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New Indicators of Credit Gap in Croatia: Improving the Calibration of the Countercyclical Capital Buffer

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Abstract

The countercyclical capital buffer (CCyB) is a key macroprudential policy instrument, whose purpose is to create additional capital in the periods of increasing cyclical risks in order to provide banks with enough space for continued smooth lending during a crisis. In the pre-crisis period, the CCyB's purpose can be to indirectly mitigate excessive lending. The calibration of the CCyB starts with the estimation of a credit gap based on statistical filters contrasting the long-term credit activity with the economic activity in order to assess the extent to which current dynamics deviates from the equilibrium. Due to a series of problems that occur in practice, this research examines options for improving credit gap estimation, assessed using the criterion of quality of crisis signalling in a historical sample and expert judgement. The main findings of the research suggest that credit and GDP series should be filtered separately, assuming that the credit cycle lasts longer than the business cycle and that the lack of knowledge about the exact duration of the credit cycle can be remedied by estimating a range of possible credit gaps. The new indicators proposed in the research were found to send earlier signals of the occurrence of crisis and are more stable than the previously used national specific indicators. All this allows for an earlier and more gradual build-up of countercyclical capital buffers, which would be less subject to change.

Keywords: credit gap, statistical filters, macroprudential policy, systemic risk, countercyclical capital buffer

JEL: C18, E32, E58, G01, G28

Sažetak

Protuciklički zaštitni sloj kapitala je jedan od ključnih instrumenata makrobonitetne politike, čija je namjena stvaranje dodatnog kapitala u razdobljima porasta cikličkih rizika, kako bi se njegovim otpuštanjem u krizi bankama osigurao prostor za nastavak nesmetanog kreditiranja, a u razdobljima koje joj prethode i posredno ublažilo prekomjerno kreditiranje. Njegova kalibracija započinje ocjenom kreditnog jaza, na način da se primjenom statističkih filtera određuje dugoročna kreditna aktivnost u odnosu na ekonomsku, kako bi se ocijenilo koliko trenutna kretanja odstupaju od ravnotežnih. Budući da se u praksi pojavio niz problema u primjeni takvih indikatora, ovim istraživanjem se razmatraju mogućnosti unapređenja procjene kreditnog jaza, koje se ocjenjuju uz primjenu kriterija kvalitete signaliziranja krize u povijesnom uzorku i stručnu procjenu. Glavni rezultati istraživanja upućuju da je potrebno zasebno filtrirati serije kredita i BDP-a uz pretpostavku da kreditni ciklus traje dulje u odnosu na gospodarski, te da se nepoznavanje točne duljine trajanja kreditnog ciklusa može premostiti promatranjem raspona mogućih kreditnih jazeva. Novi indikatori koji se predlažu u istraživanju su ranije signalizirali prethodnu globalnu financijsku krizu, te su stabilniji od prethodno korištenih specifičnih indikatora, čime se u realnom vremenu omogućava ranija i postepenija izgradnja protucikličkog zaštitnog sloja kapitala, manje podložna promjenama.

Ključne riječi: kreditni jaz, statistički filtri, makrobonitetna politika, sistemski rizik, protuciklički zaštitni sloj kapitala

JEL: C18, E32, E58, G01, G28.

Contents

1. Introduction

The literature has long acknowledged the fact that excessive credit growth in an economy can lead to a build-up of systemic risks that undermine its financial stability. Empirical research based on historical data shows that accelerated credit and asset price increases have preceded episodes of financial crises (Borio and Lowe, 2002, Borio and Drehmann, 2009, Drehmann et al., 2011, Schularick and Taylor, 2012). The last global financial crisis (GFC) has led to an increasingly active use of macroprudential policy instruments, including the countercyclical capital buffer (CCyB), which is built up during the accumulation of cyclical risks in order to strengthen the resilience of the financial system to sudden shocks and prevent the build-up of imbalances. Arbatli-Saxegaard and Muneer (2020), reviewing the use of the CCyB in thirty-three developed countries, mostly European ones, state that by the end of 2019 almost half of them were using or had announced a positive CCyB rate. All of these countries, with the exception of Luxembourg, reduced the positive CCyB rate partially or completely when the coronavirus pandemic broke out, using it for the first time in a crisis, to support the continuation of lending. By contrast, with the recovery from the pandemic, accompanied by the continued accumulation of cyclical risks, a growing number of countries introduced positive CCyB rates, including Croatia.

The main objective of this study is to improve the CCyB calibration methodology used in Croatia and present it to the wider public. This involves examining the possibilities of improving credit gap assessment in Croatia, as the first step in the CCyB calibration, which comprises various credit definitions, GDP corrections, defining and transforming credit-to-GDP ratios in a different manner as well as calculating deviations from the long-term equilibrium (i.e. credit gap), in order to identify indicators meeting the criterion of being reliable, sufficiently early and stable signals of a crisis in a historical sample. The issues addressed are whether any credit gap indicators better signalled the previous crisis in Croatia (GFC) than those used by the CNB until 2021, whether these indicators provide for a prompt build-up of the CCyB, how stable they are as well as whether they can be meaningfully interpreted in the context of credit and financial cycles and easily communicated to the public.

This research contributes to the systematisation and analysis of different approaches to the credit gap assessment and the formulation of proposals enabling its practical application. Proposals for other techniques to be used in calibration of this macroprudential instrument, techniques that take into account a broader set of cyclical risk indicators in addition to credit gap, are left for consideration in a separate study.

Under the current international financial regulation, the calibration of the CCyB starts with the assessment of the Basel credit gap. This is an internationally harmonised indicator of excessive lending, used to signal the development of cyclical risks in a large number of countries due to the availability of data needed for calculation, the simplicity of assessment and interpretation as well good crisis signalling properties (see Galán, 2019, and the sources cited in this work, in particular Detken et al., 2014). It is calculated as the difference between the ratio of credit (a broad measure of the stock of credit to the private non-financial sector) to GDP and its long-term trend, estimated with statistical filtering of ratios via the one-sided Hodrick-Prescott filter (HP, Hodrick and Prescott, 1997) with the lambda (smoothing parameter) set to 400,000. The gap is interpreted as the part of the trend in the credit-to-GDP ratio that is excessive relative to the so-called equilibrium (or long-term) state. However, as early as in 2010, the BCBS warned that when the gap widens due to a decline in GDP (rather than an actual increase in cyclical risks) its signals (i.e. reference indicators indicated by the gap) should not be followed, and that this statistical measure does not have good properties when the cycle is reversed. In addition, Edge and Meisenzahl (2011) and Bunčić and Melecky (2013) highlighted the problem of using the HP gap as a purely statistical measure: it does not reflect the equilibrium level of credit for an economy[1] (see Section 3.3 for more detail on HP filter-related problems). Therefore, according to the ESRB Recommendation, in addition to the Basel gap, designated authorities in EEA countries can calculate an alternative credit-to-GDP ratio gap that better reflects the specificities of a national financial system; this is named the specific gap. In such a calculation, the authorities should ensure that the specific gap reflects the deviation of the credit-to-GDP ratio from the long-term trend and that it is based on an empirical analysis of the national economy and chosen on the basis of an assessment of its signalling properties related to the build-up of cyclical risks followed by the emergence of systemic crises. This research aims to identify precisely such indicators.

[1] Some studies therefore consider models based on economic theory, such as an error correction model (VEC – vector error correction), which 'captures' the short-term and long-term dynamics between a certain set of variables, so that the optimal level of credit in the long-term economy is explained by economic fundamentals. However, such an approach requires longer time series, which at the moment significantly restricts the application of this method to Croatian data.

Croatia's experience with measuring and interpreting the Basel credit gap and the national-specific gap used until the end of 2021 exhibits the existence of shortcomings similar to those observed in other countries. Specifically, a strong growth of credit to the private sector in the years preceding the GFC and subsequent long-term deleveraging resulted in large negative values of the credit gap. Given the characteristics of HP filtering, the resulting credit gap will not provide prompt signals of excessive lending during the next cycle (Galán, 2019), as the assessment of the long-term trend also includes the excessive lending period followed by a severe contraction. In other words, this gap suffers from the downward bias problem, because excessive credit growth during a credit boom is included in the calculation of the long-term trend (Lang et al., 2019), which may last several years (Galán, 2019). As a result, the gap could become positive only after a prolonged period of relatively strong credit growth, so that the decision to increase the CCyB rate might be made too late, when the system has already accumulated significant cyclical risks. In addition, due to a higher volatility of a specific gap that includes the GDP value from only one quarter, deciding on whether to raise or cut the rate becomes even more difficult, especially in short time periods. Related to this, the sharp GDP contraction following the outbreak of the COVID-19 crisis led to a surge in the credit-to-GDP ratio and a narrowing of the negative gap, particularly with the national-specific indicator, contrary to the general assessment of cyclical risk accumulation.

In order to remedy the identified shortcomings, this study assesses the appropriateness of the Basel gap and the national-specific gap, defined at the time of preparation for introducing the CCyB in Croatia (CNB, 2014), for the calibration of the CCyB rate, offering alternative options for measuring and calculating the credit gap. Specifically, in accordance with the third principle of Recommendation ESRB/2014/1 regarding the risk of misleading information, macroprudential authorities should periodically re-assess the usability of the variables and models used in the CCyB calibration. In addition, the economic crisis caused by the coronavirus pandemic drew attention to the shortcomings of the existing credit gap measures and provided an additional motive for this analysis. In this regard, this study explores options to mitigate the shortcomings of measuring and calculating the gap, which have not been used so far in Croatia, based on literature findings and experiences from other countries. It relies on the model of early warning[2] (signalling) of the emergence of a systemic crisis, used in the work

[2] *Early Warning Model*, EWM.

(Drehmann et al., 2010) whose findings provided the basis for incorporating the Basel gap in international recommendations (BCBS Guidance, Recommendation ESRB/2014/1) and for the initial calibration of the national-specific credit gap in Croatia.

The main results of the research are as follows. The indicators selected among those that signalled the previous crisis (GFC) sufficiently early and with the smallest errors had the long-term credit-to-GDP ratio calculated as the ratio between separately filtered credit and GDP series, with the assumption that the financial cycle lasts 2.7 to 4 times longer than the business cycle. Both the narrower and broader definition of credit are equally good (see the definitions below) as well as the two gap calculation methods (absolute and relative gaps). Twelve best indicators outline the range of credit gaps and provide flexibility in assessing the evolution of cyclical risks and deciding on the appropriate level of the countercyclical capital buffer.

The second section starts with the outline of the calibration of the CCyB based on international standards and the national specification of the credit gap calculation formerly used in Croatia. The third section introduces alternative definitions for the calculation of the credit ratio and gap, presents potential adjustments to the statistical method for determining the long-term equilibrium and alternative methods for its assessment. The fourth section describes the methodology used to assess the appropriateness of specific indicators for crisis signalling, while the fifth section is empirical, presenting a broad set of alternative credit gap measures and CCyB rate levels based on the best selected indicators. The sixth and last section provides conclusions and recommendations for further research.

2. Calibration of the countercyclical capital buffer (CCyB) based on the credit gap calculation

The purpose of the CCyB is to build up the banking sector's resilience by increasing capital requirements during risk-accumulation periods, so that they can be partially or fully released after the outbreak of a crisis. It should enable loss absorption without any adverse consequences to lending to the economy, i.e., should maintain credit flow to the economy without endangering liquidity (ESRB, 2018b). EU countries started to implement the CCyB in 2014. The designated authorities for the implementation of macroprudential policy[3] follow the BCBS Guidance for national authorities operating the countercyclical capital buffer (BCBS, 2010), as reflected in Recommendation of the European Systemic Risk Board on guidance for setting countercyclical buffer rates (ESRB/2014/1) (ESRB, 2014a). The Recommendation specifies that the authorities decide on the CCyB following the principle of "guided discretion", combining the calculation of the Basel credit gap and the CCyB benchmark rate, in line with the BCBS Guidance that ensures the comparability of approaches within and outside the EU, with alternative methods of measuring and calculating the credit gap and the CCyB rate and their own judgement on the development of cyclical risks associated with excessive credit growth[4]. In accordance with Recommendation on guidance for setting countercyclical buffer rates (ESRB/2014/1), building on the BCBS Guidance (2010), the CCyB rate level (benchmark indicator) to be applied to the total risk exposure is the piecewise function of the credit-to-GDP gap[5]:

$$CCyB_t = \begin{cases} 0, \; gap_t \leq L \\ 0.3125 \cdot gap_t - 0.625, \; L < gap_t \leq H, \\ 2.5\%, gap_t > H \end{cases} \tag{1}$$

where the variable gap_t is defined as the difference between the actual value of the credit-to-GDP ratio in quarter t and the estimated trend value (formula (2)). L and H are the lower and upper thresholds for the exclusion and inclusion of the CCyB, set at 2 and 10 percentage points respectively considering the results[6] in BCBS (2010). The calculation of the variable *gap* is made based on the *ratio* of credit to the private non-financial sector and GDP, given that a large number of studies show that this indicator provides the best signals for banking crises (Drehmann et al., 2010, 2011; Babecký et al., 2014; Bonfim and Monteiro, 2013; Behn et al., 2013; Drehmann and Juselius, 2014; Detken et al., 2014). This credit-to-GDP gap, hereinafter referred to as the Basel gap, is calculated according to the following formula:

$$gap_t = ratio_t - trend_t \, , \tag{2}$$

[3] Pursuant to Article 2(7) of Regulation (EU) No 1024/2013 the national designated authority in the Republic of Croatia is the Croatian National Bank.

[4] The ESRB Recommendation proposes monitoring indicators warning of risks associated with excessive credit growth, such as the overvaluation of real estate or equity prices, external imbalances, relative private sector debt burden and the strength of banks' balance sheets.

[5] For the central part of the function, the initial functional record is $\frac{gap_t - L}{H - L} \cdot 2.5$

[6] Thresholds $L = 2$ and $H = 10$ in the empirical analysis resulted in the best signalling results. Wezel (2019) notes that BCBS (2011) does not provide any detailed clarifications on their calibration, which may pose a problem in practice.

where $ratio_t$ is defined by the formula:

$$ratio_t = \frac{credit_t}{\sum_{k=t-3}^{t} GDP_k} \cdot 100\%, \qquad (3)$$

where $credit_t$ is the value of a broad[7] measure of the stock of credit granted to the private non-financial sector at the end of quarter t, GDP_k is gross domestic product[8] in the one-year period until that time, i.e. in the quarters $k \in \{t\text{-}3, t\text{-}2, t\text{-}1, t\}$, $trend_t$ is the long-term trend of the variable $ratio_t$ achieved by the recursive Hodrick-Prescott (1981, 1997) filtering[9], with the smoothing parameter λ equalling 400,000. The choice of the value of the parameter λ is based on Drehmann et al. (2010) and Ravn and Uhlig (2002)[10].

The CCyB was introduced in Croatia by the Decision dated January 2015, which started to apply on 1 January 2016, setting forth the rate of 0% of the total risk exposure, because in that period, given the private sector deleveraging, reflected in the negative value of the credit gap, it was assumed that there were no cyclical risks that would require the setting of additional capital requirements for banks. The Croatian National Bank, pursuant to Article 123 of the Credit Institutions Act (Official Gazette 159/13, 19/15, 102/15, 15/18, 70/19, 47/20 and 146/20) is obliged to quarterly calculate and publish information on which it bases its decision on the CCyB rate (the level of the rate, the deviation of the credit-to-GDP ratio from the long term trend, the credit-to-GDP ratio and other relevant information).[11] It publishes the Basel gap and the relevant credit-to-GDP ratio, using for the quarterly calculation of data on the values of broadly defined credit[12] (bank placements and external debt of the private sector) and GDP realised in the previous one-year period. It also publishes a specific credit-to-GDP ratio

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[7] See Appendix 1 for the narrower and broader definition of credit used in the study.

[8] For Croatian data, seasonally adjusted values are used.

[9] The trend is estimated by minimising the target function consisting of deviations from the trend and variation in the trend growth rate. The smoothing parameter assigns the weight of the distance between the trend and data and trend variations.

[10] Hodrick and Prescott propose that λ = 1,600 be used for quarterly business cycle data, which implies that a business cycle lasts about 7.5 years. Ravn and Uhlig (2002) analyse the adjustment λ with data frequency change. They showed that it was best to multiply λ by the frequency ratio to the power of four. For example, if data frequency is changed from quarterly to annual frequency, the ratio of these frequencies is 1/4, so that λ of 1,600 is multiplied by the ratio of 1/4 to the power of four, i.e. $(1/4)^4 \cdot 1,600 = 6.25$. Drehmann et al (2010) estimate that credit cycles are 3 to 4 times as long as business cycles, so $\lambda \approx (\text{number of business cycles})^4 \cdot 1,600$, resulting in λ of 400,000 (number of business cycles = 4) or $\lambda \approx 125,000$ (number of business cycles = 3).

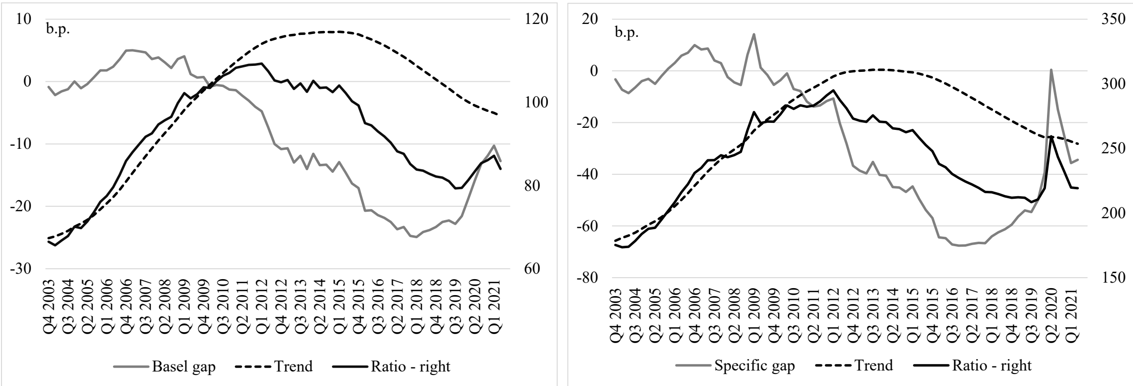
[11] The decisions and press releases are available at https://www.hnb.hr/temeljne-funkcije/financijska-stabilnost/makrobonitetne-mjere/protuciklicki-sloj-kapitala

[12] See Appendix 1 for details.

and the corresponding gap, which by the end of 2021 had been based on the monitoring of the narrower definition of credit (credit domestic banks) and GDP in the current quarter. This definition of the specific indicator is based on the analysis published in Financial Stability No 13, Box 4 *Financial cycles and countercyclical capital buffer calibration* (CNB, 2014), which determined that such a specific credit-to-GDP ratio, among 27 potential measures analysed at the time, best signalled historical crises[13].

Figure 1 Credit-to-GDP ratio and the corresponding gap

Credit-to-GDP ratio and the corresponding gap according to the standard Basel definition (left) and the national specific definition (right panel) from 2014.



Note: Basel (i.e. standardised) ratio is the ratio of total placements (domestic banks' placements and external debt) to the nominal annual GDP, while the specific ratio is the ratio of domestic credit institutions' credit to the quarterly seasonally adjusted[14] GDP. The trend was estimated by means of the one-sided HP trend, while the gap represents the difference between the ratio and the trend.

Source: CNB, authors' calculations.

Figure 1 shows the Basel ratio and the specific credit ratio (from 2014) as well as the corresponding gaps, while Figure 2 shows the CCyB rate level determined by the function from (1). It is evident that both ratios reflect strong private sector credit growth in the years before the GFC, which slowed down significantly in the next few years, when the ratio continued to grow on the back of a decrease in GDP, with a very mild

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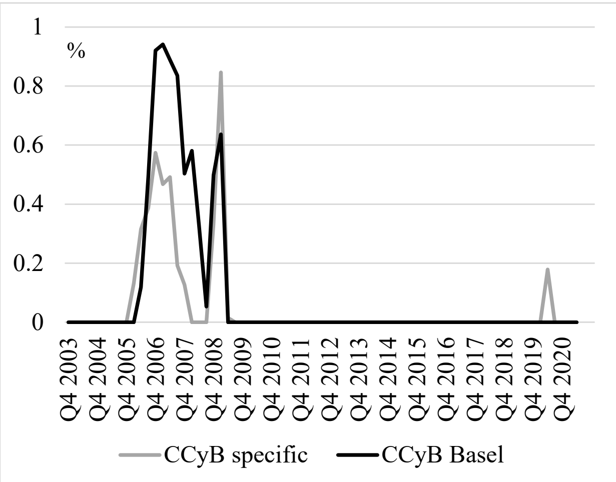
[13] The analysis defines two crisis episodes in Croatia: the crisis lasting from the first quarter of 1998 to the second quarter of 2000 and the one lasting from the third quarter of 2011 to the end of the sample (end of 2013).

[14] Seasonally adjusted GDP is the one obtained by the seasonal adjustment process, without eliminating one-off and transitory shocks. See Appendix 1 for details.

increase in credit. The non-financial corporate sector started to deleverage continuously after 2011, which, in particular after 2014, when the several-year-long economic recession ended, resulted in a decline in the credit-to-GDP ratio and increasingly negative values of the credit gap.

By contrast, a sharp GDP contraction that took place in the second quarter of 2020 after the outbreak of the COVID-19 crisis led to a surge in the credit-to-GDP ratio and the narrowing of the negative gap, with the specific gap even turning positive. Moreover, several press releases published by the CNB after the second quarter of 2020 (see, for example, press release from September or December 2020) show a spike in the movement of the CCyB benchmark rate (Figure 2), suggesting its inclusion, i.e. the announcement of the continued application of the positive CCyB rate. However, since the BCBS Guidance (2010) states that it is not necessary to follow its signals in situations in which the ratio is increasing and the gap closing due to a decline in GDP (rather than to an actual rise in cyclical risks), the CNB decided to leave the CCyB rate at 0%. Such a decision was also justified by the subsequent calculations based on updated data on GDP movements in subsequent periods, in which the CCyB benchmark rate for the second quarter of 2020 returns to 0%.

