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Introduction of the composite indicator of cyclical systemic risk in Croatia: possibilities and limitations

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Abstract

Macroprudential policy has the important task of monitoring the accumulation of cyclical systemic risks, using a wide range of indicators. Decisions on the use of instruments that seek to mitigate the pro-cyclicality of the system should be made according to properly defined and stable indicators that signal future trends in the cycle itself. In its Recommendation, the European Systemic Risk Board considers several important categories of indicators for monitoring cyclical risks. Since the credit gap, the main indicator of cyclical risks, has shown numerous shortcomings in practice over the years, composite indicators have been developed in the literature. As there has been no such composite indicator in Croatia so far, this research considers several popular approaches to constructing composite indicators of cyclical risks for Croatia. As there are several different approaches currently available, this research considers their characteristics, advantages and shortcomings, with special reference to Croatian data. Comparing the composite financial cycle indicator, the cyclogram, the systemic cyclical risk indicator, as well as additional possibilities of data aggregation in terms of principal component analysis and the overheating index, the results indicate that the issue of defining an adequate indicator for Croatia is a demanding task. This is due to the short time series, the absence of characteristics of other types of crises that are available for other countries, the instability of certain variables relevant for monitoring cyclical risks, complexity of communication with the public, etc. Finally, based on the discussion, the best indicator is chosen, and the possibilities of calibrating the countercyclical capital buffer are considered. This paper provides an overview of different approaches, with a special focus on a comparison of them, which has not been dealt with in the literature. It provides proposals for improving individual indicators and analyses the possibility of calibrating the countercyclical capital buffer.

Keywords: systemic risk, macroprudential policy, countercyclical capital buffer, composite indicators, cyclical risks

JEL: C14, C32, E32, 344

Sažetak

Makroprudencijalna politika ima važan zadatak pratiti akumulaciju cikličkih sistemskih rizika pomoću širokog raspona indikatora. Odluke o upotrebi instrumenata kojima se nastoji ublažiti procikličnost sustava trebaju se donositi temeljeni na ispravno definiranim i stabilnim indikatorima koji na vrijeme signaliziraju buduća kretanja samog ciklusa. Europski odbor za sistemske rizike u svojoj Preporuci razmatra nekoliko važnih kategorija indikatora praćenja cikličkih rizika, a kako je kreditni jaz kao glavni indikator cikličkih rizika tijekom godina pokazao brojne nedostatke u praksi, u literaturi se razvijaju kompozitni indikatori koji obuhvaćaju širi skup informacija o kretanju cikličkih rizika u ekonomiji. Kako u dosadašnjoj praksi u Hrvatskoj nije postojao takav kompozitni indikator, u ovome istraživanju se razmatra nekoliko popularnih pristupa konstrukcije kompozitnih indikatora cikličkih rizika upravo za slučaj Hrvatske. Kako se radi o nekoliko različitih pristupa koji su trenutno dostupni, ovo istraživanje razmatra njihove karakteristike, prednosti i nedostatke, s posebnim osvrtom na hrvatske podatke. Usporedbom kompozitnog indikatora financijskog ciklusa, ciklograma, indikatora sistemskog cikličkog rizika, kao i dodatnim mogućnostima agregacije podataka u pogledu analize glavnih komponenti i indeksa pregrijavanja, rezultati upućuju da je problematika definiranja adekvatnog indikatora za slučaj Hrvatske zahtjevan zadatak. Razlozi se nalaze u kratkim vremenskim serijama, gdje izostaju karakteristike različitih tipova kriza koje su zahvatile druge zemlje, nestabilnosti pojedinih varijabli relevantnih za praćenje cikličkih rizika, kao i tumačenju rezultata za komunikaciju s javnosti. Na kraju se temeljem diskusije i odabira trenutno najboljeg indikatora razmatraju mogućnosti kalibracije protucikličkog zaštitnog sloja kapitala s obzirom na dobivene rezultate. Doprinos istraživanja se sastoji u sažimanju pregleda različitih pristupa na jednome mjestu, s posebnim fokusom na usporedbu, što se prethodno ne nalazi u literaturi, u prijedlozima unapređenja pojedinih indikatora, i dodatno, što se detaljno analizira mogućnost kalibracije protucikličkog zaštitnog sloja kapitala, što također nedostaje u primjenama.

Ključne riječi: sistemski rizik, makrobonitetna politika, protuciklički zaštitni sloj kapitala, kompozitni indikatori, ciklički rizici

JEL: C14, C32, E32, 344

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1 Motivation for the introduction of a composite indicator

