Working Papers W-65

Augmented credit-to-GDP gap as a more reliable indicator for macroprudential policy decision-making

Tihana Škrinjarić

Zagreb, September 2022

HRVATSKA NARODNA BANKA · CROATIAN NATIONAL BANK

The author thanks Maja Bukovšak, Vedran Šošić, Evan Kraft, Vladimir Arčabić, Lana Ivičić, Maroje Lang, Maja Sabol and participants at the 28th DEC Dubrovnik Economic Conference (Croatia 2022) for all useful comments when writing this research.

About author

Tihana Škrinjarić, dr.sc.
Hrvatska narodna banka
E. tihana.skrinjaric@hnb.hr

Abstract

This paper aims to evaluate the possibilities of augmenting the credit-to-GDP gap series with out-of-sample forecasts to obtain a more stable indicator of excessive credit growth. The credit-to-GDP gap is a standardized and harmonized indicator of the Basel III regulatory framework used to calibrate the Countercyclical Capital Buffer (CCyB). Thus, a good indicator should be valid, stable, and represent future financial cycle movements. This research focuses on reducing the end-point bias problem of the Hodrick-Prescott (HP) filter approach to estimating this indicator. This is appropriate for those authorities whose analysis shows that the HP approach best predicts the financial crisis. Several popular models of out-of-sample forecasting are tested on Croatian data to extend the filtered original series, and the results are compared based on multiple criteria. These include the stability of the indicator, not just the usual model forecasting capabilities. The autoregressive approach, alongside the random walk model, was the best-performing one. The results of this study can be used in real-time decision-making, as they are relatively simple to estimate and communicate. Such augmented gaps reduce the bias in the series after the financial cycle turns. Moreover, the paper suggests possible corrections to the credit-to-GDP gap so that the resulting indicators are less volatile over time with stable signals for the policy decision-maker.

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

JEL: 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.)

Sažetak

Ovo istraživanje bavi se ocjenom mogućnosti korekcija kreditnih jazeva temeljem prognoziranja van uzorka. Glavna je ideja dobiti stabilnije indikatore pretjerane kreditne dinamike. Kreditni jaz, definiran u Basel III sporazumu je standardizirani i harmonizirani indikator koji se koristi za kalibraciju protucikličkog zaštitnog sloja kapitala. U tu svrhu je potrebno koristiti stabilan, valjan indikator koji odražava kretanje financijskog ciklusa neke zemlje. Ovaj rad se bavi smanjenjem pristranosti u krajnjim točkama prilikom procjene kreditnog jaza pomoću Hodrick-Prescott (HP) filtra. Stoga su nalazi korisni za one institucije čije analize pokazuju da je HP filter najbolji način za procjenu indikatora koji nagovještava buduću financijsku krizu. Nekoliko popularnih pristupa prognoziranja van uzorka se razmatra u empirijskom dijelu rada za slučaj hrvatskih podataka, kako bi se temeljem nekoliko kriterija usporedili svi i odabrao najbolji. U kriterije usporedbe su uključeni i oni vezani uz stabilnost indikatora, a ne samo tipični kriteriji usporedbe prognoziranja vremenskih serija. Najboljim pristupima su se pokazali autoregresivni model, kao i model slučajnog pomaka. Rezultati ovog istraživanja mogu se koristiti prilikom donošenja odluka u realnom vremenu, s obzirom na jednostavnost njihove primjene, kao i komunikacije rezultata. Ovako dobiveni korigirani kreditni jazevi smanjuju pristranost u seriji jaza nakon što dolazi do obrata financijskog ciklusa. Dodatno, u radu se predlažu moguće korekcije kreditnog jaza kako bi indikatori bili manje volatilni kroz vrijeme, i na taj način davali stabilne signale donositelju odluke.

Ključne riječi: kreditni jaz, prognoze van uzorka, korigiran kreditni jaz, protuciklički zaštitni sloj kapitala, neizvjesnost procjene

JEL: E32, G01, G21, C22

Content

1. Motivation for this research

The macroprudential policy has the task of tracking and monitoring the financial cycle. Accumulation and materialization of cyclical systemic risks have proven to be the origin of the previous Global Financial Crisis (GFC), as heavily documented in the literature[1]. Thus, it is not surprising that many papers focus on identifying the financial cycle, as reducing its pro-cyclicality is an operational task of the macroprudential policy. Financial cycle indicators are regularly estimated and identified in the decision-making process of macroprudential authorities. One of the primary uses of such indicators is to make decisions about the Countercyclical Capital Buffer (CCyB[2]). Many other applications use such indicators, meaning they should be valid and reliable[3]. 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 is the leading indicator of the probability of crises, alongside their severity (Drehmann et al., 2014; Schularick and Taylor, 2012; Dell Ariccia et al., 2012). This is supported by general findings that

[1] See, e.g., Ampudia et al., 2021 for a concise and concrete overview in macroprudential terms when describing the happenings before the GFC hit.

[2] 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 counter 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 facilitate 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.

[3] Some of the applications of financial cycle indicators include the estimation of a 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 macroprudential policy's effectiveness, costs, and benefits and its interaction with monetary and fiscal policy has risen in the last decade, we need to obtain valid and robust indicators regarding the financial cycle.

intense credit activity precedes crises in Gourinches and Obstfeld (2012). The Basel gap is calculated based on the credit-to-GDP ratio, 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[4]. Thus, based on the BCBS recommendation, national macroprudential authorities utilize the HP filter, using the one-sided gap approach[5].

One of the main problems in using the HP filter[6] approach that is commented on in the literature is the end-point problem, based on the way the optimization function of the filter is constructed. Although this problem has been tackled in the literature already (see the second section), this 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 the "true"[7] gap, the one-sided gaps are compared to the dynamics of the two-sided one. Moreover, each approach's out-of-sample (OOS) performance is also considered an essential factor. However, as opposed to previous literature, this research compares the OOS forecasts of credit or GDP values to the actual future realization instead of trend or gap comparisons. This is due to comparing forecasts to an actual value of a series instead of an estimated one[8]. Furthermore, the variability, i.e., resulting indicators' stability is also considered. Due to the overlapping estimation approach, the same gap value for one period is re-estimated. This means that the stability of the estimate should be examined as well. A stable and efficient estimate should have the smallest variation of this gap value possible. All of these criteria are considered when making decisions about the best-performing

---

[4] Thus, the problems stated here are not new and refer to the output gap estimation. Please see the literature review section.

[5] This means that only past information on the ratio and gap is used for decision-making. This is based on the fact that decisions have to be made in real time. So, the statistical filtering procedure of estimating the trend and the gap is based only on data up to the last available point.

[6] 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.

[7] 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.

[8] 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.

approach. As these criteria are often conflicting, the selection process should be carefully constructed. That is why a simple utility function of the macroprudential policymaker is constructed in this research.

The main results include the following ones. First, it is not easy to choose the best model and fit it for all series uniformly. 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 both for credit and GDP series. Thus, the simulations of CCyB values are based on these results and show a promising potential to use this in practice. The results of this study can be used in real-time decision-making, as they are relatively simple to estimate and communicate. Such augmented[9] gaps reduce the negative bias in the series after the GFC. As this type of result is essential 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 rest of this paper is structured as follows. The second section provides a general position of this research within the whole universe of related work, and a review of the related literature is given. Afterward, the description of the credit gap estimation and the OOS augmentations is examined in the third section. An empirical analysis of the results is provided in the fourth section, with a discussion of the results. The final fifth section concludes the paper.

2. Literature review

The end-point problem of the HP gap analysis is not a new one. However, this is a broader problem of general policy decision-making, as the output gaps are used in estimating the business cycle. Therefore, this section reviews the general issues of output gap estimation and concrete solutions in macroprudential policy decision-making.

[9] The term augmented gap in this research refers to the HP filter gap obtained with the OOS forecasts.

2.1. General discussion about end point bias problem of output gaps

Although there are many critiques of the HP filter, it is widely used for business cycle analysis (see Cogley and Nason, 1995; Blackburn et al., 1995; Harvey and Jaeger, 1993). The usual approach of extending the GDP series with out-of-sample projections is commonly found in much empirical work focusing on reducing the end-point problem in the potential output gap estimation. Such research includes de Brouwer (1998), where projections are included in the HP filtering process, and the author shows for the case of Australian data what are the differences in the end tail of the output gap series when extending the original dataset with forecasts. Jovičić (2017) has compared the HP filter to the production function and the multivariate filter approach in estimating the output gap for Croatia. The HP filter was augmented with the projections of the GDP series two years in the future. St Amant and van Norden (1997) have shown on Canadian data that the central observations receive six percent weights in some cases, with almost twenty percent weight to the end-point. That is why it is not surprising when data revisions are made that the results could be very different depending on this revision.

A common approach to reducing this problem is to include the OOS forecasts of the time series, as mentioned in the introduction. Bouthevillain et al. (2001) extended the series with three-year projections to examine the cyclically adjusted budget balances. As many institutions need to produce cyclically-adjusted budget balances, authors have explored ways to deal with usual problems in such modeling. Although the general focus was not on solving the end-point problem, the authors acknowledge it as a part of the process and utilize projections of macroeconomic time series in the estimation. Ódor and Jurašekova Kucserová (2014) is a more recent study in which authors try to find the best estimation solution for the case of Slovakian data. Thus, it is evident that these problems are still the focus of researchers and practitioners. The authors tried to find more robust estimates of the output gap for the case of Slovakian data by combining several approaches to estimating the gap. In the modeling process, the HP filter is augmented via forecasts. The focus of the research was not solely on this filter, which is why no detailed comparisons are found for this specific approach. The authors focused on several approaches to obtain a simple average of all results to obtain a more reliable base for decision-making. However, these modifications come with some costs. As St-Amant and Norden (1997) show, introducing forecasts in the whole process could result in phase shifts of the gap series. For the case of the Canadian data, the modified HP gap came with a lag of two to four quarters. As with every approach, this one has advantages and shortfalls as well.

2.2. Empirical literature review and central banks' practices regarding augmented credit-to-GDP gaps

Financial cycle indicators have some desirable properties, as discussed in Önkal et al. (2002), Lawrence et al. (2006), Kauko (2012), and Drehmann and Tsatsaronis (2014). These and other papers recognize the 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. Besides many other problems regarding this filter (see Cogley and Nason, 1995; Kamber et al.; 2018; Hamilton, 2018, Škrinjarić and Bukovšak, 2022a)[10], the end-point 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 extensive ex-post revisions due to significant deviations of GDP values in the final estimates. Such results are essential for 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 primary purpose of the credit gap is that it should be an early warning indicator of a future crisis, as shown in research focused on banking crises and the signaling properties of this and other indicators[11]. Since the credit gap has often been found as the

[10] Critiques and enhancements of the central 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), other smoothing parameters in the HP procedure (Drehmann et al., 2010; Galán, 2019; Rünstler and Vlekke, 2016; Wezel, 2019), etc.

[11] 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 decisions about the CCyB value.