Figure 2 Comparison of the CCyB rate level for ratios shown in Figure 1



Source: CNB, authors' calculations.

Although the specific ratio from 2014 was attempted to be defined as a more appropriate indicator for the Croatian financial market than the standard Basel ratio, its focus on developments in only one quarter leads to problems in a situation in which there is a sudden and strong change in GDP value. Such short-term shocks may indicate the activation of the CCyB (in accordance with formula (1)), which would be counterproductive in times of economic contraction (Repullo and Saurina, 2011; Drehmann and Tsatsaronis, 2014). One option to exclude the possibility of a sudden increase in the ratio and gap due to a sharp decline in GDP is applied in the approach of the Deutsche Bundesbank (described in Appendix 2), which disregards such signals. In addition, the use of the standard and specific gap indicator is also limited by the characteristics of the HP filtering, the bias of which was discussed in the introduction. Therefore, most macroprudential policy measures are adopted on the basis of "guided discretion", taking into account expert judgement and other indicators. Nevertheless, as it is desirable to improve the reliability of the quantitative base, this study analyses various options for calculating the credit-to-GDP ratio and the credit gap.

3. Alternative methods for calculating the credit ratio and its deviation from the long-term equilibrium

3.1. Gap calculation changes

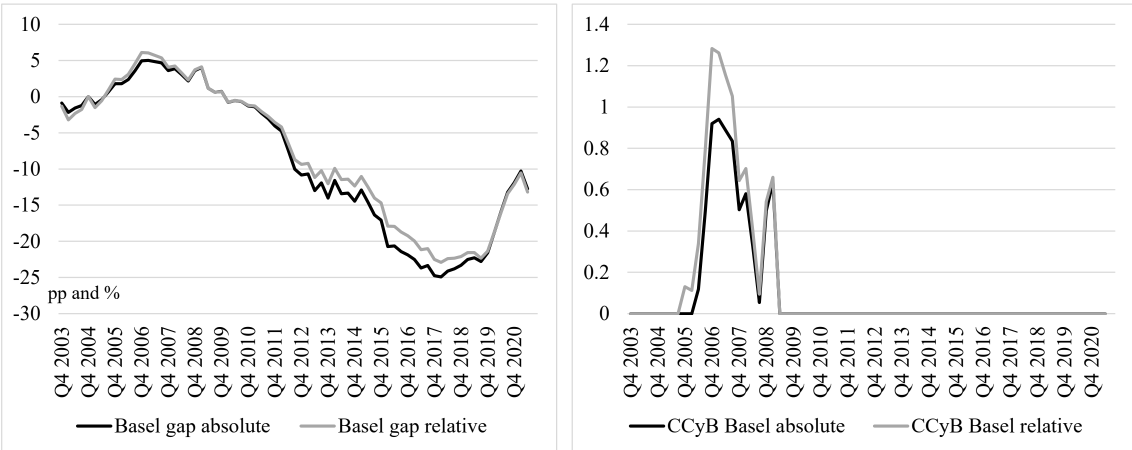
The deviation of the credit ratio from the long-term equilibrium may be calculated, instead of as the difference between the ratio and the trend (absolute gap defined in formula (1)), by an alternative approach. For instance, the ESRB (2014b:25.66) proposed that the ratio of the credit ratio to the trend be considered, instead of the difference between them, which is termed *the relative gap*:

$$Gap_t = \left(\frac{Ratio_t}{trend_t} - 1\right) \cdot 100\% \,. \tag{4}$$

In contrast to the interpretation of the absolute gap according to formula (2), which is given in percentage points, the gap is measured in percentages. The justification for using the relative gap as opposed to the absolute gap lies in the way in which the thresholds for the activation of the CCyB are set. If an absolute gap is used, then the thresholds are not independent of the level of the credit-to-GDP ratio (*ratio*). The increase in the ratio must be greater for the possible activation of the CCyB than the increase required in the calculation of the relative gap. This could result in a delay in the decision to introduce or change the level of the countercyclical capital buffer rate. If a relative gap is applied, additional capital may be required to be maintained, due to the higher required CCyB rate, as well as a somewhat earlier construction of the CCyB.

A comparison of the Basel (absolute) gap with its relative counterpart (Figure 3, left panel) and the corresponding CCyB rates (Figure 3, right panel) shows that if a relative gap is used instead of the absolute one, a somewhat earlier construction of the capital buffer and application of higher rates is possible. Therefore, as one of the alternatives to the Basel gap, this study will examine relative gaps for the selected definitions of credit ratios.

Figure 3 Basel gap and capital buffer rate level: the absolute versus the relative



Note: The absolute and relative gaps as well as the corresponding CCyB rate for the Basel ratio from Figure 1 are compared, with the reference thresholds for both calibrations being L = 2 and H = 10.

Source: CNB, authors' calculations.

3.2. HP filter modifications

The calibration of the CCyB is also influenced by the way in which the statistical filtering of the credit ratio variable is performed. Based on the findings from Drehmann et al. (2010), the BCBS (2010) and the ESRB (2014) recommend that the Basel gap be calculated using the Hodrick-Prescott filter with the lambda smoothing parameter of 400,000 for quarterly data, assuming that the length of the credit cycle is 4 times as long as that of the business cycle (see footnote 9). However, the empirical literature has no consensus on the duration of the credit cycle that could confirm the correctness of using such a definition of lambda. Schüler (2018), analysing different approaches to time series filtering in the implementation of macroprudential policy, concludes that the assumption of a single smoothing parameter of 400,000 for different countries may result in the omission of relevant country-specific fluctuations in time series, as the excessive smoothing of a long-term trend may reverse short-term cyclical movements. Therefore, different procedures are also considered in practice, given the differences in the lengths of credit cycles of individual countries and better statistical characteristics of gaps estimated in such a way.

Generally, the research literature on the length, characteristics and harmonisation of credit (and business) cycles in selected countries focuses on developed countries due to the availability of long time series of data, while research on data for Central and Eastern European countries is scarce[15]. Galati et al. (2016), using a sample of 5 large euro area countries and the US, find that the financial cycle lasts between 8 and 25 years, with large differences across countries; this is significantly longer than the business cycle (between 6 and 8 years). However, the findings of several studies could be used to determine a more appropriate value of lambda to be used on credit dynamics data in Croatia. Rünstler and Vlekke (2016) estimate that the length of the credit cycle in selected developed countries is between 12 and 18 years, depending on the share of private real estate ownership in total ownership. For Spain, where, according to the EU-SILC research, 78.6% of the total population live in their own real estate , they estimate the duration of the credit cycle to 18.9 years. Since only slightly more of the total population in Croatia live in their own real estate (89.7%), it could be assumed that the duration of the credit cycle is about 20 years or almost 2.7 business cycles. According to the formula $\lambda \approx (\text{number of business cycles})^4$ 1.600, we estimate that the lambda smoothing coefficient should in this case be 85,000.

In addition, Galán (2019) also analyses Spain when assessing the business and credit cycles of the selected countries, finding, when criticising the Basel gap methodology, that $\lambda = 25{,}000$ gives more accurate signals for crisis periods, which is a much lower value than the original λ defined in the Basel guidance. Finally, Galati et al. (2016), when assessing the duration of the credit cycle in selected countries, find that the duration for Spain is about 13 years. Assuming again that the duration of the cycle in Croatia is only slightly longer than in Spain, about 15 years, the value of λ is

[15] The use of the spectral analysis to determine the length of the financial cycle in Croatia can be found in Kunovac and Fioretti (presentation in manuscript).

approximately 25,600. An additional contribution to the use of a lower value λ is provided in Wezel (2019), which shows that in countries with a shorter financial cycle (Central and Eastern Europe) it is more appropriate to use the Basel gap variant with a smaller smoothing parameter than 400,000. The author finds that the credit cycles last between 5 and 10 years and, accordingly, considers the values of $\lambda = 1{,}600$ and 25,000, which implies that the credit cycle lasts the same as the business cycle or is only twice as long.

In addition, if the statistical characteristics of the filtering are considered, it should be noted that the lower values of the smoothing parameter in such a procedure reduce the error of revision of the one-sided gap, which is used in practice in real time, relative to the two-sided gap. In practice, the two-sided gap cannot be used due to insufficient future values of the filtered time series, so that there are differences in gaps resulting from the one-sided gap (it includes only data available up to the period for which the gap value is calculated) and the two-sided gap that can be subsequently assessed on historical data. Wolf et al. (2020) compared the characteristics of one-sided gaps obtained with lower values of the smoothing parameter and showed that they led to smaller revisions relative to two-sided gaps as well as that time series fluctuations that otherwise cannot be mitigated were less mitigated.

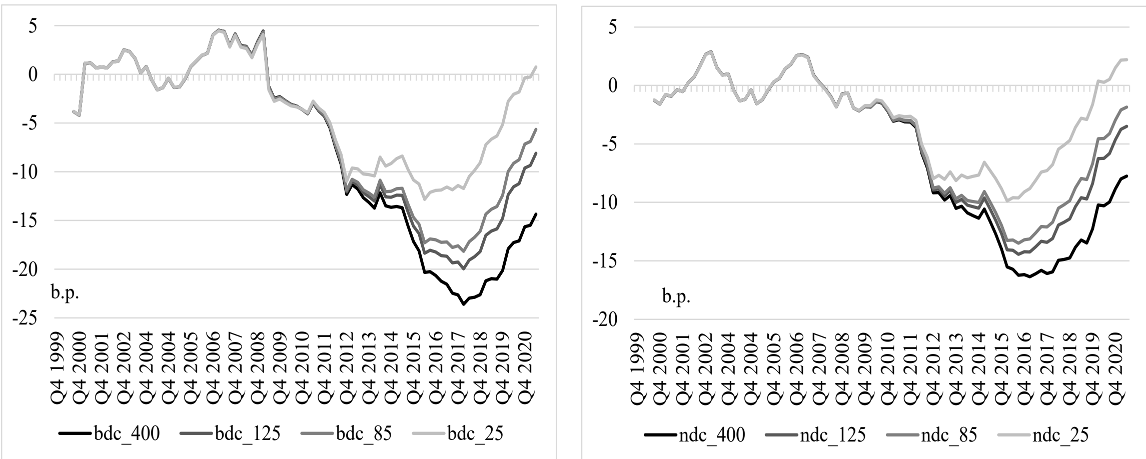
The proposed different values of the smoothing parameter are shown in Table 1, while Figure 4 shows the evolution of eight credit gaps, for two definitions of the credit coverage, estimated with the parameters in the table. In view of the relatively short period for which gaps are estimated, the gap values overlap in the first part of the sample, but there is a divergence after 2011, with the use of the smallest lambda first leading to a turnaround in the dynamics and a closing of the gap. Given the pronounced differences in the movement of gaps in Figure 4, the calibration of the capital buffer based on the analysed indicators may lead to very different conclusions. While the higher values of the smoothing parameter take some time to close the negative credit gap, others have already become positive. This reiterates the sensitivity of the HP filter to the selection of the smoothing parameter, which, on the one hand, is based on the theory of the credit cycle length and, on the other hand, on the statistical characteristics of the filter itself. To avoid these problems, individual banks are considering alternative approaches to estimating deviations from the long-term equilibrium, other than the HP filter, and these are discussed below.

Table 1 Proposal for the value of λ for the HP filter

Value of λ	Clarification and source
400.000	ESRB Recommendation (2014a, b). Drehman et al. (2010) find for OECD countries that a credit cycle is 3 to 4 times as long as a business cycle and, if it is 4 times as long it follows λ ≈ (number of business cycles=4)4 •1,600. According to Benazić and Tomić (2014), the length of a business cycle for Croatia is assumed to be 7.5 years, so that a credit cycle would last 30 years.
125.000	If, according to Drehmann et al (2010), we assume that a credit cycle is 3 times as long as a business cycle, λ ≈ (number of business cycles=3)4·1,600. This study also analyses other values of lambda, from 1,600 to 400,000.
85.000	According to the EU-SILC survey, 89.7% of Croatia’s population lived in its own property in 2019, so that Croatia is compared to Spain (see the text) based on Rünstler and Vlekke (2016), and Galáti et al. (2016). Assuming that a credit cycle is 2.7 times as long as a business cycle, in Croatia it would last 20 years.
25.600	Assuming that a credit cycle is 2 times as long as a business cycle, in Croatia it would last 15 years. Aligned with the findings of Galán (2019).
All of the above	Valinskytė and Rupeika (2015) analyse all 4 lambda values in this table for Lithuania, similar to Edge and Meisenzahl (2011).

Source: Prepared by authors according to sources in the table.

Figure 4 Comparison of credit gaps for different smoothing parameters (broader definition of credit — bdc (left panel), narrower definition of credit — ndc (right panel))



Note: as this is one-sided filtering, the first 20 quarters of the specific dynamics of the credit ratio were used for the initial period of estimation of the trend and the gap, with the result that gaps overlap in that sub-period. The larger differences at the end of the observation period in Figure 5 reflect the increasing number of data available for filtering. 400, 125, 85 and 25 refer to the smoothing parameters in the HP filter of 400,000, 125,000, 85,000 and 25,600.

Source: CNB, authors’ calculations.

3.3. Alternative approaches to calculating deviations from the long-term equilibrium (instead of using HP filters)

The use of HP filters creates different problems, which are set out below, so the literature offers alternative approaches to assessing the long-term equilibrium and gaps, i.e. deviations from this equilibrium.

First, the HP filter is a statistical method requiring the author to decide in advance on the value of the smoothing parameter, which affects the filtering result and the gap assessment, as shown in this study. Building on the original article, Hodrick and Prescott (1997), authors most often use a lambda of 1,600 (100) for quarterly (annual) data to calculate the long-term trend of the business cycle, although the literature offers alternative proposals. Research into the credit gap tends to use a lambda of 400,000, as the financial cycle is assumed to last longer than the business cycle (see Chapter 2, footnote 9).

Short time series, such as those used for Croatian data, are also a common problem. The values of the gaps obtained vary significantly depending on the length of the filtered series, given that they depend on the dynamics of the series whose trend is estimated. This is linked to the last point problem and the first point problem, dealt with in Jokipii et al. (2020) and Drehmann and Tsatsaronis (2014). The value of gaps also depends on the period of the systemic risk accumulation phase covered by the filtering itself, that is to say, the result depends on whether the series started to be filtered at the top or at the bottom of a credit cycle. Specifically for the series under review, the assessment of the long-term trend in the filtering process includes a period of credit expansion prior to the global financial crisis, followed by an extended period of declining gap values (see Lang et al., 2019; Galán, 2019).

Furthermore, the problem of a sudden change in GDP values, as in the case of the coronavirus crisis, results in an estimate of the HP trend that will not "react" on time due to the way the target function is optimised and therefore creates a large difference between the actual credit-to-GDP ratio and the ratio of their trends. This does not meet the properties of resilience and stability of the indicators listed in Kauko (2012), a problem that had already been recognised in BCBS (2010).

Finally, the HP filter generates apparent cycles (Cogley and Nason, 1995), has poor real-time properties (Kamber, Morley and Wong, 2018) and is imprecise at the ends of the time series (Hamilton, 2018).

There are many approaches that can be used instead of HP filters to assess the long-term trend, depending on the nature of the research. The most popular alternatives to the calculation of the credit gap that will not have the disadvantages present in HP filtering are: Hamilton's "linear projection" model, the calculation of local extremes, two-year (and multiannual) growth rates of the credit ratio, as well as the calculation of moving averages instead of the HP filtering trend. For the Czech Republic, Hájek et al. (2017) use the analysis of local extremes by comparing the credit-to-GDP ratio in quarter *t* to the minimum value of this ratio over the last 8 quarters[16], i.e. the credit gap is calculated as the difference between the value of the credit ratio in quarter *t* and the minimum value in the last 8 quarters. Valinskytė and Rupeika (2015), for the application in Lithuania, take a moving average of the last four quarterly values of the gap variable. Drehmann and Yetman (2018) compare the HP filter with Hamilton's (2017) "linear projection" approach, assessing the model of autoregression by regressing the variable credit value in quarter *t* to the previous values of the period five years before (*t-20*, *t-21*, *t-22* and *t-23*):

$$y_t = \beta_0 + \beta_1 y_{t-20} + \beta_2 y_{t-21} + \beta_3 y_{t-22} + \beta_4 y_{t-23} + \varepsilon_t \quad (5)$$

and the estimated residuals from model (5) constitute the gap variable.

Some analyses use credit ratio growth rates instead of the gap variable, such as the four-year growth rate of the credit-to-GDP ratio (Beutel et al., 2018) or the two-year growth rate of the credit-to-GDP ratio (Lang et al., 2019).

Table 2 provides a summary of alternative approaches used in research and in practice, while Figure 5 outlines the developments in the newly defined four gaps in Croatian data. All series show credit growth before the GFC and an increase in lending activity at the end of the observed period, when positive values of all newly defined gaps are recorded. The linear projection results in a loss of some of the data, which poses a problem when evaluating crisis signalling. In addition, all gaps are characterised by the problem of potential nonstationarity. This characteristic may result in a too frequent change in the CCyB (e.g. the lower right panel), which undermines the ability of consistent signalling, or in changes that lack a reasonable clarification in terms of deviations of credit growth from that characteristic of the long-term trend or fundamentals.

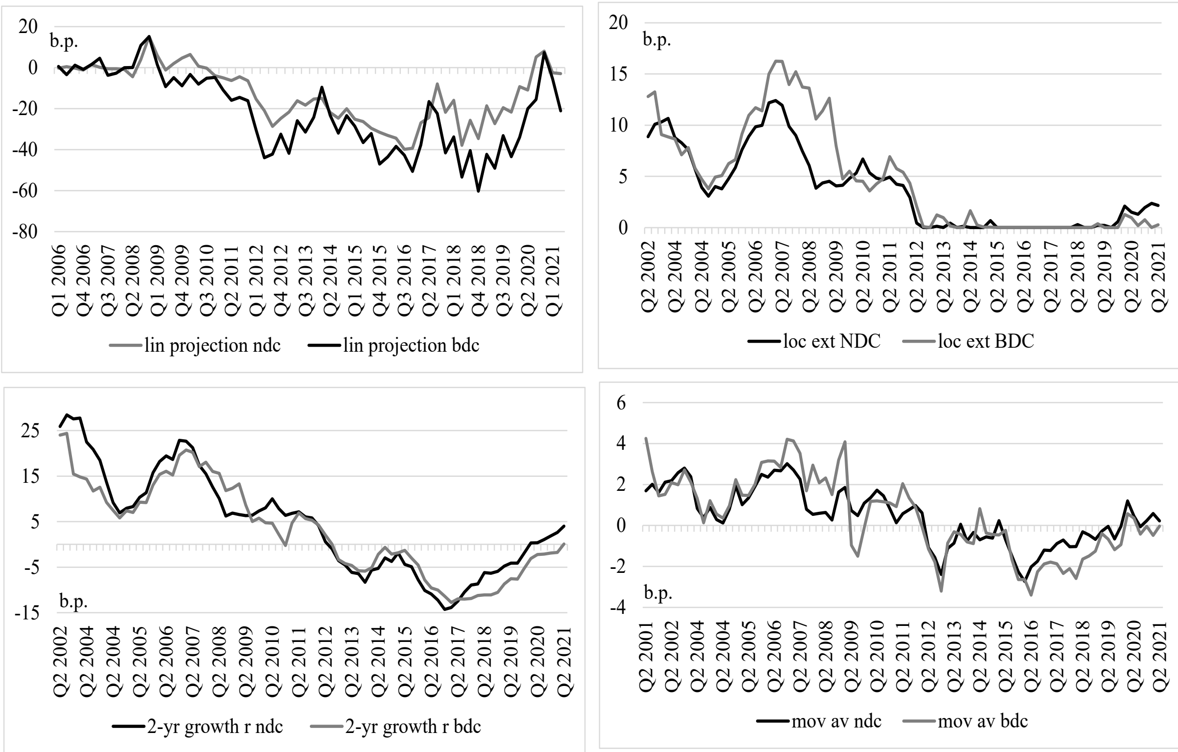
[16] They also tested other lengths of moving windows in relation to 8 and the results are robust.

Table 2 Alternative approaches to estimating the long-term trend of the credit ratio variable

Name	Description
Linear projection (the so-called Hamilton model)	Formula (5), the residual assessment represents the credit gap. The dependent variable is the credit ratio: $$gap = \hat{\varepsilon}_t = y_t - \hat{y}_t$$
Local extremes	The credit ratio in quarter t is compared with the minimum value of the ratio in the last 8 quarters, i.e. the difference between the value of the credit ratio in quarter t and the minimum value in the last 8 quarters is calculated, which represents the gap: $$gap = ratio_t - \min\{ratio_t, ratio_{t-1}, \dots, ratio_{t-7}\}$$
Moving averages	The credit ratio in quarter t is compared with the value of its 4-quarter moving average, i.e. the difference between the value of the ratio and the moving average is calculated, which represents the gap: $$gap_t = ratio_t - \frac{1}{4}\sum_{h=t}^{t-3} ratio_t$$
Credit ratio growth rate	A long-term trend is not estimated, but the multi-annual growth rate of the credit -to-GDP ratio is considered as the gap variable. Due to the fact that the time series for Croatia is short, the two-year growth rate as the gap variable according to Lang et al. (2019) is analysed: $$gap_t = \ln(ratio_t \,/\, ratio_{t-8})$$

Source: Prepared by authors according to sources in the text.

Figure 5 Gap based on a linear projection approach (upper left panel), local extremes (upper right panel), two-year credit ratio growth rate (lower left panel) and moving averages (lower right panel)



Note: *Lin projection* denotes the gaps obtained by a linear projection according to formula (5), *loc ext* denotes the gap resulting from the local extremes approach, *2-yr growth r* denotes a two-year growth rate of the credit ratio and *mov av* denotes the gap obtained by the moving average method. The abbreviations ndc and bdc denote the narrower and broader definition of credit respectively (see Appendix 1).

