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Do we get cold feet when deciding on countercyclical capital buffer? Ways to deal with uncertainty in estimating credit-to-GDP gap in real time

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Abstract

Macroprudential policymakers track cyclical risk accumulation via a wide range of indicators. To make timely policy decisions, these indicators need to be valid, stable and a good representation of (future) financial cycle movements. These indicators are used in different empirical settings as an approximation of the financial cycle. The credit-to-GDP gap (Basel gap) is the most used indicator in research and practice of EU, as it is a part of Basel III regulatory framework as a standardized and harmonized indicator. Countercyclical capital buffer (CCyB) calibration is one of several macroprudential policy concepts based on the Basel gap or on some kind of its variant, among other relevant indicators. However, due to specific problems with the way the Basel gap is calculated, macroprudential policymakers tend to possess inaction bias regarding CCyB activation. Here, the focus will be on the uncertainty of the Hodrick-Prescott (HP) filter approach and the reduction of the end-point problem. The focus of the study is on investigating how to fix the endpoint problem of the filtering process. This is appropriate for those authorities whose analysis shows that the HP approach is best in predicting financial crisis. The results of this study can be used in real-time decision-making, as they are relatively simple to estimate and communicate, and such augmented gaps reduce the bias in the gap series after the financial cycle turns. Moreover, the paper suggests possible corrections of the credit-to-GDP gap so that the resulted indicators are less volatile over time with stable signals for the policy decision-maker.

Key words: credit-to-GDP gap, out of sample forecasts, augmented credit gap, countercyclical capital buffer, estimation uncertainty

JEL classification: E32, G01, G21, C22

"It is very difficult to predict, especially the future" – Niels Bohr, source: The New Yale Book of Quotations, Shapiro and Menand (eds.)

1. Motivation for this research

Macroprudential policy has the task of tracking and monitoring the financial cycle among other relevant issues regarding the financial system and maintaining its stability. The pro-cyclicality of the financial cycle has proven to be the origin of the previous Global Financial Crisis (GFC), as heavily documented in the literature (see, e.g. Ampudia et al., 2021 for a concise and concrete overview in macroprudential terms when describing the happenings before the GFC hit). Thus, it is not surprising that a number of papers focuses on identifying the financial cycle, as reducing its pro-cyclicality is an operational task of the macroprudential policy. When indicators of the financial cycle are estimated and identified for a financial system, they are used regularly in the decision-making process of macroprudential authorities. Namely, one of the main uses of such indicators is to make decisions about the Countercyclical Capital Buffer (CCyB[1]), and a wide range of other analyses, where it is crucial to have a valid indicator that can be used on a regular basis. This includes usage of composite indicator of cyclical risk calculation (Škrinjarić, 2022; Chen and Svirydzenka, 2021; Karamisheva et al., 2019); general analysis of different questions where the indicator of the financial cycle is utilized in the empirical research (e.g. effects of financial cycle indicator on current account fluctuations in Jones et al., 2021; effects of exchange rate fluctuations on financial cycle indicator in Nier et al., 2020; monetary policy analysis where the financial cycle indicator is included, as in Caldas Montes et al., 2014), macroprudential stance evaluation in ESRB (2021), Aikman et al. (2019), and O'Brien and Wosser (2021), etc. As research on the topic of the effectiveness, costs and benefits of the macroprudential policy and its interaction with monetary and fiscal policy is rising in the last decade, we need to obtain valid and robust indicators regarding the financial cycle.

Current international financial regulation in BCBS (2010) and ESRB (2014) standardized the process of estimating the primary indicator of the financial cycle, called the Basel credit gap. It is a harmonized indicator that captures excess credit dynamics, i.e. cyclical risk accumulation. Due to the way it is calculated, it is easy to interpret and compare across countries. Literature has often recognized that the Basel credit gap is best in signaling future crises (Drehmann et al., 2010; Borio and Lowe, 2002; Borio and Drehmann, 2009; Galán, 2019, Detken et al., 2014); as well as it being the leading indicator of the probability of crises, alongside their severity (Drehmann et al., 2014; Schularick and Taylor, 2012; Dell Ariccia et al., 2012); and it is supported by general findings that strong credit activity precedes crises

[1] Within the revision of the Basel accords, the CCyB has been designed and put forward (BCBS, 2011; ESRB, 2014) as one of the key macroprudential instruments. Its main task is to help in countering some of the pro-cyclicality of the financial cycle, and its primary intent is for credit institutions to accumulate additional capital in the upward phase of the financial cycle. This can, in turn, help in facilitating the credit activity when risks materialize and the downward phase of the cycle occurs. Calibration of CCyB values depends on the indicator of the financial cycle, i.e. excessive cyclical risk accumulation.

(Gourinches and Obstfeld, 2012). The Basel gap is calculated based on the credit-to-GDP ratio, which is filtered via the Hodrick-Prescott (HP henceforward, Hodrick and Prescott, 1997) filter. This filter was selected, as it was fairly popularized in the research of business cycles. Thus, national authorities based on the BCBS recommendation utilize the HP filter, using the one-sided approach. This means that only past information of the ratio and gap is used for the decision-making process. This is based on the facts that decisions have to be made in real-time. So, the statistical filtering procedure of estimating the trend and consequently the gap is based only on data up to the last available point.

Desirable properties of financial cycle indicators were discussed in Önkal et al. (2002), Lawrence et al. (2006), Kauko (2012), and Drehmann and Tsatsaronis (2014). These and other papers recognize two most important properties of a reliable financial cycle indicator: good signaling properties in terms of minimizing errors type I and II, and stability and stationarity of indicator. It should have cyclical movement as the financial cycle itself, with some kind of mean reverting property. If the indicator is stable or stationary, it is easier to predict, alongside easier CCyB calibrating. Now, part of the research focuses on one property or the other. This research belongs to the strand that focuses on the stability of the indicator and general uncertainty at the end-point of data series. A problem always arises in HP filtering. Due to the nature of the optimization process of the HP filter, couple of last values have different weights in the trend estimation, compared to other values of the series. This is the well-known end-point problem of the HP filter. Besides many other problems regarding this filter (see Cogley and Nason, 1995; Kamber et al.; 2018; Hamilton, 2018), the end-point one could be the biggest for the macroprudential policy maker. The decisions that are made at any point in time are always affected by this problem. Edge and Meisenzahl (2011) examined the real-time estimates and the final revisions of GDP effects on the credit-to-GDP. The HP filter approach was found to have large ex-post revisions, due to large deviations of GDP values in the final estimates. Such results are important for the macroprudential decision-making in real-time and consequently, on total capital requirements that credit institutions face over time, alongside other relevant areas where the information about the financial cycle and its indicators is taken as given. This is one of the reasons why macroprudential policymakers get cold feet in the decision-making process. Increasing capital requirements is costly, and should be justified.

The focus here is on researching how to fix the endpoint problem of the HP filter within the Basel framework and ESRB (2014) guidance. Although there exist studies that find better approaches to gap estimation compared to the HP filter (Hamilton, 2018; Beutel et al., 2018; Lang et al., 2019, Barell et al., 2020, etc.), we stay within the HP approach, as there are empirical studies of central banks that found the HP approach to be the best in previous financial crises signaling (Drehmann et al., 2010; Galán, 2019; Valinskytė and Rupeika, 2015; Croatian case in Škrinjarić and Bukovšak, 2022a, b). Moreover, Deryugina et al. (2020) have shown based on Monte Carlo simulations that 12-15 years of data is sufficient to generate reliable credit-to-GDP gaps based on HP filtering and CCyB calibration anchoring. The research on the topic of alternative approaches to calculating the credit gap has been emerging in the last decade, alongside the possible augmentations of the original HP gap approach described in ESRB (2014). This paper deals with a concise overview of the alternative approaches that try to enhance the HP filtering process in the first part. Afterward, the paper deals with augmented HP filter with the oos (out of sample) forecasts. A comprehensive approach is made where the possible oos modeling approaches are discussed and contrasted one to another in the empirical part of the research. Previous research recommends solving the end-point bias problem by extending the series with forecasts (see Kaiser and Maravall, 1999; or Mise et al., 2005). This paper will give a detailed analysis of possible forecasting approaches, alongside their comparisons. Moreover, this research belongs to the strand that deals with data and measurement uncertainty, meaning that every time a new information arrives, or when data revisions are made, there always exists uncertainty in updating the results (which is done on a regular basis).

The paper contributes to the literature in several ways. It examines different models across different forecast horizons and several measures of performance. As the two-sided HP gap is considered to be the "true"[2] gap, the one-sided gaps are compared to the dynamics of the two-sided one. Moreover, the oos performance of each approach is considered an important factor as well. However, opposed to previous literature, we compare the oos forecasts of credit or GDP values to the future true realization instead of trend comparisons. This is due to comparing forecasts to a true value of a series, instead of an estimated one (see section *Evaluating the best approach* for details on not using HP gaps for oos comparisons, as they are subject to uncertainty which is then included in the comparison criteria). The variability, i.e. stability of the resulted indicators is also considered. All of these criteria are often conflicting and systematization of the results is needed. The results of this study can be used in real-time decision-making, as they are relatively simple to estimate and communicate, and such augmented gaps reduce the negative bias after the GFC. As this type of result is important for macroprudential policymakers that need to have current credit gap estimates as precise as possible, such detailed analysis provides important insights into this topic.

The results of the study show that it is not easy to choose the best model and fit it for all series in a uniform way. This is due to different criteria that the forecaster and decision-maker use often have conflicting characteristics. Shorter time horizons have smaller oos errors as expected, but longer horizons have smaller revisions towards the two-sided "true" gap. Moreover, the random walk and autoregression models have, on average, the best performance for credit and GDP series. Thus, simulations of CCyB values are based on these results, and show a promising potential to use this in practice. The rest of this paper is structured as follows. In the second section, we provide a general position of this research within the whole universe of related work, and review the related literature. Afterward, the description of the credit gap estimation and the oos augmentations is given in the third section. An empirical analysis of the results is given in the fourth section, with the discussion of the results. The final, fifth section concludes the paper.

[2] Quotation marks are added, as the true gap is never observed. This means that the uncertainty bands cannot be estimated. However, some anchoring in comparisons is needed.

2. Literature review

2.1. General research on uncertainty problems and macroprudential policy

When talking about uncertainty, a lot of today's definitions and literature are under the influence of Knightian uncertainty (F. Knight and his book *Risk, Uncertainty, and Profit*), and J. M. Keynes (his book *A Treatise on Probability*). Knight made a distinction between risk and uncertainty, via knowing or not knowing the distribution of the probabilities of different outcomes of an event, whereas Keynes defined uncertainty as "*By uncertain knowledge, let me explain, ... We simply do not know*" (Keynes, 1937: pp. 213-214). Knight's view of uncertainty stems from partial knowledge, i.e., not knowing future outcomes makes it impossible for an individual to classify outcomes (see Langlois and Cosgel 1993). Thus, if an individual is familiar with the distribution of the probability of an outcome (regardless of whether it is known *a priori* or the individual estimates statistical probabilities of outcomes), then it is a matter of risky situations in which he makes decisions (Runde, 1998). The impact of Knight's ideas on the later development of decision theory and decision psychology can be seen in Rakow (2010). Bahaj and Foulis (2017) define the Knigthian (or fundamental) uncertainty in macroprudential policymaking as situations when the policymaker needs to make judgement about the state of the world, when it is not possible to quantify the likelihood of outcomes in the economy. Now, by focusing on the type of uncertainty when we deal in modeling and policymaking, it could be divided into instrument, model, parameter, and data and measurement uncertainty.

Instrument uncertainty can be defined as policy instruments having a volatile relationship with the objective. Such uncertainty makes macroprudential policymakers less active, as discussed in Bahaj and Foulis (2017). This research is a theoretical one, in which modeling and discussion about uncertainty and its analysis is found. It has roots in the seminal work of Brainard (1967). Model uncertainty could produce different outcomes regarding the decision that needs to be made, depending on changes done in the model itself. This was analyzed in Bahaj and Foulis (2017) as well. Davies (2020) continued this theoretical analysis, by combining both instrument and model uncertainty when the macroprudential policymaker has to make decisions about certain actions that influence financial stability. The author discusses that instrument uncertainty leads to under-reactions of the policymaker, whereas model uncertainty causes over-reactions. The end results depend on the magnitude of both reactions, and in certain cases, the policymaker could be unbiased in terms of cancelling out of the different reactions of opposite signs. Moreover, an extension was made to leaning against the wind strategy that is commonly mentioned in the literature on countercyclical policy conduct. Davies (2020) obtained results that leaning against the wind is appropriate for the policymakers when the instrument uncertainty is low and model uncertainty high. General comments and remarks regarding such uncertainties, and model and parameter uncertainty when conducting monetary policy can be found in Longworth's (2004) speech, or speeches such as Sellon (2003), Donnery (2016), or Greenspan (2003). Macroprudential policy relies on a similar approach of linking the indicators to goals, as the monetary policy does. That is why the discussion can be translated to the macroprudential policy of trying to reduce all uncertainties so that the total outcome can be more efficient, inaction bias reduced, and greater credibility of the policymaker achieved.

