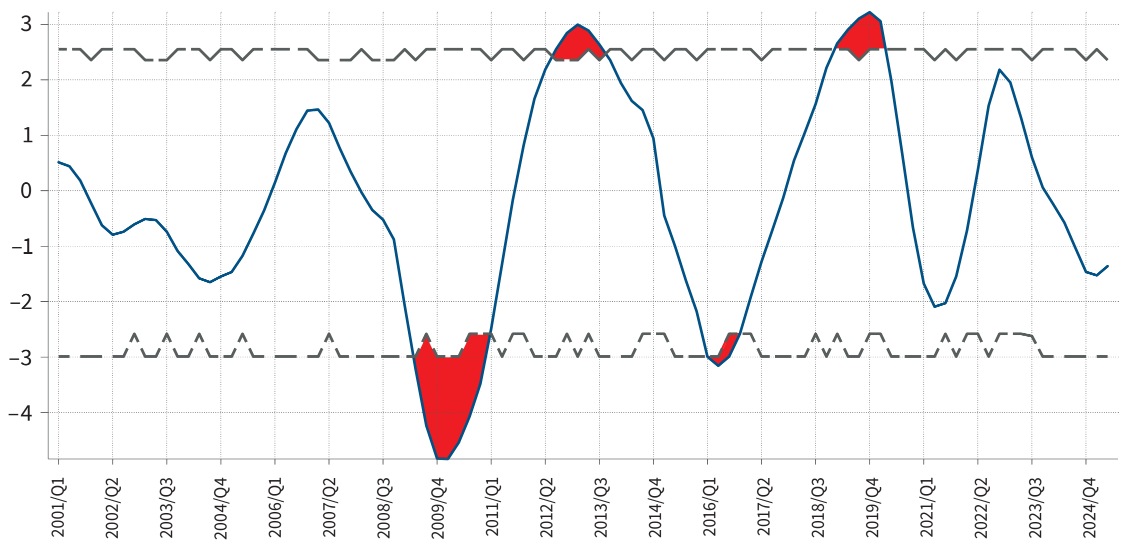
The next step is to adjust the one-sided HP filter by imposing a restriction on the trend. Since an estimate produced using the restricted two-sided HP filter is available at this step, adjustments should be made to the one-sided HP filter to ensure that the results of calculations using this filter also align with expert judgement. A similar approach is discussed in Alessandri et al., (2015) and Jokipii et al., (2021).

It is proposed that the one-sided HP filter be adjusted using a special tool. It is designed to identify the time intervals in which the difference between the one- and two-sided filters becomes statistically significant (these intervals are highlighted in red in Figure 13).

The algorithm for implementing this tool includes the following steps:

1. **Calculation of trend differences.** The difference in trend values obtained using the restricted two-sided HP filter and the one-sided HP filter for the credit-to-GDP ratio is calculated.
2. **Standardisation.** The resulting difference is standardised to zero mean and unit standard deviation.
3. **Bootstrap modelling.** For standardised difference values, bootstrap replications with replacement are performed. It is recommended that a large number of repetitions (e.g. 100,000 or more) be used to ensure high accuracy of confidence intervals.
4. **Boundary definition.** The 10^{th} and 90^{th} percentiles of the ranked series are calculated for each time period based on the bootstrapping results, forming the lower and upper bounds of the signal intervals, respectively.

Figure 13. Difference between Two- and One-Sided HP Filters in Light of the Band of Permissible Deviation Values



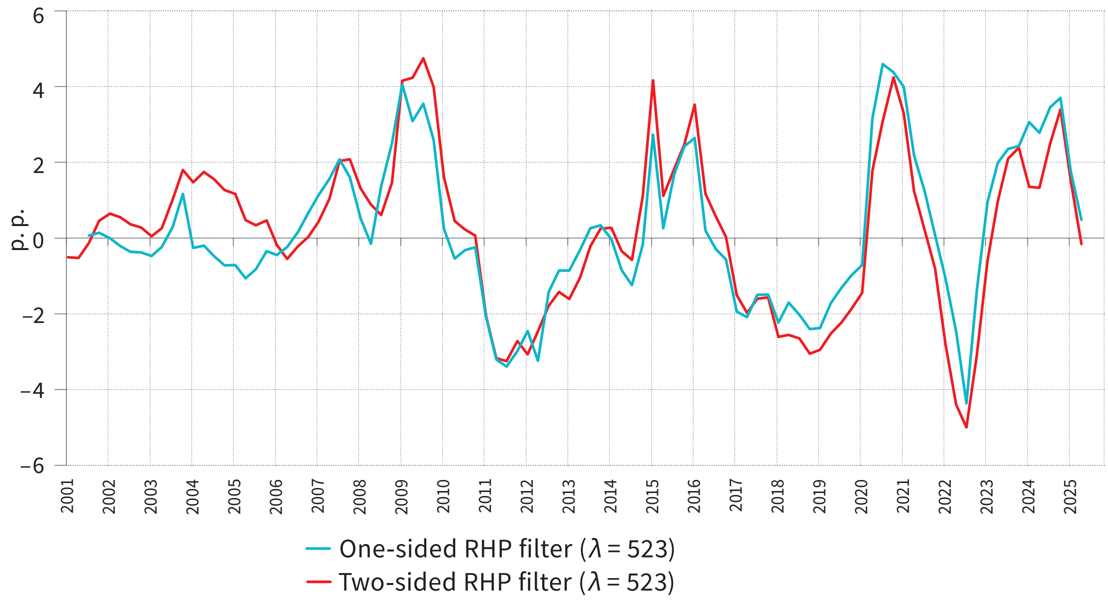
Source: authors' estimates.

As a result, the implemented adjustments to the one-sided HP filter produce a trend for the credit-to-GDP ratio and credit gap that have a logical explanation and are consistent with specific expectations (Figure 14).

In the subsequent round of credit gap re-estimation, given the new statistical data received, the researcher should process the statistical data and estimate the credit gap using the restricted one- and two-sided HP filters.