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. However, 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 more significant gaps after the turning point of the indicator. This is what previous literature on the output gap has concluded already regarding the phase shifts mentioned above in the last sub-section. As a result, the filtered series could have phase shifts in data. Furthermore, earlier literature showed that adding out-of-sample forecasts to the original filtered dataset 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, such as the house prices to income ratio, property prices index, and the 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. Here, the authors find that the augmented gaps reduce gap revisions and have better signaling properties in the early warning models approach compared to the non-augmented gaps. This was found true for the credit-to-GDP gap series and other mentioned series. Thus, the authors concluded that this approach to estimating specific gap series for Norwegian data is a novel feature in estimating financial imbalances in the central bank. Valinskytė and Rupeika (2015) utilize the repeated last value, four and eight-quarter moving averages, and linear forecasts approach 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 chosen gaps were those with the smallest revisions and variability. This is important as such gaps should give robust signals over time. The results here indicate that the four-quarter moving averages had smaller revisions of gaps. This is an important finding because the decision-making process is based on the last couple of observations that are mostly affected by the revisions. Finally, the authors evaluated this approach's early warning signal properties for the case of Latvia and Estonia. In conclusion, a recommendation is given to utilize these simple OOS forecasts in the gap estimation procedure, enabling more timely decision-making.

Bank of Portugal (BoP, 2020) has a publication about the general indicators used to calibrate 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 of the OOS forecast horizon. Other relevant contrasting approaches 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. As this working paper gives a general overview of how the BoP communicates the cyclical risk tracking and calculation and how specific important indicators are tracked and estimated, not much detail is given about some decisions regarding indicator selection. The appendix provides some insights that the mentioned models were contrasted, and the OOS forecasting performances were compared.

Geršl and Mitterling (2021) did a study on a panel of countries, including 56 different countries, for an extended period: from 1950 to 2016. The results show that OOS forecast augmentations of credit gaps improve the signaling properties of such indicators in the case of emerging markets. The results are mixed when the data is divided into developed and emerging markets. The such finding 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. Although the augmented gaps are more stable and have reduced end-point problems, such gaps could have lagged reactions when new values indicate a change in the trend. This is the already mentioned problem of utilizing such approaches that the resulting gaps could have a lagged response to important economic changes. Moreover, this could affect the timing of the turning of the cycle. Thus, it is difficult to evaluate these indicators in terms of both signaling properties, alongside the revisions of gaps over time. Other recent studies incorporating 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 for the Italian case's difference between the one and two-sided HP gap. The idea is similar to a random walk OOS estimation of the series that is being filtered. In the Italian case, the difference between the one- and two-sided approaches is estimated as a random walk model so that the difference can be predicted and reduced. Augmentation of the HP gap in both cases (Italy and Switzerland) has shown that it enhances the usability of the credit gap itself in terms of greater consistency of the estimates. Jokippii et al. (2021) conclude that the Basel gap is still a reliable measure but should be complemented with alternative approaches. Alessandri et al. (2015) add that using such augmented gaps produces better indicators that forecast the financial crises and can be used in real-time estimation and decision-making.

As can be seen, the literature on the specific topic of credit-to-GDP gap augmentation via OOS forecasts is growing, especially in the last two years. This indicates that the applications in central banks have recognized the need for greater usability of the credit-to-GDP 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 how the credit-to-GDP gap (credit gap and gap henceforward) is calculated based on the ESRB (2014) guidance and the extensions that this paper explores. The main takeaway from the credit gap is how much the credit activity exceeds 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 one-sided Hodrick-Prescott (1997) filter (HP filter and gap afterward), with the primary objective function as follows:

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

where y_t is the time series to be filtered, μt is the trend series, and λ is the smoothing parameter (or the penalization parameter), $t' = 1, \ldots, T$. 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 slope of the trend. The greater the value of lambda is, the more significant penalty is given to changes in the slope, and the trend resulting from (1) becomes smoother. The one-sided approach 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 repeated with the additional data point, but the previous values of the gap stay fixed. The new value of the gap series for period t'+1 is added to the existing series. 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 the gap from t'+2 is added. To put it differently, for the first t' periods, the gap series is set at all times. 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 that the macroprudential policymaker has to make decisions based on the available data 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.

Now, by observing problem (1), 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 these end values are not penalized as much as other values. 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, several popular approaches are 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. This research examines several models for OOS forecasting as follows (with detailed and formalized explanations in Appendix A1). A basic approach is the moving average (MA), in which the credit-to-GDP ratios[12] 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 more straightforward approach, the linear trend model is estimated from the beginning of the

[12] Although the term credit gap is mentioned here with its OOS forecasts, the empirical part of this paper deals with separate filtering of the credit series compared to the GDP series. This is due to previous research in CNB (see Škrinjarić and Bukovšak, 2022a), where among several hundred individual indicators, those that were calculated on this basis were found to be the best-performing ones.

sample until the last point *t*'. This has the 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. This is not the best way to assume that a series will have the same linear trend over time, i.e., during financial upswings and downturns. 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. This means that the forecasted series follows a linear trend only locally. Next, as the series[13] of credit-to-GDP ratio exhibit random walk (RW) properties to some extent. The fourth approach was to estimate a rolling window of an 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. Then this difference was modeled as an AR(p) process, which is invertible (a valuable property for forecasting). Several values for the lag length p were chosen, ranging from one to four, to obtain parsimony.

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 reasonably well. Some drawbacks of these other approaches are that as the estimation is done on a short-length 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. Moreover, giving weights in moving average approaches, although helpful when wanting to provide further 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. However, the same problem of the mentioned recent shock could affect the results.

[13] Or general credit and GDP series separately.

3.3. Evaluating the best approach

Several approaches 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, the results could be biased if only one crisis is included in the sample. This is commented on in Škrinjarić and Bukovšak (2022a), where authors advise taking such results with caution. Moreover, as the OOS forecasts tend to smooth out the resulting credit gap series, this affects the resulting values of AUROC and other relevant measures alongside statistical tests. Therefore, although the resulting gaps could be better in predicting a crisis than the original ones (that are not augmented in any way), the augmented values could stay positive or negative longer (due to the smoothing process). To recap, before the estimation part of the study, the term augmented gap refers to those HP filter gaps obtained with the OOS forecasts included in the whole procedure.

Nevertheless, we compare the results of all approaches in Appendix[14], in Table A1. Almost 82% of all considered augmented gaps have a greater AUROC value compared to the Basel gap. These gaps are also closely tied between the linear forecast, rolling moving average, and ARI (for both credit definitions[15]). Moreover, the individual worst performance has indicators based on a twelve-quarter forecasting horizon. Such results rely on the assumption that the same estimated behavior holds for a longer period 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 again 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). In evaluating alternative approaches

---

[14] Empirical work with more crises in the sample should take the EWM approach in the final construction of the decision-maker's utility function. Here, as previously mentioned, the resulting gaps that are being augmented are those that are based both on narrow and broad credit definitions. As no data on the broad credit definition was available for Croatian data before the banking crisis in the late 1990s, comparisons are made between the broad and narrow definitions just for the GFC crisis.

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

to cyclical risk monitoring, they do not utilize the EWM models to contrast the indicators. The 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, the 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 the smallest possible, as in line with Gerdrup et al. (2013). Written formally, for every indicator *i* we calculate the following measure:

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

where the *gap* exponent denotes that the mean absolute error (MAE) is calculated for the individual gap series, 1gap and 2gap are the resulting one 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 (3):

$$RMSE_i^{gap} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(1gap_t^i - 2gap_t^i\right)^2}. \tag{3}$$

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 $t =$ 2, 3, ... , etc. change in every subsequent estimate. The idea here is that the variation of the gap itself is smallest possible on average[16]. This means that we penalize if the recursive estimates of a gap in quarter *t*

[16] 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, a gap for the 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 the smallest variability overall.

vary too much, i.e. estimates should be consistent[17]. 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:

$$\sigma_{t,i}^{2gap} = \frac{1}{T'} \sum_{t'=1}^{T'} \left(2gap_{t'}^{i} - \overline{2gap^{i}} \right)^2, \tag{4}$$

where (4) 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:

$$\bar{\sigma}_i^2 = \frac{\sum_{i=1}^{T} \sigma_{t,i}^{2gap}}{T}. \tag{5}$$

Finally, to compare the OOS performance of each approach, we calculate the MAE and RMSE for the OOS values of credit and GDP series that are filtered and compare them to the true values of the original series. Other authors compare the OOS performance for the gap values. However, as the endpoint problem characterizes the HP filter, 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 making the comparisons recursively. Consequently, we opt to compare the forecasted values of the credit-to-GDP ratios (or original series filtered separately) in each recursive forecast to the actual 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.

[17] This is not penalizing indicators with huge amplitudes of the up and down phase. This is somewhat relatable to the efficiency of the least squares estimator. In the regression approach, we want to find the estimator with the smallest possible variance. Here, we observe several values for the same gap in period t'. The idea is that the estimate is efficient in that the variation observed in those values is the smallest possible.

4. Empirical analysis and discussion

4.1. Data description

For the purpose of empirical analysis, quarterly data on narrow and broad[18] definitions of credit and GDP values have been collected from the 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:

$$ratio_t = \frac{credit_t}{\sum_{k=t-3}^{t} GDP_k} \cdot 100\%, \tag{6}$$

and the ratios are shown in Figure 1. Both ratios increased significantly during the 2000s due to financial deepening before the GFC crisis. In the last couple of years, ratios have stagnated, reflecting a subdued recovery after the crisis. Figure 1 also depicts the HP trend series for the one- and two-sided estimation approaches. It is visible that the one-sided approach is more reactive, i.e., the trend changes more, compared to the sluggish two-sided one. Now, if we calculate the HP gaps[19] for both credit ratios in Figure 1 without any augmentations, the results are shown in Figure 2[20]. Moreover, great differences are observed when comparing the one and two-sided gaps, which makes a point of problems of decision-making in real-time obvious. 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

[18] The narrow credit definition consists of bank credits to households and non-financial corporations, whereas the broad definition includes external debt.