Monitoring risks and identifying the phases of the financial cycle as part of macroprudential policy are extremely difficult, yet very important tasks. Recognising the cyclicality of the financial system is important for the calibration and implementation of the countercyclical capital buffer (hereinafter referred to as the CCyB). More specifically, the introduction of the countercyclical capital buffer in accordance with the recommendations of BCBS[1] (2011) and ESRB[2] (2014) was aimed at mitigating the pro-cyclicality of the financial system, which was one of the causes of the global financial crisis (GFC). The literature recognises the issue of turning points in the financial cycle, namely the peak and the connection with systemic crises in the banking system, since one of the stylised facts about financial cycles is the fact that accumulated risks can be identified and measured in the expansionary phase of the cycle (see Borio, 2012). During periods of high optimism in the upward phase of the financial cycle, different types of risks can be underestimated, whether consciously or unconsciously, which affects their valuation and, coupled with the increased risk appetite, results in the build-up of systemic risks in this phase (Finansinspektionen, 2021). As one of the core tasks of macroprudential policy is to reduce the pro-cyclical nature of the financial cycle and the build-up of systemic risks, indicators that help to identify the phase of the financial cycle need to be continuously monitored. The CCyB is one of the main instruments serving this purpose. Its application and calibration are largely based on the Basel credit gap. According to the ESRB Recommendation (2014a), the CCyB is defined as a piecewise function of the credit gap, and is calculated by using the credit-to-GDP (gross domestic product) gap, given that numerous research papers in the last ten years have suggested that this is the best single indicator for signalling banking crises[3].

However, the many shortcomings[4] of the Basel credit gap have led to alternative approaches to modelling the financial cycle and the calibration of the CCyB. There are

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[1] *Basel Committee on Banking Supervision.*

[2] *European Systemic Risk Board.*

[3] 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).

[4] See Appendix 1 and the analysis provided in Škrinjarić and Bukovšak (2022a, 2022b).

even meta-analyses that have been developed, summarising the empirical findings in practice, such as BIS (2017), Tölö et al. (2018), Castro et al. (2016). For an exhaustive list of variables that have been tested in practice as predictors of financial crises, see Table 1 in Tölö et al. (2018), which provides an overview of the number of countries for which research has been conducted, details about research, as well as the variables used. There are around ninety variables within the ten categories of indicators being analysed in terms of their signalling performance (followed by many more given the different variants and transformations of the variables concerned; see Chapter 3 of this research paper). Most of the research papers consider applying early warning models for individual variables in order to identify their predictive power to signal future crises. However, such analyses are useful if there are sufficient data for the variables under consideration, covering several crisis periods. Otherwise, the results could be biased, as could be the case with Croatian data, given the short time series of relevant variables. Findings from previous research papers can certainly serve as a starting point in identifying the indicators to be monitored within the scope of macroprudential policy. The disadvantage of the early warning model is that the methodology allows for examination of the predictive power[5] of only one[6] indicator. This drawback may be addressed by using probit or logit models in which more explanatory variables can be included. However, using such models allows only for the assessment of the likelihood of a crisis, without providing much insight into the specific reference levels of individual variables to be used in the calibration process. In this case, the reference level of the likelihood of a crisis should be modelled and compared with the actual dates of crises, while further credibility of estimates can be achieved by including the experience of other countries and conducting a panel analysis (see BoL, 2015). There are also machine learning models that could be used to reap the benefits of the previous approaches. However, such an approach is still in its infancy and, according to the ECB (2019a), its robustness and modelling options are currently being explored[7].

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[5] For details on the methodology, see Lang et al. (2019), Alessi and Detken (2019), Candelon et al. (2012), Kaminsky and Reinhart (1999), and the sources mentioned in ESRB (2018).

[6] Multivariate early warning models can be considered by way of exception. However, they include a combination of early warning models for individual indicators, where the best indicators are selected and the results obtained are attempted to be synthesised by using logit or probit models, meaning that the entire procedure is too complicated for interpretation and use in practice. See Schüler et al. (2015).

[7] Some of the applications and sources of literature relating to macroprudential policy can be found in Fouliard et al. (2021), while machine learning options and applications in central banking may be found in Doerr et al. (2021).

Macroprudential policy makers have a need to synthesise the results obtained from the estimates, which may lead to different conclusions, depending on the indicator under consideration, the method of data synthesising and other factors affecting the modelling and analysis process. Consequently, central banks have been increasingly employing an approach aimed at synthesising financial cycle information from a number of indicators into a single measure, given the increasing number of indicators considered in practice. Arbatli-Saxegaard and Muneer (2020) provide an overview of the current practice of central banks in Europe concerning the analysis of certain variables for the purpose of monitoring the financial cycle and the calibration of the CCyB. Based on public information available on central banks' websites, the paper provides a chart (Arbatli-Saxegaard and Muneer, 2020:22), showing the total number of indicators used in a given country, along with the classification of indicators (credit development measures, macroeconomic measures, measures related to household sector debt burden, etc.). The countries included in the analysis use from six to thirty-five individual indicators. The Czech Republic, Norway, Cyprus, Denmark, Germany, Ireland, Sweden, the UK, Belgium, Poland and Romania use over twenty indicators. The Czech central bank uses the financial cycle indicator (FCI) index constructed in Plašil et al. (2015), the Slovak central bank uses the cyclogram developed in Rychtárik (2014) and the modified cyclogram (Rychtárik and banka Slovenska, 2018), while Lang et al. (2019) developed the d-SRI (domestic systemic risk indicator) which is based on averaging the values of variables that individually have the best power to signal future crises. The latter is used in the ECB (European Central Bank) for the euro area as part of the Financial Stability Report. All these composite measures or indicators are useful in the implementation of macroprudential policy as they summarise results into a single value (the index that is being constructed), providing insight into the dynamics of individual components of the index.