If there is a significant shift in the trend for the two-sided HP filter (following a sharp change in the credit-to-GDP ratio), the restrictions imposed on the filter previously can be revised or new ones can be introduced. In addition, given the trend bias resulting from the use of the two-sided HP filter (due to the specific features of the filter mechanism), it may be necessary to adjust the one-sided HP filter in period $t-2$.

Figure 14. Credit Gap in Russia — Restricted One-Sided HP Filter vs Restricted Two-Sided HP Filter.



Source: authors' estimates.

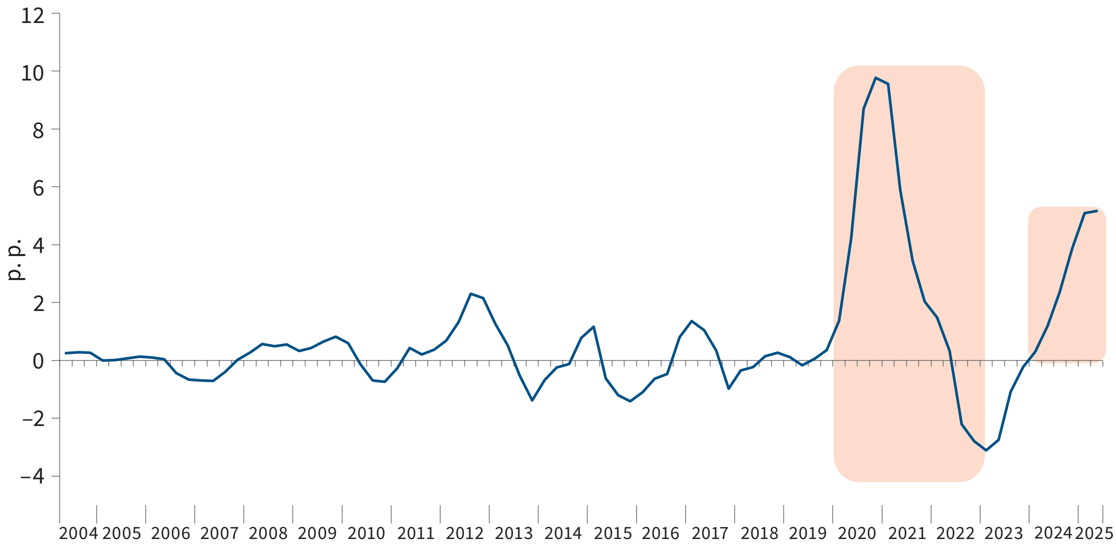
4. Results of Credit Gap Estimation

This Section presents the results of the credit gap estimation using the above methodology for the countries in question.

Armenia

Until the end of 2019, the credit gap in the Republic of Armenia had hovered around zero, occasionally dipping into positive or negative territory (Figure 15). These developments indicate balanced credit growth, which was generally in line with the pace of the country's economic development between 2004 and 2019.

Figure 15. Credit Gap in Armenia



Source: authors' estimates.

Significant changes in the trajectory of the indicator occurred in 2020–2024. The credit gap showed exponential growth from Q1 2020 onwards, reaching a peak of 9.8 p. p. by Q4 2020, the highest since 2004; the credit-to-GDP ratio was also at its peak, standing at 65.6%. It is important to note that the substantial positive gap in 2020 was not the result of credit expansion, as quarterly credit growth rates were similar to those of previous years. Instead, it was caused by a sharp contraction in GDP due to the impact of the COVID-19 pandemic during the first half of the year and the worsening situation in Nagorno-Karabakh during Q3 and Q4.

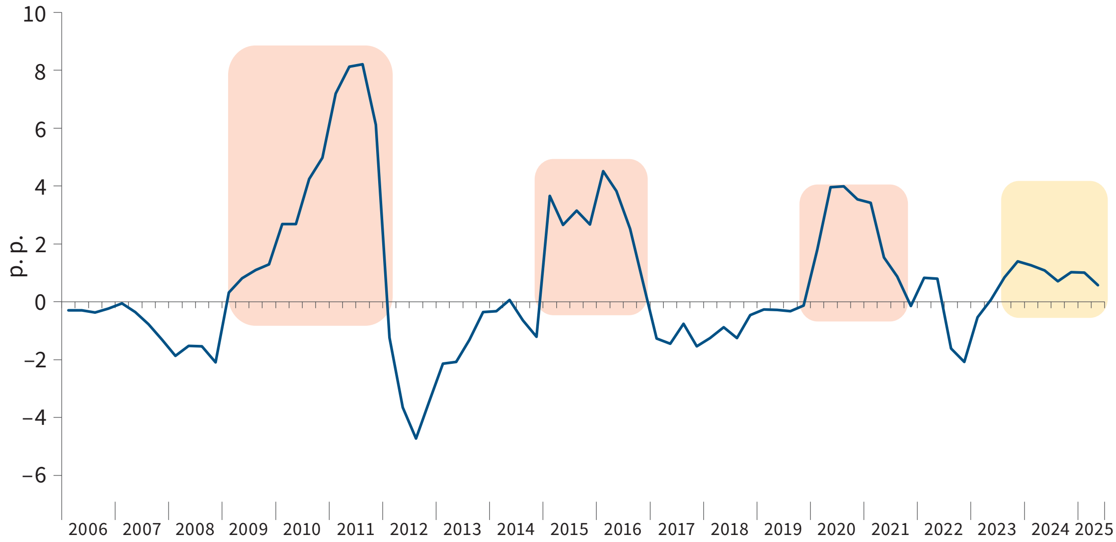
The recovery in economic activity in 2021, despite stagnant credit, led to a sharp adjustment and closure of the positive gap.

A new phase began in Q4 of 2022: accelerating economic growth was accompanied by high lending rates. Whereas the average annual credit growth rate was 13.7% in 2023, it increased to 20.8% in 2024. Additionally, amid the significant appreciation of the Armenian dram, a notable surge in lending in the local currency, up from 30% to 40% of GDP, was recorded in 2023–2024. As a result, the credit gap has widened sharply since early 2024 — we estimate it at 5.2 p. p. in Q2 2025, with a credit-to-GDP ratio of 64.3%.