Source: CNB and authors' calculations.

In addition to the credit-to-GDP ratio defined in formula (3) and its gap relative to the long-term value, the literature also considers modifications to the calculation of deviations from the long-term equilibrium. The disadvantage of formula (3) is the fact that the ratio increases not only when credit growth exceeds economic growth, but also during GDP contraction. Although this suggests that a positive CCyB rate would need to be applied, such a decision would be counterproductive under adverse economic conditions (Repullo and Saurina, 2011). Therefore, Kauko (2012) proposes two alternative indicators that use the GDP value over a longer period of time and adjust accordingly the calculation of credit gap trends:

1. Differentiated relative total credit[17] (change in relative total credit):
   $\Delta\left(\frac{5Credit_t}{\sum_{k=t-4}^{t} GDP_k}\right) \cdot 100\%$;

2. Year-on-year change in credit, $\frac{5\Delta Credit_t}{\sum_{k=t-4}^{t} GDP_k} \cdot 100\%$.

The difference arises from the fact that in the first case the differentiation of the entire fraction is analysed, while only the differentiation of the credit is analysed in the second case. Number 5 is a factor by which the value of the credit is annualised because the stock variable is in the numerator, while the denominator contains the sum of five values that are flow variables.

Since in Kauko (2012) indices *t* and *k* refer to annual frequencies, the application to quarterly data requires the use of modified formulae:

1. differentiated relative credit: $\Delta \frac{\frac{1}{4}(\sum_{t-3}^{t} Credit_k)}{\sum_{k=t-3}^{t} GDP_k} \cdot 100\%$, and

2. one-year change in credit: $\frac{4\Delta Credit_t}{\sum_{k=t-3}^{t} GDP_k} \cdot 100\%$,

where the differentiation sign refers to an annual change.

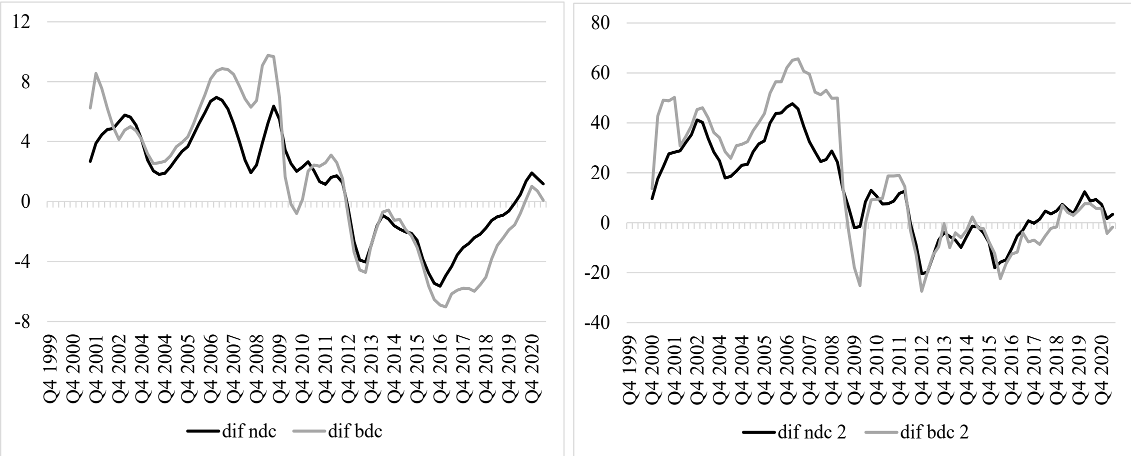
Figure 6 shows a different credit gap dynamics compared to Figures 1 and 3, as these alternative indicators are based on one-year changes rather than a long-term trend. However, the credit growth before the GFC is also "captured" in the case of credit gaps in Figure 1 as well as in the changes in Figure 6. Building up the CCyB based on changes shown in Figure 6 may be made have been made difficult in the recent period given the large increase in lending in the pre-crisis period.[18]. Furthermore, the issue of the interpretation of this indicator for the assessment of the long term or the equilibrium state of the credit ratio is worth noting because these changes are on a one-year level. While the observation of changes for a several-year period would result in smoother

[17]The author shows the formulas for a five-year period and states that they can be used for both the four-year and the six-year period. This is a subjective choice.

[18] At the end of the observed period there is less dynamics, but even though gaps become positive, they are at much lower levels than before the GFC. In the calibration of the lower threshold of the CCyB, the results of the assessments will refer to its high values (in the case of series on the right panel), which means that a large increase in these gaps will be needed for them to reach the level required for the introduction of a positive CCyB rate, as confirmed in Table 5.

series, a large number of observations would be lost, which is a significant problem in the case of Croatian relatively short time series.

Figure 6 Differentiated relative credit (left panel) and one-year change in credit (right panel)



Note: *Diff* denotes differentiated relative credit, *diff*...2 a one-year change in credit, with *ndc* being the narrower definition of credit and *bdc* the broader definition (Appendix 1).

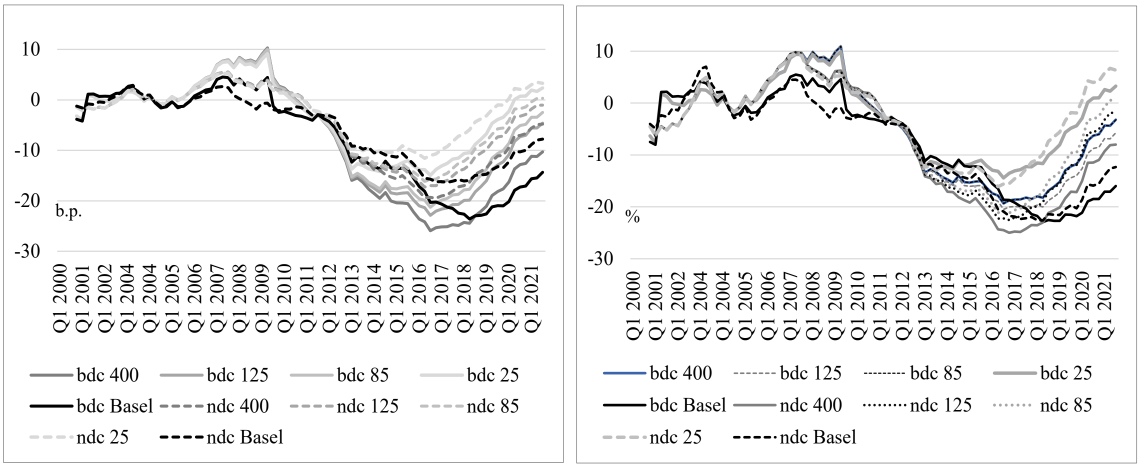
Source: CNB, authors' calculations.

3.4. Separate filtering of credit and GDP

Finally, given the problem of measuring the length of the credit cycle and the different duration of the credit and business cycles, a possible improvement for determining the long-term equilibrium of the credit-to-GDP ratio is to filter the time series of credit separately from the filtering of the GDP series prior to the calculation of their ratio. A similar approach is used by the Slovak central bank (NBS, 2014), which first filters GDP separately, before filtering the credit ratio. Instead of the double filtering of GDP as in the case of Slovakia, in this study we will filter the credit series with one smoothing parameter and the GDP series with another parameter, calculating from the series thus obtained the credit-to-GDP ratio, which will represent the long-term ratio.

GDP was filtered with the smoothing parameter of 1,600 (see Appendix 3 for details on the value of this parameter)[19], while credit values were filtered with 4 different values of lambda, as in section 3.2 (25,600, 85,000, 125,000 and 400,000). Thereafter, the ratio of the trend value of credit to the sum of four trend values of quarterly GDP is calculated, and the absolute and relative gaps are calculated from this long-term ratio. The resulting series are presented in Figure 7, which shows that prior to the GFC, ratios based on the lower values of lambda for credit begin to grow earlier and generate higher values than the Basel gap, with a similar divergence persisting after 2013. These conclusions are similar to those from Chapter 3.2 when the credit-to-GDP ratio was filtered at lower lambda values.

Figure 7 Comparison of absolute (left panel) and relative gaps (right panel) with separate credit and GDP filtering



Note: 25, 85, 125 and 400 mark the gaps for which in the long-term ratio a credit has been filtered with the lambdas of 25,600, 85,000, 125,000 and 400,000, and the quarterly GDP with the lambda of 1,600, *ndc Basel/bdc Base*l are the gaps for which the ratio of the narrower/broader definition of credit to GDP has been filtered with the lambda of 400,000.

Source: Authors' calculations.

[19] For a common approach when filtering quarterly GDP data (Hodrick and Prescott, 1997), see Ravn and Uhlig (2002). In order to confirm the robustness of the use of the smoothing parameter of 1,600, other values were also considered, with the lambda for credit set at 400,000. Specifically, as in Choudhary et al. (2013) the results of the analysis suggest that the optimal value of the parameter smoothing the business cycle differs from country to country, we simulated 20 credit gap variants, with the lambda for GDP changing from 300 to 2,200, with a difference of 100. The lower and upper thresholds were chosen in view of the results in the above-mentioned study, where the values of optimised smoothing parameters for the group of high income countries to which Croatia belongs according to the World Bank classification (see https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups) move within the mentioned range.

4. Predictive power of credit gaps in crisis signalling

The various proposals for the alternative calculation of the credit gap shown in the previous section, which, with some modifications, like the Basel gap, show the deviation of the credit-to-GDP ratio from the long-term value, display varied dynamics. Since the choice of a credit gap that would best reflect the specificities of a national economy requires testing its power to signal systemic crises, the next sections, following the description of the signalling method and the criteria for selecting the best signals (crisis indicators), present the results of statistical tests on the adequacy of the described indicators for announcing a crisis.

4.1. Description of the signalling model

Signalling models are used to assess the predictive power of potential indicators to identify a financial crisis, in order to promptly calibrate the CCyB. As the concept of the CCyB is to strengthen banks' resilience, and indirectly to mitigate excessive credit growth, while its switching off during contraction periods allows lending to continue, its inclusion needs to be indicated early enough while later on it should be promptly disconnected. In this context, it is necessary to identify a dependent model variable that reflects systemic vulnerabilities, i.e. the occurrence of a crisis, and then to assess the quality of the early forecasting of the occurrence of that vulnerable period by one of the models. The signalling approach[20] was popularised by Kaminsky and Reinhart (1999) and it was subsequently widely used (Borio and Drehman, 2009, Drehman et al., 2010, 2011, Alessi and Detken, 2011).

It is primarily necessary to determine the duration of crisis situations in historical data and then to define a discrete dependent variable that takes a value of 0 or 1 depending on the state of vulnerability. For the purpose of this study, the official dates of crises used in other surveys were selected (see Appendix 4) as confirmed in the literature describing developments in the Croatian banking market. As time series of variables used in this work are available at the earliest since 2000, the signalling model foresees only one crisis, which we define in the period *between October 2008 and June 2012*[21].

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[20] The description is based on Lang et al. (2019), Alessi and Detken (2019), Candelon et al. (2012), Kaminsky and Reinhart (1999), and the sources specified in ESRB (2018), Chapter 2.

[21] In the initial calibration in Financial Stability (HNB, 2014), official crisis dates differ from the approach taken in this research (see Appendix 4).

As the signalling is intended to announce crises in advance, it is also necessary to determine a period of vulnerability occurring before a crisis. Its duration is defined differently by authors, depending on the assessment of the time needed for the reaction after the implementation of crisis prevention or mitigation measures. In order to allow credit institutions sufficient time to raise additional capital, it should be borne in mind that the introduction of the CCyB is usually announced one year in advance, and can only in exceptional circumstances be applied earlier[22] A time lag is also needed due to the fact that information on economic and financial developments is collected and disclosed with a certain delay and its analysis requires some time. Therefore, according to Galan (2019), good indicators should provide signals at least 5 quarters before the upcoming crisis. On the other hand, it is not good for indicators to signal the crisis too early as macroprudential policy costs may arise[23]. This study will follow the ECB (2017) approach, where it is recommended to define the dependent variable $vulnerability_t$ in quarter t as follows:

$$vulnerability_t = \begin{cases} 1,\ for\ 12\ to\ 5\ quarters\ before\ crisis \\ omit\ data\ for\ 4\ to\ 1\ quarter\ before\ crisis\ and\ cirsis\ itself \\ 0, otherwise \end{cases} \qquad (6)$$

In addition, as in Behn et al. (2013), 12 to 7 quarters before the crisis are considered; as in Galán (2019) 16 to 5 quarters before the crisis; and 20 to 3 quarters, as in the first CNB's calibration (Financial Stability No. 13, 2014). After defining a dependent variable, it is necessary to determine the threshold level τ[24] for the independent variable, the exceeding of which indicates the occurrence of a crisis situation. By exceeding the reference level *t*, potential indicators are transformed into a discrete variable that takes a value of 1. In the remaining cases, the indicator takes the value of 0. The idea is to distinguish the situations when on the basis of exceeding a certain reference level one condition of the system (crisis) is signalled in contrast with another condition. A confusion matrix, presented in Table 3, examines four cases depending on whether or not a crisis period was signalled and whether or not a crisis situation was actually observed.

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[22] Credit Institutions Act (OG 159/13, 19/15, 102/15, 15/18, 70/19, 47/20, 146/20), Article 121.

[23] An example is the premature introduction of dynamic reservations in Spain, see details in Fernandez de Lis and Garcia-Herrero (2012).

[24] The reference level is based on a certain percentile of the indicator distribution (Alessi and Detken, 2011).

Table 3 Confusion matrix

Signal / vulnerability	Crisis	No crisis
Indicator signals a crisis	*A*	*B* (Type 2)
Indicator does not signal a crisis	*C* (Type 1)	*D*

The value *A* denotes the total number of true positive signals, *B* denotes the total number of false positive signals, *C* denotes the total number of false negative signals and *D* denotes the total number of true negative signals. These outcomes define[25] Type 1 error (T1, missed vulnerable states, false negative) and Type 2 error or noise ratio (T2, false alarms, FPR (false positive ratio), type II error, false positive):

$$\mathrm{T1} = \frac{C}{A+C} \tag{7}$$

and

$$\mathrm{T2} = \frac{B}{B+D} \tag{8}$$

The value of the reference level τ, which, when exceeded, identifies a potential crisis, depends on the relationship between actual and false signals, i.e. between the announcement of actual and false crises. One popular approach to determining the reference level τ, when the preferences[26] of policy makers between accurate and false crisis announcements are even or unknown, is the calculation of the AUROC (area under the operational characteristic curve). If an estimated noise ratio on the *x*-axis is analysed, as well as the estimated signal ratio[27](TPR, true positive rate) on the *y*-axis in the coordinate system for different levels τ, a ROC[28] curve (receiver operating characteristic curve) may be obtained, so that, for different levels, this curve is sketched

[25] In the literature the definition of Type 1 and Type 2 errors changes, depending on the zero hypothesis. Some authors analyse the zero hypothesis "no-crisis" (Tölö et al., 2018 and Candelon et al. 2012), while the zero hypothesis "crisis" is analysed in, for example, ESRB (2014b), therefore labels and ratios differ. This is why in the confusion matrix there is a presumption in the zero hypothesis that "it is a crisis" and Type 1 error is precisely the error of rejection of a true zero hypothesis that it is a crisis, because the selected variable indicates that it is a crisis and that H_0 is therefore rejected.

[26] The study assigns equal weights to Type 1 and Type 2 errors, given only one crisis covered by the selected time period. For this reason the attempt to change weights in the largest number of cases made the optimisation of the target function impossible.

[27] The signal ratio equals 1-T1.

[28] This is therefore a graphic representation of the cumulative distribution function.

by the different values of both ratios. The area below this curve is called the AUROC, which takes a value from the interval [0.5,1]. The value of 0.5 is the case when the surface that closes the triangle between the origin and points (0,1) and (1,1) would be calculated[29]. This is the case when the value of τ is small (a large number of crises are correctly predicted, but a large number of false signals are also indicated). When the value of τ is increased, fewer crises are predicted precisely, but fewer are also falsely signalled (which increases the AUROC, given the shape of the ROC curve), up to the value of 1, in which case we would have T2 = 0 and 1 - T1 = 1. The objective function that is optimised to determine the level τ is defined as[30]:

$$\arg\max{}_{\tau} \left(\frac{A}{A+C} + \frac{D}{D+B}\right), \qquad (9)$$

where the Youden index is maximised. The estimated value τ represents the lower threshold L, at which the positive CCyB rate is first calibrated and introduced into application. The upper threshold may be calibrated by assigning different weights to type 1 and type 2 errors, or by setting a high level of credit gap on the basis of past crisis experience, which sets a maximum CCyB maintenance requirement. For example, as there is a one-year lag since the date of announcement of a certain CCyB rate and its implementation, a credit gap value of, e.g., 6 quarters before the formal start of a crisis may be used for the H threshold.

4.2. Criteria for comparing signal variables

As we proposed a large number of alternative gap indicators in the previous chapter as potential crisis signals, criteria should be chosen for ranking them and selecting the best. There is no unified approach in the literature. Some authors compare AUROC values and rank indicators accordingly, while others analyse TPR and FPR values. Some evaluation criteria ,with many indicators compared at once, are found in ESRB (2014), where indicators characterised by the AUROC of at least 0.6 are considered for further analysis as well as a TPR of at least 0.5 and an FPR up to a maximum of 0.5. A similar approach is found in Bonfin and Monteiro (2013), who examine the TPR and FPR. A

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[29] The ROC curve always contains points (0.0) and (1.1), which represent reference levels τ from + ∞ to -∞.

[30] The first fraction represents sensitivity, i.e. the signal ratio, while the second fraction represents a specificity or a TNR ratio (true negative rate).

test may also be performed, according to Obuchowski et al. (2004), in which a zero hypothesis assumes that the AUROC value is lower than or equal to 0.5, while the alternative assumes the opposite. Therefore, this test looks at whether signalling is accidentally guessed or whether the indicator has the power to discriminate A, B, C and D cases in the confusion table. Giese et al. (2014) consider this test and the statistical significance of the AUROC when comparing several indicators. Lo Duca et al. (2017) consider the criteria: the AUROC greater than 0.65, T1 and T2 errors of less than 0.5 and 0.6 respectively. Finally, the comparison can also be made by means of a formal equivalence test for the two AUROC areas, whereby each surface is first compared with that determined by the Basel indicator and then with each other. The zero hypothesis of the test assumes that the two surfaces are equal, while the alternative is one-sided in that the AUROC value of the selected indicator is greater than the AUROC value of the Basel reference indicator (or another selected indicator). In doing so, the access in DeLong et al. (1988) can be chosen, but also the bootstrap (with, for example, 15,000 replicates) to verify robustness[31].

5. Selection of the best credit gap measures

The application of the signalling method described above considers various credit gaps, as defined in Chapter 3. In addition to the evaluation criteria described, while searching for the best credit gap indicators, we also consider whether they correct the identified problems encountered when estimating the credit gap and determining the CCyB rate level. This is guided by several basic principles, according to Kauko (2012:6), who states that an indicator used to anticipate the development of cyclical risks should have the following characteristics:

1. the predictive power of the indicator should be characterised by as few Type 1 errors, (crises not previously announced) and Type 2 errors (incorrect announcement of crises) as possible;
2. a sudden decline in GDP should not be interpreted as a signal of over-lending;
3. the indicator should be steady/stable;
4. the indicator should be resilient to structural changes.

[31] The *p*-value in the DeLong approach is estimated from the asymptotic chi-square distribution, whereas in the Bootstrap approach *p*-value is estimated from the design of the normal standardisation distribution of the difference between the two AUROC values.

Drehmann and Tsatsaronis (2014), Drehman and Juselius (2014), Önkal et al. (2002) and Lawrence et al. (2006) complement this by such characteristics as the predictive power of the indicator being required to be present early enough to enable the financial system to prepare for the realisation of systemic risks (at least 2-3 years before the onset of the crisis according to BCBS, 2010); as well as its interpretability (signals that are difficult to understand are more likely to be ignored).

In addition, expert judgement in such analyses is also important in order to make the optimal indicator applicable to decision-making and easier for communication with the public. In addition to considering the early crisis signalling approach, an expert assessment also takes into account the fact that the indicators that may be satisfactory according to formal tests do not need to have an applicative meaning. For example, for the smoothing parameter of 25,600 (see details of the analysis below), the results suggest that in a large number of cases the credit gap provides for good signalling of the crisis. However, this assumes a relatively short financial cycle, only twice as long as a business cycle (i.e. 15 years), for which there is insufficient evidence in practice. Moreover, some studies specifically examine credit to households and enterprises, given the findings from empirical research suggesting that future crises may be stronger if they are preceded by a growth of credit to households. In the first steps of this analysis, we also included separate gap indicators for household and corporate credit ratios, which in some cases signalled a crisis even better than the narrower and broader definition of credit. However, as the CCyB is applied to the total risk exposure of credit institutions, the decision on its application should be based on trends in the total placements of credit institutions to the private sector, thus excluding such partial indicators from the analysis. To sum up, in addition to the models that provide us with information on how good an indicator is, expert judgement mostly concerns the inclusion or exclusion of those indicators that do not provide full information about the credit gap, or represent extreme values (such as the duration of the financial cycle).

Tables 4 and 5 show in detail the results of the signalling method (description of the variables is presented in Appendix 5) for 4 crisis signalling intervals: 12 to 5, 20 to 3, 12 to 7 and 16 to 5 quarters before the crisis. Next, Figure 8 shows the potential CCyB rate level for the best crisis signalling indicators, at an interval of 16 to 5 quarters ahead. Before the results are analysed, it should be noted that, due to the lack of sufficiently long time series in the sample, we consider only one crisis period, which is not an ideal approach. Although the signalling method was recommended by the ESRB for the selection of national specific gaps and is also used by other central banks and macroprudential authorities, in the case of a small number of data, such as Croatian data, it may result in biased results.