There exist studies that analyze the effects of "uncertainty indicators" on selected macroeconomic variables, alongside macroprudential policy decision-making. In other words, a group of research interprets that uncertainty can be somewhat quantified via economic and political uncertainty indices, implied stock market volatility, and similar measures. Such indicators are used in macro models to obtain richer results and changes in the behavior of the connections between the typical variables. Other goals include enhancing the forecasting properties of the model. This group of research is very broad, and includes forecasting growth (Hengge, 2019; Rogers and Xu, 2019; Segnon et al., 2018), credit dynamics (Venter, 2021), forecasters' disagreement as proxies of uncertainty (Bachman et al., 2013; Rossi and Sekphosyan, 2015; Hristov and Roth, 2022; Istiak and Serletis, 2020; Charles et al., 2017), etc. There is more research on measuring general macroeconomic uncertainty and its effects within macroeconomic models, but is beyond the scope of this paper (see Jurado et al., 2015). This research deals with data and measurement uncertainty. This means that data revisions affect the outcome of the results, as well as measurement errors. Such errors occur if the economic variables are measured wrong in a fundamental way. As data revisions on GDP happen every year, this affects the values of final credit-to-GDP gap series. On the other hand, the way the gap is estimated even if we had data of best quality with no additional noise or revisions, results in measurement errors that could affect the final decision-making. This is true not only for the last couple of observed periods, but this could retroactively change decisions about the credit-to-GDP gap interpretations.

2.2.Empirical literature review and central banks' practices regarding augmented gaps

Now, if we focus on the credit-to-GDP gap itself, based on the BCBS (2010, 2011) guidance, authorities started to calculate the credit gap by following the procedure of one-sided HP filtering of the credit-to-GDP ratio. However, literature has been emerging since the early 2010s that focuses on comparisons of different approaches of calculating the credit gap. This research compared the results between countries and different crises. As many problems were found in this methodology, part of the literature focused on improving the current methodology (see Škrinjarić and Bukovšak, 2022a, for a concise list). Besides this, critiques and general improvements of HP filter in business cycle literature were already available. As the main idea of the credit gap is that it should be an early warning indicator of a future crisis, a lot of research focused on banking crises and the signaling properties of this and other indicators. Borio and Lowe (2002), and Borio and Drehmann (2009) are one of the first and often cited research on the early warning methodology approach to the signaling of crises so that appropriate indicators can be utilized when making the decisions about the CCyB value. Since the credit gap has often been found as the single best predictor in the early warning literature (Drehmann et al., 2010, 2011; Babecký et al., 2014; Bonfim and Monteir, 2013; Behn et al., 2013; Drehmann and Juselius, 2014; Detken et al., 2014), it still presents the main indicator authorities report and comment on, alongside other information relevant for monitoring cyclical risks. Critiques and enhancements of the main methodology have focused on different definitions of credit (Baba et al., 2020), using population instead of GDP in the numerator (Richter et al., 2017; Drehmann and Yetman, 2018), using different definitions of the credit gap instead of HP filter approach (Kauko, 2012; Hamilton, 2018), different smoothing parameters in the HP procedure (Drehmann et al., 2010; Galán, 2019; Rünstler and Vlekke, 2016; Wezel, 2019), etc.

If we focus on the end-point problem literature, there is evidence that subsequent revisions of data, especially of GDP could affect the signaling properties of the credit gaps (Edge and Meisenzahl, 2011). This means that adding new or revised data could change the movement of the long-term trend captured in the HP optimization process, discussed in Canova (1998), and Pedersen (2001). Consequently, the policy implications and decisions could be very different from one period to another, as pointed out in Edge and Meisenzahl (2011), and Alessandri et al. (2015). Reasoning on why such results occur is found in Gerdrup et al. (2013): the HP trend lags the actual values, which in turn creates greater gaps after the turning point of the indicator. As a result, the filtered series could have phase shifts in data. Earlier literature showed that adding out of sample forecasts to the original dataset being filtered reduces revision errors of the most recent cyclical values (Kaiser and Maravall, 1999). That is why applications of such an approach are increasing in practice.

Gerdrup et al. (2013) apply out-of-sample forecasts for the case of the Norwegian credit-to-GDP ratio. In this study, the authors have compared the traditional Basel gap to those obtained by adding rolling average forecasts, linear forecasts, and rolling linear forecasts. Moreover, the comparisons were made for other relevant series as well, such as the house prices to income ratio, property prices index, and wholesale funding ratio. The main applied comparison criteria were the difference between the one and two-sided gaps, and the usual criteria in the early warning modeling approach. Valinskytė and Rupeika (2015) utilize last value, four and eight quarter moving averages, and linear forecasts in comparing the oos performance of credit gaps in Lithuania. The main criteria of comparisons are based on Gerdrup et al. (2013) findings of the revisions of the one-sided gaps and the variability of the gaps. The gaps that were chosen were those that had the smallest revisions and variability. This is important, as such gaps should give robust signals over time.

Bank of Portugal (BoP, 2020) has a publication about the general indicators used for purposes of calibrating CCyB values. This report states that BoP uses an additional credit-to-GDP gap, obtained via oos forecasts based on an autoregressive (AR) integrated model with 28 quarters used of the oos forecast horizon. Other relevant approaches that were contrasted included the random walk, moving average, linear trend model, moving linear trend, autoregressive integrated (ARI), and one variant in which both the AR and MA (moving average) lags were estimated recursively. Geršl and Mitterling (2021) did a study on a panel of countries, including 56 different countries for a long period: from 1950 to 2016. The results show that oos forecast augmentations of credit gaps improve the signaling properties of such indicators for the case of emerging markets. As the results are mixed when dividing the data for developed and emerging markets, this indicates that individual country studies are important as well. One cannot just copy other practices as given but should test best practices based on own data. However, as oos forecasts usually can flatten the credit gaps compared to the original values, the question is how useful is such a signaling approach. Altghough the augmented gaps are more stable and have reduced end-point problem, such gaps could have lagged reactions when new values indicate a change in the trend. Thus, it is a difficult task to evaluate these indicators in terms of both signaling properties, alongside the revisions of gaps over time.

Other recent studies that incorporate oos augmentation in the filtering process include Jokipii et al. (2021), who follow Alessandri et al. (2015) approach, but for Swiss data. The latter paper developed a correction procedure of the difference between the one and two-sided HP gap for the Italian case. Augmentation of the HP gap in both cases has shown that it enhances the usability of the credit gap itself, in terms of greater consistency of the estimates. As can be seen, the literature on the specific topic of credit gap augmentation via oos forecasts is growing, especially in the last two years. This indicates that the applications in central banks have recognized such a need for greater usability of credit gap in practice. The rest of the paper gives a detailed methodological approach and estimation results for enhancing the practice of using such an approach.

3. Selected extensions of the credit-to-GDP gap calculation

3.1. Introduction of the problem

This section describes the way the credit-to-GDP gap (credit gap henceforward) is calculated, based on the ESRB (2014) guidance, as well as the extensions that this paper explores. The main takeaway obtained from the credit gap is how much does the credit activity exceed the real activity, i.e. is the credit growth compared to the growth of the rest of the economy justified. The gap is estimated with the Hodrick-Prescott (1997) filter (HP filter and gap afterward), with the main objective function is as follows:

$$\arg\min_{\{\mu_t\}_{t=0}^{T}} \left[\sum_{t=0}^{T} (y_t - \mu_t)^2 + \lambda \sum_{t=1}^{T-1} \left((\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1}) \right)^2 \right], \tag{1}$$

where y_t is the time series to be filtered, μ_t is the trend series, and λ is the smoothing parameter (or the penalization parameter), $t = 1, ..., T$. The trend series is estimated such that the deviation from the real series y from the trend series μ is minimized, alongside imposing a penalty in the second part of (1): on changes in the trends slope. The greater the value of lambda is, the greater penalty is given to changes in the slope, and the trend resulting from (1) becomes smoother.

For the purpose of the CCyB decision-making, the HP gap is calculated at every period $t' \leq T$, when new data arrives. However, the base is the recursive gap, i.e. the one-sided filter approach:

$$\arg\min_{\{\mu_t\}_{t=0}^{t'}} \left[\sum_{t=0}^{t'} (y_t - \mu_t)^2 + \lambda \sum_{t=1}^{t'-1} \left((\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1}) \right)^2 \right], t' \leq T \tag{2}$$

This means that at a given period t'>0, the HP gap is calculated as in (1), for all available data up until point t'. Then, when new data arrives in t'+1, the optimization problem in (1) is done again, with the additional data point, but previous values of the gap stay fixed. The new value of the gap series, for period $t'+1$ is added to the existing series. Now, when new data arrives again, in $t'+2$, the optimization procedure is done as previously described, but the gap series with the previous period added gap is fixed, and only gap from $t'+2$ is added. To put it differently, for the first t' periods, the gap series is fixed at all times, and when additional data becomes available, the HP filter is applied over the entire series, but only the last value of the gap is added to the existing series. The basis for this is the fact that the macroprudential policymaker has to make decisions based on the data that is available up to that point in time. The two-sided HP gap on the other hand assumes that information in the future is available when making the decision itself. Thus, it is a recommendation and common practice to utilize the one-sided gap.

Now, by observing problem (1) (or (2)), due to leads and lags of the trend series being different compared to the y series, several μ values are not included in the summation as others. Namely, values μ_0 and μ_T are included only once, μ_1 and μ_{T-1} twice, whereas all other values occur three times. This means that these end values are not penalized as much as other values are. That is why greater deviations are allowed at the end of the series. Since the decision-making process relies on the last value of the credit gap, the end-point problem is relevant in the macroprudential policy. This is especially problematic for the one-sided filtering approach.

3.2.Out of sample (oos) forecast approaches

As stated in the related literature review, there are several popular approaches to extending the sample of the credit-to-GDP ratio via out-of-sample so that the trend is stabilized at the end of the sample. We examine several models for oos as follows, with detailed and formalized explanations in Appendix A1. A basic approach is the moving average (MA) one, in which the credit-to-GDP ratios are extended in the oos part via their moving average values. The second approach is the linear forecast model, where the oos values are forecasts from the linear trend model. In a simpler approach, the linear trend model is estimated form the beginning of the sample, until the last point t' (defined in previous section). This has a drawback of assuming the same trend in data for the entire sample, both for the extreme credit-to-GDP ratio growth before GFC and subsequent decline. That is why the third approach is the variation of the linear trend model, i.e. a rolling linear forecast. Here, the forecasted values of a moving window approach are used for the oos part. Next, as the series[3] of credit-to-GDP ratio exhibit random walk (RW) properties to some extent, the fourth approach was to estimate a rolling window of a RW model and use its forecasts. Finally, an integrated autoregressive model (AR) is utilized as another common approach to forecasting, where the credit and GDP series were differenced to obtain some stationarity and then this difference was modeled as an AR(p) process, which is by definition invertible (useful property for forecasting). Several values for p were chosen (ranging from one to four to obtain parsimony).

[3] Or general credit and GDP series separately.

Now, other possible models could be utilized for forecasting purposes, such as enabling the MA part in the ARIMA models in the previous sub-section, giving weights to past values in the moving average approach, and fixing the oos values to be the last observation at time *t*, etc. However, the approaches described in the previous paragraph usually do the job fairly well, and some drawbacks of these other approaches are that as the estimation is done on a rolling window basis, adding additional parameters in the estimation procedure reduces the degrees of freedom. This refers to a full ARIMA model approach, where the AR term is more important for forecasting purposes as data series generated by autoregression is by definition an invertible process. Moreover, giving weights in moving average approaches, although useful when wanting to give greater emphasis on recent movements, could be problematic if errors and great shocks occur in the most recent periods. This would increase the uncertainty of estimates even more. Finally, fixing oos values to be the latest observation when doing the calculations, would stabilize the oos trend within the HP filtering, the same problem of the mentioned recent shock could affect the results.

3.3.Evaluating the best approach

There are several approaches that can be made to compare different indicators of credit activity, i.e. credit gaps. Usually, the early warning models (EWM) consist of comparing the TPR (true positive rate), FPR (false positive rate), AUROC (area under the receiver operating characteristic curve), etc. Details on such methodology and applications for credit dynamics indicators can be found in ESRB (2018), Lang et al. (2019), and Candelon et al. (2012). However, due to the short time available for Croatian data, as used in this study, if only one crisis is included in the sample, the results could be biased. This is commented in Škrinjarić and Bukovšak (2022a), where authors advise taking such results with caution. Moreover, as the oos forecasts tend to smooth out the resulted credit gap series, this affects the resulting values of AUROC and other relevant measures alongside statistical tests. Although the resulting gaps could be better in predicting a crisis compared to the original ones (that are not augmented in any way), the values of augmented could stay positive or negative longer (due to the smoothing process).