Belarus

There were four episodes of positive credit gaps observed in the Republic of Belarus (Figure 16).

Figure 16. Credit Gap in Belarus



Source: authors' estimates.

The first episode (Q2 2009–Q4 2011) was caused by a combination of pressure in the foreign exchange market and the National Bank's active credit expansion, including an increase in directed lending. Although this policy was intended to boost the economy, it ended up being one of the main causes of macroeconomic instability and the 2011 currency crisis.

During the second episode (Q1 2015–Q4 2016), the positive credit gap was caused by pressure in the foreign exchange market triggered by external factors. In particular, the depreciation of the Russian ruble in late 2014 put pressure on the Belarusian ruble, as Russia is Belarus' main trading partner.

The third episode (Q1 2020–Q3 2021) was directly related to the COVID-19 pandemic. Many countries, including Belarus, responded to the crisis by introducing support measures for businesses and households, resulting in a surge in credit aimed at mitigating the economic impact of the pandemic.

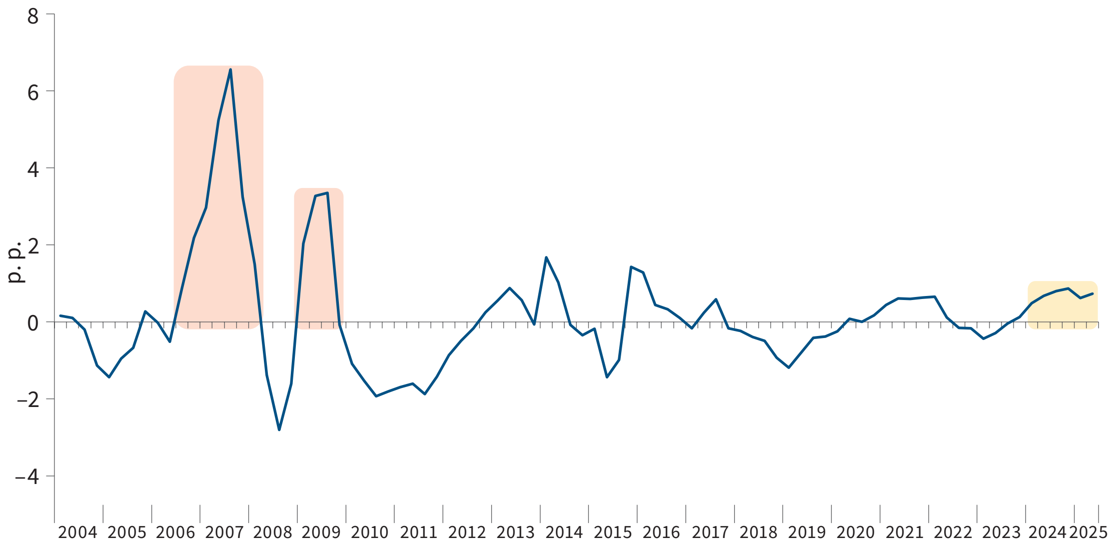
Monetary policy was expansionary between Q2 2023 and Q2 2025. In this context, a positive credit gap emerged.

Kazakhstan

In the Republic of Kazakhstan, a significant positive credit gap was recorded in 2007 and 2009 (Figure 17). These periods were characterised by substantial credit expansion, alongside an increase in external borrowing, a boost to construction and mortgage lending, and tenge depreciation. After that, starting in 2013 and until recently, the credit gap did not deviate significantly from zero.

However, since early 2024, the Republic of Kazakhstan has recorded an increasing positive credit gap. As of Q2 2025, it was about 0.7 p. p.

Figure 17. Credit Gap in Kazakhstan



Source: authors' estimates.

Kyrgyzstan

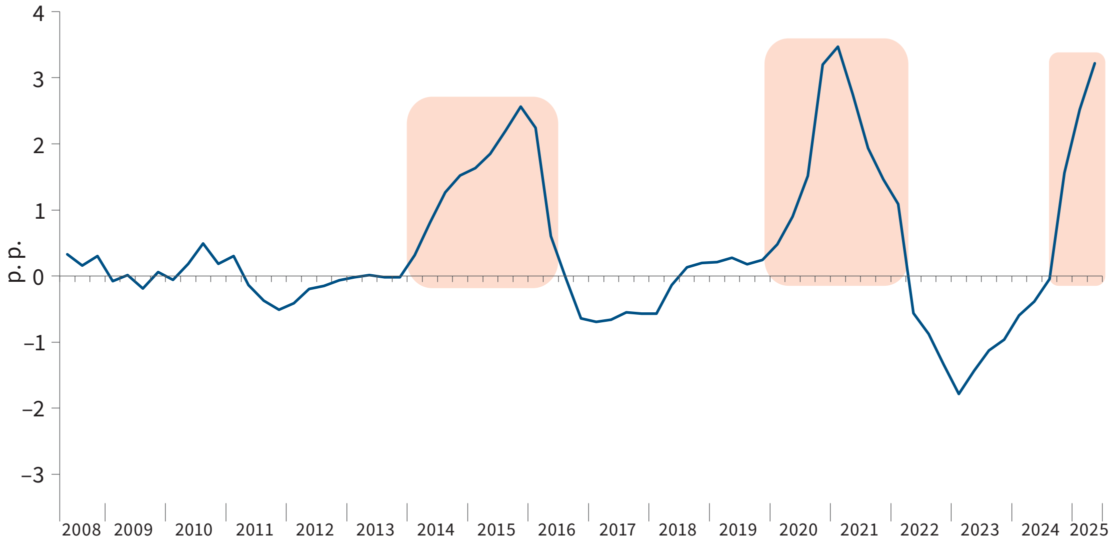
The Kyrgyz Republic saw three episodes of substantial positive credit gaps (Figure 18).