Among the results presented in Table 4, there are a number of problems that make it difficult to choose the best. The AUROC is for almost all gaps close to the value of 1, which indicates that all credit gaps are good quality indicators in signalling the selected crisis. However, when comparing indicators according to certain groups, the most significant AUROC value on average is that of a group of absolute gaps, where credit and GDP are separately filtered, then their relative variable and one-year credit differentiation, while the lowest (worst) values are for gaps obtained under the linear projection (the so-called Hamilton approach) and for relative gaps for a typical Basel credit ratio. These conclusions can be supported by TPR values, in most cases amounting to 1 (or 100%), which would mean that each indicator predicts a crisis in 100% of cases. In addition, the FPR was very low, which means that in a small number of cases, an indicator unnecessarily pointed to a crisis even though it did not occur. The positive FPR values mainly refer to those indicators that at the end of the observed period (after 2016; see positive values of the CCyB rate in Figure 8) pointed to the crossing of the reference threshold L and the consequent activation of the CCyB, although during this period the vulnerability variable takes the value of 0. When comparing indicators according to individual groups, a conclusion similar to that of the AUROC observation is reached: the absolute and relative gaps with a special filtering of the credit series and GDP have the lowest FPR values, while the share of wrongly signalled crises is the largest for the linear projection approach[32].

Table 5 shows the results of the assessment of the lower threshold L, at which the CCyB is introduced, and the p-values of DeLong and bootstrap tests comparing individual indicators with respect to the Basel gap and the specific gap currently used. It is first noticed that for a large part of the results, the estimated value of the threshold L is negative, which would mean that the buffer should be started to be built up already in the situation of a negative credit gap. Using value 2 for L (according to the ESRB Recommendation and Basel guidance) therefore results in a much later (possibly too late) reaction in the construction of the required capital buffer than in these indicators.

[32] In addition to the already mentioned problem of the loss of part of the initial sample to estimate the model in (5), the behaviour of the resulting gap over the rest of the period under review is too volatile, which poses an additional problem. This filtering approach is better when longer time series are available.

Furthermore, the shaded cells in the DeLong and bootstrap test refer to those indicators that are better than both the Basel gap and the 2014 specific gap as regards all the observed lengths of crisis signalling periods. Although in several cases one-year credit changes (1yr diff NDC and 1yr diff BDC) have *p*-values lower than theoretical normal thresholds, requiring the rejection of the hypothesis that they are not better than the Basel gap or the specific gap, these series are rather volatile and do not meet the stability principle. In all four selected signalling time bands, the best indicators are absolute and relative gaps resulting from a specific credit and GDP filtering, with different smoothing parameters (85,000, 125,000 and 400,000), the only exception being the parameter of 25,600, which in most cases (but not all) is better than the Basel gap and the specific gap. As explained in Chapter 3.2, although due to short time series there is no empirical research capable of unequivocally determining the duration of the financial cycle in Croatia, results from the international literature suggest that it is longer than the business cycle. This dispersion is much smaller in Central and Eastern European countries, which should therefore use smaller smoothing parameters in filtering than developed countries or those based on Basel guidance. In addition, as gaps with lower lambdas are closed earlier, their use allows for the timely construction of the CCyB, ensures stability by mitigating time series fluctuations to a lower degree and leads to smaller revisions following the arrival of "fresh" data compared to two-sided gaps (Wolf et al., 2020). All of this should be borne in mind when analysing the movements of indicators based on different lambdas, especially if their conclusions are not unambiguous. For this reason we consider it appropriate to consider all proposed smoothing parameters in parallel, in order to obtain a more complete picture of the evolution of the credit gap.

Poor results for other indicators suggest that they are not recommended to be used for Croatia, as they are not better according to the formal test, and some of them also have undesirable characteristics, such as instability and volatility. These alternative gaps are characterised by the problem of nonstationarity, which, although present in the best gaps, is a small obstacle, as they still lead to mean reverting, not present for some alternative gaps. The volatility of some worse indicators would result in a too frequent change in the CCyB (see Appendix 6), which undermines the ability of consistent signalling, or in changes that lack a reasonable clarification in terms of deviations of credit from the long-term trend or fundamentals. Finally, the alternative approaches also suffer from the problem of inability to assess them: in the case of a linear projection, a part of the initial series loses data that is highly relevant when assessing the quality of crisis signalling.

Figure D6 in Appendix 6 shows the potential levels of the CCyB rate[33] if it were determined on the basis of each of the indicators considered, in the event of a crisis signalling of 16 to 5[34] quarters in advance. The first panel anticipates the dynamics for absolute Basel credit gaps, one-year changes in the credit ratio and the two-year growth rate. All values "capture" the accelerated credit growth at the beginning of 2000, until the global financial crisis. Due to the lower smoothing parameter, the Basel NDC 25 K gap as early as in 2020 points to a positive CCyB rate because of the closing of the negative gap. Furthermore, the second panel compares relative Basel gaps, differentiated credit and gaps resulting from the linear projection. Again, this dynamics is similar, except in the case of linear projections, the problems of which are already visible in the case of positive CCyB values in the period when they should amount to 0 (negative economic developments). The third panel compares absolute gaps in the case of special credit-to-GDP filtering, gaps based on local extremes and moving averages. In the present case, the evolution of the gaps with moving averages is problematic, as they are too volatile. The last, fourth panel compares the relative gaps for specific credit and GDP filtering and the specific indicator currently used, albeit with recalibration (the estimate of new) L and H thresholds.

The proposed CCyB rate levels based on the best gaps, selected according to the results in Tables 4 and 5, are further presented in Figure 8, where both panels (the upper for the absolute gap and the lower for the relative gap) show the same dynamics of the required construction of the countercyclical capital buffer. The gaps arising from specific credit and GDP filtering, with the value of the credit smoothing parameter of 85,000, at the end of the observed period point to the need to introduce positive CCyB rates, which may be explained by an earlier closing of the credit gap. The appropriateness of selecting this set of indicators can be checked by using a filtering procedure with out-of-sample forecasts, which evaluates the possible range of different gap values depending on the use of different forecasting models, thus addressing the problem of trend instability at the end of the time series (see Appendix 8 for the description of the

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[33] The calibration of the CCyB rate level for all four crisis signalling cases was made as follows: The estimate from Table 5 is used as the lower threshold L, based on the reference level τ in the formula (9). For the upper threshold H, the value of the individual credit gap from the last quarter in which the vulnerability variable takes value 1 in the formula (6) is used.

[34] In order to ensure sufficient time to build the CCyB, but also to achieve the pre-crisis maximum value early enough, signalling was selected for the period of 16 to 5 quarters before the crisis. In addition, such calibration of the CCyB is optimal based on the lower volatility of the CCyB rate, as well as step-by-step construction, while major problems (e.g. sudden spikes in the rate from 0% to 2.5%) are present in the calibration for other signalling periods. See Appendix 7 for the remaining figures.

procedure for HP filter application with corrections by forecasting according to broad definition credit) [35]. It is also possible to verify the appropriateness of different credit gap measures using the interval assessment of the gap and the CCyB rate shown in Appendix 9. Both approaches show that the actual[36]credit gap is positioned within the gap interval with a lower (85,000) and a higher (400,000) smoothing parameter.

On the basis of all the results presented, it can be concluded that the use of some alternative gaps is not recommended. These are the gaps that are based on linear projections, which, due to too short time series, are too volatile in the observed period, and the resulting calibration of the CCyB does not give the desired result (construction of an additional buffer during a period of excessive credit growth). Furthermore, the problem of volatility and frequent variability of conclusions on the (non-)construction of the CCyB is also present in the case of gaps derived from moving averages. In the case of a change in the smoothing parameter used in filtering the credit-to-GDP ratio (the "regular" Basel gap), the results of the DeLong and the bootstrap tests suggest that lower lambda values do not result in a gap that is better than the initial one (lambda = 400,000), contrary to the findings in Spain.

However, when special filtering of the credit series, in particular of GDP, is applied, the absolute and relative gaps obtained are better than the Basel gap and the specific gap from 2014. This may be due to the fact that business cycles in the economy have different lengths compared to credit cycles, which is better captured by the specific filtering of each series on its own. Given that both smaller and higher values of the smoothing parameter for credit series have resulted in gaps that, according to statistical tests, are better than reference gaps for practical use, it is recommended that all series in Figure 8 be used at the same time as new measures of the national-specific credit gap, in order to facilitate decisions regarding the CCyB rate level. Naturally, in addition to these indicators, other information on the development of cyclical risks will have to be analysed in order to decide on the need to increase the CCyB rate, which will have to be complemented by expert judgement. These results are in line with the practice of other

[35] The use of time series filtering with corrections by out-of-sample forecasts addresses the end-point problem that occurs as a result of the filtering process, as the last point gets greater weight in the trend assessment and thus has a stronger impact on the results. In practice it is applied by the central banks of Norway, Poland, Lithuania and Portugal.

[36] The actual credit gap is the one that could be observed and calculated with certainty if we knew the length of the financial cycle, as well as if the problem of the last point in the filtering of the data was solved. Both analyses (Appendices 8 and 9) confirm that the "actual" gap lies somewhere within the observed ranges. Consequently, the calibration of the CCyB is sufficiently reliable in the light of the results obtained.

EU countries, as the calibration of the CCyB value is based on the estimated lower threshold *L,* which best separated the information in the data on whether it was a pre-crisis period or not. It has already been mentioned that only one crisis is examined, so that the resulting thresholds may be subject to further changes, when this methodology will be revised if necessary. This may depend on the nature of future financial cycles, which may not be characterised by an increase in the credit ratio to the extent covered by this analysis.

Table 4 Comparison of signalling model results for selected credit gaps

Indicator:	AUROC				TPR				FPR			
	12 to 5	20 to 3	12 to 7	16 to 5	12 to 5	20 to 3	12 to 7	16 to 5	12 to 5	20 to 3	12 to 7	16 to 5
Basel NDC 400K	0.93	0.87	0.93	0.88	1	1	1	1	0.12	0.24	0.12	0.30
Basel BDC 400K	0.97	0.89	0.95	0.90	1	1	1	1	0.14	0.22	0.14	0.24
Basel NDC 125K	0.93	0.87	0.93	0.88	1	1	1	1	0.12	0.24	0.12	0.30
Basel BDC 125K	0.97	0.89	0.96	0.90	1	1	1	1	0.12	0.22	0.12	0.24
Basel NDC 85K	0.93	0.87	0.93	0.88	1	1	1	1	0.12	0.24	0.12	0.30
Basel BDC 85K	0.97	0.89	0.96	0.90	1	1	1	1	0.12	0.22	0.12	0.24
Basel NDC 25K	0.9	0.79	0.89	0.82	1	1	1	1	0.21	0.36	0.21	0.41
Basel BDC 25K	0.97	0.87	0.96	0.88	1	1	1	1	0.12	0.28	0.12	0.30
Basel NDC r 400K	0.92	0.87	0.92	0.88	1	1	1	1	0.14	0.22	0.14	0.28
Basel BDC r 400K	0.95	0.88	0.93	0.88	1	1	1	1	0.19	0.22	0.19	0.24
Basel NDC r 125K	0.92	0.87	0.92	0.88	1	1	1	1	0.14	0.22	0.14	0.28
Basel BDC r 125K	0.95	0.88	0.93	0.88	1	1	1	1	0.19	0.22	0.19	0.24
Basel NDC r 85K	0.92	0.87	0.92	0.88	1	1	1	1	0.14	0.22	0.14	0.28
Basel BDC r 85K	0.95	0.88	0.93	0.88	1	1	1	1	0.19	0.22	0.19	0.24
Basel NDC r 25K	0.88	0.79	0.89	0.81	1	1	1	1	0.22	0.36	0.22	0.41
Basel BDC r 25K	0.95	0.85	0.93	0.87	1	1	1	1	0.19	0.30	0.19	0.30
Diff NDC	0.96	0.88	0.94	0.90	1	1	1	1	0.17	0.22	0.17	0.26
Diff BDC	0.96	0.89	0.94	0.90	1	1	1	1	0.15	0.22	0.15	0.22
1-yr diff NDC	0.98	0.90	0.98	0.94	1	1	1	1	0.07	0.2	0.07	0.19
1-yr diff BDC	0.99	0.91	0.99	0.93	1	1	1	1	0.09	0.22	0.09	0.21
Lin NDC	0.88	0.88	0.92	0.88	1	1	1	1	0.27	0.27	0.16	0.27
Lin BDC	0.88	0.85	0.92	0.88	1	1	1	1	0.30	0.30	0.16	0.30
Loc extr NDC	0.96	0.90	0.95	0.91	1	1	1	1	0.12	0.14	0.12	0.19
Loc extr BDC	0.98	0.93	0.97	0.93	1	1	1	1	0.04	0.14	0.04	0.17

2-yr NDC rate	0.89	0.87	0.89	0.86	1	1	1	1	0.14	0.14	0.14	0.19
2-yr BDC rate	0.95	0.91	0.94	0.90	1	1	1	1	0.10	0.14	0.10	0.19
Mov av NDC	0.94	0.86	0.98	0.92	0.875	0.944	1	1	0.05	0.28	0.05	0.24
Mov av BDC	0.97	0.9	0.98	0.94	0.875	1	1	1	0.02	0.23	0.02	0.14
NDC 125K	1	0.96	1	0.97	1	1	1	1	0	0.12	0	0.11
NDC 25K	0.98	0.89	0.98	0.92	1	1	1	1	0.09	0.26	0.09	0.24
NDC 400K	1	0.96	1	0.97	1	1	1	1	0	0.12	0	0.11
NDC 85K	1	0.95	1	0.97	1	1	1	1	0	0.18	0	0.15
BDC 85K	1	0.94	1	0.97	1	1	1	1	0	0.22	0	0.15
BDC 125K	1	0.94	1	0.97	1	1	1	1	0	0.22	0	0.15
BDC 25K	1	0.89	1	0.94	1	1	1	1	0	0.34	0	0.26
BDC 400K	1	0.94	1	0.97	1	1	1	1	0	0.22	0	0.15
NDC r 125 K	1	0.96	1	0.97	1	1	1	1	0.02	0.14	0.02	0.11
NDC r 25 K	0.98	0.89	0.98	0.92	1	1	1	1	0.07	0.28	0.07	0.24
NDC r 400 K	1	0.96	1	0.97	1	1	1	1	0.02	0.12	0.02	0.11
NDC r 85 K	1	0.95	1	0.97	1	1	1	1	0.02	0.18	0.02	0.15
BDC r 85 K	1	0.94	1	0.96	1	1	1	1	0	0.22	0	0.15
BDC r 125 K	1	0.94	1	0.96	1	1	1	1	0	0.22	0	0.15
BDC r 25 K	1	0.89	1	0.94	1	1	1	1	0	0.34	0	0.26
BDC r 400 K	1	0.94	1	0.96	1	1	1	1	0	0.22	0	0.15
Spec	0.97	0.88	0.96	0.90	1	1	1	1	0.1	0.27	0.1	0.27

Note: Due to there being fewer data for the gap based on a linear projection, the results should be taken with caution. TPR denotes true positive rate and FPR false positive rate. Bolded indicators (Spec and Basel NDC 400K) are the specific gap and the Basel gap, which are currently used by the CNB and serve for comparison with the new gaps defined in this research.

Source: Authors' calculations.

Table 5 Comparison of the estimated lower thresholds *L* for the CCyB calibration and the comparison of all indicators with respect to the Basel gap and the specific gap

Indicator:	Assessment of the threshold *L*				DeLong test				Bootstrap test			
	12 to 5	20 to 3	12 to 7	16 to 5	12 to 5	20 to 3	12 to 7	16 to 5	12 to 5	20 to 3	12 to 7	16 to 5
Basel NDC 400K	0.28	-1.58	0.28	-1.58	0.96 0.99	0.79 0.95	0.93 0.99	0.83 0.97	0.95 0.99	0.78 0.94	0.91 0.98	0.82 0.96
Basel BDC 400K	0.77	-2.71	0.77	-1.35	-	-	-	-	-	-	-	-
Basel NDC 125K	0.28	-1.57	0.28	-1.57	0.96 0.99	0.81 0.96	0.93 0.99	0.84 0.97	0.95 0.99	0.80 0.95	0.91 0.98	0.83 0.96
Basel BDC 125K	0.81	-2.70	0.81	-1.35	0.24 0.60	0.50 0.62	0.24 0.84	0.24 0.81	0.27 0.58	0.50 0.62	0.26 0.80	0.27 0.79
Basel NDC 85K	0.28	-1.57	0.28	-1.57	0.96 0.99	0.81 0.96	0.93 0.99	0.84 0.97	0.95 0.99	0.80 0.95	0.91 0.98	0.83 0.96
Basel BDC 85K	0.81	-2.70	0.81	-1.35	0.15 0.50	0.24 0.60	0.14 0.74	0.15 0.77	0.19 0.50	0.27 0.59	0.18 0.70	0.19 0.76
Basel NDC 25K	0.30	-1.56	0.30	-1.56	0.99 1.00	0.99 1.00	0.99 1.00	0.99 1.00	0.99 1.00	0.99 1.00	0.99 0.99	0.99 1.00
Basel BDC 25K	0.81	-1.69	0.81	-1.34	0.15 0.50	0.93 0.87	0.14 0.74	0.87 0.92	0.19 0.50	0.92 0.87	0.19 0.70	0.86 0.91
Basel NDC r 400K	-0.09	-3.61	-0.09	-3.61	0.98 1.00	0.77 0.92	0.98 1.00	0.83 0.96	0.98 0.99	0.76 0.91	0.96 0.99	0.82 0.95
Basel BDC r 400K	0.67	-4.58	0.67	-1.94	0.97 0.92	0.98 0.84	0.94 0.93	0.96 0.94	0.96 0.92	0.96 0.83	0.93 0.93	0.94 0.93
Basel NDC r 125K	-0.08	-3.60	-0.08	-3.60	0.98 1.00	0.77 0.92	0.98 1.00	0.83 0.96	0.98 0.99	0.76 0.91	0.96 0.99	0.82 0.96
Basel BDC r 125K	0.67	-4.52	0.67	-1.94	0.97 0.92	0.98 0.84	0.94 0.93	0.96 0.94	0.96 0.92	0.96 0.83	0.93 0.93	0.94 0.93
Basel NDC r 85K	-0.08	-3.22	-0.08	-3.22	0.98 1.00	0.77 0.92	0.98 1.00	0.83 0.96	0.98 0.99	0.76 0.91	0.96 0.99	0.82 0.96
Basel BDC r 85K	0.67	-4.48	0.67	-1.94	0.97 0.92	0.98 0.84	0.94 0.93	0.96 0.94	0.95 0.92	0.96 0.83	0.93 0.93	0.94 0.96
Basel NDC r 25K	0.56	-3.56	0.56	-3.56	1.00 1.00	0.99 1.00	1.00 1.00	1.00 1.00	1.00 1.00	0.99 1.00	0.99 1.00	0.99 1.00
Basel BDC r 25K	1.07	-2.48	1.07	-1.92	0.97 0.92	1.00 0.97	0.94 0.93	0.99 0.98	0.95 0.92	0.99 0.96	0.93 0.93	0.99 0.98
Diff NDC	3.50	1.77	3.50	1.85	0.80 0.73	0.91 0.71	0.80 0.83	0.75 0.69	0.79 0.72	0.90 0.70	0.79 0.83	0.73 0.68
Diff BDC	4.23	2.03	4.23	2.64	0.70 0.67	0.86 0.60	0.70 0.76	0.70 0.65	0.69 0.67	0.85 0.60	0.69 0.76	0.68 0.64
1-yr diff NDC	32.49	17.74	32.49	22.68	0.09* 0.07*	0.22 0.25	0.03** 0.06*	0.02** 0.03**	0.11 0.09*	0.23 0.26	0.04** 0.07*	0.02** 0.04**
1-yr diff BDC	43.20	19.71	43.20	31.14	0.06* 0.11	0.06* 0.27	0.05* 0.13	0.01** 0.12	0.07* 0.12	0.08* 0.28	0.06* 0.14	0.02** 0.14