Nevertheless, we compare the results of all approaches in Appendix, in Table A1. Almost 82% of all considered augmented gaps have greater AUROC value compared to the Basel gap. They also exhibit a close tie between the linear forecast, rolling moving average, and ARIMA (for both credit definitions[4]). Moreover, the individual worst performance have indicators that are based on twelve quarter forecasting horizon. Such results rely on the assumption that the same estimated behavior holds for a longer period of time in the oos horizon. This observation is independent of the lambda value and particular oos forecasting model selection. However, the random walk model has the worst performance overall regarding the AUROC values and their significance. A caveat should be mentioned here, as one crisis is included in the analysis, which affects the results. This should be considered as additional information and taken with a dose of caution. This is corroborated by Baba et al. (2020), who in their evaluation of alternative

[4] See empirical part of the paper for explanations.

approaches to cyclical risk monitoring do not utilize the EWM models to contrast the indicators, as authors state that focusing solely on one part of the financial cycle could produce indicators that perform poorly in other phases. The best view to take, in their opinion, is to produce indicators that track the financial cycle entirely. Unfortunately, authors do not provide further ground for constructing such indicators.

That is why the proposition here is to compare all of the approaches by observing the values of each resulting in a one-sided gap to the two-sided final gap. I.e., mean absolute error and root mean squared error for each approach will be calculated; where the one and two-sided gaps will be compared. Here, the idea is that the revisions of augmented gaps are smallest possible, as in line with Gerdrup et al. (2013). Written formally, for every indicator *i* we calculate the following measure:

$$MAE_i^{gap} = \frac{1}{T}\sum_{t=1}^{T}\left|1gap_t^i - 2gap_t^i\right|, \tag{3}$$

where the *gap* exponent denotes that the mean absolute error (MAE) is calculated for the gap series, 1gap and 2gap are the resulting one sided and two sided gap series at the end of the observed period *T*. Moreover, the root mean squared error (MSE) for every indicator *i* is calculated via formula (4):

$$RMSE_i^{gap} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(1gap_t^i - 2gap_t^i\right)^2}. \tag{4}$$

Besides these measures, the variation of each approach is considered as the variance of each gap estimate at every quarter *t*, such that we collect the gap values in every quarter *t* for an approach. Then, at period *T*, we calculate the variance of the gap value for period *t* = 1 for all recursive estimates. In other words, as the gap series are estimated at every period *t*, the values for period *t* = 1, 2, ... , etc. change in every subsequent estimate. The idea here is that the variation of the gap itself is smallest possible on average[5]. This means that we penalize if the recursive estimates of a gap in quarter *t* vary too much, i.e. estimates should be consistent. This is not penalizing those indicators that have huge amplitudes of the up and down phase.

In order to calculate the measure representing this, firstly we calculate the variance for each gap_t of an indicator *i* for every period *t*, as follows:

$$\sigma_{t,i}^{2gap} = \frac{1}{T'}\sum_{t'=1}^{T'}\left(2gap_{t'}^i - \overline{2gap^i}\right)^2, \tag{5}$$

[5] This is somewhat comparable to the regression coefficient efficiency. Efficiency means that the parameter that is being estimated has the smallest variance. Similar holds here. As we are doing estimates in overlapping window fashion, gap for same period *t'* is going to have a couple of dozen values that are re-estimated. This depends on the length of the rolling window. Now, as we collect all of those re-estimations, we want these estimates to have smallest variability overall.

where (5) is just the formula for the variance based on observation of the gap value and the average gap value for every period *t'*. Then, all of the variances are used to calculate the average variance of an indicator, i.e.:

$$\bar{\sigma}_i^2 = \frac{\sum_{i=1}^{T} \sigma_{t,i}^{2gap}}{T}. \tag{6}$$

Finally, in order to compare the oos performance of each approach, we calculate the MAE and RMSE for the oos values of credit-to-GDP ratios compared to the true values of the ratio. Other literature (such as Gerdrup et al., 2013) compare the oos performance for the gap values. However, as the HP filter is characterized by the endpoint problem even when we utilize the two-sided approach, the uncertainty is too high for the last estimated value of the gap series at each point in time when doing the comparisons recursively. Consequently, we opt to compare the forecasted values of the credit-to-GDP ratios in each recursive forecast, to the true value that occurred later when new data was added. For every chosen indicator *i* we calculate the MAE and RMSE for the oos values, as usually done in forecasting time series.

4. EMPIRICAL ANALYSIS AND DISCUSSION

4.1. Data description

For the purpose of empirical analysis, quarterly data on narrow and broad[6] definitions on credit and GDP values have been collected from CNB (2022a) website. The time span for the analysis ranges from 4Q 1999 to 4Q 2021. The credit-to-GDP ratios were calculated via the following formula:

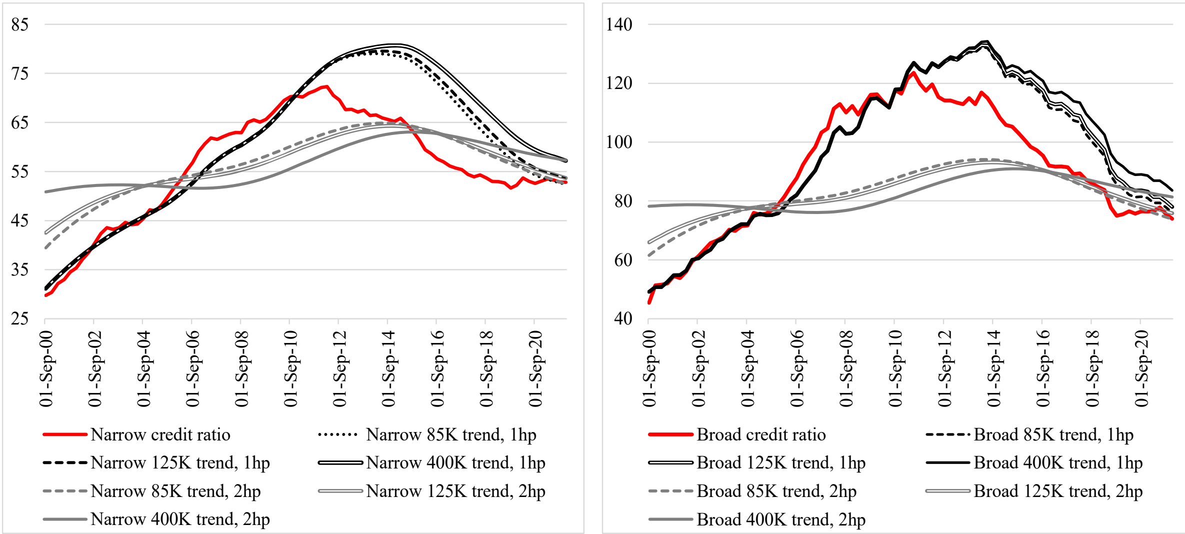
$$ratio_t = \frac{credit_t}{\sum_{k=t-3}^{t} GDP_k} \cdot 100\%, \tag{7}$$

and the ratios are shown in Figure 1. Both ratios have increased significantly during 2000s due to financial deepening, and before the GFC crisis. In the last couple of years, ratios are somewhat stagnating, reflecting a subdued recovery after the crisis. Figure 1 also depicts the HP trend series, for the one- and two-sided approaches of estimation. It is visible that the one-sided approach is more reactive, i.e. the trend changes more, compared to the sluggish two-sided one.

[6] Narrow credit definition consists of bank credits to households and nonfinancial corporations, whereas broad definition includes external debt as well.

Figure 1. Credit-to-GDP ratios and one- and two-sided trends, in %

a. Narrow credit definition b. Broad credit definition



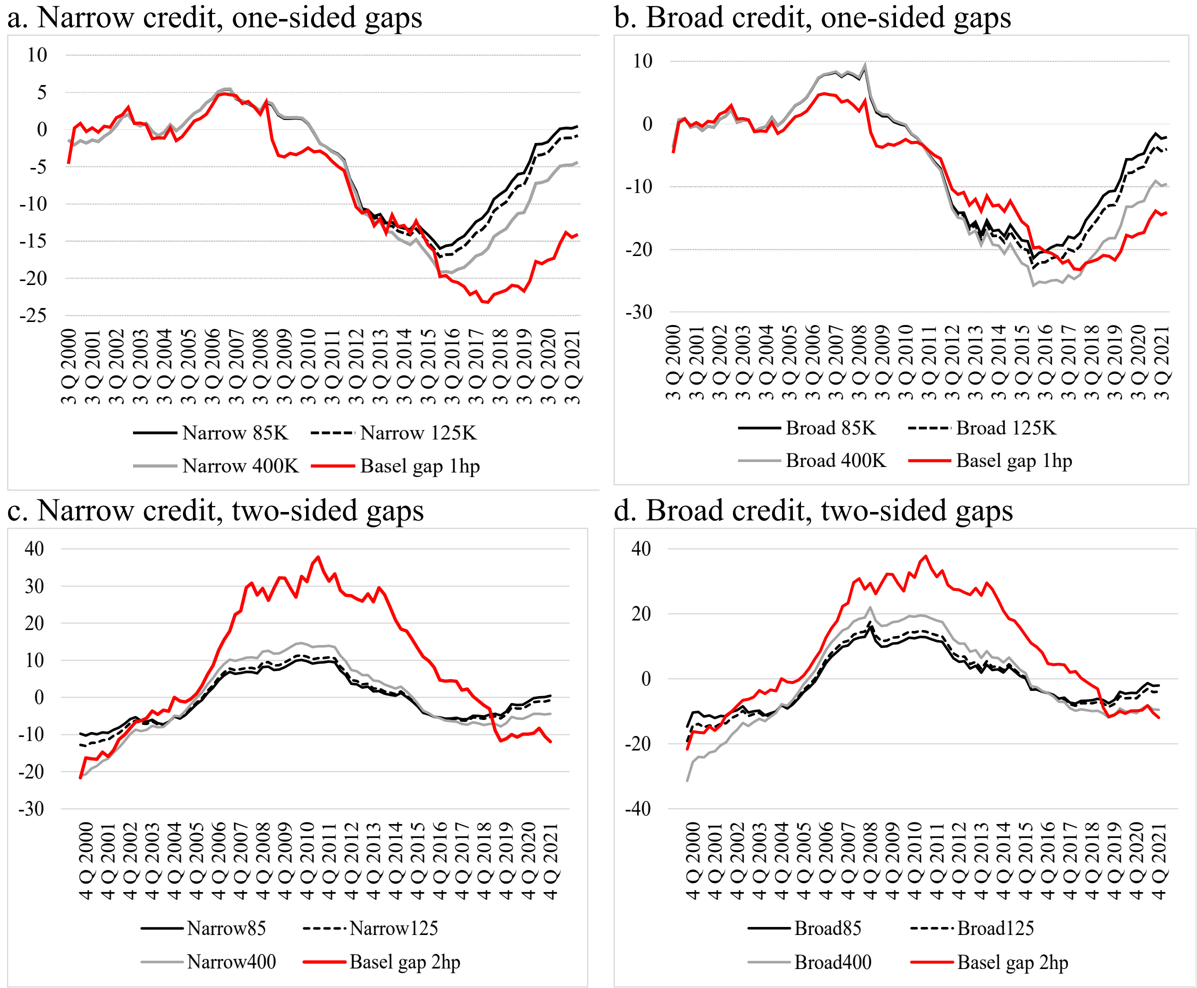
Source: CNB, author's calculation.
Note: 85k, 125k and 400k denote smoothing parameters in HP filter, equal to 85.000, 125.000 and 400.000 respectively. 1hp and 2hp denote one- (in black) and two-sided approach (in grey).

Now, if we calculate the HP gaps[7] for both credit ratios in Figure 1 without any augmentations, the results are shown in Figure 2[8]. Moreover, great differences are observed when comparing the one and two-sided gaps, which makes the point of problems of decision-making in real-time obvious. The augmented credit gaps will be observed in the next sub-section, where the oos forecasts will be made for each of the gaps in panels a. and b. of Figure 2. The Basel gap is in red in every panel, so that the differences between these alternative gaps and the Basel one are visible: alternative gaps increased earlier before the previous GFC, and did not stay positive for so long after it (two-sided ones), or did not have a great negative bias after the crisis as the Basel one did (one-sided approach).

[7] See Škrinjarić and Bukovšak (2022a, b), and the CNB (2022b) Box 2 for details on why these gaps are chosen here.