The first episode (Q2 2014–Q2 2016) was triggered by a surge in credit in early 2014, followed by worsening of the situation due to distress in the foreign exchange market. This distress was caused by external factors, primarily heavy depreciation of the Russian ruble in late 2014, which put significant pressure on the exchange rate of the local currency, the Kyrgyz som.

The second episode of the gap expansion (Q2 2020–Q1 2022), as in many other countries, was a direct consequence of the COVID-19 pandemic. To mitigate its economic impacts, large-scale measures were implemented to support businesses and households, which led to a surge in credit activity.

The third — and the current — episode of a positive gap began in Q4 2024 driven by continued strong credit growth. In particular, while the average annual growth of the loan portfolio was 19.8% in 2023, it accelerated to 25.3% in 2024. As a result, the positive credit gap has shown a steady upward trend since Q4 2024, reaching 3.2 p. p. in Q2 2025.

Figure 18. Credit Gap in Kyrgyzstan



Source: authors' estimates.

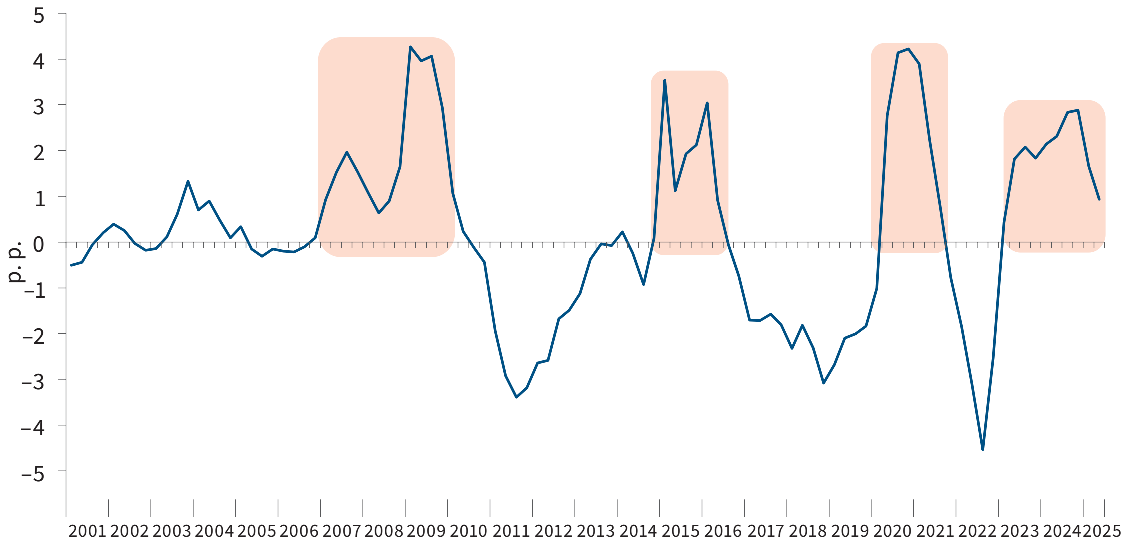
Russia

There were four episodes of positive credit gaps observed in the Russian Federation (Figure 19).

The first episode (Q1 2007–Q1 2010) was driven by strong credit growth in the run-up to the 2008–2009 global financial crisis.

The second episode (Q1 2015–Q2 2016) of a positive credit gap was mainly triggered by depreciation of the Russian ruble in late 2014 amid a sharp drop in global oil prices and the introduction of international sanctions against Russia.

Figure 19. Credit Gap in Russia



Source: authors' estimates.

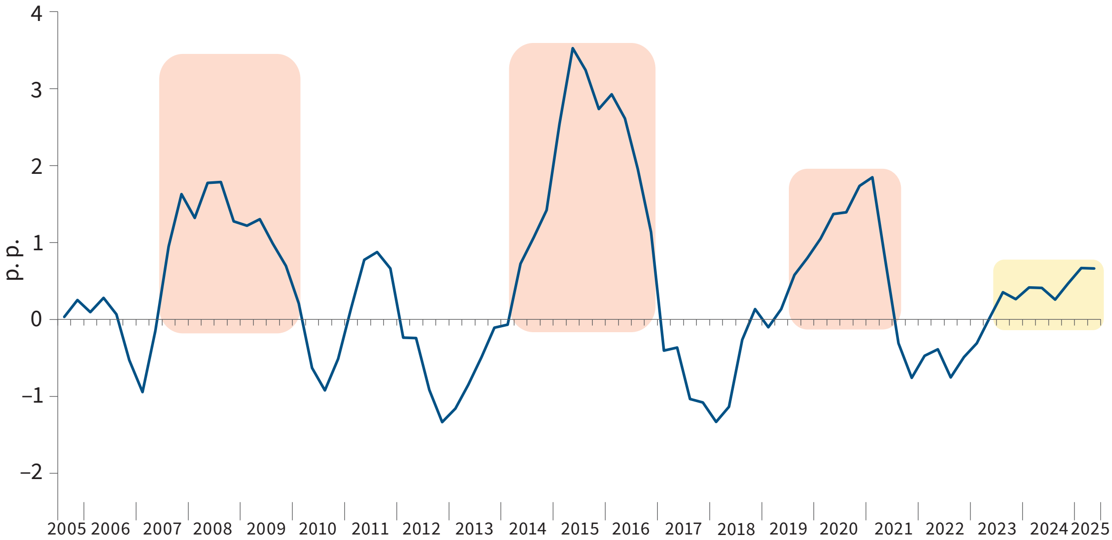
The third episode (Q2 2020–Q3 2021) was directly related to the COVID-19 pandemic. Russia responded to the crisis by introducing support measures for businesses and households, resulting in a surge in credit aimed at mitigating the economic impact of the pandemic.

The fourth episode (Q1 2023–Q2 2025) was a result of the active Government policy of import substitution and credit support for priority sectors of the economy in the context of sanctions pressure, as well as the growth of mortgage lending.