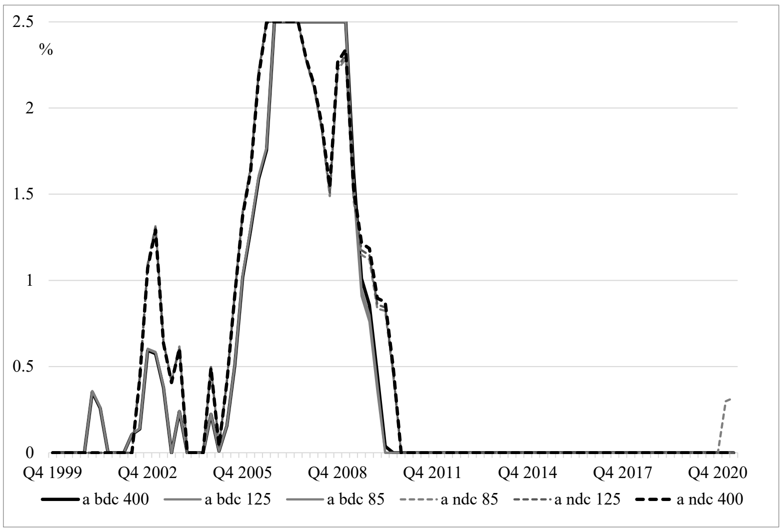
Lin NDC	-3.64	-3.64	-4.61	-3.64	1.00 1.00	1.00 1.00	1.00 1.00	1.00 1.00	1.00 1.00	1.00 1.00	1.00 1.00	1.00 1.00
Lin BDC	-4.83	-4.60	-7.40	-4.83	1.00 1.00	1.00 1.00	1.00 1.00	1.00 1.00	1.00 1.00	1.00 1.00	1.00 1.00	1.00 1.00
Loc extr NDC	7.60	2.71	7.60	3.42	0.79 0.86	0.94 0.70	0.62 0.84	0.87 0.78	0.77 0.82	0.92 0.69	0.61 0.80	0.84 0.75
Loc extr BDC	9.11	2.94	9.11	4.83	0.23 0.26	0.26 0.11	0.23 0.31	0.24 0.20	0.24 0.26	0.28 0.12	0.24 0.31	0.25 0.22
2-yr NDC rate	14.70	5.46	14.70	7.42	0.99 0.99	0.99 0.96	0.99 0.99	0.99 0.99	0.99 0.99	0.98 0.95	0.99 0.99	0.99 0.99
2-yr BDC rate	12.78	3.93	12.78	6.40	0.75 0.73	0.82 0.52	0.64 0.73	0.82 0.74	0.74 0.73	0.81 0.52	0.64 0.72	0.81 0.74
Mov av NDC	2.22	0.26	2.27	0.69	0.74 0.80	0.88 0.89	0.14 0.20	0.32 0.41	0.75 0.80	0.88 0.89	0.14 0.21	0.32 0.41
Mov av BDC	2.77	0.36	2.77	1.46	0.50 0.53	0.33 0.35	0.19 0.27	0.09* 0.15	0.50 0.53	0.34 0.35	0.19 0.27	0.09* 0.15
NDC 125K	2.15	-0.87	2.15	-0.22	0.06* 0.06*	0.00*** 0.00***	0.05* 0.06*	0.00*** 0.00***	0.06* 0.06*	0.00*** 0.00***	0.05* 0.06*	0.00*** 0.00***
NDC 25K	2.14	-0.87	2.14	-0.22	0.17 0.25	0.48 0.54	0.16 0.30	0.22 0.37	0.19 0.26	0.48 0.54	0.18 0.32	0.23 0.38
NDC 400K	2.15	-0.87	2.15	-0.22	0.06* 0.06*	0.00*** 0.00***	0.05* 0.06*	0.00*** 0.00***	0.06* 0.06*	0.00*** 0.00***	0.05* 0.06*	0.00*** 0.00***
NDC 85K	2.15	-0.87	2.15	-0.22	0.06* 0.06*	0.01** 0.01**	0.05* 0.06*	0.00*** 0.01**	0.06* 0.06*	0.01** 0.01**	0.05* 0.06*	0.00*** 0.01**
BDC 85K	2.19	-1.82	2.19	-0.01	0.06* 0.06*	0.01** 0.03**	0.05* 0.06*	0.00*** 0.01**	0.06* 0.06*	0.01** 0.04**	0.05* 0.06*	0.00*** 0.01**
BDC 125K	2.19	-2.16	2.19	-0.01	0.06* 0.06*	0.01** 0.03**	0.05* 0.06*	0.00*** 0.01**	0.06* 0.06*	0.01** 0.04**	0.05* 0.06*	0.00*** 0.01**
BDC 25K	2.56	-1.70	2.56	-0.01	0.06* 0.06*	0.50 0.57	0.05* 0.06*	0.08* 0.18	0.06* 0.06*	0.50 0.57	0.05* 0.06*	0.09* 0.18
BDC 400K	2.19	-2.16	2.19	0.00	0.06* 0.06*	0.01** 0.03**	0.05* 0.06*	0.00*** 0.01**	0.06* 0.06*	0.01** 0.04**	0.05* 0.06*	0.00*** 0.01**
NDC r 125 K	4.28	-1.89	4.28	-0.47	0.05* 0.05*	0.00*** 0.00***	0.04** 0.05*	0.00*** 0.00***	0.05* 0.06*	0.00*** 0.00***	0.04** 0.05*	0.00*** 0.00***
NDC r 25 K	4.33	-1.90	4.33	-0.49	0.18 0.24	0.52 0.59	0.13 0.24	0.24 0.39	0.20 0.25	0.52 0.58	0.14 0.25	0.25 0.39
NDC r 400 K	4.28	-2.11	4.28	-0.47	0.05* 0.05*	0.00*** 0.00***	0.04** 0.05*	0.00*** 0.00***	0.06* 0.06*	0.00*** 0.00***	0.04** 0.06*	0.00*** 0.00***
NDC r 85 K	4.27	-2.11	4.27	-0.48	0.05* 0.05*	0.01** 0.01**	0.04** 0.05*	0.01** 0.01**	0.05* 0.06*	0.01** 0.01**	0.04** 0.05*	0.01** 0.01**
BDC r 85 K	3.21	-2.45	3.21	-0.01	0.06* 0.06*	0.01** 0.04**	0.05* 0.06*	0.00*** 0.01**	0.06* 0.06*	0.01** 0.04**	0.05* 0.06*	0.00*** 0.01**
BDC r 125 K	3.22	-3.72	3.22	-0.01	0.06* 0.06*	0.01** 0.04**	0.05* 0.06*	0.00*** 0.01**	0.06* 0.06*	0.01** 0.04**	0.05* 0.06*	0.00*** 0.01**
BDC r 25 K	3.53	-2.31	3.53	-0.01	0.06* 0.06*	0.50 0.57	0.05* 0.06*	0.09* 0.19	0.06* 0.06*	0.50 0.57	0.05* 0.06*	0.10 0.20

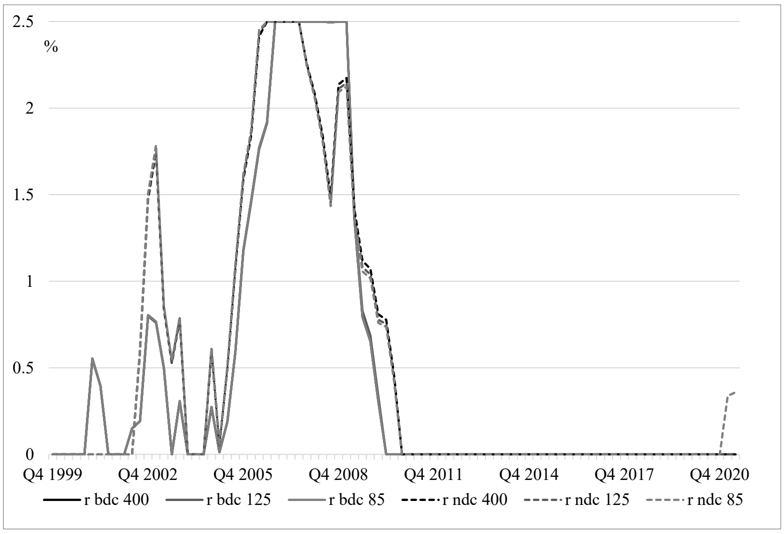
BDC r 400 K	3.21	-2.45	3.21	-0.01	0.06* 0.06*	0.01** 0.04**	0.05* 0.06*	0.00*** 0.01**	0.06* 0.06*	0.01** 0.05**	0.05* 0.06*	0.00*** 0.01**
Spec	1.28	-6.10	1.28	-4.85	-	-	-	-	-	-	-	-

Note: De Long and bootstrap columns contain the p-values of the one-sided test with a zero hypothesis that the AUROC values of the selected indicator and the Basel gap or the specific credit gap are the same. The first row shows the p-values in the case of comparison with the Basel gap, while in the latter they are presented for comparison with the specific gap. *, ** and *** denote the statistical significance at the levels of 10%, 5% and 1% respectively. Shaded cells refer to the indicators that are better in all four selected signalling time bands than the currently used Basel gap and specific gap.

Source: Authors' calculations.

Figure 8 CCyB rate level for the best crisis signalling indicators (top panel - absolute gap, lower panel - relative gap), 16 to 5 quarters in advance





Note: *a* and *r* denote the absolute and the relative gap respectively, *bdc* and *ndc* the broader and the narrower definition of credit (Appendix 1), and 25, 85, 125 and 400 the size of the lambda smoothing parameter for the credit series (as described in Chapter 3.4).

Source: CNB, authors' calculations.

6. Conclusion

The literature has recognised accelerated credit growth as one of the main indicators of the build-up of risks and the possibility of crises occurring in the financial system. Therefore, the credit-to-GDP gap is in macroprudential regulations determined as the baseline indicator for the calibration of the countercyclical capital buffer. Despite the efforts to ensure transparency and consistency by using a simple and internationally comparable credit gap indicator, macroprudential policy makers face numerous challenges in its assessment in practice. Although numerous proposals for improvements and various solutions have been applied in practice, there is still no consensus concerning the measurement of excessive credit growth (Baba et al., 2020), so that regulators, when calibrating countercyclical buffers, make extensive use of the flexibility allowed under existing regulations.

In designing the countercyclical capital buffer, the Croatian National Bank followed international guidelines and recommendations, facing challenges similar to those of other countries, related to the extraction of information on changes in the credit cycle based on the credit gap. Relatively short time series, subject to structural changes, hinder the quantitative analysis of time series and the determination of the actual length of the cycle, as well as the use of HP filters to assess the long-term equilibrium. In order to focus only on the assessment of the credit gap indicator, this study presents in a systematic manner various options to modify its calculation and selects the most appropriate indicators for the calibration of the countercyclical capital buffer rate in Croatia.

The results of the analysis, based on the usual methods for assessing the quality of crisis signalling in the historical sample and expert judgement, show that a total of twelve credit gap indicators signal a crisis better than the Basel gap and the previously used specific gap indicator (from 2014). The selected indicators combine two credit coverage variants (only domestic banks' credit and broader defined placements augmented by external debt) and two ways of calculating the gap (absolute and relative). Gaps are estimated according to a separate filtering of credit series relative to GDP, in order to reflect the assumption provided in numerous international surveys on the different lengths of business and credit cycles. Several values of smoothing parameter are used in credit filtering; they are significantly higher than those used in GDP filtering, and the robustness of this approach is confirmed by filtering using out-off sample forecasts. The selected new specific credit gap indicators are characterised by lower volatility, somewhat earlier and stronger growth in the historical period and a faster closing of the gap vis-à-vis the Basel gap and the formerly used specific gap.

This allows for an earlier and more proactive implementation of macroprudential policy as well as the creation of additional capital requirements at an early stage of cyclical risks. In line with the trends in the assessed gap, calibrated countercyclical capital buffer rates take positive values earlier than the Basel gap and the specific gap used thus far. In addition to the period before the GFC, this is also evident in the recent period, as two of the 12 indicators turned positive in 2021. In contrast, according to current expectations about future developments in credit and GDP, the Basel standard gap will not be closed for several years, so that reliance on its signals might result in a delayed decision to increase capital requirements.

However, one may ask how the appropriate moment for deciding to change the CCyB rate is to be determined. The answer can only be given by considering the costs and benefits of an earlier introduction of this buffer in comparison with the later stages. If this instrument is used too late, it will not lead to a sufficiently large increase in capital, which could be released in a crisis to ensure continued lending[37], but it will prevent or mitigate the undesirable short-term effects of higher capital requirements on lowering credit activity and economic growth at the time of implementation (Drehmann and Gambacorta, 2012; Jiménez et al., 2012; Bank of England, 2016). On the other hand, these negative effects would be stronger and would materialise sooner in the event of an earlier introduction of a countercyclical buffer, as suggested by indicators based on the assumption of a shorter cycle duration. However, from a long-term perspective, the build-up of the CCyB in the periods when cyclical risks start to evolve has advantages. It enables credit institutions to start increasing their capital and resilience sooner and stronger. Finally, when a crisis occurs, it enables them to deal with it more easily.

This study is not a comprehensive evaluation of all the strengths and weaknesses of analytical methods used to identify the development of cyclical risks associated with excessive credit growth in order to formulate a countercyclical capital buffer in Croatia, but should be seen as a starting point for improving the methodology that will enable informed decision-making drawing on a broad set of relevant indicators as well as

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[37] See some specific applications in Škrinjarić (2022) and Arbatli-Saxegaard and Muneer (2020), countries such as Bulgaria, the Czech Republic, Norway and Slovakia, which had positive CCyB rates prior to the COVID-19 crisis, released some of this capital buffer precisely during 2020.

expert judgement. It shows that there are numerous issues related to the existing and the newly proposed methodology, and how some approaches to defining the credit gap do not meet the basic principles for the identification of cyclical risks and real-time decision-making based on reliable results. In subsequent studies, additional corrections to the HP filtering method may also be considered, such as its application to a longer time series which will also include out-of-sample forecasts. Further options to consider and refine this methodology are found in non-linear gaps derived from non-linear filters, such as those in Morley and Panovska (2020) and Donayre and Panovska (2021).

In addition to possible improvements related to the topic of this work, comprehensive risk measures can also be used when calibrating and building capital buffers. The system for assessing cyclical risks may be improved by including variables other than the credit ratio, which can be confirmed to possess good predictive crisis signalling properties. In practice, developments in credit, real estate prices, private sector debt burden, bank balance sheet strength measures and foreign trade imbalances are often monitored jointly in a single index, which includes information on the accumulation of systemic risks (for external experiences see results in Tölö et al., 2018 and their references), for which a separate study is planned.

Finally, if a much more conservative approach to building a counter-cyclical capital buffer is desired, this can be achieved by applying a positive neutral (or positive normal) CCyB rate[38], in the periods without pronounced cyclical pressures, in order to cope better with sudden shocks that may arise without a prior build-up of cyclical risks (Behn et al., 2020). In other words, the introduction of a positive CCyB rate, without indication of an upward stage of the credit cycle allows for more flexibility in the events of sudden shocks that could occur at any point in the cycle. An absence of previously positive CCyB, as the only releasable capital buffer could make it more difficult to resolve problems in the banking system in times of crisis (Banque de France, 2019). As an additional reason for the positive neutral rates, the ESRB (2018a, 2019) states changes in the financial cycle in Europe, which make it difficult to adequately determine the degree of cyclical risks evolution. This study does not set a basis for the introduction of a positive neutral rate in Croatia, but refers to it as an example of

[38] The UK was the first country in Europe that introduced a positive neutral rate, setting it at 1% in 2016 (Bank of England, 2016), which was increased to 2% in 2019, while other countries followed this approach (Lithuania, the Czech Republic).

building this capital requirement at a much earlier stage than that indicated by the Basel credit gap or other gap measures.

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Appendices

Appendix 1 — Definition of credit for the credit ratio

The BIS[39] (2010:10) believes that the ideal definition of credit should include all credit to households and other non-financial private corporations in the economy, irrespective of the form of credit and the identity of the funds provider. On the other hand, it should not include credit to the public sector, as this reduces the credit-to-GDP predictive power for the CCyB calibration.[40] The starting point of the analyses of the ESRB (2014b) and Dembiermont et. al (2013) are total claims against the domestic non-financial private sector. Although the CCyB applies only to banks, banks may also suffer the consequences of an excessive increase in borrowing from other sources of financing. That is why the ESRB (2014b:11) recommends, that, in addition to bank credit, foreign credit and debt securities issued by the non-financial sector also be included in the analysis.

The criticism of the broader definition of credit is as follows. A credit aggregate within a broader definition may show a different dynamics than individual categories. Some research finds that the narrower definition of credit has better properties to signal bank crises than the broader definition (Detken et al., 2014, Aldasoro et al. 2018, CNB, 2014). Galati et al. (2016) take the total credit and bank credit as two definitions of credit to measure financial cycles. For the EA (euro area) countries in the analysis, the authors obtain similar results for both credit definitions in the signalling models. This is in line with the findings of Dell'Ariccia et al. (2012), where the largest differences

[39] Bank for International Settlements.

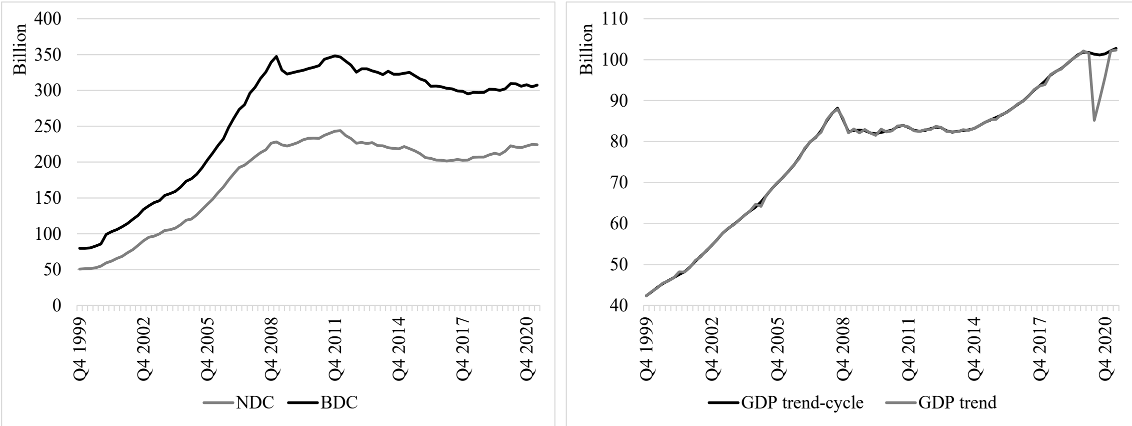
[40] However, some believe that the disadvantage of the Basel ratio is that public debt is not included (see Rychtárik, 2014, where public debt is also considered as a source of vulnerability in the financial system). On the other hand, Baba et al. (2020) state that there is no need to include the public sector, but recommend monitoring public debt developments with regard to possible effects on systemic risk.

between the use of bank credit and total credit are found for those countries that do not have a bank-centred financial system.

In the CNB's previous practice and in this paper, the narrower definition of credit refers to bank credit to households and non-financial corporations (kuna and foreign currency, Table D5, available on the CNB website), while total placements of credit institutions to households and non-financial corporations, increased by the gross external debt of households and non-financial corporations, are observed under the broader definition of credit (Tables D1, D5 and H15 available on the CNB website). The time series for the broader definition of credit was revised from the beginning of 2009 to the beginning of 2019 to smooth a structural break resulting from the reclassification of external debt of individual private enterprises in 2019.

In the calculation of the ratio, credit is related to the seasonally adjusted nominal gross domestic product. In order to mitigate the one-off negative impact of the pandemic on GDP, this study uses seasonally adjusted GDP with corrections, which extrapolate the values representing a particular shock based on the reference values of the deviations from the long-term trend. This means that when estimating the trend value of GDP that remains after eliminating the seasonal effect, atypical values deviating significantly from the trend are smoothed by the inclusion of binary variables for occasional shocks in the model assessment process. Naturally, with the arrival of new data, the trend thus obtained after the extrapolation of the shocks may contain a small break for some time, but it can be expected that after sufficient time has passed after the individual shock the resulting trend will be brought into line with that seen in the period before. It should be noted that given the problems of temporary shocks (such as COVID-19), but also the problem of the last point, it is very useful to consider filtering with out-of-sample forecasts (Appendix 8) or other methods of adjustment of the GDP series (Appendix 9). Figure D1a (left panel) shows the developments in the credit value in the case of the narrower and broader definition, as well as (right panel) the movements of the seasonally adjusted GPD used in this study.

Figure D1a Developments in credit, narrower and broader definition, (left) and seasonally adjusted GDP, with and without corrections (right)



Note: GDP trend is the seasonally adjusted value of GDP, including one-off and transitory shocks, GDP trend-cycle is seasonally adjusted GDP without one-off transitory shocks.

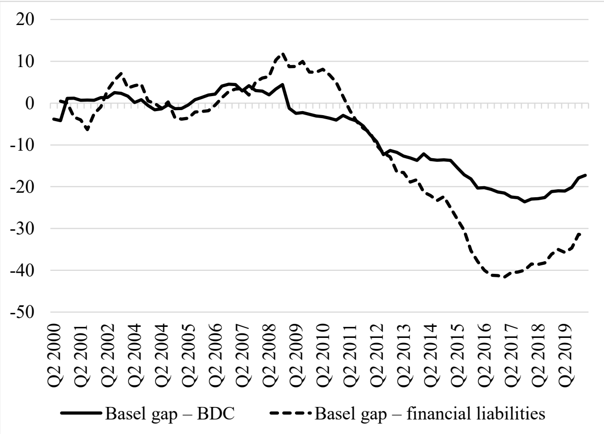
Sources: CNB (Tables D1, D5 and H15 on time series of credit); CBS (original series of nominal GDP, seasonally adjusted in the CNB).

Further consideration is given to the broadest coverage of private sector debt based on data on the stock of total financial liabilities of enterprises and households from the financial accounts (including borrowing through leasing companies, which was used to avoid restrictions on credit growth imposed on banks by the CNB in the period prior to the GFC). This definition of total credit is also used by the ECB in its credit gap calculations for Croatia. However, as official quarterly data for this series have only been available since the beginning of 2012, this introduces bias in assessing the long-term trend through HP filters. Since for the period prior to 2012 financial account data are only available on an annual frequency, for the purposes of this analysis intra-annual quarterly values of financial liabilities for the periods prior to 2012 are interpolated by developments in a broader definition of credit, separately for households and for enterprises.

Figure D1b compares the credit gap based on financial liabilities and the broader definition of credit (both obtained by filtering the credit ratio and the sum of GDP from the current and previous three quarters, with the smoothing parameter 400,000; hence the name Basel gap), where larger gap amplitudes for the broadest definition of financial liabilities are observed. This is also linked to the fact that a large increase in borrowing in the early 2000s had an impact on the upward bias in the trend of financial liabilities, which is why the second wave of a positive credit gap for total financial liabilities before the GFC occurred later in relation to the broader definition of credit (BDC).

Formal assessments and quality tests for crisis signalling were carried out in the preparation for this study, using the indicator of total financial liabilities (as in Chapter 5), which resulted in non-rejection of the zero hypothesis that the gap in the series of financial liabilities is no better in signalling the crisis than the Basel gap based on the broader definition of credit (BDC). In addition, the financial liability based gap is also worse when calculated according to alternative ways chosen in this work as the best (filtering credit and GDP series separately) using the narrower and broader definition of credit.