[8] As this work continues on the previous work in CNB, the gaps that are estimated here are based on separate filtering of credit series compared to the GDP. Moreover, we observe absolute gaps in this study (six), whereas the other six (relative gaps) are calculated from the absolute ones and the analysis does not have to be done separately for relative gaps. In calculating the oos augmented gaps presented in this paper, the oos models chosen for credit series have been paired with matching models for the GDP series. Although the oos forecasting performance of different types of models differs when we compare credit and GDP series (see in text below), we still match equal model selection for both series. E.g. if we pick the random walk model with h = 8 for the credit series in the filtering process, then the resulting trend series is paired with the GDP trend series with the same random walk and h = 8 model selection, as this eases the communication purposes. Furthermore, we tested the results by pairing the best performing models overall without matching the model selection of credit to GDP series, and the results are very similar. This means that the dynamics of gaps is primarily driven by the credit dynamics. Finally, we tested the results by fixing the credit filtering approach and changed the smoothing parameter of GDP series, ranging from 100 to 2200 with 100 increments. The results were also the same

Figure 2. One and two sided HP gaps for credit ratios in Figure 1, in p.p.



Source: CNB, author's calculation.

Note: 85k, 125k and 400k denote smoothing parameters in values of 85.000, 125.000 and 400.000. Overlapping in panels a and b are due to fixing the beginning of the sample[9] to produce initial trend and gap series. 1hp and 2hp denote the one- and two-sided Basel gaps.

4.2. Estimation results

For each of the five approaches of forecasting, we employ forecast horizons of $h = 4$, 8, and 12 quarters. Moreover, for the autoregressive model, values of $p = 1$, 2, 3, and 4 are utilized. Since we observe both narrow and broad credit definitions, for every credit category, in total 72 different augmented gaps were estimated for credit series. A smaller number of matching augmented gaps were estimated for the GDP series, as the only smoothing parameter used here is 1.600 (see footnote 8). Table 1 shows a brief summary of different approaches that were explained in section four.

[9] First 20 Q.

Table 1. Summary of oos model approaches

Series	Smoothing parameter	Forecast horizon	Model approach
Credit (narrow and broad separately)	85.000 125.000 400.000	4, 8 and 12 quarters	Moving average Linear forecast Rolling linear forecast Random walk ARIMA
GDP	1.600		

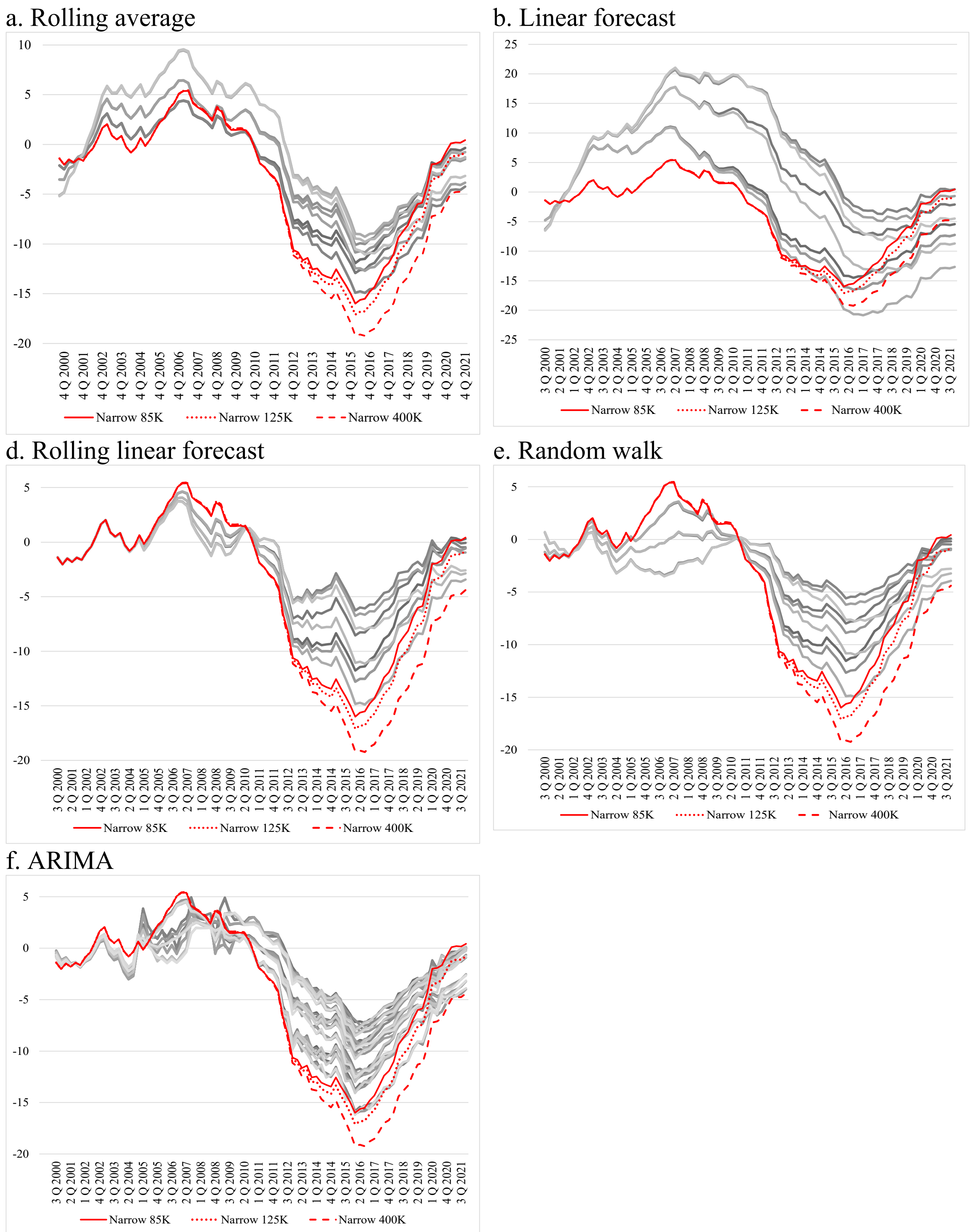
Source: author's elaboration in text

Figure 3 shows all of the augmented gaps based on every approach for the narrow credit-to-GDP ratio, whereas analogous gaps for the broad credit definition are shown in Figure 4[10]. By observing Figure 3, it is apparent that the worst-performing one is the linear forecast on panel b, due to the dynamic being far away from the original indicators without augmentation (the red ones), and being positive almost in the entire observed period. Although the values have been declining in the recession period, such an indicator would guide positive CCyB values in the entire period. Other augmented indicators are not characterized by this problem. The majority of the augmented gaps do not have a big negative bias after the GFC period when compared to the original gaps without forecasts (the red denoted ones). In some cases, the range of the estimated gap is almost 10 percentage points, which we could interpret as greater uncertainty. This shows that it is hard to make decisions in real-time, especially when the value of the gap is such that it is close to the threshold of the CCyB activation.

Similar is true for the broad credit definition gaps in Figure 4. Moreover, it is obvious in Figures 3 and 4 that it is hard to decide which approach could be the best in the decision-making process (besides the linear forecasts approach). As these are some of the basic and popular approaches to univariate forecasting, the problem would be even greater if other more sophisticated approaches would be used. Finally, it is worthy to mention that if we observe the ranges of indicators in Figures 3 and 4 as greater or smaller uncertainty, it could be stated that the uncertainty is greater around turning points of the financial cycle. This is in line with the literature that focuses on the uncertainty of business cycle forecasting (see Berge, 2020).

[10] The initial window for the estimation is 20 quarters long. This is the fixed period for all indicators (i.e. $q = 20$).

Figure 3. Augmented gaps, narrow credit definition

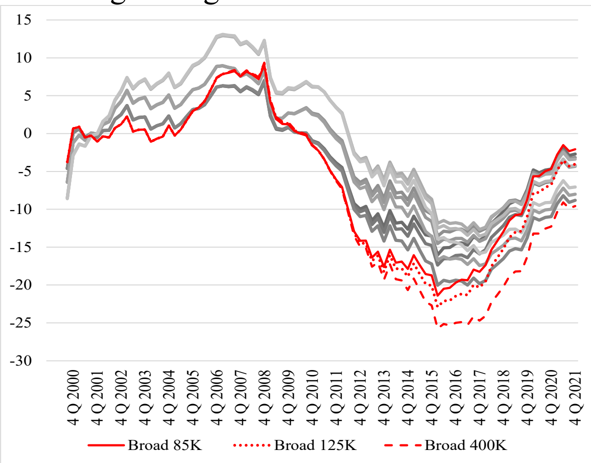


Source: CNB, author's calculation

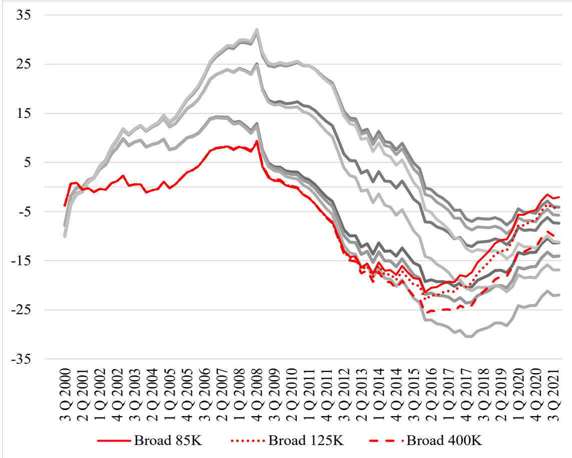
Note: narrow 85k, 125k and 400k are the credit gaps for smoothing parameters of 85.000, 125.000 and 400.000 without any oos augmentations. Red curves denote credit gaps without any augmentation, grey ones are variations of augmented gaps.

Figure 4. Augmented gaps, broad credit definition

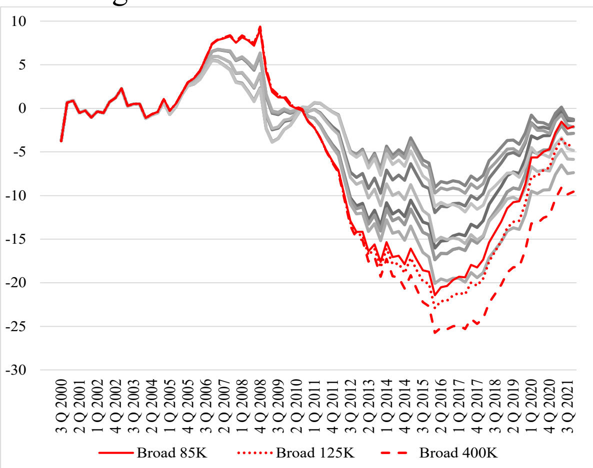
a. Rolling average



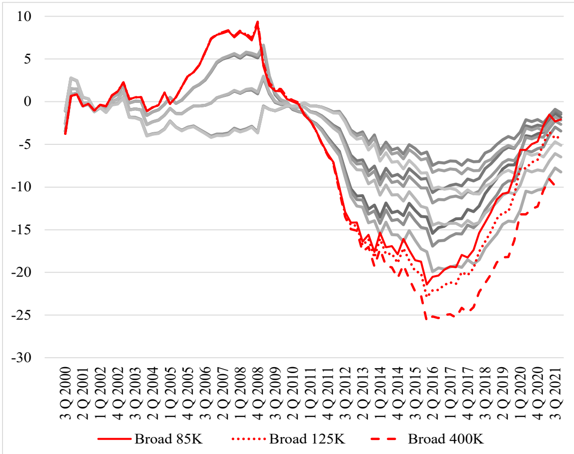
b. Linear forecast



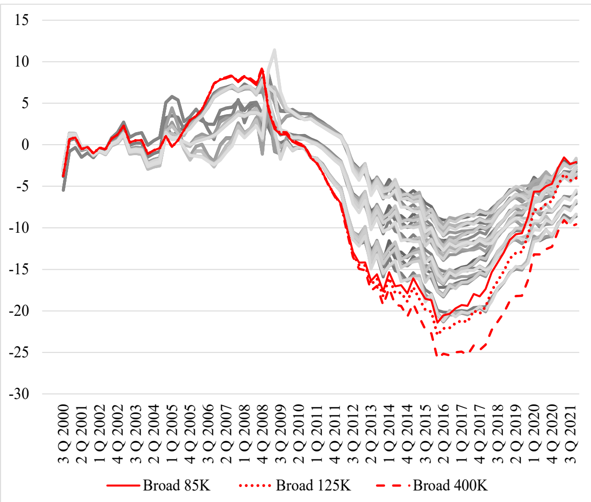
d. Rolling linear forecast



e. Random walk



f. ARIMA



Source: CNB, author's calculation

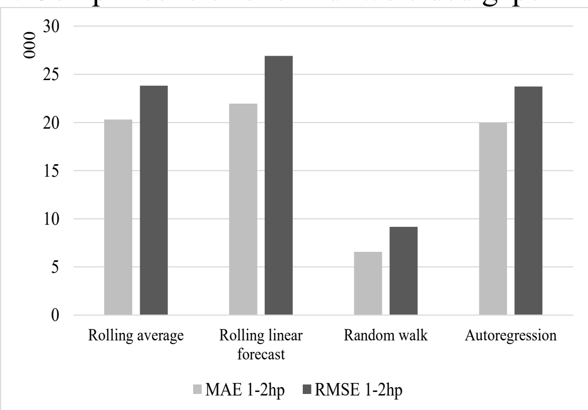
Note: broad 85k, 125k and 400k are the credit gaps for smoothing parameters of 85.000, 125.000 and 400.000 without any oos augmentations. Red curves denote credit gaps without any augmentation, grey ones are variations of augmented gaps.