Taking into account the results of the previous research on predicting financial cycles based on a large set of indicators, the next step involves synthesising the selected variables into a composite indicator, in order the better to understand information on the financial cycle, rather than considering several individual indicators. The main topic of this paper is to give an overview of the current approaches to constructing a composite indicator, as well as to analyse their strengths and shortcomings, with a particular emphasis on Croatian data. The paper's main contribution is the calibration of the CCyB value based on the obtained results, which is not often found in the literature because it is a relatively challenging task, which the regulators tend to undertake with a certain degree of flexibility, and are unwilling to share all the details with the public.

Therefore, macroprudential policy makers may benefit from the results of this research paper given that the synthesising of data in the form of composite indicators makes it easier to monitor the dynamics of the individual variables they comprise, and given that it provides guidance on how to determine the level of the CCyB by taking into account the assessment of the level of accumulation of systemic risks in the system, i.e. the assessment of the position of the economy in the financial cycle. In addition, the use of such an indicator can contribute to at least mitigating, if not preventing, systemic financial crises, of the kind that have resulted in significant losses in the past (for more information on assessing the effects of crises on the reduction in total output, see Laeven and Valencia, 2012, and Lo Duca et al., 2017).

The main results of the working paper are presented below. Obviously, it is hard to select a single indicator that would be most suitable in terms of signalling systemic risk cyclicality trends in a timely manner and of meeting the criteria pertaining to simplicity, communication with the public, stability and other criteria relevant for macroprudential policy makers. Based on the comparison of the financial cycle composite indicator, the cyclogram, the indicator of cyclical systemic risk, as well as additional data aggregation options regarding the analysis of main components, the overheating index and several proposed modes of transformation and aggregation of data, the results suggest that attention should be paid to both the importance of individual categories of risk cyclicality measures and the interpretation of the final result. Against this background, it has been concluded that the composite indicator of cyclical systemic risk, as defined in Lang et al. (2019) and adjusted to Croatian data, is adequate for monitoring the cyclicality of systemic risk. The calibrations of the CCyB values based on this indicator result in comprehensible interpretations, although attention should be paid to the problem of short time series and the specific behaviour of some variables related to the most recent global financial crisis.

The remainder of this paper is structured as follows. Part 2 deals with the properties and the construction of composite indicators in general. Part 3 contains a description of variables used in calculating most indicators in practice, providing an insight into why certain variables and categories of variables are considered in modelling. Parts 4, 5 and 6 provide explanations of the individual indicators used in the construction of the composite indicator and their relevance for continuous monitoring, presenting the results of the analysis of each of the composite indicators. These three parts deal with three indicators and contain a description of the approach used, of the reasons why certain variables have been selected, as well as of the transformations and methods of aggregation, providing a complete overview of these approaches. Part 7 deals with a comparison of them and the selection of the indicator appropriate for Croatia. Part 8 covers additional ways of the aggregation of data that can be applied to the previously analysed complete indicators, as well as their strengths and disadvantages. Part 9 deals with the calibration of the CCyB values taking into account the selected constructed indicators. Lastly, part 10 concludes the paper.

2 Cyclical composite indicators in general

When constructing cyclical composite indicators, the following properties should be kept in mind, according to the handbook on cyclical composite indicators prepared by the EU[8] and UN[9] (2017). First, composite indicators should aim to extract, in real time or for the near future, relevant signals of the phenomenon under consideration, with such signals being either cyclical or latent (not directly measurable). Cyclical signals are criticised for their application of statistical filters that depend on a number of assumptions (such as the HP filter[10] and the credit gap). The main principles for the compilation of cyclical composite indicators are objectivity and impartiality, methodological soundness, clarity, transparency, interpretability and readability, consistency and comparability. In practice, not all of these principles can always be fully complied with, given that, for example, the selection of variables included in a particular indicator is to a certain extent biased. Interpretability from the perspective of the general public may also be an issue, given the underlying methodology used. The latter is of utmost importance in order to preserve the credibility of macroprudential policy, through clear and timely communication.

In addition, the OECD (2012) defines the desirable properties of variables comprising composite indicators, ranging from economic relevance and wider scope of the described term to as high as possible frequency of data, smaller number of revisions of the series used for decision-making, without breaks or publication delays. This is also hard to attain in practice, meaning that certain trade-offs among these properties should be made. Generally speaking, regardless of the methodological details pertaining to the compilation of an indicator (relating to the combining of the values of individual

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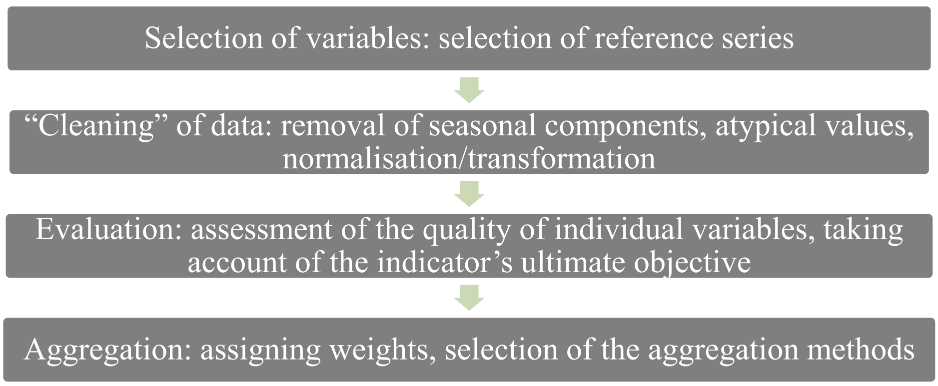
[8] European Union.