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

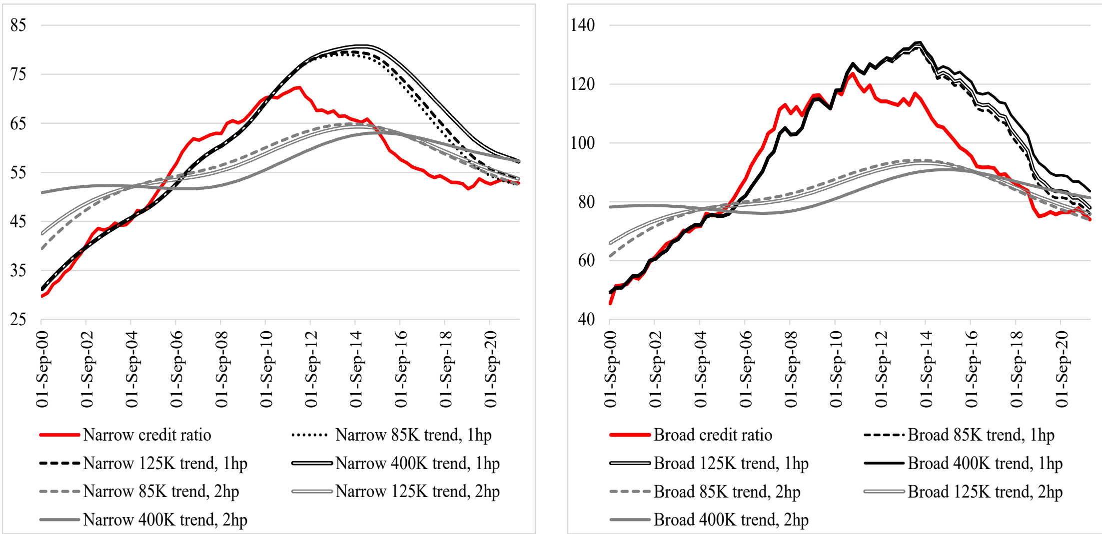
[20] As this work continues on the previous work in CNB, the gaps estimated here are based on separate filtering of credit series compared to the GDP. Moreover, we observe absolute gaps in this study (six), whereas the other six (relative gaps) are calculated from the absolute ones, and the analysis 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 the credit series have been paired with matching models for the GDP series. Although the OOS forecasting performance of different models differs when we compare credit and GDP series (see in the text below), we still match equal model selection for both series. E.g., suppose we pick the random walk model with $h = 8$ for the credit series in the filtering process. In that case, the resulting trend series is paired with the GDP trend series with the same random walk and $h = 8$ model selection, as this eases communication purposes. Furthermore, we tested the results by pairing the best-performing models overall without matching the model selection of the credit-to-GDP series, and the results are very similar. This means that credit dynamics primarily drive the dynamics of gaps. Finally, we tested the results by fixing the credit filtering approach and changed the smoothing parameter of the GDP series, ranging from 100 to 2200 with 100 increments. The results were also the same.

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).

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

a. Narrow credit definition

b. Broad credit definition

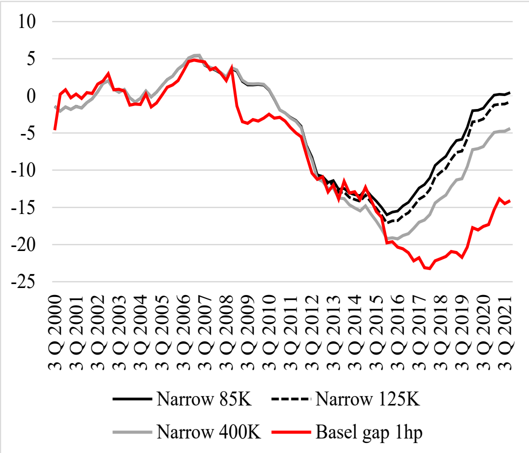


Note: 85k, 125k and 400k denote smoothing parameters in HP filter, equal to 85.000, 125.000 and 400.000 respectively. 1hp and 2hp denote one- (in black) and two-sided approach (in grey).

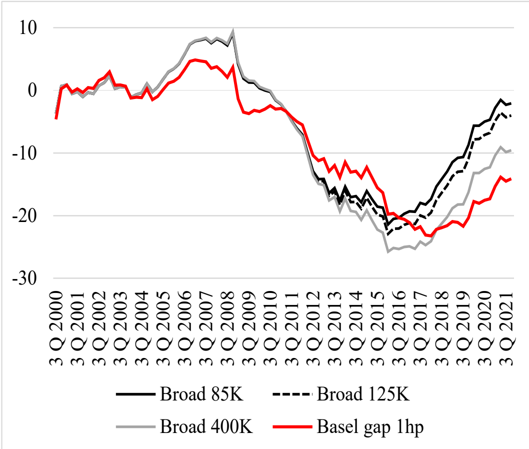
Source: CNB, author's calculation.

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

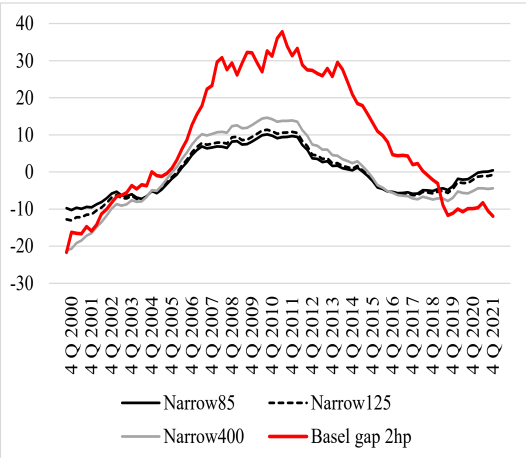
a. Narrow credit, one-sided gaps



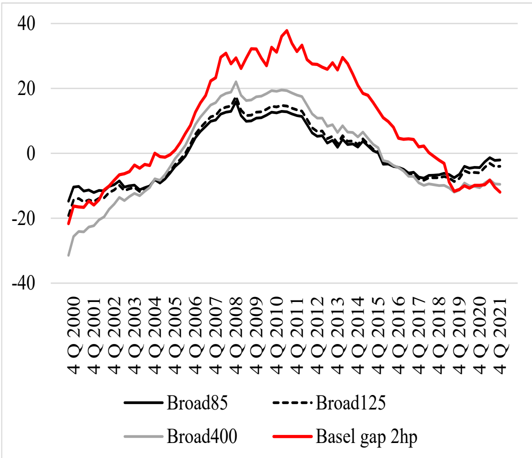
b. Broad credit, one-sided gaps



c. Narrow credit, two-sided gaps



d. Broad credit, two-sided gaps



Note: 85k, 125k and 400k denote smoothing parameters in values of 85.000, 125.000 and 400.000. Overlapping at the beginning of the sample in panels a and b are due to fixing the beginning of the sample[21] to produce initial trend and gap series. 1hp and 2hp denote the one- and two-sided Basel gaps.

Source: CNB, author's calculation.

[21] First 20 Q.

4.2. Estimation results

We employ forecast horizons of $h = 4$, 8, and 12 quarters for each of the five forecasting approaches. 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, 72 different augmented gaps were estimated for the 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 20). Table 1 shows a summary of different approaches explained in section four.

Table 1. Summary of OOS model approaches

Series	Smoothing parameter	Forecast horizon	Model approach
Credit (narrow and broad separately)	85000 125000 400000		Moving average
		4, 8 and 12 quarters	Linear forecast Rolling linear forecast Random walk
GDP	1600		ARI

Source: author's elaboration in text

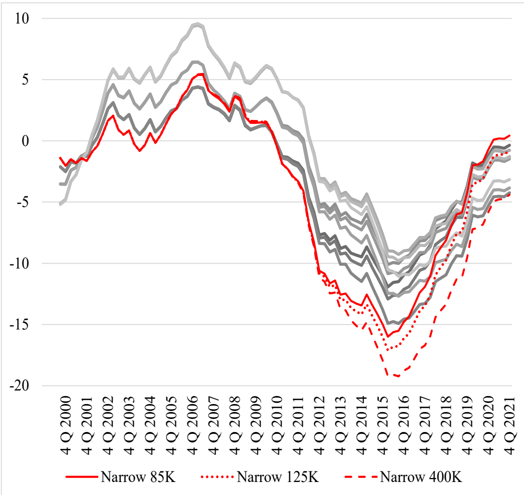
Figure 3 shows the augmented gaps based on every approach for the narrow credit-to-GDP ratio, whereas analogous gaps for the broad credit definition are shown in Figure 4[22]. By observing Figure 3, it is apparent that the worst-performing one is the linear forecast on panel b due to its dynamic being far away from the original indicators without augmentation (the red ones) and being positive almost in the entire observed period. Although the values have declined in the recession period, such an indicator would guide positive CCyB values in the whole period. This problem does not characterize other augmented indicators. Most augmented gaps do not have a significant negative bias after the GFC period compared to the original gaps without forecasts (the red ones). Moreover, in some cases, the range of the estimated gap is almost ten

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

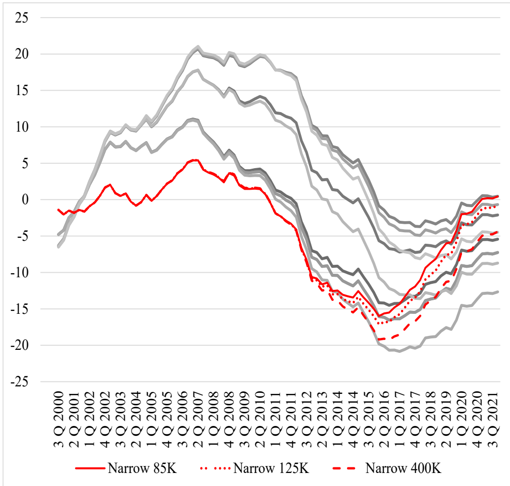
percentage points in the same OOS forecasting approach. This could be interpreted as more significant uncertainty. This shows that it is hard to make decisions in real time, especially when the value of the gap is such that it is close to the threshold of the CCyB activation.

Figure 3. Augmented gaps, narrow credit definition

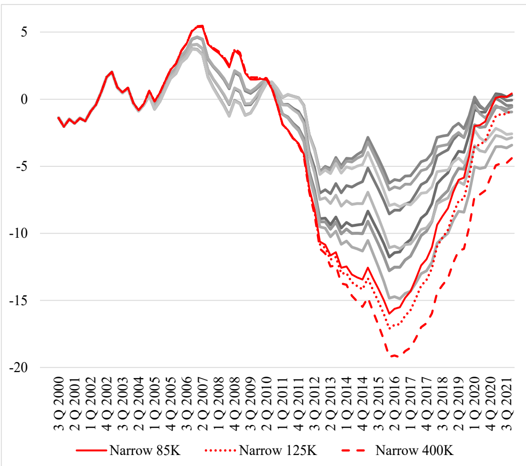
a. Rolling average



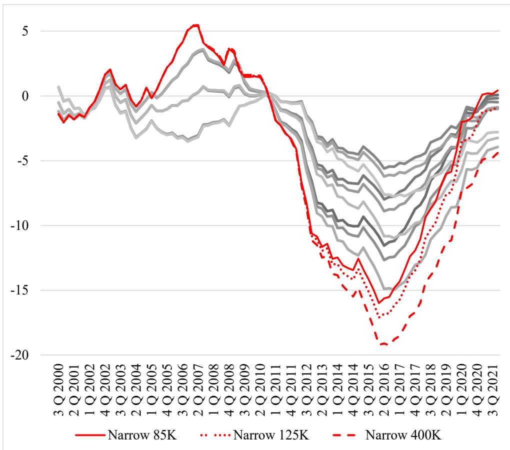
b. Linear forecast



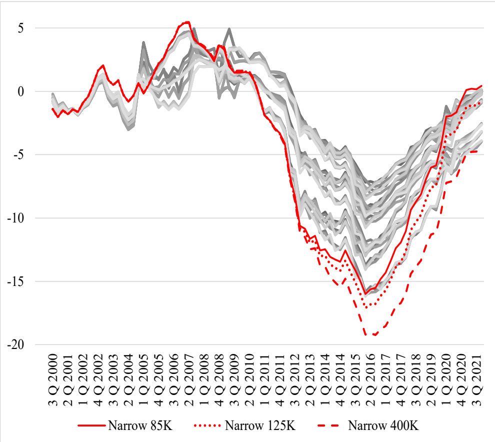
d. Rolling linear forecast



e. Random walk



f. ARI



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.