4.3.Comparison results

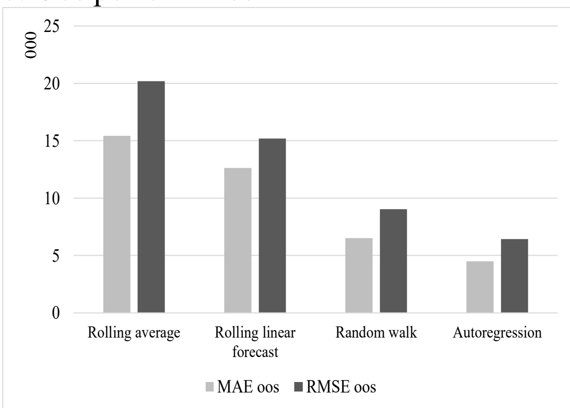
Next, for each of the five approaches, average values of comparison criteria have been calculated, and are shown in Figure 5[11] (narrow credit) and A2 (broad credit)[12]. Again, it is obvious that the worst performance is observed for the linear forecast. By comparing the approaches by the revisions from the one to the two-sided gaps, the random walk has the smallest error; however, the ARIMA approach has smallest variability and oos forecasting performance. This means that for the narrow and broad credit definitions the uncertainty around estimating credit gap is smallest on average for the autoregression approach. The opposite is true for the GDP gap series (Table A4 and Figure A4): the random walk has smallest uncertainty, i.e. variability, and the ARIMA approach has smallest revisions towards the two-sided gaps.

Figure 5. Average values of comparison criteria, narrow credit definition, by forecasting method

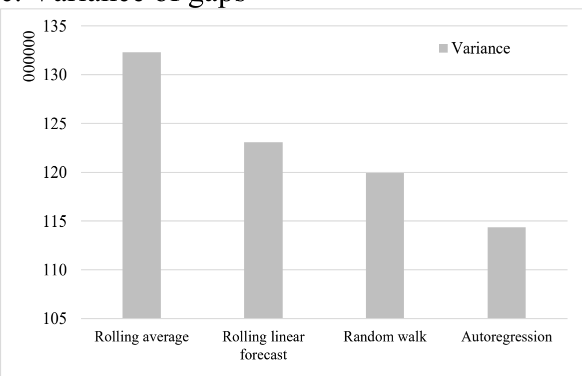
a. Comparisons of one and two sided gaps



b. Oos performance



c. Variance of gaps



Source: CNB, author's calculation

Note: value comparison with the linear forecast is given in Appendix in Figure A1. These values are obtained for narrow credit series filtering[13].

[11] Due to linear forecasts having worse results, we omit them here, but all results can be seen in Appendix, in Figure A1.

[12] The concrete values are given in the Appendix, in Tables A2 and A3, and corresponding values for GDP are given in Table A4.

[13] Without introducing GDP, i.e. filtering the credit series separately.

Dealing with many information at once, especially when considering conflicting criteria, could be based on some kind of utility function approach[14]. For this research, we define a simple utility function as the sum of the values in Figure 5 for the case of the narrow credit definition, Figure A2 for broad credit, and Figure A3 for GDP. Since the function is the sum of the errors, the smaller the value of the sum, the better is the outcome (denoted with O1). The results are shown in Table 2. To balance between the oos forecasting results and smaller revisions towards the two-sided gap possible, we define two other utility functions. One approach is to give a greater penalty to greater deviations from the two-sided gap (denoted with O2, where the penalty gives a greater weight to the MAE and RMSE 1-2hp values (times 2)). The other approach is to give a greater penalty to the poor oos forecasting of an approach (O3 in Table 2, again the weight was twice as big for this case). Overall, the random walk approach is best for the cases of narrow credit definition and the GDP series, whereas broad credit definition has ARIMA as the best approach. Now, this information is useful for the decision-making process when observing augmented gaps, at least as a support in detecting the range a gap without any augmentation could fall into.

Table 2. Summary of performance measures from Figures 5, A2 and A3

Group	Narrow credit definition			Broad credit definition			GDP		
	O1	O2	O3	O1	O2	O3	O1	O2	O3
Rolling average	1,324	1,324	1,324	2,665	2,665	2,665	1,062	1,067	1,071
Linear forecast	18,23	18,24	18,24	35,53	35,53	35,53	74,39	74,42	74,46
Rolling linear forecast	1,231	1,232	1,232	2,522	2,523	2,522	0,479	0,483	0,486
Random walk	1,199	**1,200**	**1,200**	2,516	2,516	2,516	**0,354**	**0,357**	**0,357**
Autoregression	**1,144**	1,145	1,144	**2,416**	**2,417**	**2,416**	0,613	0,616	0,617

Note: bolded values denote the best performance for each column. Values for linear forecast are taken from figures A1 and A2. O denotes outcome value.
Source: CNB, author's calculation

Besides the general information so far, about the model approach of forecasting, other important information can be obtained by looking at the performance over the forecasting horizons and smoothing parameters. This is done as follows. The evaluation criteria from Figure 5 is now contrasted in Figure 6 for the narrow credit definition[15] via boxplots over *h* and smoothing parameters. Overall, smallest revisions towards the two-sided gaps is, on average, observed for the 12 quarter horizon (rows 1 and 2), regardless of the smoothing parameter. The reason could be that as the estimated dynamic is prolonged in a longer period in the future at each point in time, those values differ away from the one-sided dynamic more and go towards the two-sided gaps that have fairly different dynamics overall. However, the variability of the average revision is greatest for $h = 12$. This is true for both narrow and broad

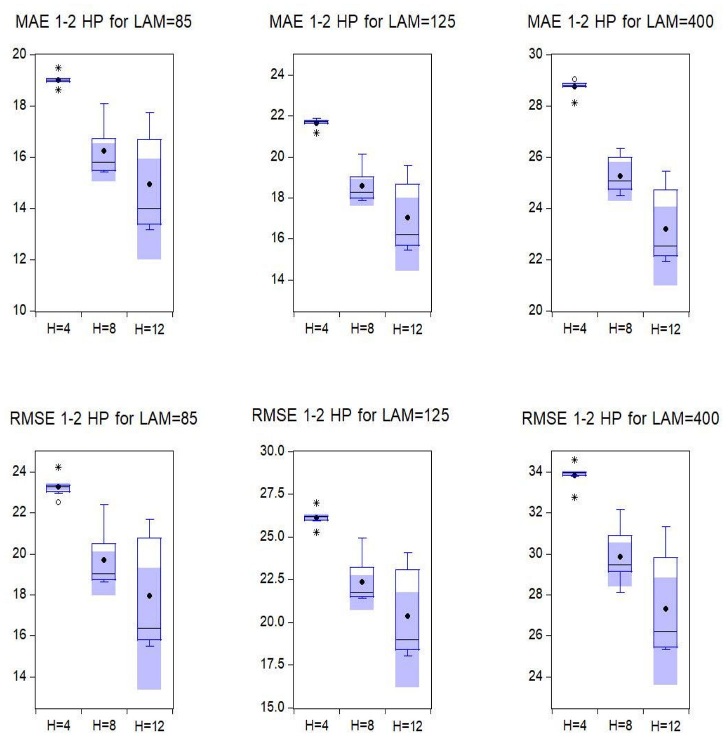
[14] As decisions about CCyB depend on the prudence of the policymaker, we opt to consider a utility approach here. Other approach could be Bayesian averaging, that is mentioned in the conclusion, as it is beyond the scope of this paper.

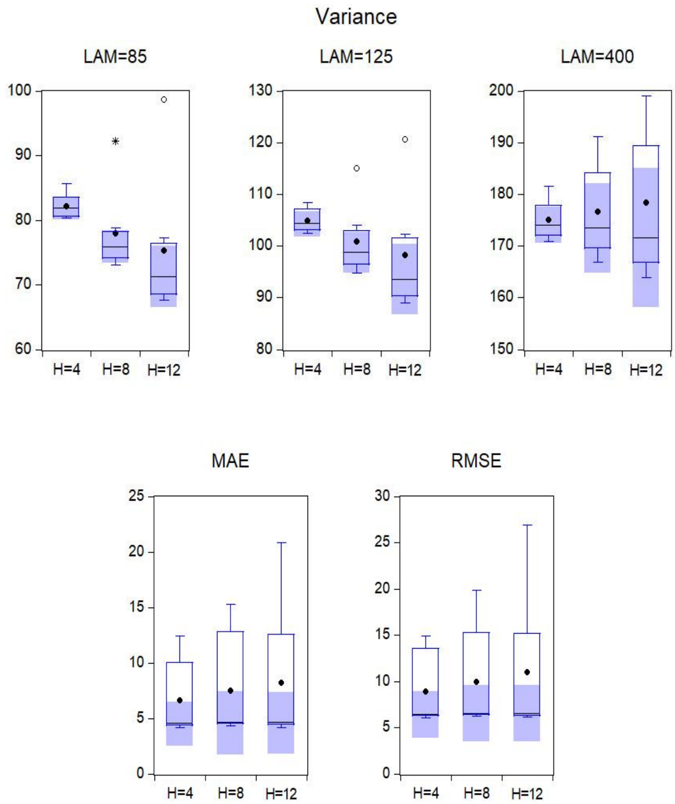
[15] Broad credit definition and GDP series corresponding analyses are shown in Figures A4 and A5.

credit series, whereas the GDP series have almost equal median values of all gap revisions, but the variability increases as the value of h increases (first and second panel in Figure A5).

When looking at variance performance (third rows in Figure 6 and A4; third panel in Figure A5), the h = 12 has the best performance almost, but this is due to such gaps resembling more the two-sided gaps that have overall smaller variability. The emphasize is on the almost, as although the average value of the variance is declining as h rises, its variability is rising for all smoothing parameters. Moreover, there is an increase both in the variance and the variability of the variance for the value of 400.000. This is prominent for all three series. The macroprudential decision-maker is also interested in obtaining good forecasts of an approach, measured by comparing the true credit values to the forecasted ones. We would like the one-sided gap to be as close as possible to the two-sided one, but on the other hand, the decisions are made based on the one-sided ones. Thus, the best horizon regarding the oos RMSE and MAE values for the forecasting part of the estimation procedure are 4 quarters for the majority of the results. These conclusions stand for all three observed series. Now, we see a trade-off here, between having the smallest revisions of the one-sided gaps and variance on one hand, and between having the smallest errors of forecasting on the other. To summarize the results in this subsection, the random walk and ARIMA approaches generate the best results, alongside horizon lengths of 8 and 4 quarters. The smoothing parameter of 400.000 has the worst results in terms of increasing variability of several criteria.

Figure 6. Boxplots of comparison criteria, narrow credit definition, by h and smoothing parameter





Note: lam denotes lambda (smoothing parameter in HP filter) of values 85.000, 125.000 and 400.000 for 85, 125 and 400 abbreviations respectively. H is the length of the forecasting horizon, MAE 1-2HP and RMSE 1-2HP are measures given in formulae (8) and (9), variance is defined in (10), and MAE and RMSE[16] denote the oos forecasting performance measures. Median value is denoted with a horizontal line inside the central box, with purple shading denotes approximate confidence interval[17] for the median value. Average values are denoted with a black dot.
Source: CNB, author's calculation.