[9] United Nations.

[10] *Hodrick-Prescott* filter, Hodrick and Prescott, 1997.

indicators into one single measure, weight, etc.), several common steps should nevertheless be taken, as shown in Figure 1, where the logical sequence describes the choice of variables (based on theory, empirical results or some other criterion), their adjustment to make them comparable during evaluation and finally, their aggregation into a single measure. In practice, the steps presented in Figure 1 are repeated until the indicator's purpose has been attained, taking into account problems and dilemmas that arise in the application. Furthermore, according to the mentioned handbook compiled by the EU and UN (2017), indicators can be leading, coinciding or lagging, depending on their purpose. Leading indicators are used to anticipate the future dynamics of the phenomenon under consideration, coinciding indicators serve to describe current situation in real time, while lagging indicators are intended to reproduce the past pattern of the economy, in order to fill gaps in data. Leading indicators prove particularly interesting for the purpose of calibrating the CCyB values as described in the last part of this paper. However, coinciding indicators are also important in order to capture the current phase of the financial cycle. Given the nature of the data needed for macroprudential policy, in practice the construction of leading indicators proves difficult. However, they may be based on the properties of early warning models that analyse the power to signal a future crisis. The following text contains description of individual approaches, and they are further compared in terms of their properties, strengths and drawbacks in Chapter 6.

Figure 1 Steps for compiling a composite indicator



Source: author's adaptation, based on OECD[11] (2012).

[11] *Organisation for Economic Co-operation and Development.*

Considering the purpose and the properties of composite indicators in general, without a specific focus on a particular indicator (which is done in the following sections), the advantage of composite indicators is that they summarise information about the state and the movement of systemic risks, where both the total result and sector-specific developments can be represented graphically. This allows for identifying the sector that makes the biggest contribution to the dynamics of the indicator. However, according to Iossifov and Dutra (2021)[12], risk measures defined in such a way can lead to the underestimation or overestimation of systemic risk. This is why Comelli and Ogawa (2021) recommend monitoring not only the total value of the composite indicator, but also its components. This allows for the detection of potential different dynamics in the behaviour of individual indicators that make up a composite indicator. It should be noted that this task is quite challenging, given the economic interpretation of indicators, the results and the quantitative background used to synthesise the information. Calibrating the countercyclical capital buffer based on the results thus obtained also poses a difficult task. In this respect, BCBS (2017) comments that there is no mapping between the indicator and a particular level of the CCyB, adding that even though certain central banks (in Denmark, France, Italy and Spain) use heat maps that take into consideration several indicators at the same time, they do not synthesise all movements into a single composite indicator. Even though several papers dealing with the calibration of a CCyB based on composite indicators have been found, this approach is still in its infancy.

3 Selection of variables for composite indicators

This section describes the categories of measures to be monitored apart from credit dynamics, which are used in constructing composite indicators. The idea is to monitor the dynamics of the variable over time, and to detect any cyclicality in its behaviour. The dynamics is analysed by applying different transformations of the variables. The ESRB Recommendation on governance and operationalisation of CCyB (2014) recommends the following set of measures be monitored in parallel with the credit gap:

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[12] They claim that systemic risk is pro-cyclical, and that, as by definition when properly identified it should be at its highest prior to its materialisation, while financial frictions can give rise to feedback loops between asset prices and economic agents' net worths and liquidity spirals. As a result, metrics that serve as proxies for liquidity and solvency risks can exhibit countercyclical behaviour, resulting in the underestimation of risks and accentuation of the cycle.

(a) measures of overvaluation of property prices;
(b) measures of credit developments;
(c) measures of external imbalances;
(d) measures of the strength of bank balance sheets;
(e) measures of private sector debt burden;
(f) measures of potential mispricing of risk;
(g) measures derived from models that combine credit gap and a selection of the above measures from (a) to (f).

The following paragraphs explain the choice of indicators in each of the above categories, according to how available data are and the explanations found in the relevant literature, as follows. Most variables will be considered as 1-year and (annualised) 2-year growth rates because they capture different degrees of acceleration or slowdown in the dynamics of each measure (Stremmel, 2015), and the medium-term component of the cycle is better captured through this type of transformation (Comin and Gertler, 2006). In addition, for some types of indicators, gaps obtained by statistical filtering (Hodrick-Prescott, HP filter, hereinafter referred to as HP) will also be considered, given that statistical gaps of selected variables are also often used in monitoring cyclical behaviour over time. This provides an opportunity to consider different types of transformation of original variables in order to identify the best transformation that will correctly capture cyclical movement over time. Schüler (2018) adds that different transformations in the form of growth rates or changes can avoid spurious cycles that can be captured by statistical filters. It is also useful to consider the specificities of movements of country-specific variables by adjusting the smoothing parameters in statistical filter to these specificities.