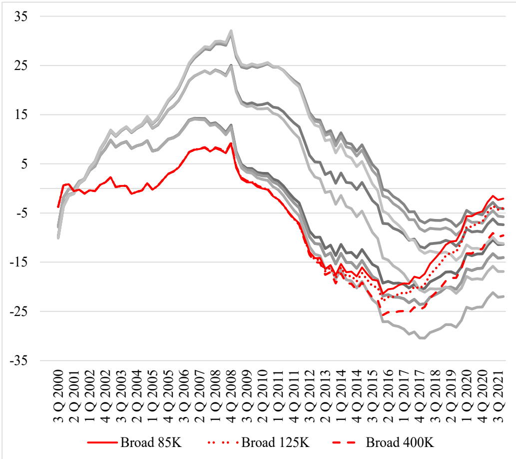
Source: CNB, author's calculation

Similar is valid for the broad credit definition gaps in Figure 4. Moreover, it is evident 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 primary and popular techniques for univariate forecasting, the problem would be even greater if other more sophisticated methods were used. Finally, it is worth mentioning 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).

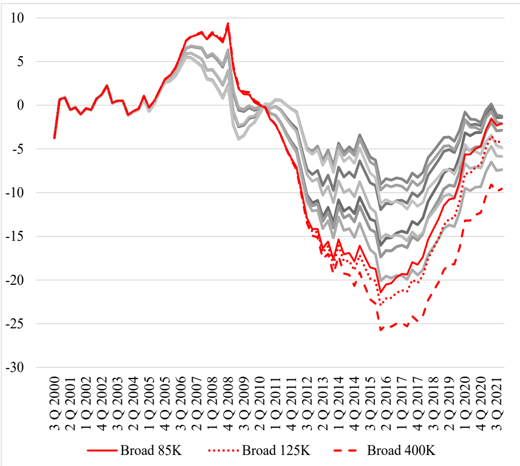
Figure 4. Augmented gaps, broad credit definition

a. Rolling average

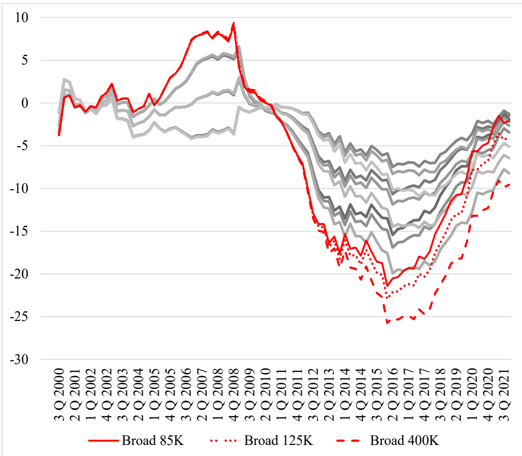
b. Linear forecast



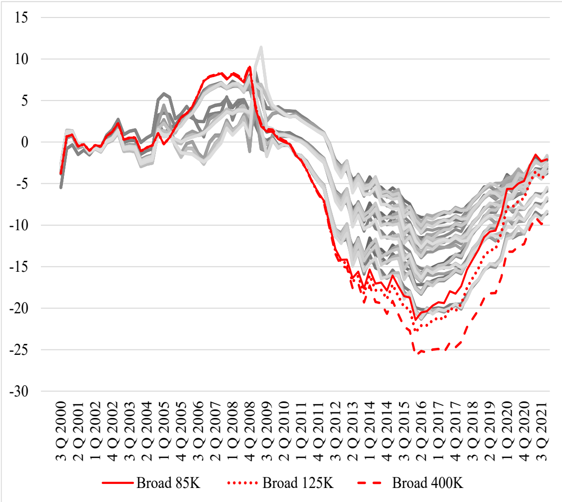
d. Rolling linear forecast



e. Random walk



f. ARI



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.

Source: CNB, author's calculation

4.3. Comparison results

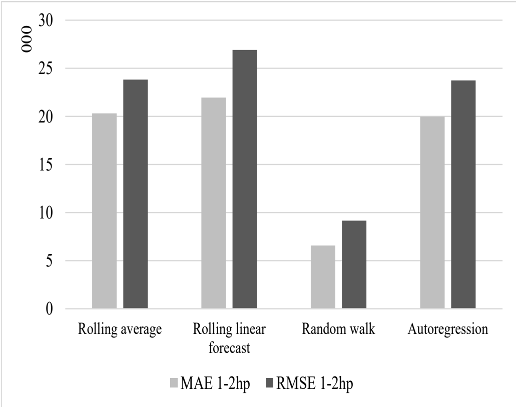
For each of the five approaches, average values of comparison criteria have been calculated and are shown in Figures 5[23] (narrow credit) and A2 (broad credit)[24]. Again, it is evident that the worst performance is observed for the linear forecast. By comparing the approaches by the revisions from the one to the two-sided gaps, the random walk has the smallest error. However, the ARI approach has the smallest variability and OOS forecasting performance. This means that for the narrow and broad credit definitions, the uncertainty around estimating the credit gap is the 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 the smallest uncertainty, i.e., variability, and the ARI approach has the smallest revisions towards the two-sided gaps.

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

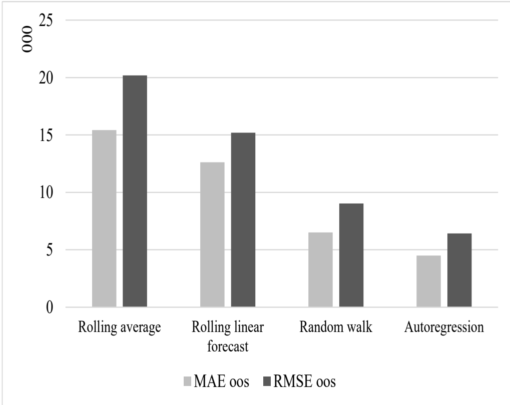
[24] The concrete values are given in the Appendix, in Tables A2 and A3, and corresponding values for GDP are shown in Table A4.

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

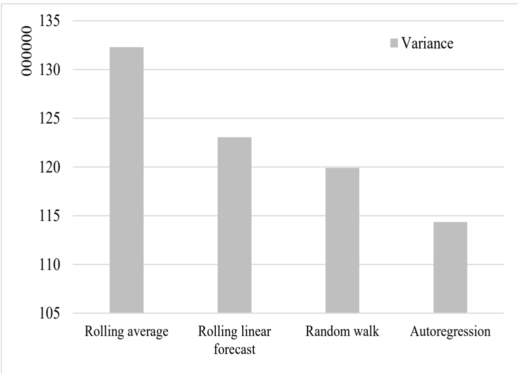
a. Comparisons of one and two sided gaps



b. OOS performance



c. Variance of gaps



Note: value comparison with the linear forecast is given in Appendix in Figure A1.
These values are obtained for narrow credit series filtering[25].

Source: CNB, author's calculation

Dealing with much information simultaneously, especially when considering conflicting criteria, could be easier to handle with a utility function approach[26]. As many individual indicators need to be contrasted based on several criteria, it is easier to establish a

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

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

ranking system based on a one-number comparison. 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 the outcome (denoted with O1). The results are shown in Table 2. To balance the OOS forecasting results and smaller revisions towards the possible two-sided gap, 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 greater weight to the MAE and RMSE 1-2hp values (times 2)). The other approach is to provide a greater penalty for 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 the broad credit definition has ARI as the best approach. This information is helpful for the decision-making process when observing augmented gaps, at least as 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, other vital aspects of the indicator performance should be considered. This includes the effects of the length of *h* and the smoothing parameter on the results. Thus, we observe the evaluation criteria from Figure 5 differently in

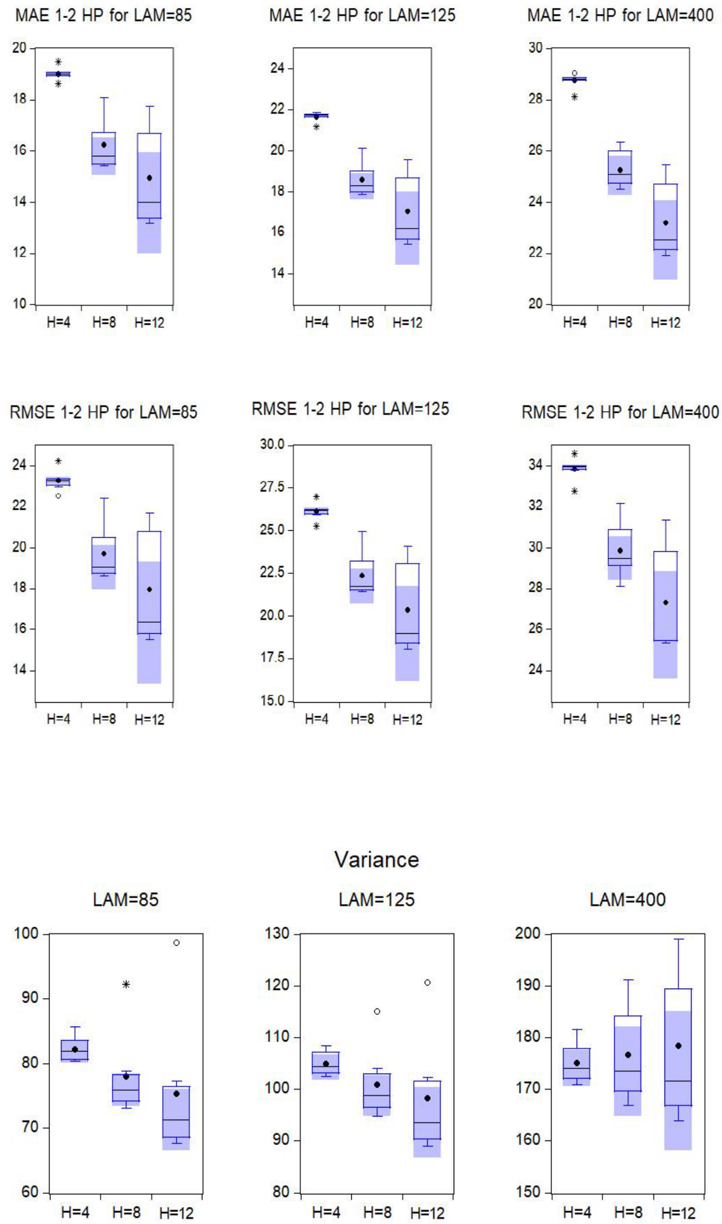
Figure 6[27]. There, boxplots are constructed for different values of h and smoothing parameters. Overall, the smallest revisions towards the two-sided gaps are, on average, observed for the 12-quarter horizon (rows 1 and 2), regardless of the smoothing parameter. The reason could be that the estimated dynamic is prolonged for a longer period in the future at each point in time. That is why those values drift away from the one-sided dynamic and go towards the two-sided gaps with fairly different dynamics overall. However, the variability of the average revision is greatest for h = 12. This is true for both narrow and broad credit series. In contrast, 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).