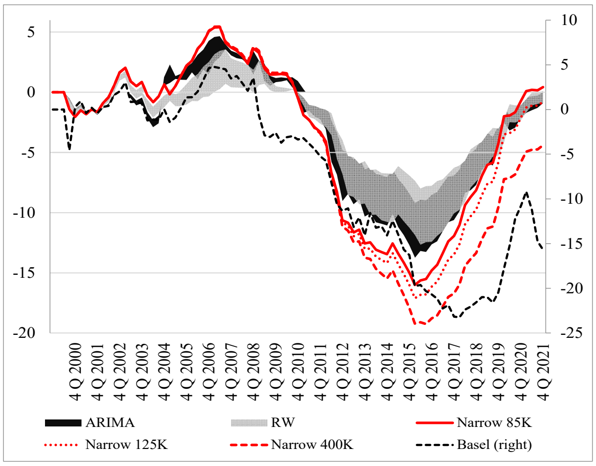
Figure 7 contrasts the six original credit gaps that are currently used in CNB to the ranges of augmented gaps based on the results in the previous subsection. It is clear in panels a. and b. that the original gaps have greater negative bias in the period from 2010 to 2016, which is solved with the augmented intervals. As the intervals are obtained with the end-point problem reduced, they could be observed as some kind of certainty intervals. Gaps obtained with the highest smoothing parameter are the furthest to rest of the series, which could be interpreted as this parameter being too large for the case of the analyzed data. Consequently, the decision about the capital requirements could be made too late, which is not in line with "leaning against the wind". When decisions about the CCyB values are made, as simulated in panels c. and d., the macroprudential policymaker could have more confidence and such approach can

[16] Due to MAE and RMSE not depending on the smoothing parameter, the last row in Figure 8 is shown depending solely on values of *h*. The same holds for Figures A4 and A5.
[17] Defined via median enlarged or reduced by 1.57*(interquartile range)/sqrt(N), where sqrt is the square root and *N* is the number of observations.

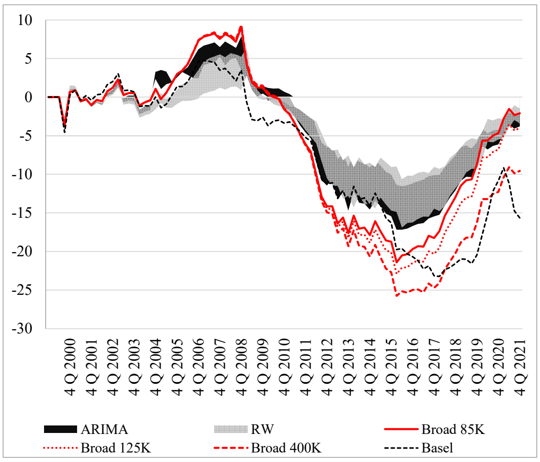
contribute to reducing the inaction bias. The values in panels c. and d. have a similar dynamics, where the reduction of CCyB values when the crisis hit for augmented gaps fell more compared to the original six gaps. This could be another information used to decide when the CCyB should be reduced, alongside tracking the financial stress indicators that are usually often observed and talked about when commenting on releasing CCyB values (see De Nora et al., 2020). Finally, when looking at the improvements related to the Basel gap and its resulting CCyB values, the increase of intervals before the crisis was much earlier. This could have enabled the policymaker to introduce a gradual increase of this capital buffer compared to much later increase for the original Basel gap.

Figure 7. Range of best augmented gaps and resulting CCyB ranges

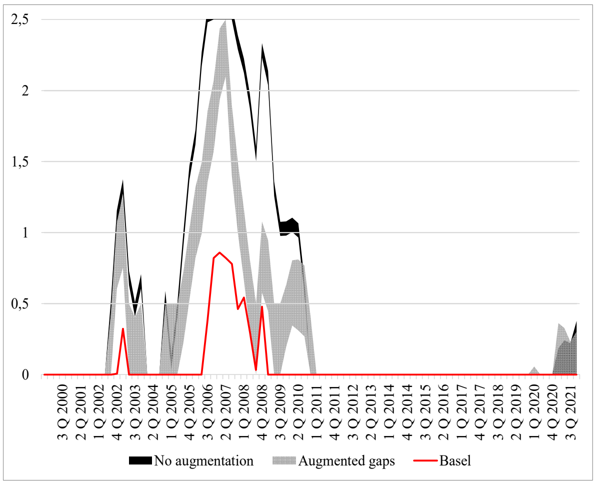
a. Range of best oos augmented gaps, narrow credit definition



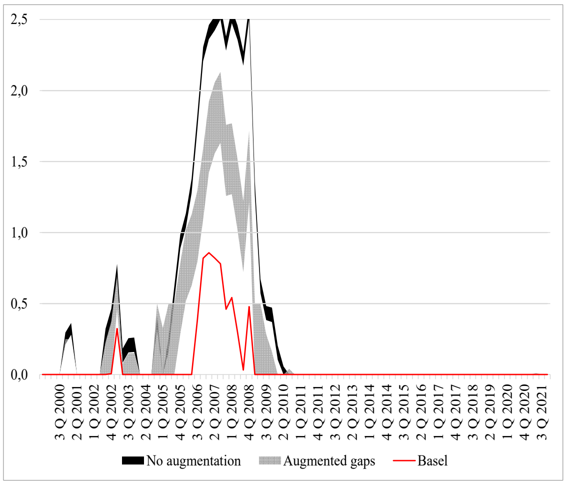
b. Range of best oos augmented gaps, broad credit definition



c. Range of CCyB values, narrow credit definition



d. Range of CCyB values, broad credit definition



Note: Grey shaded areas were made transparent so that overlapping with black shaded area can be seen.
Source: CNB, author's calculation

4.4.Discussion

To summarize all of the findings, it can be said that there will be a tradeoff between choosing the best oos forecasting approach and the approach with the least corrections towards the two-sided gap approach. As the results here are based on a relatively short period that includes one crisis in the sample, the early warning models signaling approach is not considered a good approach to contrast the gaps one to another. This is due to the possible bias in the results, alongside the need to fix a certain initial window for the estimation procedure of the recursive gap estimation. Now, as the comparisons were made based on stability and oos forecasting accuracy, the results hold for such findings that focus on these criteria. In general, the findings here are in line with related research in Gerdrup et al. (2013), and Valinskytė and Rupeika (2015), where linear projections had smaller variability, but overall worst other performance. This is due to the nature of other approaches, where it is important to take into consideration that the estimation should be based on a rolling window basis. The coefficients of estimated forecasting models surely change over time as financial cycle enters into different phases.

Moreover, stability of the indicator is important as well, in sense that it provide constant signals over time, and this is especially important when the decisions of the CCyB rate have to be made. Ideally, an indicator should be stationary, reverting to a mean value constantly, i.e. it should reflect the cyclicality in the credit-to-GDP ratio. However, due to the dynamics of the original values, and the disadvantages of the HP approach to estimating the gap, this is rarely found in practice. Thus, the variability of the indicator, in general, can be considered always, but it does not have to be the main criteria to make final decisions. It could be said that the shorter length of the forecasting horizon could be better due to having smaller oos errors. This is not surprising, as the error accumulates in the predicted values when the forecast horizon increases. On the other side, this is a drawback for HP trend purposes, as this will not contribute to the trend stabilization at the end of the sample as a longer period would. This again corroborates the initial statement that tradeoffs will be permanent characteristics in such an approach.

5. CONCLUSIONS

The credit-to-GDP gap measured via the HP filter as an indicator of cyclical risks is used both in practice and in empirical research. However, literature critiquing this type of indicator is almost as broad as those that generally deal with benefits of this indicator. Several branches of the literature try to solve some of the many problems regarding the HP gap so it can be more reliable in practice. This paper belongs to the strand that deals with the end-point problem, via out-of-sample forecasts augmented gaps. In that way, the uncertainty surrounding the last estimated value can be somewhat reduced due to obtaining a range of possible values that the "true" gap could fall into. As was seen in the results, there will be a trade-off between the forecast accuracy of an approach, and the revision of the gap series toward the two-sided gap, which is considered the "true" one. Now, obtaining final results, i.e. final approaches to obtain augmented gaps will depend on the policymakers prudence to act before or later with respect the results in terms of cyclical risk aggregation. That is why results in Figure 7 allow for flexible decision making, as now we have some intervals that can be used as guidance in a relaxed way. Furthermore, the results obtained in this study can be now used in the composite indicator of cyclical risk, alongside repeating this procedure for other indicators that are obtained via HP filtering. Other mentioned applications in the introduction can benefit from such results, so that robustness checking can be made.

A downside of this research is that due to the short period in the analysis, one crisis is included in the sample. This disables the analysis of the early warning signaling models, where the future crises signaling of an indicator can be evaluated. This has been calculated in the empirical part of the research, but it corroborated the discussion about bias of the results, as many indicators were found to have high AUROC values. Nevertheless, other studies that focus on similar topics as this one could include the EWM results in the ranking process if the researcher deals with longer time series. Thus, future work should extend such results with the early warning models approach, to get greater information about the characteristics of each approach to augment the original gap series. Another possible way of going further is the Bayesian model averaging and Bayesian forecasting. This is not found in related literature, but is used in many different fields in forecasting (see Fragoso and Neto, 2018).

Several important aspects were considered in this study. As the policymaker has to make decisions in real-time, the signals provided by the indicator should be as consistent as possible. This is captured in the variability of individual approaches. Next, as the policymaker utilizes out-of-sample forecasts to obtain estimates of the in-sample gap, such forecasts should be as reliable as possible. Instead of observing the errors of trend values, we opted to compare the errors between the forecasted credit ratio series to the true ones that were realized afterward. Although this makes the comparisons done retroactively, at least we obtain information about past performance, to have some basic insights into future developments of such approaches. Of course, the results are not straightforward. Some approaches give better values of smaller variability over time, whereas others have better out-of-sample forecasting capabilities. The picture is more complicated when observing the indicators in groups based on the forecasting horizon. Naturally, the longer the forecast horizon, the error of forecasting gets greater.

By incorporating this type of analysis in the regular decision-making process, the overall uncertainty composed of many different uncertainties could be reduced. This would provide incentive for the policymaker to reduce the inaction bias, and to rekla enable regular rule-based decisions, leading to more transparency and better communication with the public. What could be recommended to use in the decision-making process of the macroprudential policy regarding the specific topic of this research is to at least plot the range of specific augmented gaps alongside the original indicators. Based on the preferences towards the variability of the one-sided gap, its mean distance to the two-sided gap, the forecasting performance of an approach, a choice could be made in order to obtain a quasi-interval estimation of the corrected original gap. Of course, the decision-making process is always based on a range of other relevant criteria, such as the private sector debt burden, external imbalances, overvaluation of property prices, mispricing of risk, general economic conditions, as well as different economic and political events that could affect the indicators, the decisions, and overall macroprudential policy maker's choices.

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Appendix

Appendix A1. Details on oos forecast approaches

Moving averages

Moving averages (MA), denoted with

$$y_{t+h} = \sum_{s=t-n-1}^{t} y_s, \tag{1}$$

i.e. MA(n) are observed as a simple way to extend time series. That is, we observe moving averages of the credit-to-GDP ratio values based on the current quarter and previous n quarters for out-of-sample forecasts. For the first oos value (h = 1), the last observed value and previous n-1 are used. As we are forecasting several oos values (h = 1, 2, …, H), the second, third, etc. value until the last one H are estimated such that previous oos values based on the MA model are included in the calculation of the next moving average. As the procedure is recursive (one-sided filtering), the idea is that for the first fixed window of length x of the credit-to-GDP ratio, the series is extended via MA(n) values. The HP filter is utilized and first x values are collected. Then, when the next data becomes available, the procedure is repeated and the latest data point is added to the first x fixed values. This is repeated until the end of the current sample of the study. In this way, real-time decision-making is simulated, as with other approaches.

Linear forecast

A model of linear trend is estimated in the following way

$$y_{1:t} = a_{1:t} + b_{1:t} \cdot t, \tag{2}$$

in which forecast for horizon h in current quarter made based on a constant a and the linear trend t, which are estimated via OLS (ordinary least squares) for all data available upon that point. That is, for the first x series, model (2) is estimated in sample, estimates of a and b are collected, and oos forecasts for h horizons are made based on those estimates: $y_{t+h} = \hat{a}_{1:t} + \hat{b}_{1:t}$ (t+h). The original series y is extended with oos forecasts, the HP filter is utilized and first x gap values are collected. Then, when the new data becomes available, the estimation of (4) is redone with the additional data point, oos forecasts are made, HP filter is applied again, and the procedure is repeated until the last data point available.

Rolling linear forecast

Similar to the previous approach, the linear trend model is estimated, but now instead of using the entire sample up to the last point, a moving window model is estimated:

$$y_{(t-q):t} = a_{(t-q):t} + b_{(t-q):t} \cdot t, \tag{3}$$

where the sample is now moving, from period t-q to t, where q-1 is the desired length of the rolling window. Thus, the length of the window is fixed, but the starting and ending points change. When the estimated values of the parameters in (3) are obtained, oos values are estimated and added to the real series, HP filter is applied and gap series is collected. The procedure is repeated until the end of the sample, with again, first x values being fixed and one by one additional value of the gap series being added throughout.