Tajikistan

Three significant episodes of positive credit gaps were identified in the Republic of Tajikistan (Figure 20).

Figure 20. Credit Gap in Tajikistan



Source: authors' estimates.

The first episode (Q3 2007–Q3 2009) was largely technical in nature. Its emergence was due to two main factors: strong credit expansion against a relatively low base in the previous period, which started in 2007; and stagnation of nominal GDP in 2008, caused by exogenous shocks (the global financial crisis).

The second episode (Q2 2014–Q4 2016) was marked by the largest positive credit gap, reaching 3.5 p. p. in Q2 2015. As with Belarus and Kyrgyzstan, the cause lies largely in an external shock that provoked pressure on the foreign exchange market and a slowdown in economic activity while credit continued to grow.

It is important to note that the country's banking sector was also in distress during this period. From 2014 onwards, the unstable economic situation of Tajikistan's main trading partners and the impact of external shocks created the threat of a systemic crisis for the country's banking sector. The share of bad loans was above 10% as at the end of 2014. A number of credit organisations in Tajikistan — including Agroinvestbank, OJSC, and Tojiksodirotbank, OJSC (both systemically important), Tajprombank, CJSC, and Fononbank, CJSC — suffered from liquidity problems. To improve the soundness of the financial system and minimise its negative impact on other sectors of the economy, the Government of the Republic of Tajikistan opted to recapitalise the banks. The rehabilitation and subsequent liquidation of the troubled credit organisations was also initiated. These factors contributed to the positive credit gap closing in early 2017.

The third significant episode (Q1 2020–Q2 2021) was directly related to the COVID-19 pandemic and the implementation of large-scale Government support measures for businesses and households.

Since the second half of 2023, a new — and so far insignificant — positive credit gap has emerged in Tajikistan's economy, reaching 0.7 p. p. in Q2 2025.

Conclusion

This study addresses the important macrofinancial stability problem of measuring the credit gap as a key indicator of the credit cycle and as part of a system for early detection of macrofinancial imbalances and systemic risk accumulation.

The analysis confirmed that blindly following the unified methodology reflected in the BIS recommendations — using the one-sided HP filter with parameter λ = 400,000 — could lead to significant estimation errors, particularly in developing economies with short time series and distinctive economic development trajectories. Effective use of the credit gap requires a meaningful combination of international recommendations and local analytical practices, based on empirically sound, adaptive, and transparent assessment methods, rather than straightforward employment of standardised approaches.

This Working Paper presents an improved credit gap estimation algorithm that has been developed and tested to address the key limitations of traditional approaches. The main findings and results of the study are as follows:

1. **The need for an adaptive approach to the smoothing parameter.** For each of the countries in question — Armenia, Belarus, Kazakhstan, Kyrgyzstan, Russia, and Tajikistan — unique optimal values of parameter λ for the Hodrick—Prescott filter were determined on the basis of spectral density analysis (ranging from 173 for Kazakhstan to 523 for Russia). This supports the premise that there is no single value that can be assigned to the parameter, and that it must be calibrated to the specifics of each economy's credit cycle.
2. **The importance of employing the one- and two-sided HP filters in tandem.** The comparative analysis revealed that the estimates obtained using the one- and two-sided HP filters showed systemic differences. Although the two-sided filter provides an accurate historical estimate, it is subject to end-point bias and continuous data revision. The one-sided filter excludes historical trend revisions, but tends to overestimate the trend during boom periods, resulting in a delayed signal of risk accumulation. Therefore, no single method is sufficient on its own.
3. **Efficiency of the restricted one- and two-sided HP filters.** The restricted HP filter (RHP filter) was successfully used to address the methodological shortcomings of the filters. Imposing restrictions on trends based on economic logic (as illustrated by Russia in the periods of 2005–2007, 2017–2019, and 2023–2025) enabled known erroneous estimates to be adjusted and economically justified values of the credit gap to be produced.
4. **Proposed algorithm for credit gap estimation.** As a final solution, an algorithm comprising six consecutive steps is proposed for credit gap estimation, from data preparation and determination of optimal parameter λ to the use of the two- and one-sided RHP filters. This approach produces balanced and more robust estimates of the credit gap.
5. **Features of credit trends in EFSD recipient countries.** The results of the credit gap estimation for the countries in question, derived using the proposed algorithm, revealed significant positive credit gaps in Armenia, Russia, and Kyrgyzstan in the most recent period (2023–2025) — an indication of active credit expansion and potential risk accumulation. Analysis of historical data also revealed common patterns across many countries: the response of the credit cycle to global shocks (such as the 2008–2009 financial crisis, the

2014–2015 oil price drop, and the impact of the pandemic) and vulnerability to pressures in foreign exchange markets.

Therefore, the credit gap estimation algorithm presented in the Working Paper combines the rigour of quantitative methods with the flexibility of qualitative expert analysis, which makes it possible to identify the phase of the credit cycle more accurately and in a timely manner and to justify decisions to change the CCyB to ensure macrofinancial stability.

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Annex A

Algorithm for Solving the Optimisation Problem for the Two-Sided HP Filter

To minimise function (2), we calculate the first-order conditions for values $g_1, g_2, g_3, \ldots, g_T$:

$$-2(y_1 - g_1) + 2\lambda((g_3 - g_2) - (g_2 - g_1)) = 0, \quad \text{(A.1)}$$

$$-4\lambda(g_3 - 2g_2 + g_1) - 2(y_2 - g_2) + 2\lambda(g_4 - 2g_3 + g_2) = 0, \quad \text{(A.2)}$$

$$2\lambda(g_3 - 2g_2 + g_1) - 4\lambda(g_4 - 2g_3 + g_2) - 2(y_3 - g_3) + 2\lambda(g_5 - 2g_4 + g_3) = 0, \quad \text{(A.3)}$$

$$-2(y_{T-1} - g_{T-1}) + 2\lambda(g_{T-1} - 2g_{T-2} + g_{T-3}) - 4\lambda(g_T - 2g_{T-1} + g_{T-2}) = 0, \quad \text{(A.4)}$$

$$-2(y_T - g_T) + 2\lambda(g_T - 2g_{T-1} + g_{T-2}) = 0. \quad \text{(A.5)}$$

When solved with respect to g_t ($t = 1, 2, \ldots, T$), the system of equations can be presented in the following matrix form:

$$y - g = \lambda F g. \quad \text{(A.6)}$$

When the equation is solved with respect to g, we get the following result:

$$\hat{g} = (I + \lambda F)^{-1} y, \quad \text{(A.7)}$$

where $y, \hat{g}$ are vectors of size $T \times 1$, and I, F are matrices of size $T \times T$.