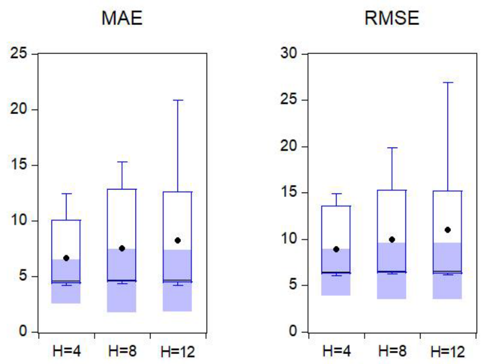
When looking at the variance performance (third rows in Figure 6 and A4; third panel in Figure A5), the h = 12 has almost the best performance. This is due to gaps based on h = 12 resembling the two-sided gaps more, meaning that they have smaller overall variability. The emphasis is on the word almost, as although the average value of the variance declines as h rises, its variability rises for all smoothing parameters. Moreover, there is an increase both in the variance and the variability of the variance for the value of the smoothing parameter of 400.000. This is prominent for all credit series.

The macroprudential decision-maker is also interested in obtaining good forecasts, measured by comparing the actual credit (GDP) values to the forecasted ones. Naturally, 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 (last row in Figure 6) for the forecasting part of the estimation procedure is four quarters for most 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 the one hand and between having the smallest forecasting errors on the other. To summarize the results in this subsection, the random walk and ARI approach generate, on average best results, alongside horizon lengths of 8 and 4 quarters. On the other hand, the smoothing parameter of 400.000 has the worst results in increased variability of several criteria.

[27] Figure 6 depicts the results for the narrow credit definition. Broad credit definition and GDP series corresponding analyses are shown in Figures A4 and A5.

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[28] 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[29] 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 currently used in CNB with the ranges of augmented gaps based on the results in the previous subsection. It is evident in panels a. and b. that the original gaps have a greater negative bias in the period from 2010 to 2016, which is solved with the augmented indicators denoted with shaded intervals. These intervals could be observed as certainty intervals, as they were obtained such that the end-point problem was reduced. Gaps obtained with the highest smoothing parameter are the furthest from to rest of the series, which could be interpreted as this parameter is 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. Such an approach could reduce the usual inaction bias. The values in panels c. and d. have similar dynamics, where the reduction of CCyB values when the crisis hit for

---

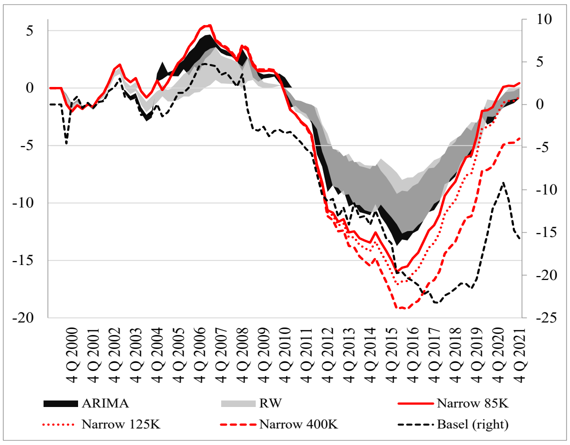
[28] Due to MAE and RMSE not depending on the smoothing parameter, the last row in Figure 8 is shown depending solely on values of *h*. The same holds for Figures A4 and A5.

[29] 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.

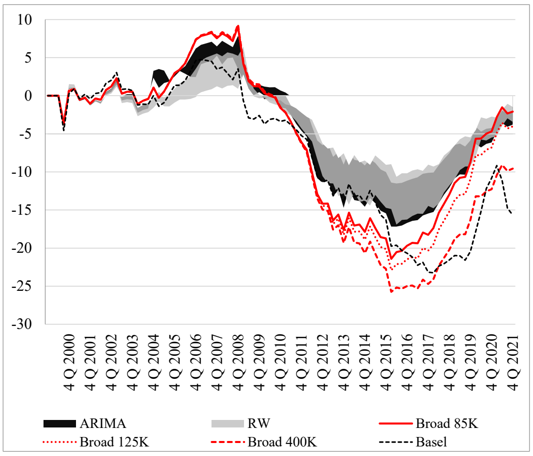
augmented gaps fell more compared to the original six gaps. This could be another piece of information used to decide when the CCyB should be reduced, alongside tracking the financial stress indicators that are usually often observed and talked about when commenting on releasing CCyB values (see De Nora 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 gradually increase this capital buffer compared to the much later growth for the original Basel gap.

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

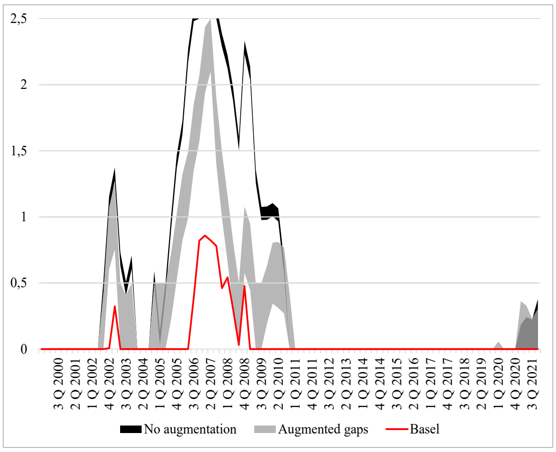
a. Range of best OOS augmented gaps, narrow credit definition



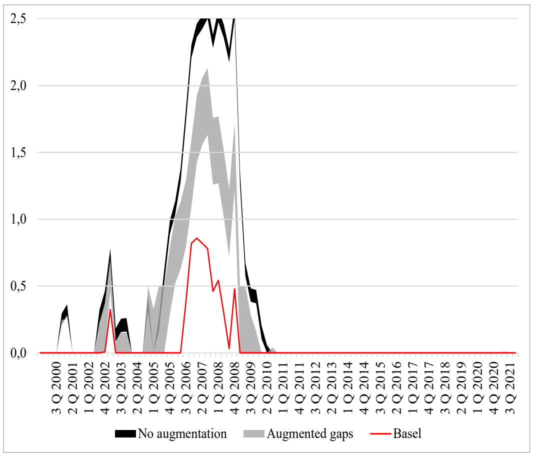
b. Range of best OOS augmented gaps, broad credit definition



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 the findings, there will always be a tradeoff between choosing the best OOS forecasting approach and the approach with the least corrections towards the two-sided gap approach. The results of this paper are based on a relatively short period that includes one crisis in the sample. This means that the early warning model signaling approach is not considered a good approach to contrast the gaps. This is due to the possible bias in the results, alongside the need to fix a specific initial window for the estimation procedure of the recursive gap estimation. Now, as the comparisons were made based on stability and OOS forecasting accuracy of individual indicators, the results hold for findings that focus on such criteria. In general, the findings align with related research in Gerdrup et al. (2013) and Valinskytė and Rupeika (2015), where linear projections had smaller variability but overall worst performance regarding other criteria. This is due to the nature of different approaches, where it is essential to consider that the estimation should be based on a rolling window basis. The estimated forecasting models' coefficients change over time as the financial cycle enters into different phases.

Moreover, the stability of the indicator is also important because it provides constant signals over time, which is especially important when decisions on the CCyB rate have to be made. Ideally, an indicator should be stationary and reverting to a mean value constantly (i.e., it should reflect the cyclicality in the credit-to-GDP ratio). However, this is rarely found in practice due to the dynamics of the original values and the disadvantages of the HP approach. Thus, the variability of the indicator, in general, can be considered an important criterion, but it does not have to be the main one to make final decisions. For example, 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 more prolonged period would. This again corroborates the initial statement that tradeoffs will be permanent characteristics in such an approach.

Finally, additional analysis was made in terms of another approach to dealing with the end-point problem in the HP filter, as in Bruchez (2013). Instead of the usual OOS forecast augmentation approach, different weights were put on the last observations before the filtering optimization was done. Bruchez (2013) advises multiplying the smoothing parameter for the first and the last observation with factor three, whereas the second and the penultimate ones should have the smoothing parameter multiplied with 3/2. Figure A6 in the appendix compares the trend and gap series for both narrow and broad credit series for the case of the original filter, and the weighted augmented one described here. The results show that although the series has some differences due to the different weighting schemes, those differences are minimal and do not affect the results. This is in line with the results of Bruchez (2013), who also did not find that such an approach results in vastly different conclusions and possible policy decision-making. This could be why this approach is not commonly found in existing literature, and authors utilize the OOS forecasting approach instead.

5. Conclusions

The credit-to-GDP gap measured with the HP filter approach as an indicator of cyclical risks is used in practice and empirical research. This paper deals with a concise overview of the alternative methods that try to enhance the HP filtering process in the first part. Augmented HP filter gaps were contrasted one to another by a comprehensive approach. 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). 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. The results are based on combining several techniques for forecasting, which is a positive finding, according to Timmermann (2006). The author states that using multiple forecasts offers diversification gains, as some approaches could be more subject to errors or structural shocks than others.

The final decision about the gap estimation approach to obtain augmented gaps will depend on the policymakers' prudence to act sooner or later with respect to 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 directly used in the composite indicator of cyclical risk, alongside repeating this procedure for other indicators obtained via HP filtering[30].

A downside of this research is that one crisis is included in the sample due to the short period in the analysis. This disables the analysis of the early warning signaling models, where the future crisis signaling of an indicator can be evaluated. This has been calculated in the empirical part of the research, but it corroborated the discussion about the bias of the results, as many indicators were found to have high AUROC values. Nevertheless, other studies focusing on similar topics 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 better information about the characteristics of each OOS modeling approach. 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 forecasting fields (Fragoso and Neto, 2018).

Several essential aspects were considered in this study. First, 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.

Incorporating this type of analysis in the regular decision-making process could reduce the overall uncertainty. This would incentivize the policymaker to reduce the inaction bias and enable everyday rule-based decisions, leading to more transparency and better communication with the public. Moreover, it could be recommended to plot the range of

[30] Other mentioned applications in the introduction can benefit from such results so that robustness checking can be made.

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, and the forecasting performance of an approach, a choice could be made 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.

References

Aikman, D., Bridges, J., Hoke S. H. and O'Neill, C. (2019.): *Credit, capital and crises: a GDP-at-Risk approach*. BoE Staff Working Paper No. 824, Bank of England.

Alessandri, P., Bologna, P., Fiori, R. and Sette, E. (2015.): *A note on the implementation of the countercyclical capital buffer in Italy*. Questioni di Economia e Finanza (Occasional Papers), No. 278. Banca D'Italia.

Ampudia, M., Lo Duca, M., Farkas, M., Pérez-Quirós, G., Pirovano, M., Rünstler, G. and Tereanu, E. (2021.): *On the effectiveness of macroprudential policy*. ECB Working Paper Series, No. 2559. European Central Bank.

Baba, C., Dell'Erba, S., Detragiache, E., Harrison, O., Mineshima, A., Musayev, A. and Shahmoradi, A. (2020.): *How Should Credit Gaps Be Measured? - An Application to European Countries*. IMF working paper 20/6, International Monetary Fund.

Babecký, J., Havránek, T., Matějů, J., Rusnák, M., Šmídková, K. and Vašíček, B. (2014.): *Banking, debt, and currency crises in developed countries: Stylized facts and early warning indicators*. Journal of Financial Stability, Volume 15, pp. 1-17.

Bank of Portugal (2020.): *The countercyclical capital buffer in Portugal*. Available at: https://www.bportugal.pt/sites/default/files/ccb_portugal_en.pdf.