Figure D1b Comparison of the credit gap for the broader definition of credit (BDC) and total financial liabilities, according to the Basel gap calculation methodology



Note: In the official press releases on the calculation of the Basel gap, the CNB uses the broader definition of credit (Basel Gap — BDC), as quarterly data on total financial liabilities have only been available since 2011 (this shows extrapolation based on annual data and dynamics of the broader definition of credit).

Source: CNB, authors' calculations.

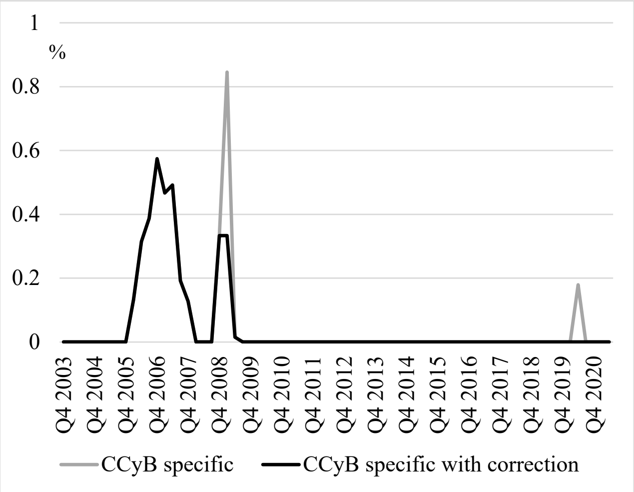
Appendix 2 — Correction of the CCyB according to the Deutsche Bundesbank approach

A possible solution in the case of sudden changes in the CCyB rate level, as was the case in Figure 2, is provided by the approach of Deutsche Bundesbank (Tente et. al., 2015). This is an additional correction, depending on GDP's trend. If the annual GDP growth rate is negative in a quarter, so that the value of the calibrated CCyB rate level is higher than in the previous quarter, the value from the previous quarter is applied, i.e.:

$$CCYB_t = \begin{cases} CCYB_{t-1}, \text{if } y_t < 0 \; and \; CCYB_t > \; CCYB_{t-1} \\ CCYB_t, \text{otherwise} \end{cases}, \qquad (10)$$

where y_t is the annual GDP growth rate. Figure D2 presents the CCyB with a correction in (10), where the peak is resolved in the calibration of the CCyB rate level after the crisis outbreak (Q1 2009 and Q2 2020). However, this complicates the procedure and the initial indicator again does not have the desirable quality of stability and absence of unnecessary reaction when there are immediate shocks to change in GDP.

Figure D2 Calibration of the CCyB without further correction in relation to the correction according to formula (10)



Source: CNB, authors' calculations.

Appendix 3 — Credit gap estimation for different smoothing parameters of GDP series

For a common approach when filtering quarterly GDP data (Hodrick and Prescott, 1997), see Ravn and Uhlig (2002). In order to confirm the robustness of the use of a smoothing parameter of 1,600 other values were also considered, with the lambda for credit set at 400,000. Due to the results in Choudhary et al. (2013) suggesting that the optimal value of the smoothing parameter for the business cycle differs from country to country, we simulated 20 credit gap variants, with the lambda for GDP changing from 300 to 2,200, with differences of 100. The lower and upper thresholds were chosen with regard to the results in the above-mentioned study, where the values of optimised smoothing parameters for the group of countries to which Croatia belongs according to the World Bank classification[41] move within the mentioned range. Figure D3 compares the evolution of these gaps, where very small differences in the values of such gaps can be observed. Therefore, the improvement of the calibration of the CCyB is mostly based on different values of the smoothing parameter related to the credit series.[42]

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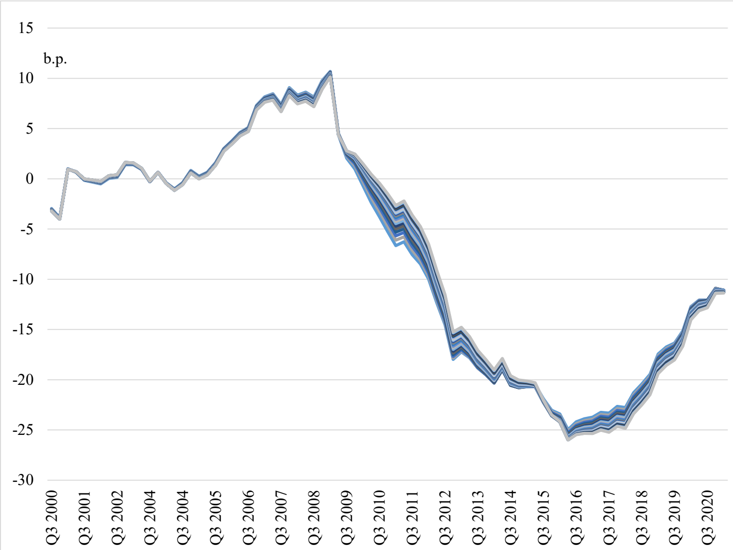
[41] For high income countries, see https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

[42] On the other issues related to the assessment of business cycles, see Arčabić and Škrinjarić (2021).

Figure D3 Comparison of credit gaps in the case of a change in the smoothing parameter when filtering the GDP series



Source: CNB, authors' calculations.

Appendix 4 — Definition of formal crises related to excessive credit growth

For the purpose of this paper, the crisis periods in Croatia, following the ESRB's recommendation and the literature that addresses developments in the Croatian banking market and describes crisis periods, are determined, as the periods: *April 1998 – January 2000* and *October 2008 – June 2012.* Due to short time series, only the second crisis is effectively used in the analysis. While its duration is defined differently from the approach used in the first calibration of the countercyclical buffer in Croatia (CNB, 2014)[43],we consider it more appropriate for the need to calibrate a countercyclical capital buffer, as it would allow for a much earlier accumulation of capital in the period before the outbreak of the global financial crisis. The arguments supporting this choice are set out in the rest of the text.

[43] The crisis in Croatia was defined as lasting from the first quarter of 1998 to the second quarter of 2000 and from the third quarter of 2011 to the end of the analysis (2013). The definition of the period of the second crisis was justified by the bankruptcies of smaller banks and a decline in aggregate bank earnings that occurred.

In the application of the signalling method, the ESRB (2018b) recommends defining the dependent variable of the banking crisis in such a way that it covers the periods of wide systemic crises related to excessive credit growth. The criteria for defining crises according to the ECB (2017) and the ESRB (2014) are as follows:

i) deposit withdrawals or losses of the banking system (non-performing loan ratio of more than 20% or bankruptcy of banks representing at least 20% of the system's assets) or public intervention in response to losses of the banking system in order to prevent such losses from being incurred,

ii) an assessment of the members of the expert group who:
   a. have excluded crises that are not systemic banking crises;
   b. have excluded periods of systemic banking crises that are not linked to the domestic credit or financial cycles;
   c. have included periods in which regulators reacted to certain domestic developments related to the credit or financial cycles that would otherwise have led to a systemic banking crisis or an external event that mitigated the financial cycle.

International research indicates several potential dates for the duration of the crisis in Croatia. According to the ECB (2017), the banking crisis in Croatia lasted from April 1998 to January 2000, and from September 2007 to June 2012, because both periods were characterised by (inter alia) excessive credit growth before its outbreak[44], which was of macroprudential significance according to the criteria specified in the ECB (2017:11). Duprey and Klaus (2017) assess the episodes of systemic financial stress for EU countries, and for Croatia these periods are: March 1999 to January 2000, October 2008 to December 2010, and September 2011 to October 2012. Finally, Dimova et al. (2016) analyse the macroeconomic characteristics of the selected CEE countries, including Croatia, in the period from 2003 to 2012, reporting that Croatia was characterised by strong foreign capital flows and credit growth until the last quarter of 2008. This is why, in addition to the first crisis taken from the ECB (2017), they define as the second crisis the one that started early in the fourth quarter of 2008 and continued until the second quarter of 2012, when the last macroprudential measures were taken (see the list in Dimova et al., 2016:74-75).

[44] Table with data for European countries is available at: https://www.esrb.europa.eu/pub/financial-crises/html/index.en.html

This conclusion is also confirmed by the assessment of Kraft and Huljak (2020), who state that two credit booms and two crises have been recorded in Croatia since the beginning of independence, referring to previous literature findings (Kraft and Jankov, 2005; Kraft and Galac, 2011). In the early 1990s, Croatia granted a relatively free entry into the banking market, followed by a credit upswing, and many of the new banks failed in 1998 and 1999. A new credit upswing emerged in the early 2000s, to which the central bank reacted by introducing strict macroprudential measures, which slowed down lending to a certain degree. When the global financial crisis hit Croatia in autumn 2008, this resulted in a halt to the inflow of foreign capital and the withdrawal of a part of deposits from domestic banks. The central bank began to release accumulated liquidity reserves with the revocation or easing of macroprudential and monetary measures (CNB, 2008 Annual Report). Several banks failed in the coming years, without the need for fiscal intervention, while Dumičić (2015) states that most of the materialised systemic risks were related to credit risk and an increase in the share of non-performing loans (particularly corporate loans). In addition, Dumičić and Šošić (2014) and Rohatinski (2011) report the monetary and macroprudential measures implemented by the CNB to increase the resilience of the system and reduce risks that would be higher had the measures not been implemented.

Appendix 5 — Gaps observed in the signalling model, abbreviations and brief description

Abbreviation	Description of gap — indicator
Basel BDC 400K	Basel gap, formula (2) – absolute, broad definition credit, credit-to-GDP ratio filtered with the parameter 400,000 – basis for comparison with other gaps ("actual" Basel credit gap)
Basel BDC r 400K	Basel gap, formula (4) — relative, broad definition credit, credit-to-GDP ratio filtered with the parameter 400,000
Basel NDC 400K	Basel gap, formula (2) — absolute, narrow definition credit, credit-to-GDP ratio filtered with the parameter 400,000
Basel NDC r 400K	Basel gap, formula (4) — relative, narrow definition credit, credit-to-GDP ratio filtered with the parameter 400,000
Basel BDC 125K	Basel gap, formula (2) – absolute, broad definition credit, credit-to-GDP ratio filtered with the parameter 125,000
Basel BDC r 125K	Basel gap, formula (4) — relative, broad definition credit, credit-to-GDP ratio filtered with the parameter 125,000
Basel NDC 125K	Basel gap, formula (2) — absolute, narrow definition credit, credit-to-GDP ratio filtered with the parameter 125,000

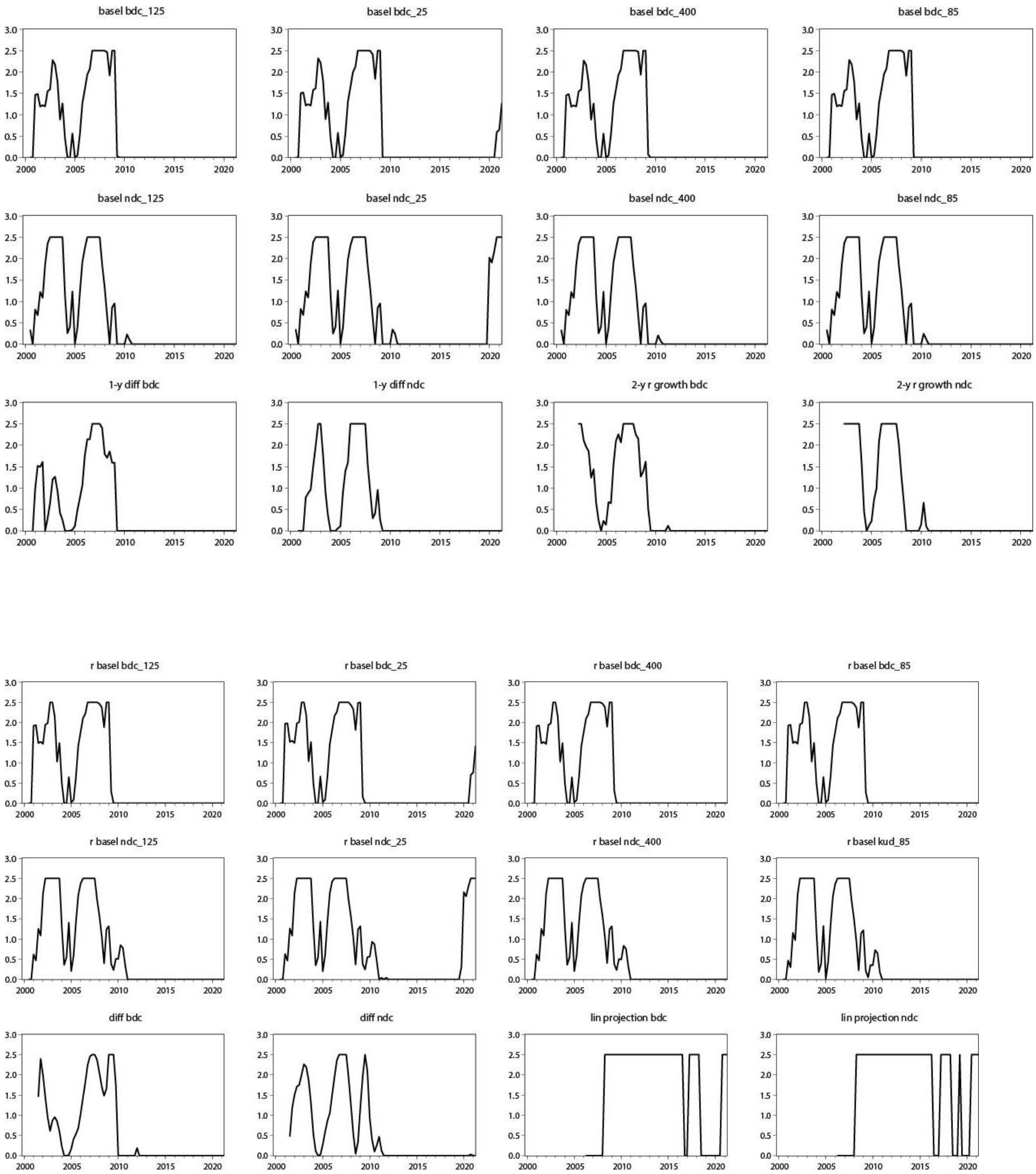
Basel NDC r 125K	Basel gap, formula (4) — relative, narrow definition credit, credit-to-GDP ratio filtered with the parameter 125,000
Basel BDC 85K	Basel gap, formula (2) – absolute, broad definition credit, credit-to-GDP ratio filtered with the parameter 85,000
Basel BDC r 85K	Basel gap, formula (4) – relative, broad definition credit, credit-to-GDP ratio filtered with the parameter 85,000
Basel NDC 85K	Basel gap, formula (2) — absolute, narrow definition credit, credit-to-GDP ratio filtered with the parameter 85,000
Basel NDC r 85K	Basel gap, formula (4) — relative, narrow definition credit, credit-to-GDP ratio filtered with the parameter 85,000
Basel BDC 25K	Basel gap, formula (2) – absolute, broad definition credit, credit-to-GDP ratio filtered with the parameter 25,600
Basel BDC r 25K	Basel gap, formula (4) – relative, broad definition credit, credit-to-GDP ratio filtered with the parameter 25,600
Basel NDC 25K	Basel gap, formula (2) — absolute, narrow definition credit, credit-to-GDP ratio filtered with the parameter 25,600
Basel NDC r 25K	Basel gap, formula (4) — relative, narrow definition credit, credit-to-GDP ratio filtered with the parameter 25,600
Diff BDC	Differentiated relative credit, broad definition
Diff NDC	Differentiated relative credit, narrow definition
1-yr diff BDC	one-year change in credit, broad definition
1-yr diff NDC	one-year change in credit, narrow definition
Lin BDC	linear projection, broad definition credit
Lin NDC	linear projection, narrow definition credit
Loc extr BDC	local extremes, broad definition credit
Loc extr NDC	local extremes, narrow definition credit
2-yr rate BDC	two-year growth rate of credit ratio, broad definition
2-yr rate NDC	two-year growth rate of credit ratio, narrow definition
Mov av BDC	Moving average, broad definition credit
Mov av NDC	Moving average, narrow definition credit
BDC 400K	Basel gap, formula (2) — absolute, broad definition credit, credit specifically filtered with the parameter 400,000
BDC r 400K	Basel gap, formula (4) — relative, broad definition credit, credit specifically filtered with the parameter 400,000
NDC 400K	Basel gap, formula (2) — absolute, narrow definition credit, credit specifically filtered with the parameter 400,000
NDC r 400K	Basel gap, formula (4) — relative, narrow definition credit, credit specifically filtered with the parameter 400,000
BDC 125K	Basel gap, formula (2) — absolute, broad definition credit, credit specifically filtered with the parameter 125,000

BDC r 125K	Basel gap, formula (4) — relative, broad definition credit, credit specifically filtered with the parameter 125,000
NDC 125K	Basel gap, formula (2) — absolute, narrow definition credit, credit specifically filtered with the parameter 125,000
NDC r 125K	Basel gap, formula (4) — relative, narrow definition credit, credit specifically filtered with the parameter 125,000
BDC 85K	Basel Gap, formula (2) — absolute, broad definition credit, credit specifically filtered with the parameter 85,000
BDC r 85K	Basel Gap, formula (4) — relative, broad definition credit, credit specifically filtered with the parameter 85,000
NDC 85K	Basel gap, formula (2) — absolute, narrow definition credit, credit specifically filtered with the parameter 85,000
NDC r 85K	Basel gap, formula (4) — relative, narrow definition credit, credit specifically filtered with the parameter 85,000
BDC 25K	Basel Gap, formula (2) — absolute, broad definition credit, credit specifically filtered with the parameter 25,600
BDC r 25K	Basel Gap, formula (4) — relative, broad definition credit, credit specifically filtered with the parameter 25,600
NDC 25K	Basel gap, formula (2) — absolute, narrow definition credit, credit specifically filtered with the parameter 25,600
NDC r 25K	Basel gap, formula (4) — relative, narrow definition credit, credit specifically filtered with the parameter 25,600
Spec	Specific gap currently used by the CNB (Figure 1)

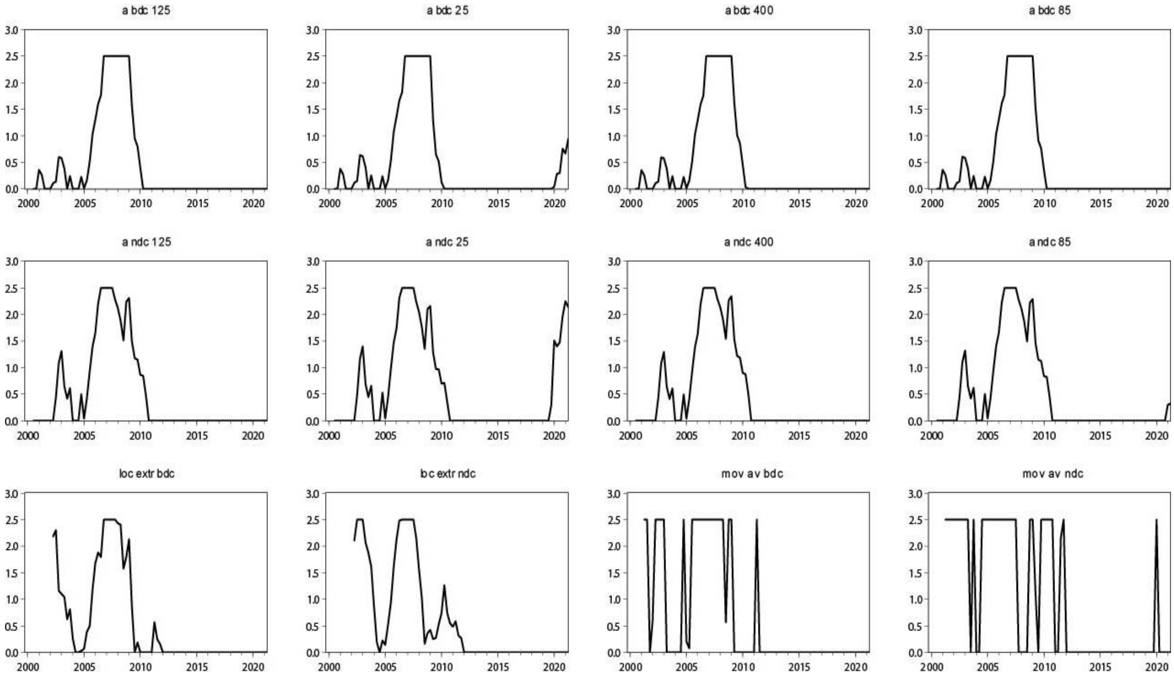
Source: Authors' materials prepared based on the discussion in Chapter 3

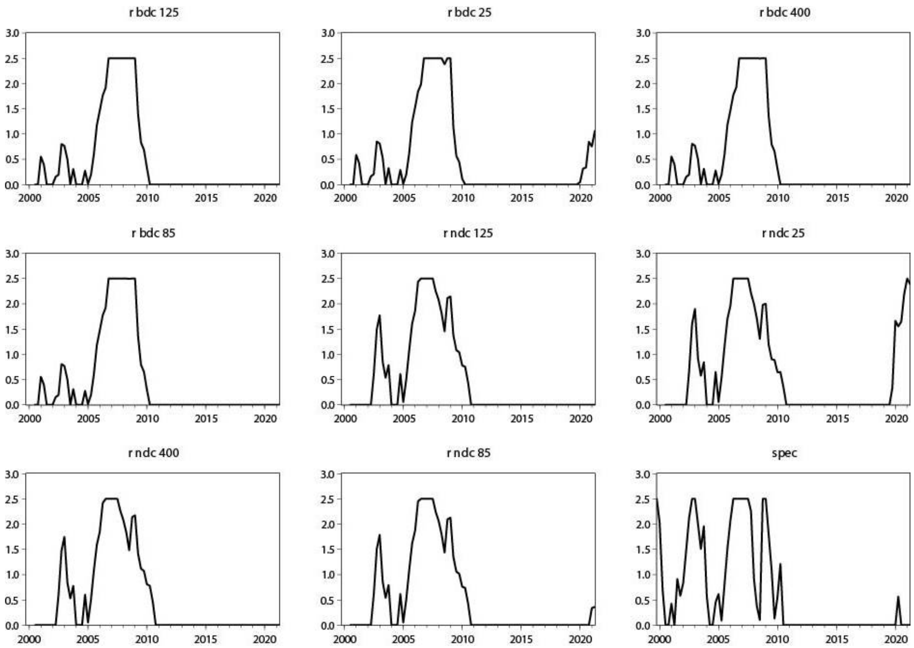
Appendix 6 — CCyB rate evolution, according to the results of estimates of lower and upper thresholds in Tables 4 and 5, for the period 16 to 5 quarters prior to the crisis