It should be noted that for certain composite indicators and generally the construction of a risk map to be used in monitoring the developments in different sectors of the economy, some central banks and working papers (see Venditti et al., 2018; Arbatli-Saxegaard and Muneer, 2020, or Dahl et al., 2011) do not categorise measures strictly according to the ESRB categorisation, but instead refer to them as “household sector”, “banking sector”, etc. In addition, special measures, such as “macroeconomic climate”, are also defined, involving additional variables other than typical variables included in the mentioned six categories from (a) to (f), such as developments in unemployment, GDP gap, surplus yields on government bonds of a country relative to another country that is less risky (spreads), etc. Such approaches sometimes involve the construction of composite indicators, even though heat maps are more frequently monitored in such cases, and they are not directly used for the calibration of the CCyB. Sometimes such macroeconomic variables lag behind in the event of changes in systemic risks and in such case the indicators thus obtained are not suitable for the calibration of the CCyB (particularly if this involves, for instance, GDP and its dynamics). This chapter describes variables according to the six main categories of measures used to monitor risk over time, while Appendix 2 contains their graphic representation and description of their movements. The selected approach follows the ESRB Recommendation since it includes indicators whose dynamics are supposed to precede crises (which is not possible in some of the above approaches) and since it enables better comparability across countries, in view of publicly available disclosures in reports relating to financial stability and macroprudential policy in general.

3.1 Overvaluation of property prices

With regard to category (a) which concerns the measures of overvaluation of property prices, the relevant literature suggests that the most common combination used for the purpose of signalling crises are measures related to the accelerated credit growth and those related to the overvaluation of property prices (see Borio, 2012; Jordá et al., 2015; Behn et al., 2013). There is a strong correlation between credit dynamics in the economy and property prices, given that real estate is usually financed through lending and given that such loans account for a large share in credit portfolios on banks' balance sheets, making them vulnerable in the event of major changes in property prices (Tölö et al., 2018). The wealth effect (see discussion and references in Bakker, 2015) is one of the factors boosting the increased demand for real estate, creating price pressures in the upward phase of the cycle, which further stimulate credit expansion due to the increase in the value of collateral (Bernanke and Gerlter, 1995). Some research papers even suggest that the changes in residential real estate prices preceded changes in the loan market (e.g. Grinderslev et al., 2017), meaning that changes in the real estate market may provide an insight into what will happen with lending in the future.

Trends in property prices may be a source of risk for households, corporations and banks alike. High property prices pose a burden to households purchasing real estate by taking loans, forcing them to reduce other consumption due to the rise in property prices, which in turn affects GDP, as well as corporations as the source of supply. Of course, the changes in property prices also influence the value of banks' balance sheets where real estate is held as collateral. The importance of variables related to the measurement of property overvaluation is further elaborated in Borio and Drehmann (2009), Barrel et al. (2011), Behn et al. (2013) or Jordá et al. (2015).

This paper examines the (real[13]) house price index (HPI), HPI-to-disposable income ratio, rent, volume index of construction works and their different transformations, as shown in Figure D.1 in Appendix 2.

3.2 Measures of credit developments

Credit developments are probably most frequently monitored in practice, as well as in empirical research, as lending is banks' core activity, and thus credit developments have the greatest impact on financial stability and the accumulation of cyclical risks. Credit developments and developments in real estate prices have been identified in the empirical literature as the best predictors of crises in the past (see Borio and Lowe, 2002; Borio and Drehmann, 2009 or Aldasoro et al., 2018). The periods of economic upswing are accompanied by increasingly optimistic expectations and economic agents usually display a decreasing ability to recognise risk; faced with the prospect of rising future incomes as the result of such economic growth, the private sector is more willing to borrow and the banking sector may be more willing to lend to riskier clients (Plašil et al., 2015). In addition, Jimenéz and Saurina (2006) find that loans granted during boom periods have a higher probability of default than those granted during periods of slow credit growth. Most studies analysing credit cycles include measures that are used to analyse the dynamics of lending to private sector: Borio et al. (2012), Giese et al. (2014), Borio (2014), Schularick and Taylor (2012), Borio and Drehmann (2009), Babecký et al. (2013). The credit gap obtained by statistical filtering (HP filter) or the so-called Basel gap, as described in the ESRB Guidelines (2014), is the most commonly used variable informing the decision on the calibration of the CCyB. However, many issues[14] related to this definition of the measure of credit developments resulted in the definition of alternative measures in an attempt to remedy some of the shortcomings of the Basel gap. Credit growth should clearly reflect the underestimation of risk, and the Basel gap is often not an appropriate indicator for use in this case (see e.g. Edge and Meisenzahl, 2011; Bunčić and Melecky, 2014; Galán, 2019 or Lang et al., 2019).

[13] See Appendix 2 for the description of all the variables and data sources.

[14] See footnote 4.

Current applications involve several variants used for measuring credit developments[15]. For the narrower or broader definition of credit, most of them take into account 1-year, 2-year or 3-year (real) credit growth rate or change, separately for households and corporations, or corresponding growth rates and gaps obtained by statistical filtering (see Tölö et al., 2018 and the cited resources).