$$F = \begin{bmatrix} 1 & -2 & 1 & 0 & 0 & 0 & \ldots & 0 \\ -2 & 5 & -4 & 1 & 0 & 0 & \ldots & 0 \\ 1 & -4 & 6 & -4 & 1 & 0 & \ldots & 0 \\ 0 & 1 & -4 & 6 & -4 & 1 & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & 0 & 0 & 0 & 0 & \ldots & 1 \end{bmatrix} \quad \text{(A.8)}$$

It should be noted that accurate analytical formulae for calculating HP filter weights were proposed in the last decade (De Jong and Sakarya, 2013; Cornea-Madeira, 2017; Yamada and Jahra, 2019). These formulae help determine the coefficients directly and update them as new data become available.

Let us consider an algorithm for imposing restrictions on the two-sided HP filter using the approach set out by Julio (2011). It should be noted that this paper imposes restrictions to function (2). Similar restrictions can also be imposed when the Kalman filter is used instead of function (2) (Simon, 2010). Following Julio's approach (2011), we can express optimisation problem (2) in matrix form:

$$(y - g)^T(y - g) + \lambda g^T C^T C g, \tag{A.9}$$

where y is the one-dimensional vector of input data of size $T \times 1$,
g is the one-dimensional vector of the unobserved component of size $T \times 1$,
C is the matrix of size $(T - 2) \times T$.

Matrix C includes the following elements:

$$C = \begin{pmatrix} 1 & -2 & 1 & 0 & \dots & \dots & 0 & 0 & 0 \\ 0 & 1 & -2 & 1 & \dots & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots\vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \dots & \dots & 1 & -2 & 1 \end{pmatrix} \tag{A.10}$$

Let us consider the minimisation of (A.9) subject to m linear constraints ($1 \le m \le T$), which we can present as follows:

$$R^T g = \tau, \tag{A.11}$$

where R is the matrix of zeros and ones of size $T \times m$,
τ is the matrix of size $m \times 1$.

To solve optimisation problem (A.9) taking into account linear constraints (A.11), we use the method of Lagrange multipliers. Let δ be the vector ($m \times 1$) of Lagrange multipliers. Then the Lagrange function can be presented as follows:

$$L(g, \delta) = (y - g)^T(y - g) + \lambda g^T C^T C g - 2\delta(R^T g - \tau). \tag{A.12}$$

The first-order conditions for g and δ will be equal to:

$$\frac{\partial L}{\partial g} = -2(y - g) + 2\lambda C^T C g - 2R\delta^T = 0, \tag{A.13}$$

$$\frac{\partial L}{\partial \delta} = 2(R^T g - \tau) = 0. \tag{A.14}$$

Solving equation (A.13) with respect to g, we get:

$$y - g = \lambda C^T C g - R\delta^T, \tag{A.15}$$

$$y + R\delta^T = g + \lambda C^T C g, \tag{A.16}$$

$$g = (I + \lambda C^T C)^{-1} y + (I + \lambda C^T C)^{-1} R\delta^T. \tag{A.17}$$

If $A = (I + \lambda C^T C)^{-1}$, we have:

$$\hat{g}_{HPR} = \hat{g}_{HP} + AR\delta^T. \tag{A.18}$$

Now, let us eliminate δ^T from equation (A.18). To achieve this, we multiply both parts by R. The result is as follows:

$$R^T\hat{g}_{HPR} = R^T\hat{g}_{HP} + R^T AR\delta^T \Rightarrow \tau = R^T\hat{g}_{HP} + R^T AR\delta^T. \tag{A.19}$$

Solving equation (A.19) with respect to δ^T, we find $\delta^T = (R^T AR)^{-1}(\tau - R^T\hat{g}_{HP})$. Inserting δ^T in equation (A.18), we get the following equation:

$$\hat{g}_{HPR} = \hat{g}_{HP} + AR(R^T AR)^{-1}(\tau - R^T\hat{g}_{HP}), \tag{A.20}$$

where $\hat{g}_{HPR}$, $\hat{g}_{HP}$ are the trend components calculated using the HP filter with and without restrictions, respectively.

Annex B

Spectral Density and its Properties

The definition and properties of the spectral density function are presented here based on findings by Hamilton (1994).

Let $\{Y_t\}_{t=-\infty}^{\infty}$ be a covariance stationary process characterised by the following first and second moments:

$$E(Y_t) = \mu, \tag{B.1}$$

$$\gamma_j = \sum_{t=0}^{T} (Y_t - \mu)(Y_{t-j} - \mu). \tag{B.2}$$

The generating function is a way of recording information about a given sequence of numbers. If $\{\gamma_j\}_{j=-\infty}^{\infty}$ is an autocovariance sequence and $\sum_{j=-\infty}^{\infty} |\gamma_j| < \infty$, then the generating function for the autocovariance can be presented as follows:

$$g_y(z) \equiv \sum_{j=-\infty}^{\infty} \gamma_j z^j. \tag{B.3}$$

In this function, any number that lies on the complex unit circle is taken as argument z. All points on the unit circle are known to satisfy the Euler equation:

$$e^{-iw} = cos(w) - i \times sin(w) = z, \tag{B.4}$$

where $i = \sqrt{-1}$, w is the radian that forms z with real coordinate axes. If we calculate the value of function $g_y(z)$ at point $z = e^{-iw}$ and divide the result by 2π, we get function $s_Y(w)$ for the radian. The aim of division by 2π is to normalise the function so that the sum of all its values is equal to 1. The resulting function will look as follows:

$$s_Y(w) = \frac{1}{2\pi} g_y(e^{-iw}) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \gamma_j e^{-iwj}. \tag{B.5}$$