Random walk (RW)

Most economic time series could be approximated well via a random walk model. Here, we observe the case of a moving window estimation of a RW model:

$$y_{(t-q):t} = a_{(t-q-1):(t-1)} + y_{(t-q-1):(t-1)}, \tag{4}$$

where the RW is estimated with a drift, that changes for each window. Based on the estimated model (4), oos values are forecasted for h horizons. Then, the HP filter is applied over an extended series. Again, as in previous cases, the first x values of the gap series are fixed, h additional values from the RW forecasts are added, HP filter results are obtained. Then, as we add every new data point, the procedure is repeated, with adding the last gap point to the existing series, up until the end of the sample.

ARIMA (p,1,0)

As credit-to-GDP ratios are nonstationary in practice, we observe a variant in which the ratio is differenced (thus, d = 1 in the ARIMA setting) and then for the purpose of forecasting, an AR(p) is defined, with p being a small whole number. The window for the estimation is on a rolling basis, as the previous approaches, i.e.:

$$y_{(t-q):t} = a_{(t-q-1):(t-1)} + \sum_{j=1}^{p} \theta_j y_{j,(t-q-1):(t-1)}, \tag{5}$$

where the notation j refers to the lag of variable y, up to p, and the rest of the index notations in parentheses refer to the rolling windows. When model (5) is estimated for the first window of x values, the oos values are forecasted based on the estimates, then they are added to the original credit ratio set of x values. The HP filter is applied to such sample, gaps are obtained up to the value x. Then, new data point is added to the initial sample, the model in (5) is re-estimated for the second window, and the procedure is repeated as previously. This is, again, repeated until the end of the full sample.

Table A1. AUROC values for individual augmented gaps, signaling 16 to 5 Q before the crisis

Indicators, narrow credit	AUROC	Indicators, broad credit	AUROC
roll_average_ma4_narrow_lam_85	0,960	roll_average_ma4_broad_lam_85	0,970
roll_average_ma4_narrow_lam_125	0,960	roll_average_ma4_broad_lam_125	0,970
roll_average_ma4_narrow_lam_400	0,960	roll_average_ma4_broad_lam_400	0,970
roll_average_ma8_narrow_lam_85	0,973	roll_average_ma8_broad_lam_85	0,978
roll_average_ma8_narrow_lam_125	0,973	roll_average_ma8_broad_lam_125	0,978
roll_average_ma8_narrow_lam_400	0,973	roll_average_ma8_broad_lam_400	0,976
roll_average_ma12_narrow_lam_85	0,985	roll_average_ma12_broad_lam_85	0,987
roll_average_ma12_narrow_lam_125	0,985	roll_average_ma12_broad_lam_125	0,987
roll_average_ma12_narrow_lam_400	0,985	roll_average_ma12_broad_lam_400	0,987
lin_forecast_4_narrow_lam_85	0,972	lin_forecast_4_broad_lam_85	0,969
lin_forecast_8_narrow_lam_85	0,997	lin_forecast_8_broad_lam_85	0,997
lin_forecast_12_narrow_lam_85	0,988	lin_forecast_12_broad_lam_85	0,985
lin_forecast_4_narrow_lam_125	0,972	lin_forecast_4_broad_lam_125	0,969
lin_forecast_8_narrow_lam_125	0,997	lin_forecast_8_broad_lam_125	0,997
lin_forecast_12_narrow_lam_125	0,990	lin_forecast_12_broad_lam_125	0,985
lin_forecast_4_narrow_lam_400	0,972	lin_forecast_4_broad_lam_400	0,969
lin_forecast_8_narrow_lam_400	0,997	lin_forecast_8_broad_lam_400	0,997
lin_forecast_12_narrow_lam_400	0,990	lin_forecast_12_broad_lam_400	0,991
roll_lin_forecast_4_narrow_lam_85	0,951	roll_lin_forecast_4_broad_lam_85	0,966
roll_lin_forecast_8_narrow_lam_85	0,949	roll_lin_forecast_8_broad_lam_85	0,961
roll_lin_forecast_12_narrow_lam_85	0,943	roll_lin_forecast_12_broad_lam_85	0,957
roll_lin_forecast_4_narrow_lam_125	0,964	roll_lin_forecast_4_broad_lam_125	0,967
roll_lin_forecast_8_narrow_lam_125	0,963	roll_lin_forecast_8_broad_lam_125	0,963
roll_lin_forecast_12_narrow_lam_125	0,952	roll_lin_forecast_12_broad_lam_125	0,960
roll_lin_forecast_4_narrow_lam_400	0,964	roll_lin_forecast_4_broad_lam_400	0,967
roll_lin_forecast_8_narrow_lam_400	0,963	roll_lin_forecast_8_broad_lam_400	0,963
roll_lin_forecast_12_narrow_lam_400	0,955	roll_lin_forecast_12_broad_lam_400	0,960
rw_forecast_4_narrow_lam_85	0,949	rw_forecast_4_broad_lam_85	0,957
rw_forecast_8_narrow_lam_85	0,823	rw_forecast_8_broad_lam_85	0,857
rw_forecast_12_narrow_lam_85	0,522	rw_forecast_12_broad_lam_85	0,555
rw_forecast_4_narrow_lam_125	0,958	rw_forecast_4_broad_lam_125	0,957
rw_forecast_8_narrow_lam_125	0,871	rw_forecast_8_broad_lam_125	0,863
rw_forecast_12_narrow_lam_125	0,518	rw_forecast_12_broad_lam_125	0,597
rw_forecast_4_narrow_lam_400	0,960	rw_forecast_4_broad_lam_400	0,957
rw_forecast_8_narrow_lam_400	0,888	rw_forecast_8_broad_lam_400	0,865
rw_forecast_12_narrow_lam_400	0,628	rw_forecast_12_broad_lam_400	0,695
ar1_4_narrow_lam_85	0,997	ar1_4_broad_lam_85	0,997
ar1_8_narrow_lam_85	0,997	ar1_8_broad_lam_85	0,999
ar1_12_narrow_lam_85	0,988	ar1_12_broad_lam_85	0,988
ar1_4_narrow_lam_125	0,997	ar1_4_broad_lam_125	0,997
ar1_8_narrow_lam_125	0,997	ar1_8_broad_lam_125	0,999
ar1_12_narrow_lam_125	0,988	ar1_12_broad_lam_125	0,988
ar1_4_narrow_lam_400	0,997	ar1_4_broad_lam_400	0,997
ar1_8_narrow_lam_400	0,997	ar1_8_broad_lam_400	0,999
ar1_12_narrow_lam_400	0,990	ar1_12_broad_lam_400	0,988
ar2_4_narrow_lam_85	0,994	ar2_4_broad_lam_85	0,994
ar2_8_narrow_lam_85	0,991	ar2_8_broad_lam_85	0,979
ar2_12_narrow_lam_85	0,961	ar2_12_broad_lam_85	0,897
ar2_4_narrow_lam_125	0,994	ar2_4_broad_lam_125	0,994
ar2_8_narrow_lam_125	0,991	ar2_8_broad_lam_125	0,979
ar2_12_narrow_lam_125	0,966	ar2_12_broad_lam_125	0,896
ar2_4_narrow_lam_400	0,994	ar2_4_broad_lam_400	0,996
ar2_8_narrow_lam_400	0,991	ar2_8_broad_lam_400	0,979
ar2_12_narrow_lam_400	0,966	ar2_12_broad_lam_400	0,893

ar3_4_narrow_lam_85	0,994	ar3_4_broad_lam_85	0,987
ar3_8_narrow_lam_85	0,981	ar3_8_broad_lam_85	0,960
ar3_12_narrow_lam_85	0,871	ar3_12_broad_lam_85	0,857
ar3_4_narrow_lam_125	0,994	ar3_4_broad_lam_125	0,987
ar3_8_narrow_lam_125	0,981	ar3_8_broad_lam_125	0,960
ar3_12_narrow_lam_125	0,887	ar3_12_broad_lam_125	0,859
ar3_4_narrow_lam_400	0,994	ar3_4_broad_lam_400	0,987
ar3_8_narrow_lam_400	0,981	ar3_8_broad_lam_400	0,960
ar3_12_narrow_lam_400	0,897	ar3_12_broad_lam_400	0,860
ar4_4_narrow_lam_85	0,988	ar4_4_broad_lam_85	0,991
ar4_8_narrow_lam_85	0,975	ar4_8_broad_lam_85	0,958
ar4_12_narrow_lam_85	0,859	ar4_12_broad_lam_85	0,821
ar4_4_narrow_lam_125	0,990	ar4_4_broad_lam_125	0,991
ar4_8_narrow_lam_125	0,975	ar4_8_broad_lam_125	0,958
ar4_12_narrow_lam_125	0,869	ar4_12_broad_lam_125	0,826
ar4_4_narrow_lam_400	0,991	ar4_4_broad_lam_400	0,991
ar4_8_narrow_lam_400	0,975	ar4_8_broad_lam_400	0,958
ar4_12_narrow_lam_400	0,882	ar4_12_broad_lam_400	0,824
Narrow_125	0,970	Broad_125	0,970
Narrow_400	0,920	Broad_400	0,970
Narrow_85	0,970	Broad_85	0,970

Note: The Basel gap for Croatian data has AUROC value of 0,90. The crisis period is defined as in Dimova et al. (2016) and Škrinjarić and Bukovšak (2022a, b): October 2008 – June 2012. Final three rows include credit gaps without oos augmentation.
Source: CNB, author's calculation

Table A2. Average values of comparison criteria, narrow credit definition

Group	MAE 1-2hp	RMSE 1-2hp	Variance	MAE oos	RMSE oos
Rolling average	20,321	23,836	13,230	15,429	20,183
Linear forecast	38,642	41,520	182,352	151,252	155,910
Rolling linear forecast	21,962	26,915	12,306	12,633	15,194
Random walk	**6,577**	**9,159**	11,991	6,506	9,034
Autoregression	19,983	23,754	**11,436**	**4,502**	**6,422**

Source: CNB, author's calculation
Note: bolded values denote best performance in each column

Table A3. Average values of comparison criteria, broad credit definition

Group	MAE 1-2hp	RMSE 1-2hp	Variance	MAE oos	RMSE oos
Rolling average	29,964	34,565	26,635	20,522	29,423
Linear forecast	53,123	57,431	355,268	212,376	219,324
Rolling linear forecast	32,217	38,737	25,207	18,283	23,465
Random walk	**8,857**	**14,293**	25,153	8,707	13,978
Autoregression	29,625	34,355	**24,154**	**6,662**	**10,527**

Source: CNB, author's calculation
Note: bolded values denote best performance in each column

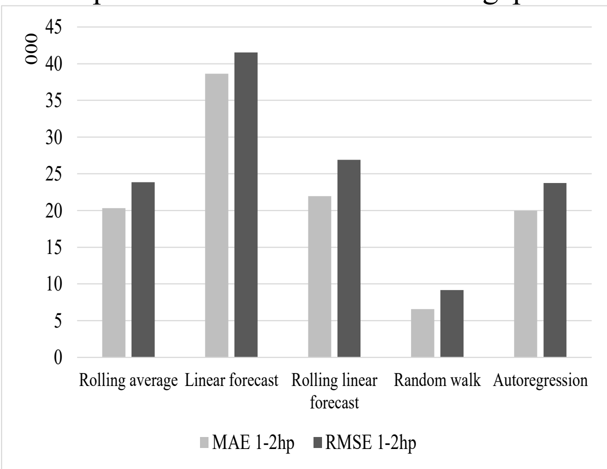
Table A4. Average values of comparison criteria, GDP

Group	MAE 1-2hp	RMSE 1-2hp	Variance	MAE oos	RMSE oos
Rolling average	2,202	2,732	1,048	3,957	5,111
Linear forecast	15,089	16,600	74,281	38,758	39,573
Rolling linear forecast	1,633	2,256	0,468	2,971	4,029
Random walk	1,389	2,311	**0,346**	**1,398**	**2,285**
Autoregression	**1,185**	**1,591**	0,606	1,422	2,573

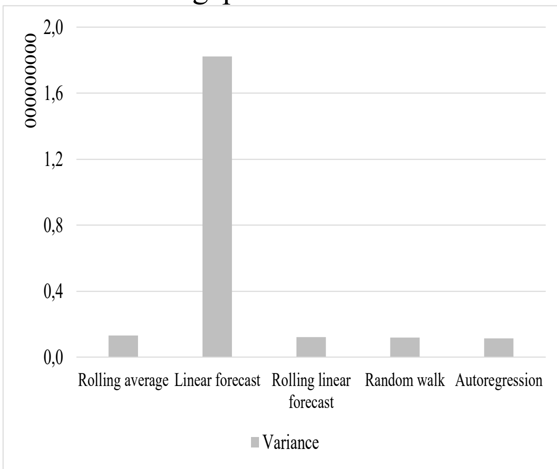
Source: CNB, author's calculation
Note: bolded values denote best performance in each column