In this working paper, credit developments were analysed as follows. Bank lending data for households and corporations were first collected, and various mentioned transformations were calculated. Loans to households were considered separately from corporate loans, in the light of empirical findings suggesting that the growth in household loans leads to the decline in the GDP growth over the long term, once the share of household lending in GDP reaches a certain percentage (see Arcand et al., 2015, IMF[16], 2017). Therefore, even though the literature recognises the issue of growth in loans to households relative to loans to non-financial corporations, the dynamics in both categories needs to be taken into account for the purpose of attaining full coverage. To be more precise, when considering the narrower or broader definition of credit to calculate the Basel credit gap, both of them cover both sectors. Similarly, such information should also be included in the composite indicator. Figure D.2 in Appendix 2 shows various credit developments considered in the paper.

3.3 Measures of external imbalances

The disparity between savings and investments in a country is reflected in the external imbalances concerning the current account, since its definition is based not only on the

[15] In the construction of the FCI indicator (see Chapter 4), Plašil et al. (2014, 2016) take into account only newly-granted loans, explaining that unlike the change in the stock of loans, new loans are not affected by the exclusion of non-performing loans from bank balance sheets. As a possible alternative to new loans, data on household and corporate loan transactions could be collected from financial accounts. However, quarterly transaction data before 2012 for Croatia are not available. In this case, temporal disaggregation into quarterly data by applying the Chow and Lin (1971) approach is usually employed, using quarterly values of a variable for which quarterly data are available for the period before 2012, provided that its dynamics is very similar to credit transaction dynamics in the period following 2012. In the absence of such a variable, we use credit growth rates, referred to by Castro et al. (2016) as proxy for new credit, despite the shortcomings of such proxy. In the paper concerned, credit changes are further divided by the sum of GDP as in the Basel ratio in one variant. This is not done in this particular case given that the dynamics is almost identical (see Figure D.5 in Appendix 2) and given that the private sector debt burden measures are based on dividing credit and income or gross operating surplus, meaning that almost identical variables would be considered.

[16] International Monetary Fund.

difference between exports and imports, but also on the difference between savings and investments (Krugman, 1991). Feldstein (1992) explains that, in the short term, foreign capital inflow may lead to a difference between domestic investments and savings, while in the long term the current account rebalancing should derive mostly from investments. This is because the propensity to save in the long term is conditioned by households' attitudes towards saving and borrowing and fiscal stimuli or the lack of such stimuli for private savings. In the case of current account deficit, domestic investment is higher than savings, which is precisely due to foreign capital inflows (the following applies: *current account deficit = domestic investment – domestic private savings – public savings).* The opposite is true if domestic savings exceed investments, meaning that the financial capital surplus will be invested abroad. A country that borrows from abroad, having a large current account deficit, is characterised by high domestic savings or low investment. More information can be found in seminal papers such as Feldstein and Horioka (1980), while some applications can also be found in Olivei (2000).

Credit growth that is larger than the growth in domestic savings will lead to financing foreign borrowing with foreign money (Tölö et al., 2018). For these reasons, relevant research looks at the balance of payments in order to complement information on the possible accumulation of risks related to the overall cyclical risks in the economy. Current account deficit is interpreted as greater investment in the economy than the sum of private and public sector savings (Plašil et al., 2015), which may lead to difficulties in repaying foreign loans in the future (Giese et al., 2014). Thirty-nine out of forty-one economies analysed in Laeven and Valencia (2008) faced current account deficits in years preceding crises, while some authors have found that net exports or capital and financial account of the balance of payments can signal future financial vulnerabilities (Tölö et al., 2018). A part of the literature is dedicated to currency crises. More details on the experiences of various countries may be found in Kaminsky et al. (1998), where movements in exports and imports and the terms of trade are also considered. Figure D.3. in Appendix 2 shows the dynamics of measures and appropriate transformations of external imbalances considered below.

3.4 Measures of the strength of bank balance sheets

Banking sector vulnerabilities should also be discernible from the banks' balance sheets. However, in their extensive research into the relevant literature, Tölö et al. (2018) have found that variables measuring the strength of bank balance sheets and the accumulation of risks therein are only rarely used. They find that this might be because banks' financial statements tend to be published on a yearly basis, with a certain delay, and contain structural breaks due to changes in the accounting standards. In addition, in their empirical analysis, Detken et al. (2014) have found that leverage ratio as the measure of the strength of bank balance sheets did not perform well in predicting the crises included in the analysis. However, other authors offered empirical evidence that higher leverage ratio had a stabilising effect on the financial system (see Laina et al., 2015, or Kamin and DeMarco, 2012). Therefore, a credit institution's capital measures the capacity to absorb losses in the case of private sector defaults. The higher the capital, the greater the possibility to absorb these losses and the lower the likelihood that credit institutions will resort to deleveraging in the downward phase of the financial cycle. Additionally, negative loan-to-deposit ratio in the private sector is also considered, as it gives information on credit institutions' ability to obtain financing from stable long-term sources of funding and not to be dependent on the issuance of securities or borrowing.