In spectral analysis, function $s_Y(w)$ is referred to as spectrum Y. The value of $s_Y(w)$ is that it accumulates all the cyclical information contained in Y. Applying the Euler equation for e^{-iwj}, we can infer:

$$e^{-iwj} = cos(wj) - i \times sin(wj). \tag{B.6}$$

Inserting e^{-iwj} in function $s_Y(w)$, and considering that $\gamma_j = \gamma_{-j}$, we have:

$$\begin{aligned} s_Y(w) &= \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \gamma_j (cos(wj) - isin(wj)) = \frac{1}{2\pi} \gamma_0 (cos(0) - isin(0)) + \\ &+ \frac{1}{2\pi} \left\{ \sum_{j=1}^{\infty} \gamma_j (cos(wj) + cos(-wj) - isin(wj) - isin(-wj)) \right\}. \end{aligned} \tag{B.7}$$

Applying the rules of trigonometry and, in particular, $cos(0) = 1$, $sin(0) = 0$, $sin(-\theta) = -sin(\theta)$, $cos(-\theta) = cos(\theta)$, we have:

$$s_Y(w) = \frac{1}{2\pi}\left\{\gamma_0 + 2\sum\nolimits_{j=1}^{\infty}\gamma_j\, cos(wj)\right\}. \tag{B.8}$$

The autocovariance generating function is sometimes replaced by an autocorrelation generating function. To do this, the function is divided by γ_0 and the result is the spectral density function of the time series:

$$s_Y(w) = \frac{1}{2\pi}\left\{1 + 2\sum\nolimits_{j=1}^{\infty}\rho_j\, cos(wj)\right\}, \tag{B.9}$$

where $\rho_j = \frac{\gamma_j}{\gamma_0}$.

In practice, however, due to the lack of the general population required for calculating the spectral density function, it is customary to use a sample periodogram instead. The formula for the sample periodogram is similar to the formula for the spectral density. The only difference is that the summation is performed over a limited interval rather than the entire number axis:

$$\hat{s}_Y(w) = \frac{1}{2\pi}\sum\nolimits_{j=-T+1}^{T-1}\hat{\gamma}_j e^{-iwj}. \tag{B.10}$$

This paper uses the sample periodogram to estimate the optimal value of λ and analyse information on the cyclical behaviour of the credit-to-GDP ratio.

Spectral density $s_Y(w)$ is used to explain the variance of a time series and to infer other useful characteristics. In spectral analysis, for example, the equation that describes the relationship between the spectral density of the input and the filtered time series is known. We can visualise this relationship as follows (Stoica and Moses, 2005; Pollock, 2024):

$$s_X(w) = |H(e^{-iw})|^2 s_Y(w), \tag{B.11}$$

where $s_Y(w)$ and $s_X(w)$ are the spectral densities of the input and the filtered series, respectively, and $|H(e^{-iw})|^2$ is the power transfer function.

As can be seen from the above relationship, the spectral density of the filtered time series is described using the power transfer function and the spectral density of the input time series.

Annex C

Justification of ARIMA Model Selection for Time Series Forecasting

King and Rebelo (1993) show that the cycle component of a time series can be calculated based on the symmetric two-sided filter:

$$\hat{c}_t = H(L)y_t, \; H(L) = \frac{(1-L)^2(1-L^{-1})^2}{\lambda^{-1} + (1-L)^2(1-L^{-1})^2}, \tag{C.1}$$

where L is the lag operator.

The HP filter is optimal in the sense that it minimises the sum of squared errors when the data are generated by the rule (Mise et al., 2005):

$$\begin{aligned} (1-L)^2 g_t &= A(L)\varepsilon_t, \\ c_t &= A(L)u_t, \end{aligned} \tag{C.2}$$

where $E(\varepsilon_t u_s) = 0 \; \forall \; t, s$ and $\lambda = \left(\frac{\sigma_u}{\sigma_\varepsilon}\right)^2$.

It is generally recognised that many economic time series are integrated by order $d = 1$ or $d = 2$. As $y_t = g_t + c_t$, we can present it in the following way:

$$(1-L)^2 y_t = A(L)\varepsilon_t + (1-L)^2 A(L)u_t = A(L)(\varepsilon_t + (1-L)^2 u_t) = A(L)(1 - \gamma_1 L - \gamma_2 L^2)\eta_t. \tag{C.3}$$

Based on (C.3), it can be shown that the movements in y_t will follow the ARIMA process. For this purpose, assume that y_t is a second-order integrable series, i. e. $I(2)$ with autoregressive operator $\phi(L)$ of order p and reversible operator $\theta(L)$ of the moving average of order q. Based on operators $\phi(L)$ and $\theta(L)$, we can infer:

$$A(L) = \frac{\theta(L)}{\phi(L)(1 - \gamma_1 L - \gamma_2 L^2)}. \tag{C.4}$$

Inserting (C.4) in (C.3), we get:

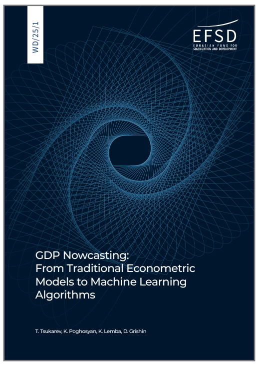
$$\phi(L)(1-L)^2 y_t = \theta(L)\eta_t. \tag{C.5}$$

It follows from equation (C.5) that if y_t is I(2), then this time series follows the ARIMA(p, 2, q) process and hence its components g_t and c_t will follow the ARIMA(p+2, 2, q) and ARIMA(p+2, 0, q), respectively.