BCBS (2011.): *Basel III: A global regulatory framework for more resilient banks and banking systems - revised version*. Basel Committee on Banking Supervision.

Behn, M., Detken, C., Peltonen, T. and Schudel, W. (2013.): *Setting Countercyclical Capital Buffers Based on Early Warning Models: Would It Work?*. ECB Working Paper No. 1604, European Central Bank.

Berge, T. J. (2020.): *Time-varying uncertainty of the Federal Reserve's output gap estimate*. Finance and Economics Discussion Series 2020-012. Washington: Board of Governors of the Federal Reserve System.

Beutel, J., List, S. and von Schweinitz, G. (2018.) *An evaluation of early warning models for systemic banking crises: Does machine learning improve predictions?*. Discussion Paper Deutsche Bundesbank No 48/2018, Deutsche Bundesbank

BIS (2010.): *Guidance for national authorities operating the countercyclical capital buffer.* Bank for International Settlements, Available at: https://www.bis.org/publ/bcbs187.htm

Blackburn, K., Orduna, F. and Sola, M. (1995.): *Exponential smoothing and spurious correlation: a note*. Applied Economics Letters, Vol. 2, No. 3, pp. 76–79.

Bonfim, D. and Monteiro, N. (2013.): *The Implementation of the Countercyclical Capital Buffer: Rules versus Discretion.* In: Financial Stability Report, pp. 87–110, Banco de Portugal.

Borio, C. and Drehmann, M. (2009.): *Assessing the risk of banking crises – revisited*. BIS Quarterly Review, pp. 29-46, Bank for International Settlements.

Borio, C. and Lowe, P. (2002.): *Assessing the Risk of Banking Crises*. BIS Quarterly Review, pp. 29-46, Bank for International Settlements.

Bouthevillain, C., Cour-Thimann, P., van de Dool, G., Hernández de Cos, P., Langenus, G., Mohr, M., Momigliano, S. and Tujula, M. (2001.): *Cyclically adjusted budget balances: an alternative approach*. Working Paper Series 77, European Central Bank.

Bruchez, P.A. (2003.): *A Modification of the HP Filter Aiming at Reducing the End-Point Bias.* Working paper, Swiss Federal Finance Administration, Bundesgasse 3, CH-3003 Bern.

Caldas Mntes, G. and Taveres Peixoto, G. B. (2014.): *Risk-taking channel, bank lending channel and the "paradox of credibility": Evidence from Brazil*. Economic Modelling, Vol. 39, pp. 82-94.

Candelon, B., Dumitrescu, E.-I. and Hurlin, C. (2012.): *How to Evaluate an Early-Warning System: Toward a Unified Statistical Framework for Assessing Financial Crises Forecasting Methods.* IMF Economic Review, Vol. 60, No. 1, pp. 75-113, International Monetary Fund.

Canova, F. (1998.): *Detrending and Business Cycle Facts*. Journal of Monetary Economics, Vol. 41, No. 3, pp. 475–512.

Chen, S. and Svirydzenka, K. (2021.): *Financial Cycles – Early Warning Indicators of Banking Crises?*. IMF Working paper, WP/21/116, International Monetary Fund.

CNB (2022a.): *Croatian National Bank, data* available online at: https://www.hnb.hr/en/statistika/statisticki-podaci/sve-tablice-po-datumu-objave .

CNB (2022b.): *Macroprudential diagnostics, No 16, Box 2 Improvements in the methodology of countercyclical buffer identification and calibration in Croatia*. Croatian National Bank, Available at: https://www.hnb.hr/documents/20182/4129930/e-mpd-16-2022.pdf/ca45830d-196a-e18d-6b53-bb8808a8bb0d .

Cogley, T. and Nason, J.M. (1995.): *Output dynamics in real-business-cycle models*. American Economic Review, Vol. 85, No. 3, pp. 492-511.

de Brouwer, G. (1998.): *Estimating output gaps*. Economic Research Department Research Discussion Paper, No. 9809, Reserve Bank of Australia.

De Nora, G., O'Brien, E. and O'Brien, M. (2020.): *Releasing the CCyB to support the economy in a time of stress*. Central Bank of Ireland Financial Stability Notes, Vol. 2020, No. 1, Central Bank of Ireland.

Dell Ariccia, G., Igan, D., Leaven, L. and Tong, H. (2012.): *Policies for macrofinancial stability: How to deal with credit booms.* IMF Staff Discussion Note. International Monetary Fund.

Deryugina, E., Ponomarenko, A. and Rozhkova, A. (2020.): *When are credit gap estimates reliable?*. Economic Analysis and Policy 67, pp. 221–238.

Detken, K., Weeken, O., Alessi, L., Bonfim, D., Boucinha, M., Castro, C., Frontczak, S., Giordana, G., Giese, J., Jahn, N., Kakes, J., Klaus, B., Lang, J., Puzanova, N. and Welz, P. (2014.): *Operationalising the Countercyclical Capital Buffer: Indicator*

Selection, Threshold Identification and Calibration Options. ESRB Occasional Paper, No. 5, European Systemic Risk Board.

Dimova, D., Kongsamut, P. and Vandenbussche, J. (2016.): *Macroprudential Policies in Southeastern Europe*. Working Paper 16/29, World Bank.

Donnery, S. (2016.): *Speech, Macroprudential policy: action in the face of uncertainty Address by Sharon Donnery*. Deputy Governor of the Central Bank of Ireland at the Dublin Economic Workshop Annual Economic Policy Conference.

Drehmann, M., Borio, C., Gambacorta, L., Jimenez, G. and Trucharte, C. (2010.): *Countercyclical capital buffers: exploring options*. BIS Working Papers, No. 317, Bank for International Settlements.

Drehmann, M., Borio, C. and Tsatsaronis, K. (2011.): *Anchoring Countercyclical Capital Buffers: The Role of Credit Aggregates*. International Journal of Central Banking, Vol. 7, No. 4, pp. 189– 240.

Drehmann, M., Borio, C. and Tsatsaronis, K. (2014.): *The credit-to-GDP gap and countercylical capital buffers: questions and answers*. BIS Quarterly Review, Bank for International Settlements.

Drehmann, M. and Juselius, M. (2014.): *Evaluating Early Warning Indicators of Banking Crises: Satisfying Policy Requirements*. International Journal of Forecasting, Vol. 30, No. 3, pp. 759–780.

Drehmann, M. and Tsatsaronis, K. (2014.): *The credit-to-GDP gap and countercyclical capital buffers: questions and answers*. BIS Quarterly Review, pp. 55-73, Bank for International Settlements.

Drehmann, M. and Yetman, J. (2018.): *Why you should use the Hodrick-Prescott filter – at least to generate credit gaps.* BIS Working Papers, No. 744. Bank for International Settlement.

Edge, R. M. and Meisenzahl, R. R. (2011.): *The unreliability of credit-to-GDP ratio gaps in real-time: Implications for countercyclical capital buffers*. International Journal of Central Banking, Vol. 7, No. 4, pp. 261–298.

ESRB (2021.): *Report on the Expert Group on Macroprudential Stance – Phase II (implementation) A framework for assessing macroprudential stance*. European Systemic Risk Board.

ESRB. (2014.): *Recommendation of the European Systemic Risk Board of 18 June 2014*. ESRB/2014/1, European Systemic Risk Board. Available at: https://www.esrb.europa.eu/pub/pdf/recommendations/140630_ESRB_Recommendation.en.pdf .

ESRB. (2018.): *The ESRB handbook on operationalising macroprudential policy in the banking sector*. European Systemic Risk Board.

Fragoso, T. M. and Neto, F. L. (2018.): *Bayesian model averaging. A systematic review and conceptual classification*. International Statistical Review, International Statistical Institute, Vol. 86, No. 1, pp. 1-28.

Galán, J. E. (2019.): *Measuring Credit-to-GDP Gaps, The Hodrick-Prescott Filter Revisited.* Documentos de Trabajo, No. 1906, Banco de España.

García, J. A. and Manzanares, A. (2007.): *Reporting biases and survey results. Evidence from European professional forecasters*. ECB Working paper series, No. 836. European Central Bank.

Gerdrup, K.R., Kvinlog, A. B. and Schaanning, E. (2013.): *Key Indicators for a Countercyclical Capital Buffer in Norway - Trends and Uncertainty*. Norges bank staff memo, 13/2013, Norges Bank.

Geršl, A. and Mitterling, T. (2021.): *Forecast-Augmented Credit-to-GDP Gap as an Early Warning Indicator of Banking Crises*, Finance a úvěr-Czech Journal of Economics and Finance, Vol. 71, No. 4, pp. 323-351.

Hamilton, J. (2018.): *Why you should never use the Hodrick-Prescott filter.* Review of Economics and Statistics, Vol. 100, No. 5, pp. 831-843.

Harvey, A. C. and Jaeger, A. (1993.): *Detrending, stylized facts and the business cycle*. Journal of Applied Econometrics, Vol. 8, No. 3, pp. 231–247

Hodrick, R. J. and Prescott, E. C. (1997.): *Postwar U.S. Business Cycles: An Empirical Investigation.* Journal of Money, Credit and Banking, Vol. 29, No. 1, pp. 1-16.

Jokipii, T., Nyffeler, R. and Riederer, S. (2021.): *Exploring BIS credit-to-GDP gap critiques: the Swiss case*. Swiss Journal of Economics and Statistics, Vol. 157, No. 7, pp. 1-19.

Jones, C., Rabanal, P. and Leigh, D. (2021.): *Credit Cycles, Fiscal Policy, and Global Imbalances*. IMF Working Paper, Vol. 2021, Issue 043, International Monetary Fund.

Jovičić, G. (2017.): *Procjena potencijalnog rasta i jaza BDP-a u Hrvatskoj (Estimating Potential Growth and Output Gap in Croatia)*, CNB Surveys, No. S-29, Croatian National Bank.

Kaiser, R. and Maravall, A. (1999.): *Estimation of the Business Cycle: A Modified Hodrick-Prescott filter*. Spanish Economic Review, Vol. 1, pp. 175–206.

Kamber, G., Morley, J. and Wong, B. (2018.): *Intuitive and reliable estimates of the output gap from a Beveridge-Nelson filter.* Review of Economics and Statistics, Vol. 100, No. 3, pp. 550-566.

Karamisheva, T., Markova, G., Zahariev, B. and Pachedzhiev, S. (2019.): *Financial Cycle in the Bulgarian Economy and Its Interaction with the Business Cycle*. BNB Discussion Papers DP/113/2019, Bulgarian National Bank.

Kauko, K. (2012.): *Triggers for countercyclical capital buffers*, MPRA Paper No. 85692. Available at: https://mpra.ub.uni-muenchen.de/85692/.

Lang, J, H., Izzo, C., Fahr, S. and Ruzicka, J. (2019.): *Anticipating the bust: a new cyclical systemic risk indicator to assess the likelihood and severity of financial crises*. ECB Occasional Paper Series, No. 219. European Central Bank.

Lawrence, M., Goodwin, P., O'Connor, M. and Önkal, D. (2006.): *Judgmental forecasting: a review of progress over the last 25 years*. International Journal of Forecasting, Vol. 22, br. 3, pp. 493–518.