Figure A1. Average values of comparison criteria, narrow credit definition

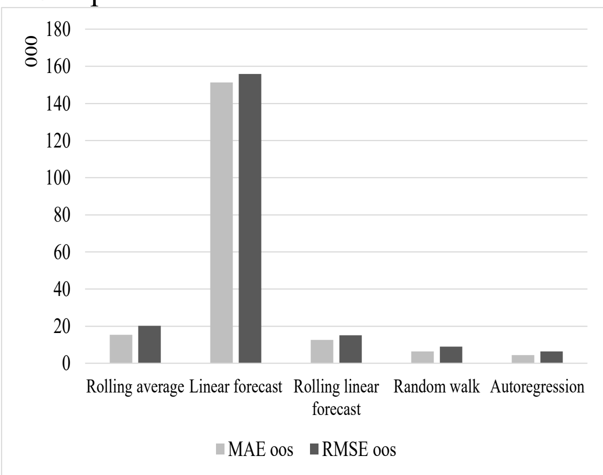
a. Comparisons of one and two sided gaps



b. Variance of gaps



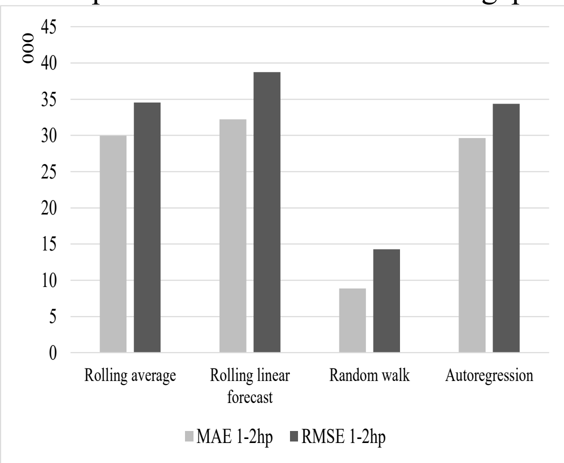
c. Oos performance



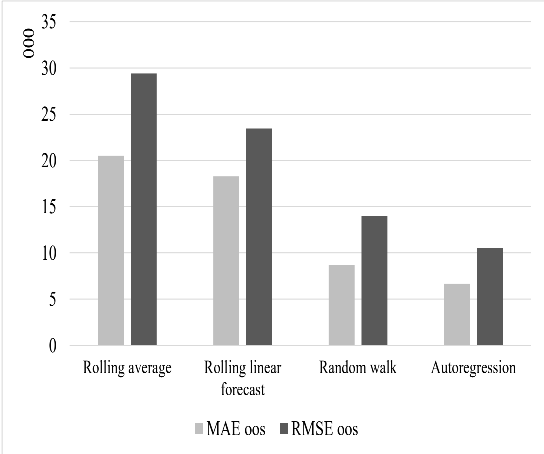
Source: CNB, author's calculation

Figure A2. Average values of comparison criteria, broad credit definition

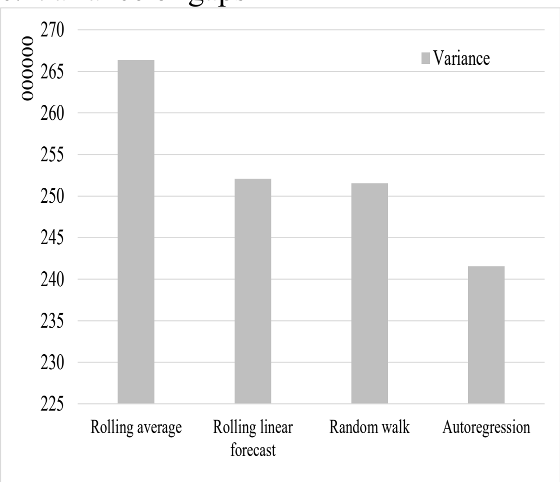
a. Comparisons of one and two sided gaps



b. Oos performance



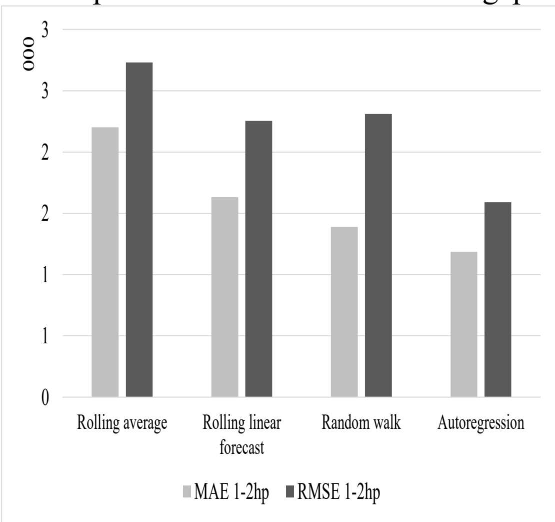
c. Variance of gaps



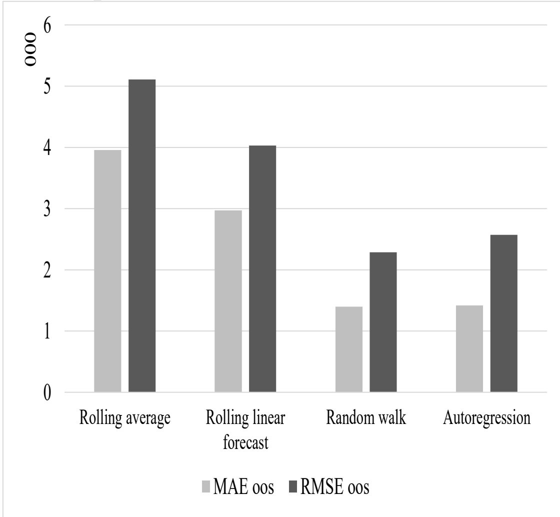
Source: CNB, author's calculation
Note: value comparison with the linear forecast is available upon request.

Figure A3. Average values of comparison criteria, GDP series

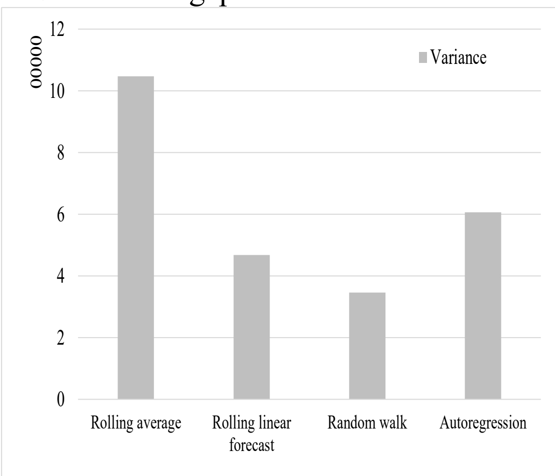
a. Comparisons of one and two sided gaps



b. Oos performance

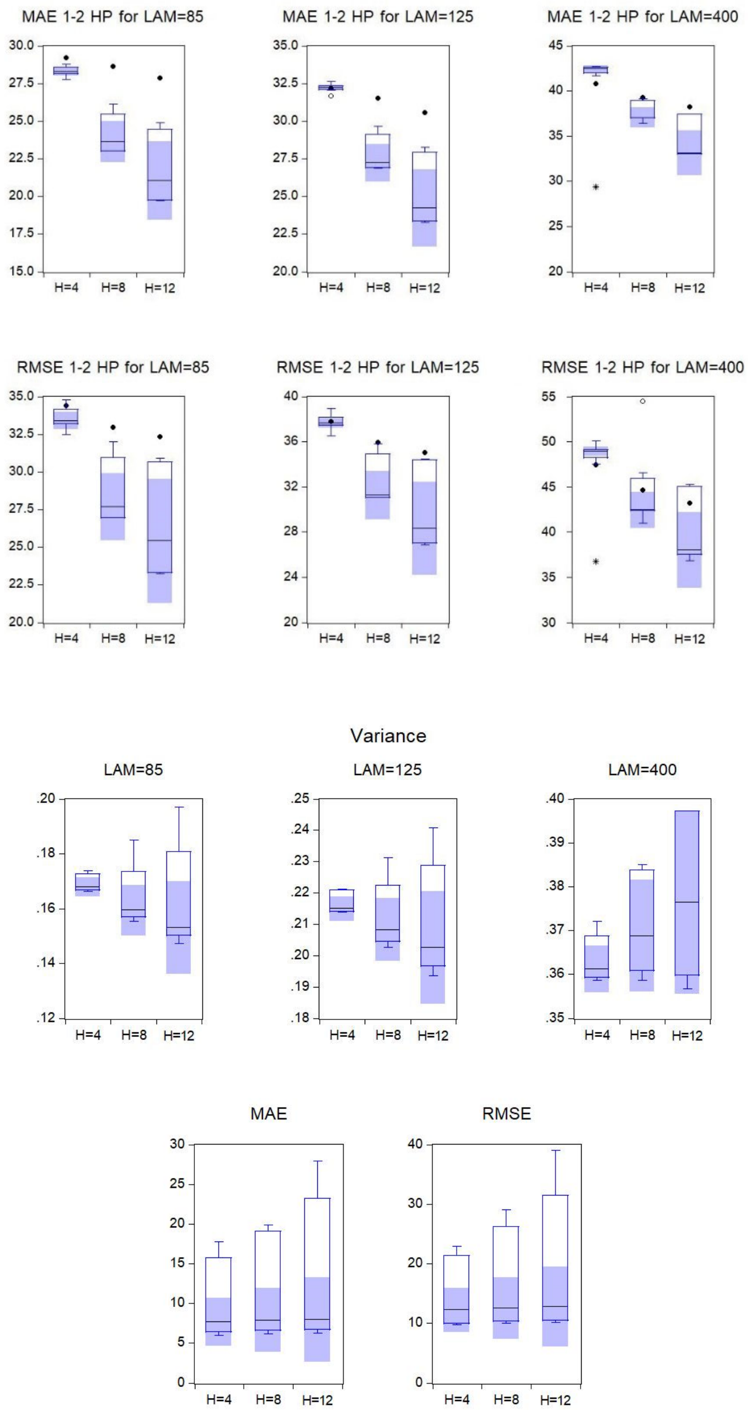


c. Variance of gaps



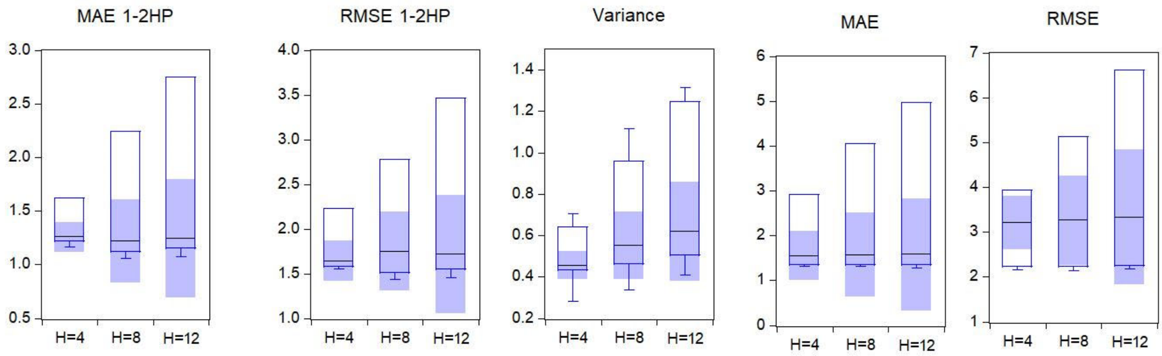
Source: CNB, author's calculation
Note: value comparison with the linear forecast is available upon request.

Figure A4. Boxplots of comparison criteria, broad credit definition, by *h* and smoothing parameter



Note: lam denotes lambda (smoothing parameter in HP filter) of values 85.000, 125.000 and 400.000 for 85, 125 and 400 abbreviations respectively. H is the length of the forecasting horizon, MAE 1-2HP and RMSE 1-2HP are measures given in formulae (3) and (4), variance is defined in (6), and MAE and RMSE denote the oos forecasting performance measures. Median value is denoted with a horizontal line inside the central box, with purple shading denotes approximate confidence interval for the median value.
Source: CNB, author's calculation.

Figure A5. Boxplots of comparison criteria, GDP series, by *h*



Note: H is the length of the forecasting horizon, MAE 1-2HP and RMSE 1-2HP are measures given in formulae (3) and (4) variance is defined in (6), and MAE and RMSE denote the oos forecasting performance measures. The values of lambda do not differ here, as GDP was filtered with lambda equal to 1.600 (see footnote 8). Median value is denoted with a horizontal line inside the central box, with purple shading denotes approximate confidence interval for the median value.
Source: CNB, author's calculation.