Croatia's experience has shown that before the global financial crisis, banks relied on foreign borrowing in order to finance credit growth that was faster than the growth in deposits, which increased external imbalances. In practice, some approaches do not include this category of measures, such as the financial conditions indicator (FCI) in Plašil et al. (2015) and the ECB approach in Lang et al. (2019), suggesting that these measures do not cover the accumulation of imbalances, but instead measure banking system resilience. Therefore, this paper will seek to examine variants of some indicators by including the measures of the strength of bank balance sheets, and by excluding these measures. Figure D.4 in Appendix 2 shows indicators belonging to this category of measures, together with their respective transformations.

3.5 Measures of private sector debt burden

Rinaldi and Sanchis-Arellano (2006) analyse a theoretical and empirical model, which takes into account the link between private sector indebtedness, i.e. household debt to-disposable income ratio and the occurrence of credit risk, whose rapid build-up impairs financial stability in a country. In addition, the accumulation of private sector debt affects consumption and GDP growth in the short run, but also makes the entire system vulnerable in the long run (Lombardi et al., 2017). As a result, the relevant literature has been increasingly dealing with analyses of debt ratios or the private sector debt servicing-to-income ratio (Giese et al., 2014; Detken et al., 2014; Drehmann and

Juselius, 2014; 2012). Plašil et al. (2015) explain that accelerated growth in the debt-to-disposable income ratio may be a sign that the private sector has been overestimating its future debt servicing ability, leading to a decrease in its solvency in the case of the deterioration in the financial situation. This also goes for the corporate sector. Selected variables and their transformations presented in Figure D.5 in Appendix 2 are analysed within this set of measures.

3.6 Measures of mispricing of risk

Measures of mispricing of risk, as set out in item (f) in the ESRB Recommendation, may include mispricing of risk by credit institutions, but also by other sectors of the economy in general. The misperceptions of risk during certain stages of the financial cycle can lead to the build-up of risks, by both credit institutions and financial market participants. This is why this category of measures usually involves monitoring the lending/financing conditions, reflecting the perception of risk by credit institutions, which may provide loans in the upward phase of the cycle to borrowers to whom they would otherwise not lend (risky groups), because of lower interest rates, while underestimating the risk involved. On the other hand, when a risk materialises, the opposite occurs. Financing conditions include differences in interest rates on selected loans and benchmark rates (such as Euribor, etc.). The second measure of mispricing of risk considers the growth rate or the change in equity prices, given that it may complete the picture of excessive optimism or a lack of optimism concerning future equity prices (Plašil et al., 2015). On the other hand, in some research, equity price changes are not closely linked to the financial cycle and are instead more associated with the business cycle (Borio, 2012, Drehmann et al., 2012), which is why transformations are adjusted taking into account such information. Furthermore, the yield spread on government bonds of the country under consideration relative to another, less risky country, can also be analysed as part of the measure of mispricing of risk.

Pfeifer and Hodula (2018) explain that during a financial boom, major errors occur in the banks' estimation of the future collectability of loans, while profits are higher than average and provisioning/loan loss provisions are lower, and that this is when macroprudential measures need to be introduced. In other words, economic booms are accompanied by an acceleration in credit growth and an improvement in loan portfolio quality, leading to a drop in provisioning and a decrease in the risk premium. However, if the share of non-performing loans in total loans is very low at the peak of the cycle, banks also receive a cyclically overestimated profit, while the still non-materialized expected loss is the cyclically overestimated interest income. The banking prudence indicator (BPI) developed by Pfeifer and Hodula (2018) is one of the measures of the mispricing of risk, and its changes in the cycle occur before the changes of the credit cycle:

$$BPI_t = \frac{interest\ margin_t}{\frac{loan\ loss\ provisions_t}{total\ loans\ to\ private\ sector_t}}, \qquad (1)$$

where the interest margin in a given quarter *t* is calculated as the ratio of net interest income to loans from risk category A according to the CNB Decision (2019). Figure D.6 in Appendix 2 shows the measures of mispricing of risk and their corresponding transformations.

3.7 Other selected macroeconomic measures

As already mentioned at the beginning of this Chapter, certain approaches serve to complement the information obtained from the previous six categories of measures with additional trends in the selected macroeconomic variables. For some composite indicators, additional variables considered will be mentioned in the description, while those for which Croatian data are available are shown in Appendix 3, together with the selected transformations. We present and compare them in the analysis for sake of completeness, even though these variables are linked with the business rather than the credit cycle: GDP, unemployment rate and developments in monetary aggregates (see Tölo et al., 2018, where these, as well as other variables are analysed). However, some of these variables are not suitable for monitoring the cyclicality of the financial system if they are linked to business cycle, which does not usually overlap with the financial system. Finally, some variables reflect one-off and structural shocks that do not reflect the cyclical nature of the financial system.