Mise, E., Kim, T. H. and Newbold, P. (2005.): *On Suboptimality of the Hodrick-Prescott Filter at Time Series Endpoints*. Journal of Macroeconomics, Vol. 27, No. 1, pp. 53–67.

Nier, E. W., Olafsson, T. T., Rollinson, Y. G. and Gelos, G. (2020.): *Exchange Rates and Domestic Credit-Can Macroprudential Policy Reduce the Link?.* IMF Working Paper, Vol. 2020, Issue 187, International Monetary Fund.

O'Brien, M. and Wosser, M. (2021.): *Growth at Risk & Financial Stability*. Financial stability notes, Vol. 2021, No. 2, Central Bank of Ireland.

Ódor, L. and Jurašekova Kucserová, J. (2014.): *Finding Yeti: More Robust Estimates of Output Gap in Slovakia*. Council for Budget Responsibility Working Paper No. 2.

Önkal, D., Thomson, M. and Pollock, A. (2002.): *Judgmental forecasting*. In: Clements, M. i Hendry, D. (eds.), A companion to economic forecasting. Blackwell Publishers, Malden and Oxford.

Pedersen, T. M. (2001.): *The Hodrick Presscott Filter, the Slutzky Effect, and the Distortionary Effect of Filters.* Journal of Economic Dynamics and Control, Vol. 25, pp. 1081–1101.

Richter, B., Schularick, M. and Wachtel, P. (2017.): *When to lean against the wind.* CEPR Discussion Paper, No. 12188. Centre for Economic Policy Research.

Rünstler, G. and Vlekke, M. (2016.): *Business, Housing, and Credit Cycles*. ECB Working Paper Series, No. 1915, European Central Bank.

Schularick, M. and Taylor, A. M. (2012.): *Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008*. American Economic Review, Vol. 102, No. 2, pp. 1029–1061.

St Amant, P. and van Norden, S. (1997.): *Measurement of the Output Gap: A Discussion of Recent Research at the Bank of Canada*. Technical Reports 79, Bank of Canada.

Škrinjarić, T. (2022.): *Uvođenje kompozitnog indikatora cikličkog sistemskog rizika u Hrvatskoj: mogućnosti i ograničenja (Introducing a composite indicator of cyclical systemic risk in Croatia: possibilities and limitations)*. Research I-70, Hrvatska narodna banka (Croatian National Bank).

Škrinjarić, T., Bukovšak, M. (2022a.): *Novi indikatori kreditnog jaza u Hrvatskoj: unapređenje kalibracije protucikličkog zaštitnog sloja kapitala (New indicators of credit gap in Croatia: improving the calibration of Countercyclical Capital Buffer.)*. Research I-69, Hrvatska narodna banka (Croatian National Bank).

Škrinjarić, T. and Bukovšak, M. (2022b.): Unapređenje kalibracije protucikličkog zaštitnog sloja kapitala: novi indikatori kreditnog jaza u Hrvatskoj (*Improving the* *calibration of countercyclical capital buffer: new indicators of credit gap in Croatia).* accepted for publication in Economic Thought and Practice, forthcoming.

Timmermann, A. G. (2005.): *Forecast Combinations*. CEPR Discussion Papers 5361, Centre for Economic Policy Research.

Valinskytė, N. and Rupeika, G. (2015.): *Leading indicators for the countercyclical capital buffer in Lithuania*. Available at: https://www.lb.lt/uploads/publications/docs/op_4.pdf

Wezel, T. (2019.): *Conceptual Issues in Calibrating the Basel III Countercyclical Capital Buffer*. IMF Working paper, No. 19/86. International Monetary Fund.

Appendix 1 – 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:

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

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:

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

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 ARI 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.

Appendix 2 - 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

Appendix 2 - Table A1. AUROC values for individual augmented gaps, signaling 16 to 5 Q before the crisis

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

Appendix 2 - Table A1. AUROC values for individual augmented gaps, signaling 16 to 5 Q before the crisis

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

Appendix 3 - 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**

Note: bolded values denote best performance in each column

Source: CNB, author's calculation

Appendix 4 - 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**

Note: bolded values denote best performance in each column

Source: CNB, author's calculation

Appendix 5 - Table A4. Average values of comparison criteria, GDP

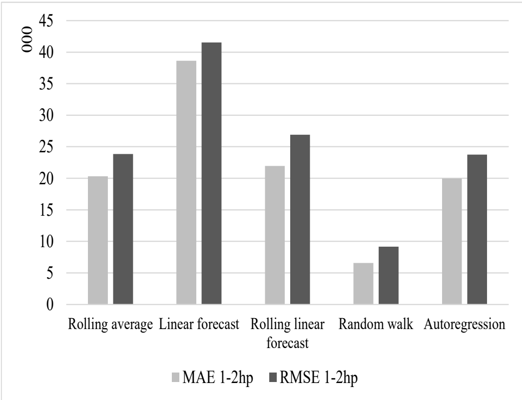
Group	MAE 1-2hp	RMSE 1-2hp	Variance	MAE OOS	RMSE OOS
Rolling average	2,202	2,732	1,048	3,957	5,111
Linear forecast	15,089	16,600	74,281	38,758	39,573
Rolling linear forecast	1,633	2,256	0,468	2,971	4,029
Random walk	1,389	2,311	**0,346**	**1,398**	**2,285**
Autoregression	**1,185**	**1,591**	0,606	1,422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

Note: bolded values denote best performance in each column

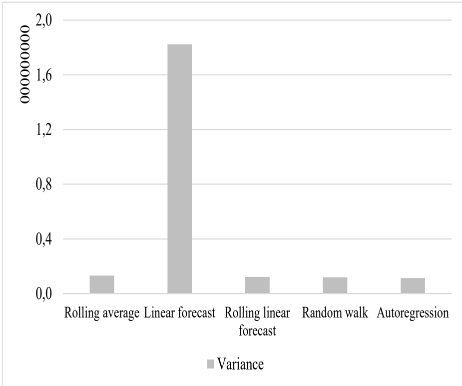
Source: CNB, author's calculation

Appendix 6 - Figure A1. Average values of comparison criteria, narrow credit definition

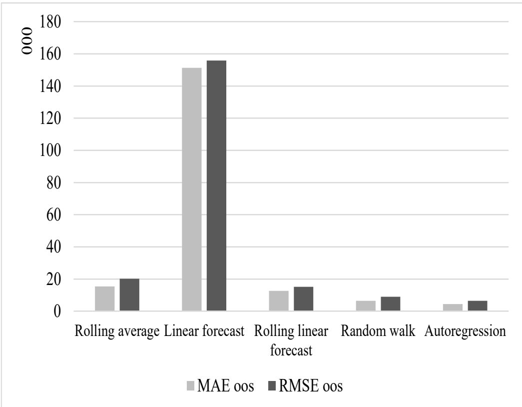
a. Comparisons of one and two sided gaps



b. Variance of gaps



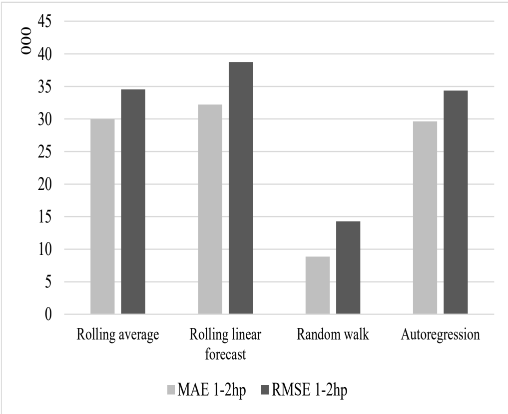
c. OOS performance



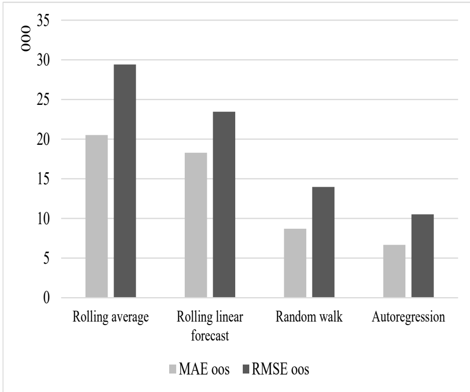
Source: CNB, author's calculation

Appendix 7 - Figure A2. Average values of comparison criteria, broad credit definition

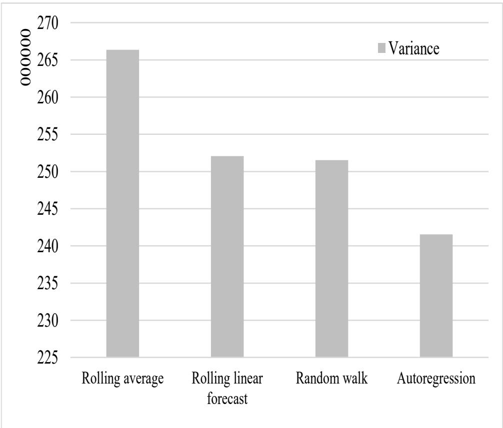
a. Comparisons of one and two sided gaps



b. OOS performance



c. Variance of gaps

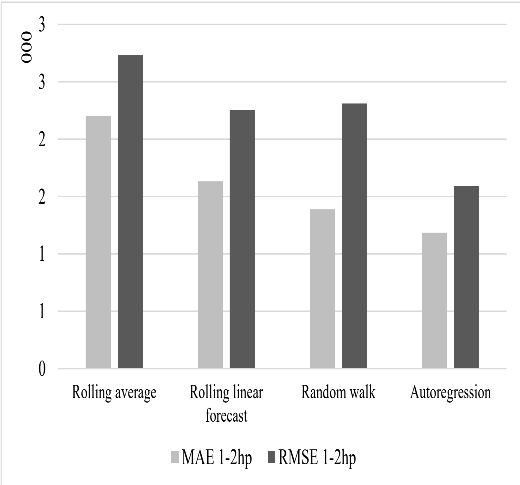


Note: value comparison with the linear forecast is available upon request.