Similar conclusions can be reached if we consider y_t as I(1). In this case, equation (C.5) will appear as follows:

$$\phi(L)(1 - L)y_t = \theta(L)\eta_t. \qquad \text{(C.6)}$$

Based on equations (C.5) and (C.6), we build forecasts for time series y_t at points $t + 1$ and $t + 2$, which we then use to estimate the optimal change in the cycle component in period t as shown in Mise et al. (2005).



Working paper WP/25/1
(RU/EN)

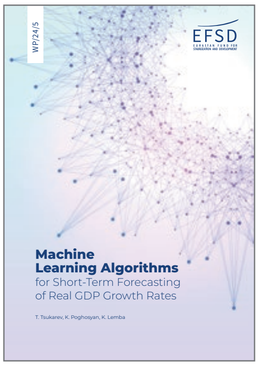
GDP Nowcasting: From Traditional Econometric Models to Machine Learning Algorithms

The study explores whether machine learning methods and algorithms have the potential to improve the accuracy of estimates of macroeconomic variables.

Report on sovereign financing for 2024
(RU/EN)

Sovereign Financing in Eurasia in 2024: Record Amounts of IFIs Support

The Report focuses on the monitoring of sovereign financing in Eurasia for 2024, relying on a database maintained by the EFSD.



Working paper WP/24/5
(RU/EN)

Machine Learning Algorithms for Short-Term Forecasting of Real GDP Growth Rates

The paper evaluates the accuracy of short-term forecasts produced by machine learning methods and algorithms compared to conventional econometric models.

Joint Working Paper by the EFSD and the CAREC Institute
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Country-level interest rate risk impact on debt and fiscal sustainability: potential use of floating-rate and inflation-indexed liabilities

The Paper examines the interest rate risks associated with recent dynamic of LIBOR (SOFR) and EURIBOR, as well as considers the potential inclusion of obligations with floating-rate and indexed principal in domestic debt portfolios of the countries under review.

Working paper WP/24/4
(RU/EN)

EFSD Early Warning System: Developing Tools to Predict Currency Crises

The paper presents a methodology and a step-by-step algorithm for the development of tools to identify imbalances (crises) and stress situations in the economy. The main emphasis was placed on detection of growing tensions in the foreign exchange market.

Working paper WP/24/3
(RU/EN)

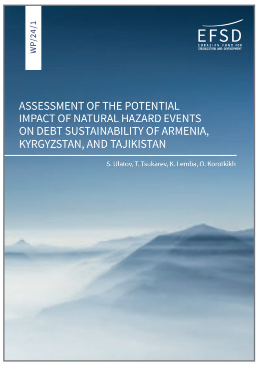
Sovereign financing in Eurasia: 1H 2024.

The Paper focuses on the monitoring of sovereign financing in Eurasia for 1H 2023.

Working paper WP/24/2
(RU/EN)

Sovereign financing in Eurasia: trends and areas

The Report focuses on the monitoring of sovereign financing in Eurasia, relying on a database maintained by the EFSD.



Working paper WP/24/1
(RU/EN)

Assessment of the Potential Impact of Natural Hazard Events on Debt Sustainability of Armenia, Kyrgyzstan, and Tajikistan

The paper presents an algorithm that can be used to assess the impact of natural hazards on macroeconomic indicators and debt sustainability of various countries.

Working paper WP/23/3

(RU/EN)

International Reserves as the core element of the GFSN for developing economies

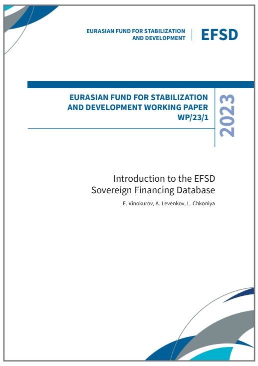
The paper assesses factors affecting the decision of developing economies on the source of anti-crisis support. The study showed that international reserves are the most sought-after instrument among all the elements of the GFSN.

Working paper WP/23/2

(RU/EN)

Sovereign Financing in Eurasia: Water Sector and Hydropower Generation

The purpose of this Working Paper is to analyse operations of IFIs, climate funds, and development agencies in the water and HPP sector between 2008 and H1 2023 in 11 countries of the Eurasian region.

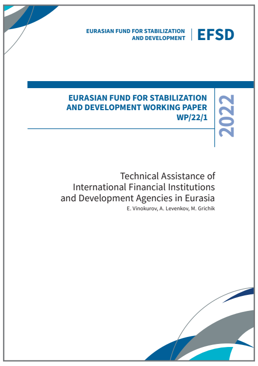


Working Paper WP/23/1

(RU/EN)

Introduction to the EFSD Sovereign Financing Database.

In this Working Paper the Sovereign Financing Database (SFD) Methodology is presented and also quantitative and qualitative analysis of sovereign financing operations in 11 countries of the region from 2008 to 2022 is carried out.



Working Paper WP/22/1

(RU/EN)

Technical Assistance of International Financial Institutions and Development Agencies in Eurasia.

The purpose of this analytical document is to review technical assistance projects implemented by international financial institutions and development agencies in 2009–2021 in 11 Eurasian countries with a detailed thematic and institutional breakdown.

Measuring Credit Gaps:
A Restricted Hodrick—Prescott Filter Approach

T. Tsukarev, K. Poghosyan, K. Lemba, D. Grishin, A. Yanushkevich

The Eurasian Fund for Stabilization and Development (EFSD) totaling over US$ 9 billion was established on June 9th, 2009 by the governments of the Republic of Armenia, the Republic of Belarus, the Republic of Kazakhstan, the Kyrgyz Republic, the Russian Federation, and the Republic of Tajikistan. The objectives of the EFSD are to assist its member countries in overcoming the consequences of the global financial crisis, ensure their economic and financial stability, and foster integration in the region. More information about the EFSD is available at: efsd.org/en/.

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