Figure D6 Comparison of simulated CCyB rates (all in %) for signalling the crisis 16 to 5 quarters ahead



Appendix 6 — CCyB rate evolution, according to the results of estimates of lower and upper thresholds in Tables 4 and 5, for the period 16 to 5 quarters prior to the crisis



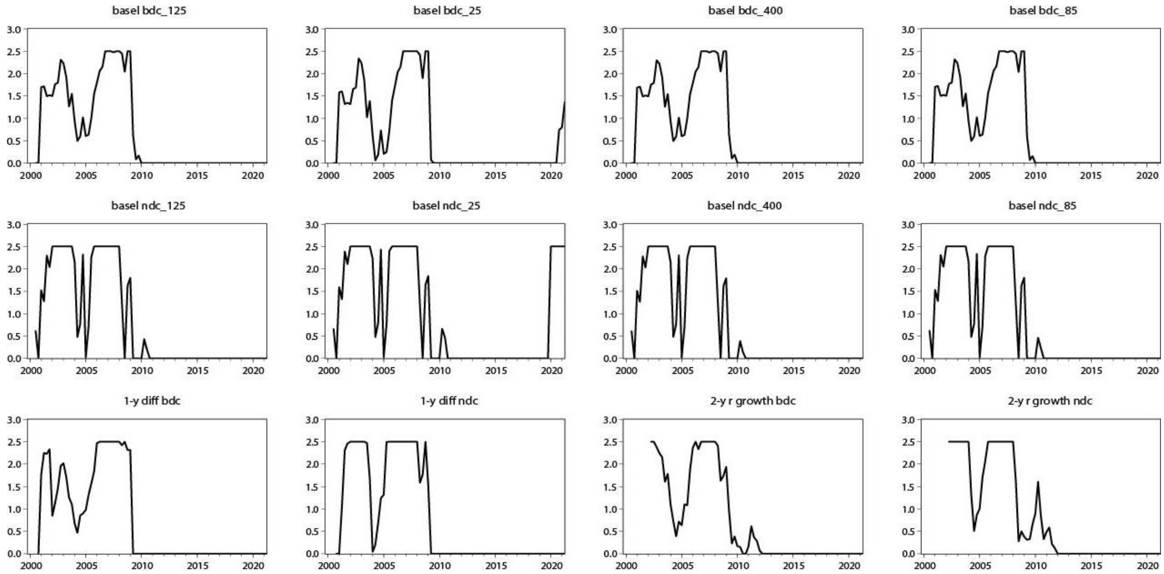


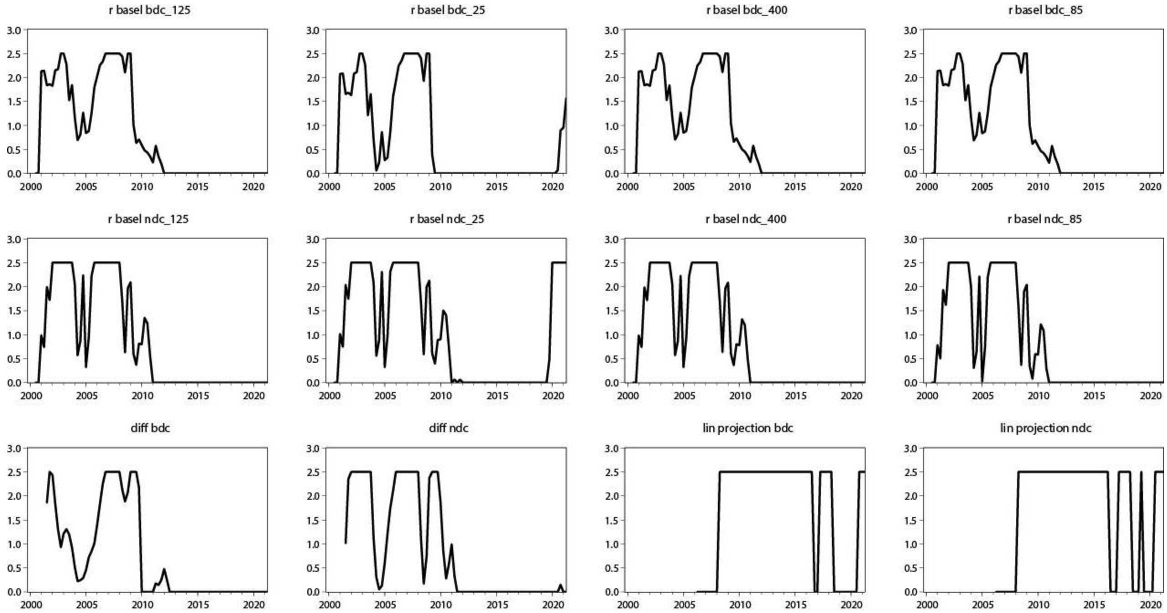
Note: a description of the series according to the abbreviations shown is given in Appendix 5.

Source: CNB, authors' calculations.

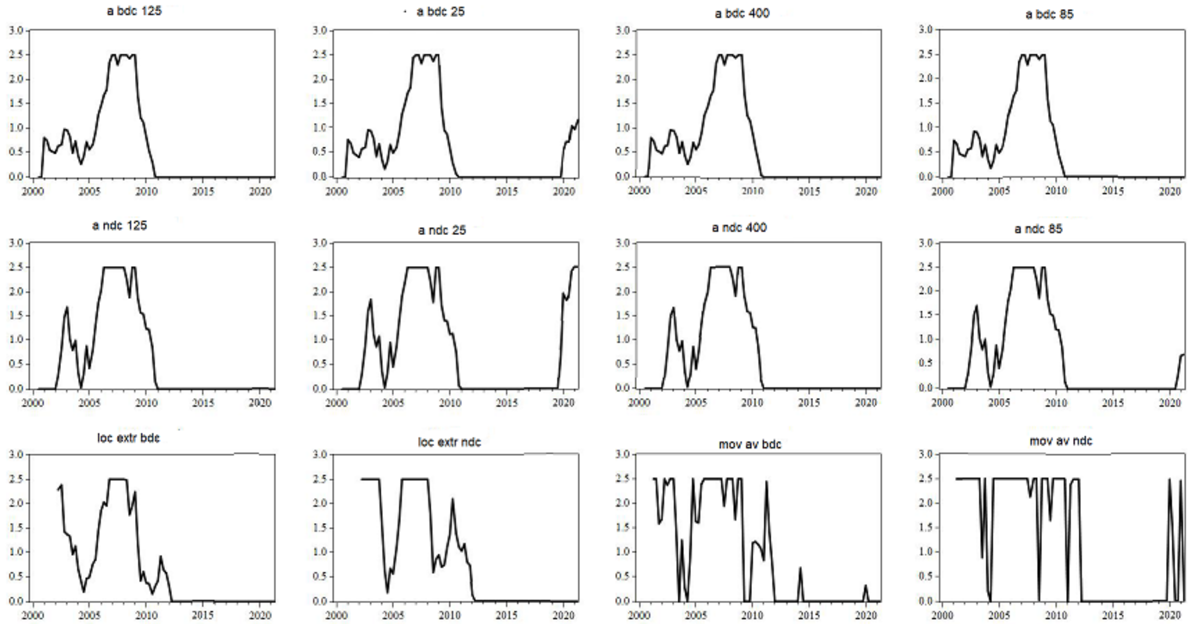
Appendix 7 — CCyB rate evolution, according to the results of the estimates of lower and upper thresholds in Tables 4 and 5, for the period 20 to 3, 12 to 7 and 12 to 5 quarters before the crisis

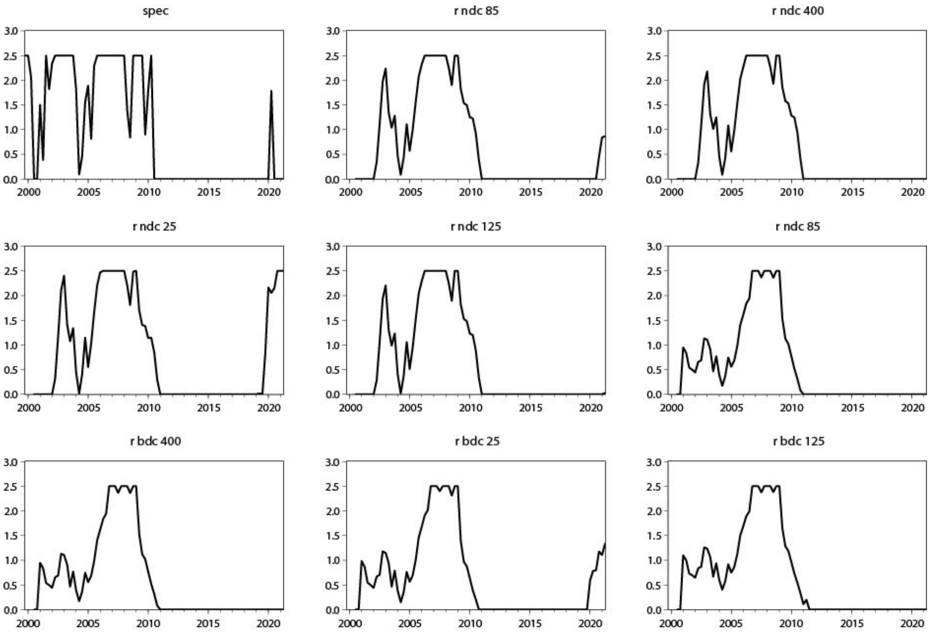
20 to 3 quarters;



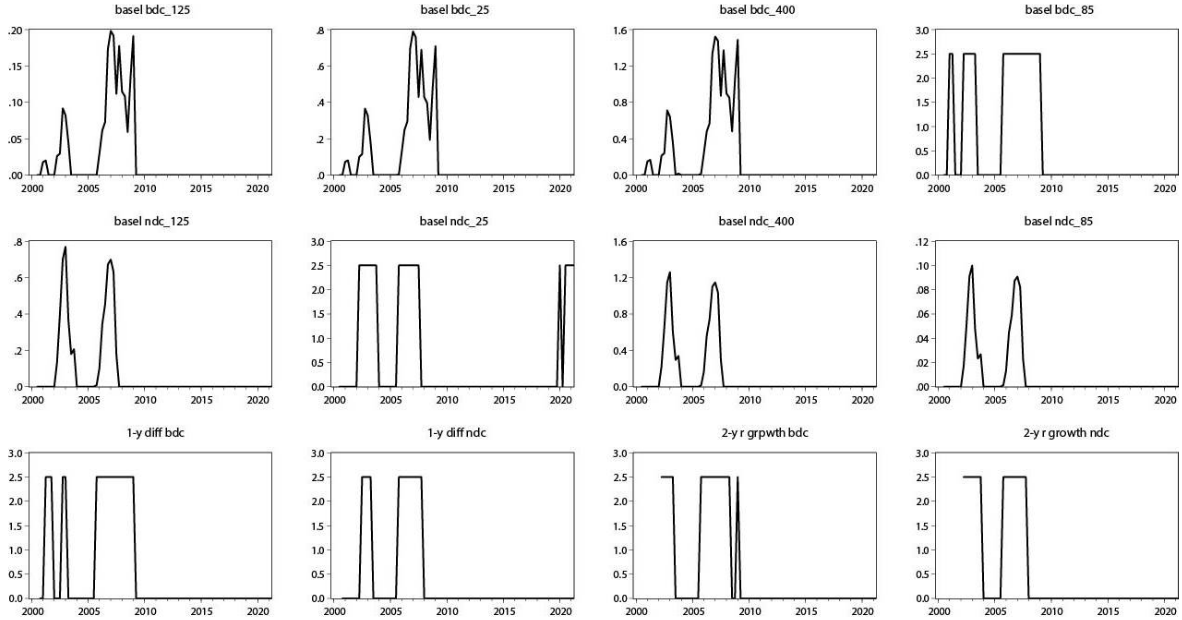


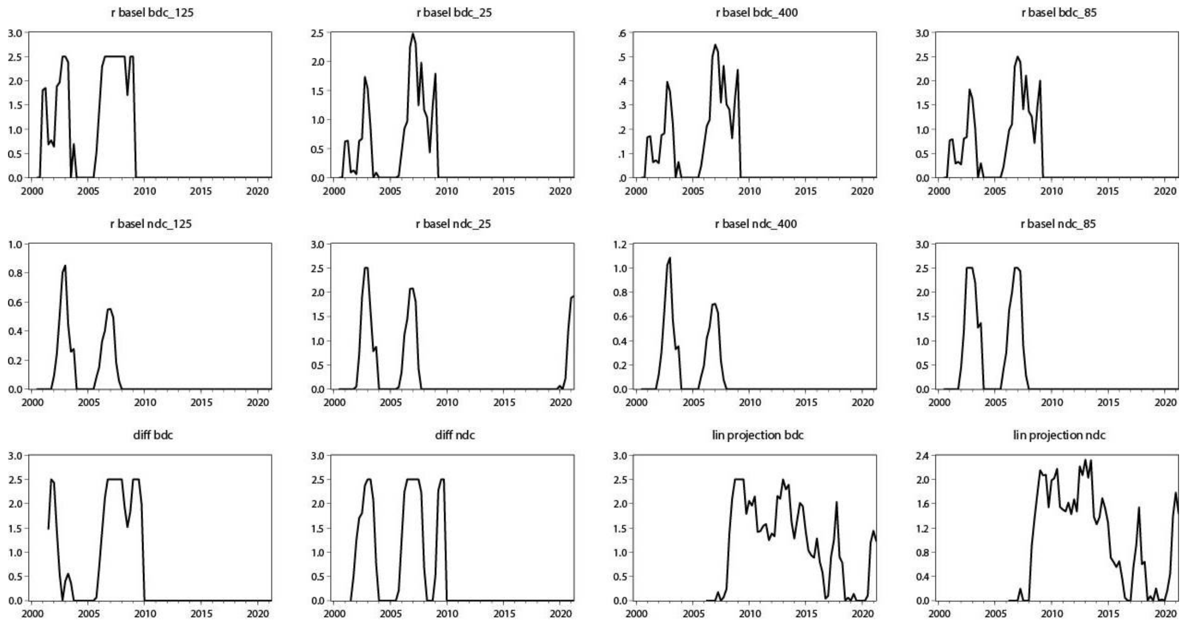
Appendix 7 — CCyB rate evolution, according to the results of the estimates of lower and upper thresholds in Tables 4 and 5, for the period 20 to 3, 12 to 7 and 12 to 5 quarters before the crisis



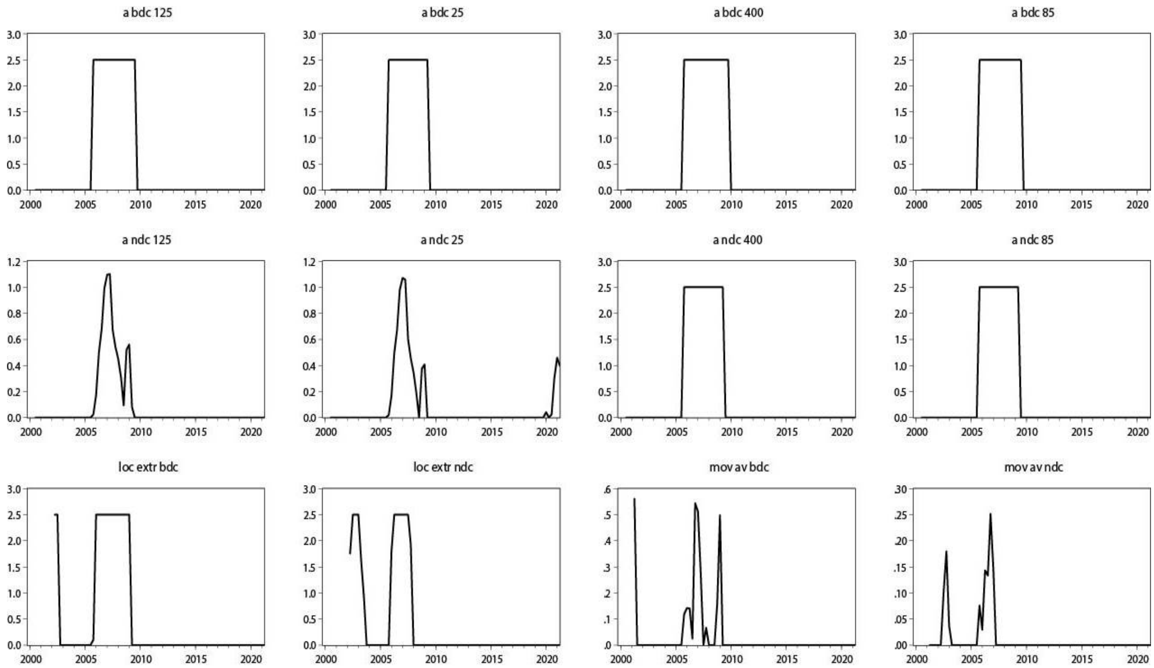


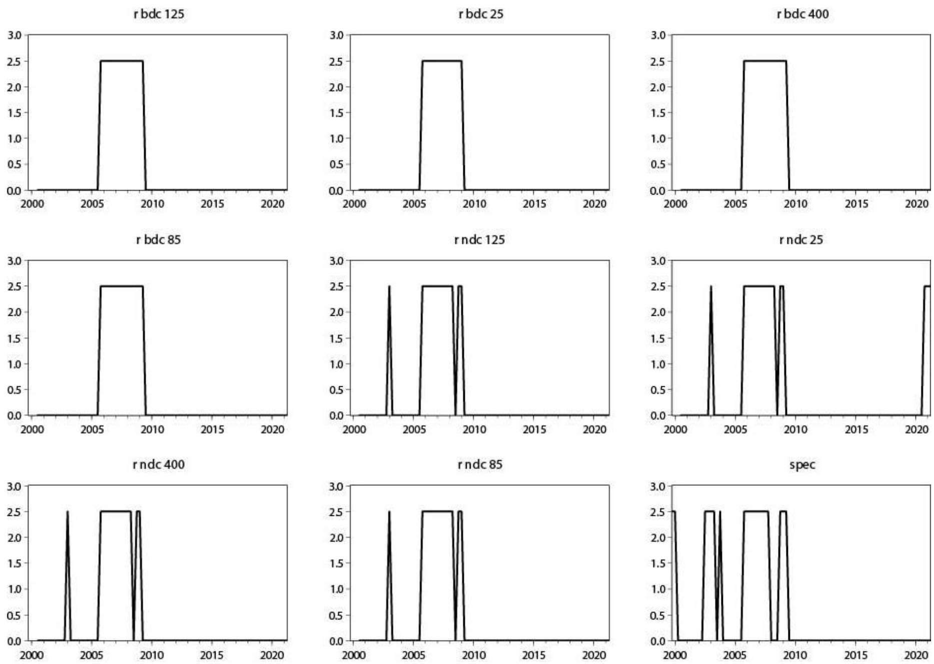
12 to 7 quarters;