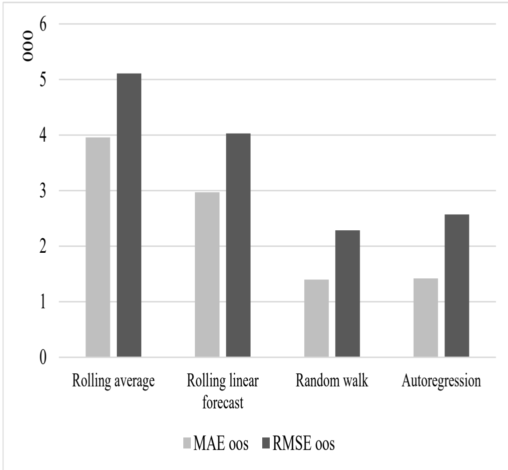
Source: CNB, author's calculation

Appendix 8 - Figure A3. Average values of comparison criteria, GDP series

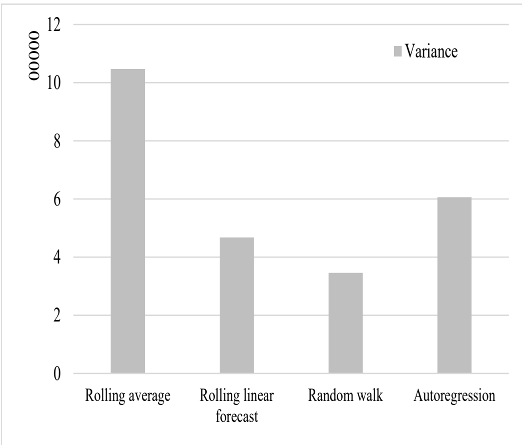
a. Comparisons of one and two sided gaps



b. OOS performance



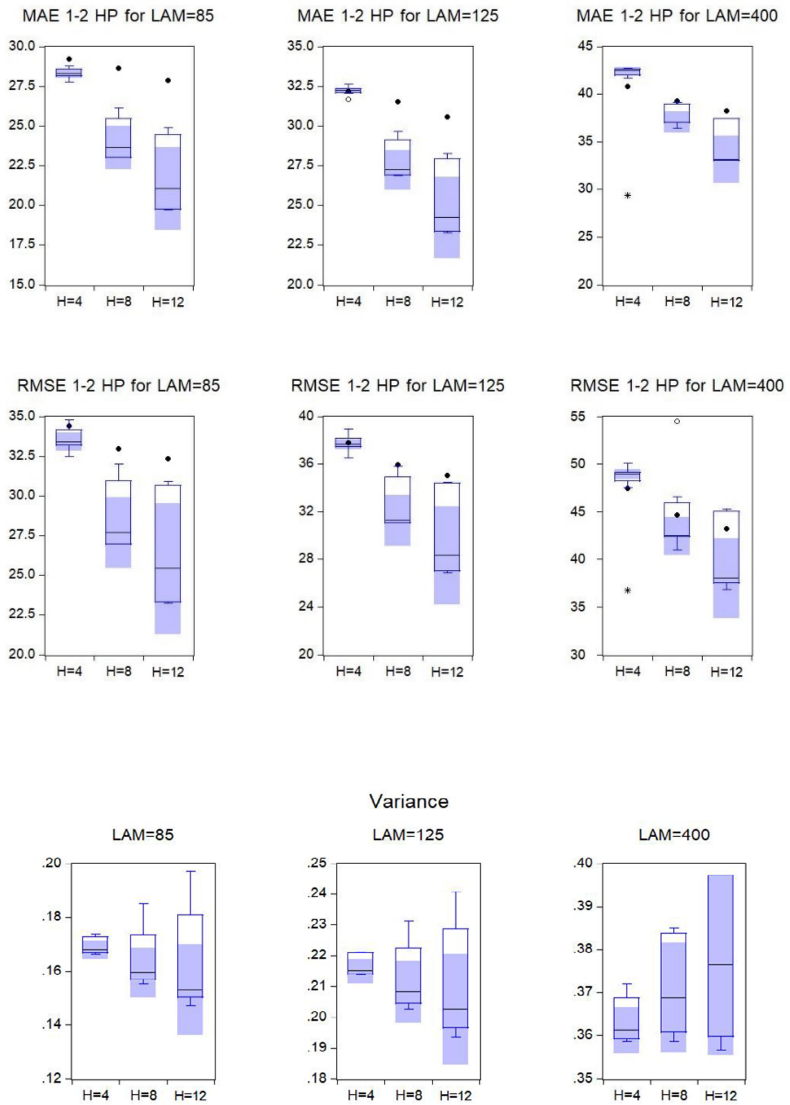
c. Variance of gaps



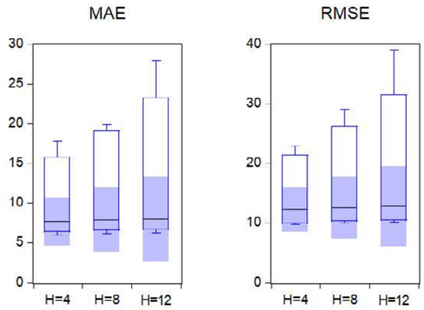
Note: value comparison with the linear forecast is available upon request.

Source: CNB, author's calculation

Appendix 9 - Figure A4. Boxplots of comparison criteria, broad credit definition, by *h* and smoothing parameter



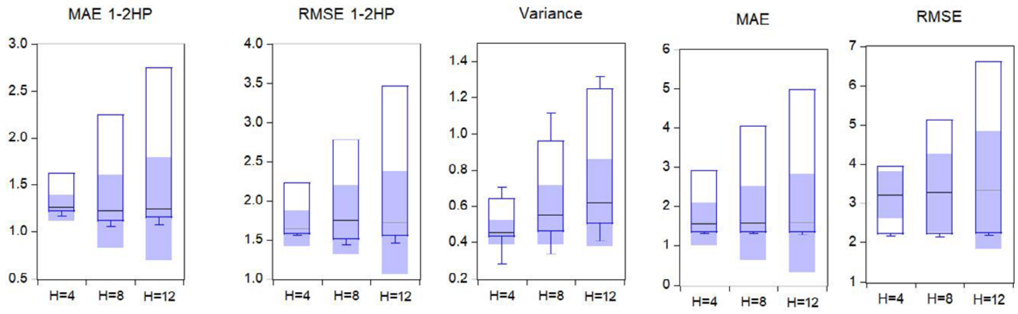
Appendix 9 - Figure A4. Boxplots of comparison criteria, broad credit definition, by h and smoothing parameter



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.

Appendix 10 - Figure A5. Boxplots of comparison criteria, GDP series, by *h*

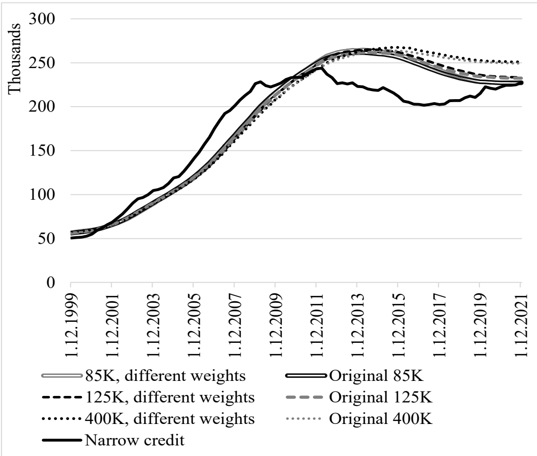


Note: H is the length of the forecasting horizon, MAE 1-2HP and RMSE 1-2HP are measures given in formulae (3) and (4) variance is defined in (6), and MAE and RMSE denote the OOS forecasting performance measures. The values of lambda do not differ here, as GDP was filtered with lambda equal to 1.600 (see 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.

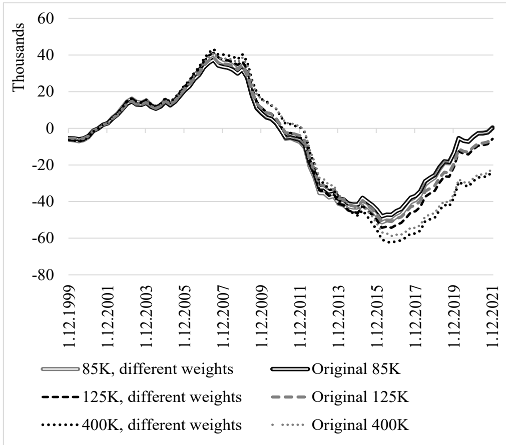
Source: CNB, author's calculation.

Appendix 11 - Figure A6. Comparison of trends and gaps for the case of original HP filtering process and the weight restricted approach

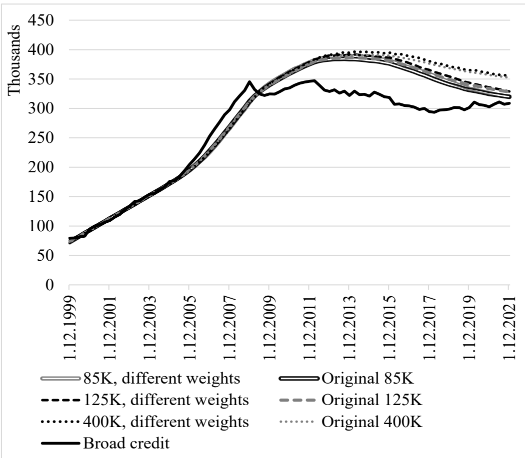
a. Narrow credit definition, trends



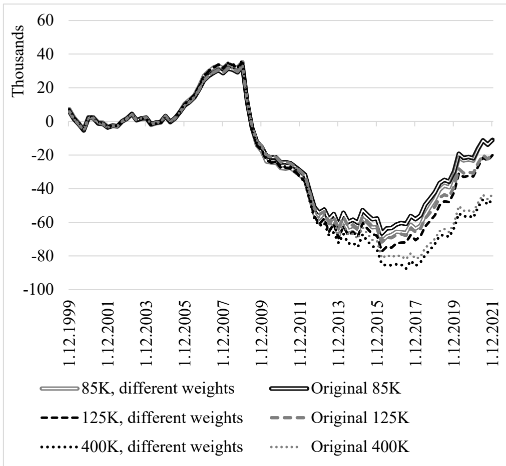
b. Broad credit definition



c. Broad credit definition, trends

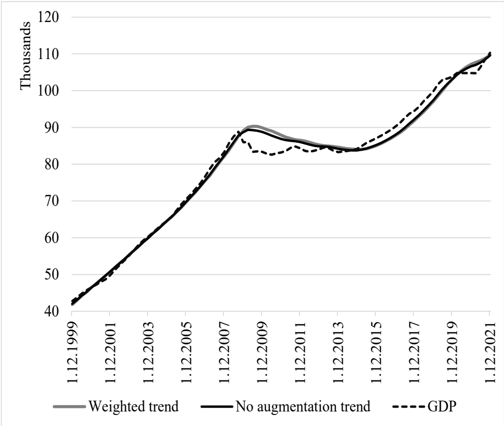


d. Broad credit definition, gaps

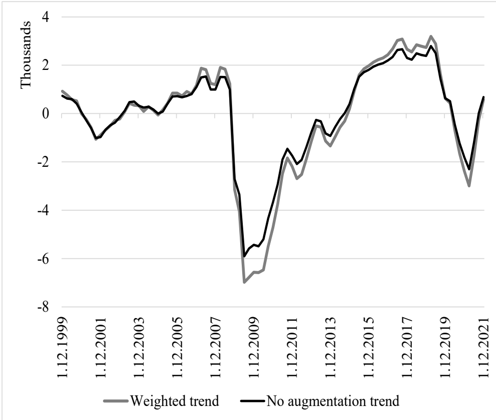


Appendix 11 - Figure A6. Comparison of trends and gaps for the case of original HP filtering process and the weight restricted approach

e. GDP, trends



f. GDP, gaps



Note: different weights denotes the HP version with different weights for the end points compared to the rest of the series. No augmentation is the one-sided filter without any weights augmentation. See the main text and the discussion section for the details.

Source: CNB, author's calculation

PUBLISHER
Croatian National Bank
Trg hrvatskih velikana 3
10000 Zagreb
T. +385 1 4564 555
www.hnb.hr

ISSN 1334-0131 (online)

Augmented credit-to-GDP gap as a more reliable indicator for macroprudential policy decision-making

ISSN 1334-0131 (online)

HNB