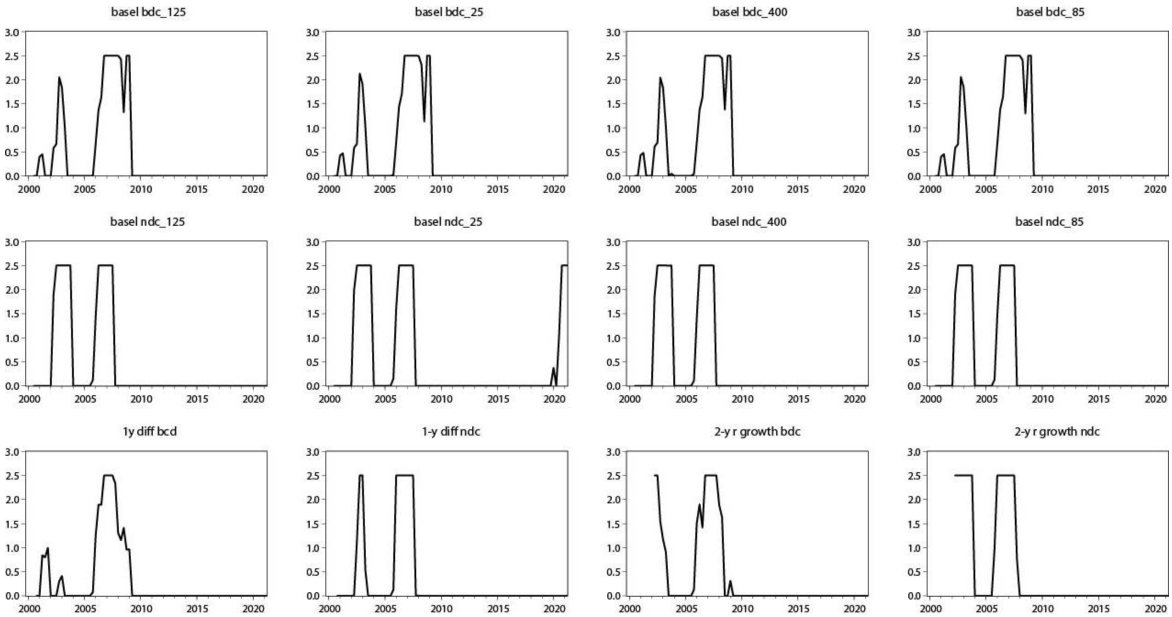


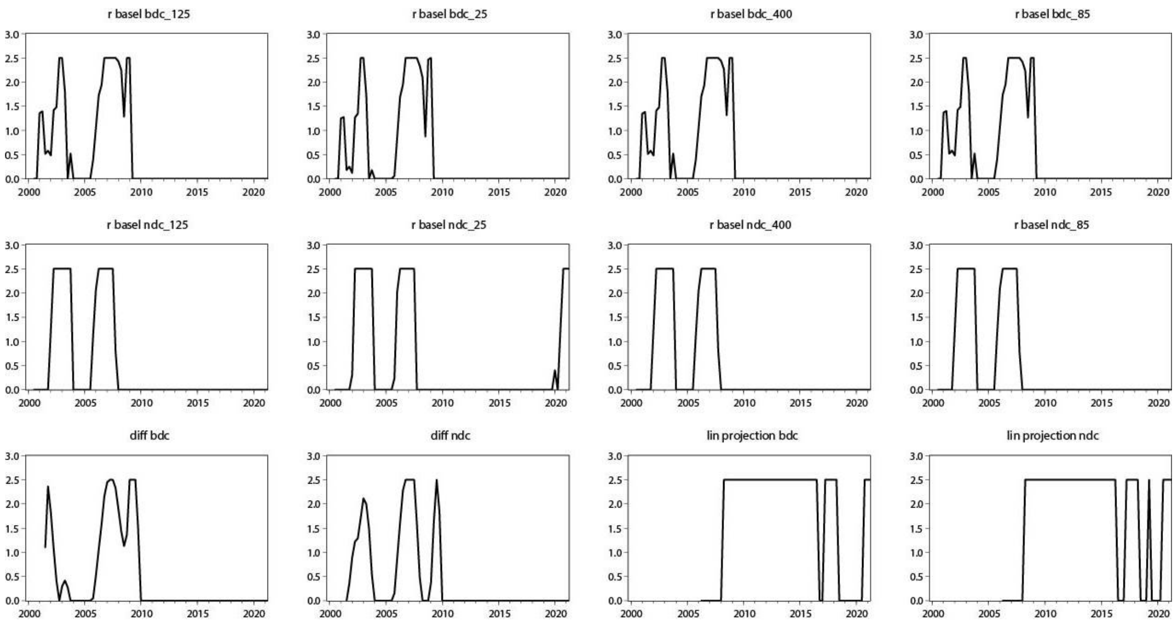
Appendix 7 — CCyB rate evolution, according to the results of the estimates of lower and upper thresholds in Tables 4 and 5, for the period 20 to 3, 12 to 7 and 12 to 5 quarters before the crisis



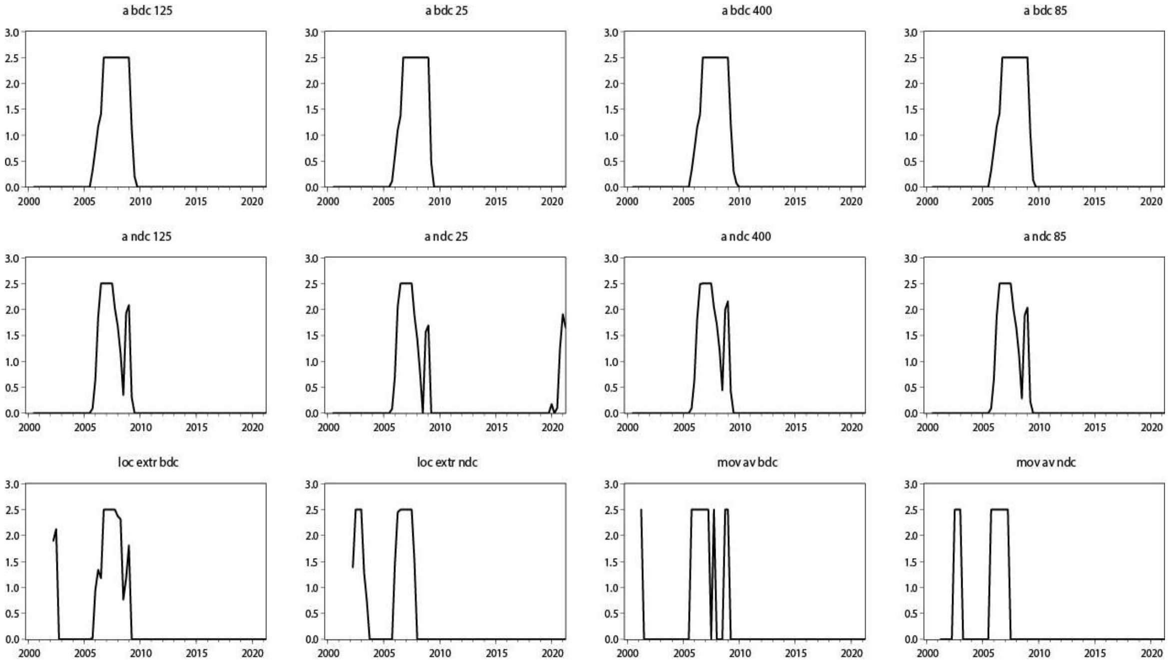


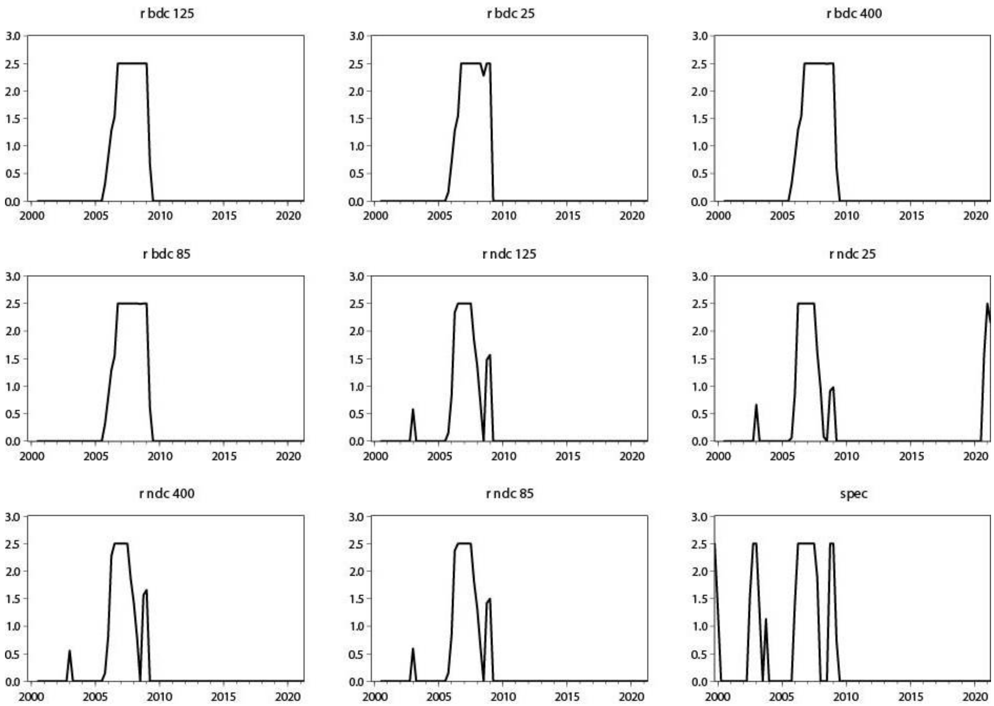
12 to 5 quarters;





Appendix 7 — CCyB rate evolution, according to the results of the estimates of lower and upper thresholds in Tables 4 and 5, for the period 20 to 3, 12 to 7 and 12 to 5 quarters before the crisis





Source: CNB, authors' calculations.

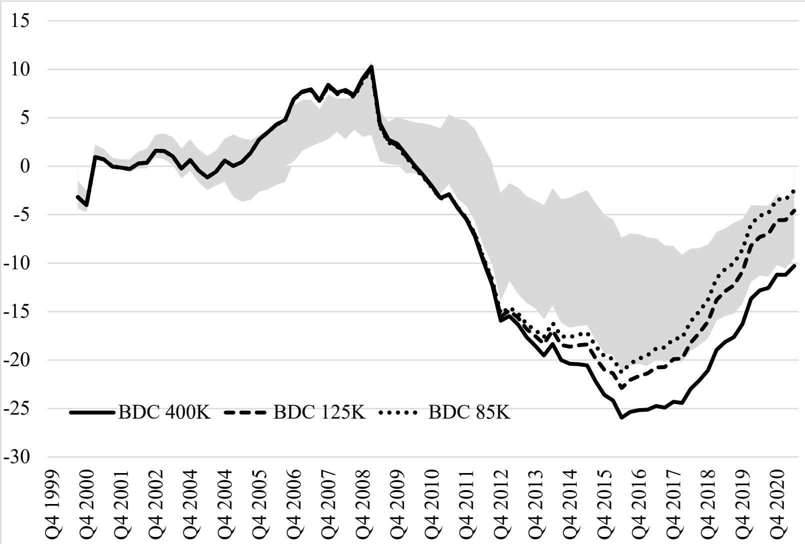
Appendix 8 — Example of HP filter with forecasting corrections

The following HP filter correction procedure was implemented for the example of credit ratios calculated by specific GDP filtering with the smoothing parameter 1,600 and by filtering the broad definition credit (BDC) with the smoothing parameters 85,000, 125,000 and 400,000. For the first t (= 20) quarters, the HP filter was performed (separately for the credit series, separately for the GDP series) in order to estimate the credit gap for the initial period. Thereafter, for all subsequent data, in the period t+1, t+2, until the end of the sample, two types of forecast are used to extend the original series. The filtering is thus carried out on a longer series of data, which mitigates the "last point problem" (in the filtering process, the last point gets greater weight in the trend assessment and thus has a stronger impact on the results).

The first approach to the forecast calculation is the estimate of the moving average for h = 4 or 8 quarters in advance, based on the previous 3 quarters and the current quarter, i.e. the previous 7 quarters and the current quarter (two variants, MA 4 and MA 8). Such forecast values are added after the initial t data, a HP filter is carried out on the extended series to calculate the long-term trend and gap at time t+1. When data for credit and GDP in the period t+1 become available, they are added to the first t values of the credit and GDP, new forecast values are estimated at MA 4 or MA 8 moving averages, which are added to the series after the first t+1 observations, and the HP filter is used on such extended series to calculate the gap at the time t+2. The procedure is repeated until the end of the sample of available data, considering the same value of moving averages for the last h observations.

The second approach is the application of the AR(p) model for p equal to 1, 2, 3 and 4, where the variable ratio is differentiated due to the non-stationarity of the credit gap. For the first 20 datapoints of the differentiated ratio the following h = 8, 12, 16 and 20 out of the sample values (from 21 onwards) are projected, which are added to the original data. Then, the HP filter is implemented on such extended series, and the first 20 values of the long-term trend and gap are collected. Thereafter, for ratios from 2 to 21 quarters, a new model is estimated, h values are forecasted, which are added to the original HP filter series, taking the 21st gap value, repeating the process until the end of the sample.

Figure D8 Distribution of HP filter credit gaps with forecasting corrections (shaded area)



Source: CNB, authors' calculations.

Figure D8 shows the filtering results on extended time series by means of forecasts, using broad definition credit subject to three different smoothing parameters. The shaded area represents the distribution of about forty credit gaps obtained using different models of projection outside the sample (from the different length of the forecast horizon, to the value of the number of backward shifts in moving averages or autoregressive components). A reduction in the gap amplitude can be observed compared to the application of the "normal" HP filter (without forecasts), and that at the end of the sample the best indicators were selected in line with the filtering results with forecasting corrections (i.e. they are within or close to its distribution). We hereby confirm the appropriateness of selecting new alternative gap indicators.

In future research, this adjusted long-term trend calculation approach can be improved by analysing additional models for out-of-sample forecasts and applying filters with forecast corrections to other alternative credit gaps. Some further potential corrections to the GDP series are presented in Appendix 10.

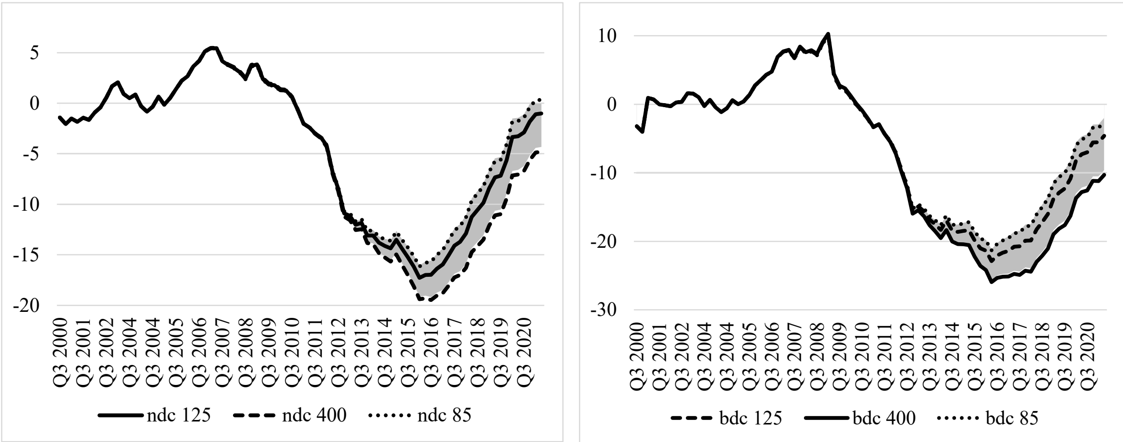
Appendix 9 — Interval assessments of selected best gaps and corresponding CCyB rates

As credit gaps have been subjected to the point estimate, it is also necessary to consider what impact the so-called interval assessment would have on credit gap assessment and real-time decision-making. Given the specific nature of the method used to calculate the selected indicators, we believe that it is not possible to calculate confidence intervals in a conventional way — in the sense that the state space representation of the HP filter is estimated and the estimation errors are analysed from this estimate. This is because the credit and GDP series are filtered separately, the corresponding series of trends are included in the calculation of the credit and GDP trend ratio, which is compared with the actual ratio in order to calculate the gap. Therefore, the interval assessments in this procedure can only be used for the purpose of observing either the credit gap or the GDP gap, but not the credit gap that is the primary objective of this study.

However, an average and standard deviation for a given quarter will be calculated in order to assess robustness for some groups of indicators and a lower and upper threshold for the estimate will be made. This was done on the example of the absolute gap for the narrower (NDC) and broader (BDC) definition of credit, as well as the corresponding CCyB interval, shown in figures D9a and D9b. As the distributions are very small (especially on the right panel), almost negligible, the correct selection of the best specific indicators is confirmed. However, only 3 indicators are used to calculate the interval estimates, as due to the definitions of absolute and relative gaps, and the narrower and broader definition of credit, these indicators need to be separated for the purpose of calculating average values and standard deviations. Therefore, the best 12 indicators must finally be divided into 4 groups of 3 indicators, although the interval estimate would be much more meaningful and produce more reliable results if several dozen instead of 3 indicators were available. Therefore, when making interval assessments, we recommend using those based on the out-of-sample forecast shown in Appendix 8.

Figure D9a Interval assessments of absolute gaps

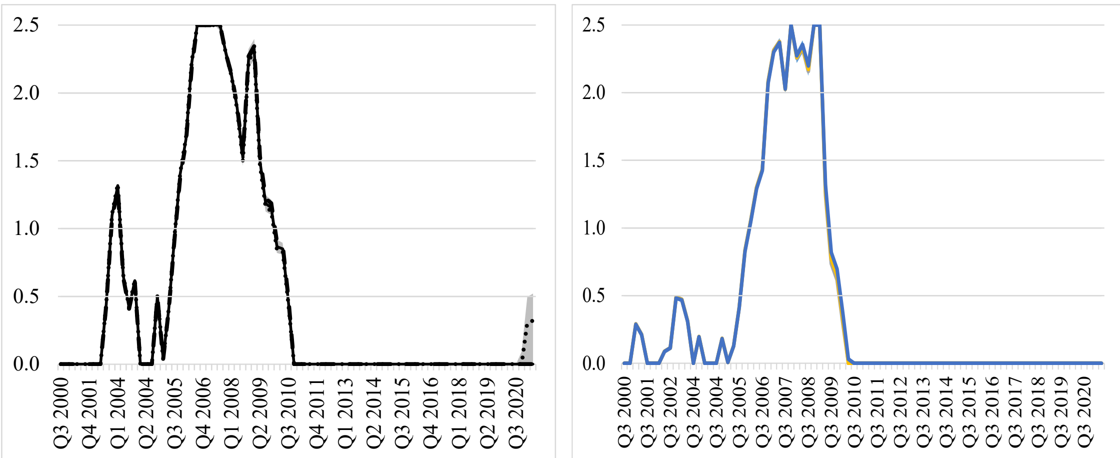
a. NDC credit definition **b. BDC credit definition**



Source: CNB, authors' calculations.

Figure D9b Interval assessments of CCyB values

a. NDC credit definition **b. BDC credit definition**



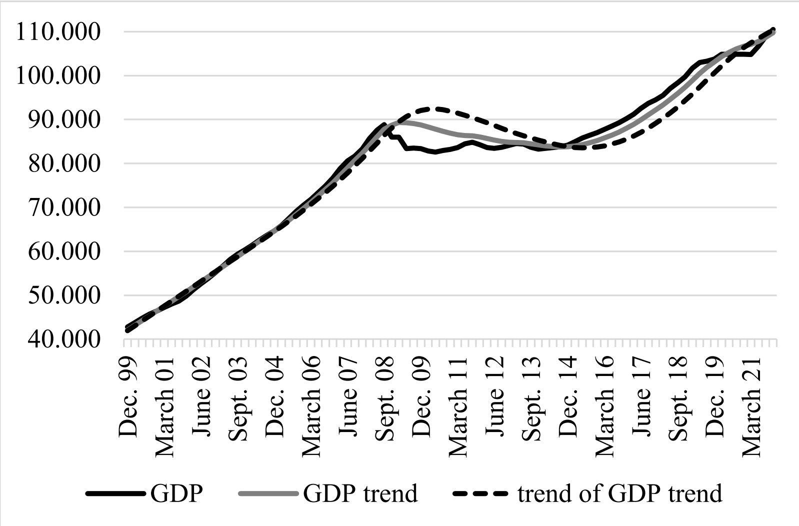
Source: CNB, authors' calculations.

Appendix 10 — Options for correcting the GDP series in case of exceptional shocks

This research was prepared during the COVID-19 pandemic, which had a considerable negative impact on GDP value, making it significantly more difficult to estimate its cyclical and long-term developments. Calculations and calibrations are subject to new information in each quarter. The smoothing of series can be done during seasonal adjustment, and the assessment of the GDP gap, as well as by the examination of the GDP series before statistical filtering. While the entire dynamics of GDP, including shocks such as the one caused by the coronavirus, is important, because of the importance of the maintenance of stability in the credit gap assessment, we will consider additional possibilities in which GDP can be smoothed.

In practice, there are several ways to correct the GDP series, which we describe briefly and state which was ultimately chosen. Some central banks use the HP trend of GDP as an "actual" value, which then enters into the calculation of the ratio to credit (see Slovakia or Switzerland), which means that the GDP series is filtered twice. This makes the interpretation of the results difficult, so that, due to the nature of the optimisation process for the calculation of the HP trend, the dynamics of the obtained series is additionally decelerated. In addition, the periods during which GDP is gradually contracted, such as the one at the time of the GFC, are characterised by a GDP series that becomes too smooth, which further distorts the picture of the credit ratio, since the way the target function is optimised in the HP filter leads to a gap in the reaction of the trend to newly added GDP data. As a result, the implementation of the HP filter over the GDP trend would result in a new trend that would capture the GDP contraction too late, with the result that the decision on the value of the CCyB could be made too late as well in relation to real GDP dynamics (see Figure D10). For these reasons, we did not select this approach to the correction of GDP.

Figure D10 Comparison of GDP dynamics, GDP trend and trend of GDP trend



Source: CNB, authors' calculations.

Another approach is the application of the Kalman filter as part of the state space of the HP filter representation (see details in Jönsson, 2017). In this context, binary variables can be included in the observed values equation or the equation of stock, which may have resulted from a temporary shock (demand shock) or a permanent shock (supply shock). In order to test this approach, and following the results in Grgurić et al. (2021), several dozens of different models were estimated, in which we changed parametric values with binary variables that take into account shocks during 2020, as well as the combinations of types of shocks. However, if the approach taken in the mentioned study is followed, there is still a large GDP gap that leads to jumps in the credit-to-GDP ratio and the associated gap. Given the demanding process of calibration and the unsatisfactory results, this approach is also not considered suitable for calculating the credit gap to be communicated to the general public. Finally, the simplest approach would be to fix the value of GDP to the period before the outbreak of the negative shock in GDP, e.g. in the case of the COVID pandemic to Q1 2020 or the 2019 average. In order to generalise the application of the correction for any quarter, it can be applied only to changes in GDP that are so strong that they are at the tails of the distribution. Consequently, quarterly GDP growth rates were examined for the period from 2000 to the first quarter of 2020 (until the outbreak of the COVID-19 crisis) and the 1st and 99th percentile of the correction were set for the lower and upper threshold of the correction. In practice, when the growth rate is below the 1st percentile or above the

99th percentile, GDP in that quarter would be adjusted by taking on the value of the previous quarter GDP, and further calculations would include such a "new" GDP. If necessary, the process would continue in the next quarter. In the whole historical period, this approach only resulted in GDP corrections from the second to the fourth quarter of 2020, when we took on the value from the first quarter of the same year for new GDP values, and to the second quarter of 2009. The result of this adjustment of the GDP series was that the estimate of the CCyB level remained almost unchanged, relative to the analysis carried out with data up to the third quarter of 2021. This provided a basis for the follow-up to situations of extremely large changes in GDP and credit gap.

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