4 Composite financial cycle indicator[17]

4.1 On the composite financial cycle indicator

The composite financial cycle indicator (FCI) was developed in the Czech Republic (Plašil et al., 2015) in order to assess the country's position in the financial cycle more effectively by relying on the information obtained from this indicator. Variables have been selected and aggregated based on the ideas and concepts found in Borio (2012), Borio and Zhu (2011) and Plašil et al. (2015), where the financial cycle is analysed by looking at changes in risk perception by economic agents, allowing for a variable risk tolerance, depending on the state of the economy, wealth and balance sheets. This approach to analysing the variability in risk tolerance is rooted in the work of Minsky (1975, 1982, 1986) and the financial instability hypothesis. This hypothesis suggests that, following a turbulent period, an economy is on the path to balance, and that such a recovery is characterised by a period of financial tranquillity, when borrowers are able to service their debt. Policy makers and financial regulators tend to ease their regulatory standards, risk premiums drop, lenders start providing loans to borrowers to whom they would otherwise not lend, while borrowers start exhibiting increasing speculative behaviour, and lending increases. Over time, such behaviour leads to a financial crisis, characterised by an increase in interest rates and a decrease in lending. This is in turn followed by recovery, and the whole cycle repeats[18].

In addition, Borio and Zhu (2011) explain the changing risk tolerance in the context of monetary policy and its impact on banks' behaviour, which could also be reflected in the macroprudential policy framework. They explain the concept of the so-called risk-taking channel, defined as the effect of changes in interest rates on the perception of risk or risk aversion, which consequently also affects the riskiness of portfolios, valuation of assets and funding. The value of the FCI in a given period will be interpreted as the build-up of risk in the financial system, depending on misperceptions and mispricing of risk by various economic agents. The idea is that increased optimism and risk-appetite in a given sector should result in a higher FCI value, and it would be good for the signal to become stronger in cases in which several sectors show the build-up of systemic risks

[17] Description according to Plašil et al. (2015). In addition to the above-mentioned paper, the same approach was also employed in the case of the Slovak central bank; see Kupkovič and Šuster (2020).

[18] More details on the Minsky hypothesis can be found in Mehrling (1999).

at the same time. The index is constructed based on the methodological approach employed in Holló et al. (2012), which involves a non-linear function based on the weights of individual variables, which are determined by cross-correlations of movements of variables. This serves to amplify the effect of a rise or a decrease in risk, given that correlations between variables are also taken into account. The methodology used to calculate the FCI is described below.

4.2 Indicator methodology

$w = (w_1, w_2, ..., w_M)$ is the vector of weights assigned to a variable that will form an integral part of the FCI; M is the total number of variables included in the index; $s_t = (s_{t,1}, s_{t,2}, ..., s_{t,M})$ is the vector of the transformed values of individual variables in period t, and C_t is the correlation matrix with coefficients of the correlation between variables included in s_t for period t. The FCI_t in period t is calculated as follows:

$$\mathrm{FCI}_t = (w \odot s_t)' \cdot C_t \cdot (w \odot s_t), \tag{2}$$

where $\odot$ denotes the Hadamard-product. Correlations in matrix C_t were estimated by using the EWMA method (*EWMA – exponentially weighted moving average*), with a smoothing parameter $\lambda = 0.94$ as follows (according to RiskMetrics, 1996):

$$\begin{gathered} \sigma_{ij,t} = \lambda\sigma_{ij,t-1} + (1-\lambda)\tilde{s}_{i,t}\tilde{s}_{j,t} \\ \sigma_{i,t}^2 = \lambda\sigma_{i,t-1}^2 + (1-\lambda)\tilde{s}_{i,t}^2 \quad , \\ \rho_{ij,t} = \sigma_{ij,t} / (\sigma_{i,t}\sigma_{j,t}) \end{gathered} \tag{3}$$

where $\sigma_{i,t}^2$ denotes the variance of series s_i in period t, while $\sigma_{i,t}$ represents a standard deviation, $\sigma_{ij,t}$ is a covariance between s_i and s_j, $\rho_{ij,t}$ is the correlation coefficient for the two series, and is $\tilde{s}_{i,t}$ the value of series i after subtracting the median value ($s_{i,t}$ – 0.5) and λ denotes the smoothing parameter, usually ranging from 0.85 to 0.97 (Alexander, 2007), depending on the assumptions concerning volatility persistence, data frequency and generally the behaviour of the series under consideration.

Unfortunately, there is no one-size-fits-all solution to how to select a smoothing parameter, and it is difficult to extrapolate the values from analyses of financial time series that mostly use the EWMA method. However, this approach is used in the construction of the FCI because the estimates are simple, compared to some other approaches to modelling the correlation structure. Also, with the application of parsimony (relative to, e.g. dynamic conditional correlation (DCC)), it produces similar results as in some GARCH (*generalized autoregressive conditional heteroskedasticity*) models (see Alexander, 1998). Furthermore, the nature of this research calls for the application of EWMA method, given that some models with fewer data cannot be estimated due to assumptions that must be met. Despite its shortcomings (e.g. the same smoothing parameter is assumed for the behaviour of all the variances and covariances in a model), some studies have shown that, as part of backtesting strategies, EWMA modelling was found to be better than some standard GARCH approaches (see Alexander and Leigh, 1997). The selection of smoothing parameter in this research is based on the results presented in Plašil et al. (2015). The value of lambda should ideally be determined by minimising one of the forecasting measures (such as RMSE (root mean squared error), see Bollen, 2014). The problem with such research is that it does not deal with financial data, where the estimate can be compared with realised volatility. However, the standard error of variance estimator is lower the higher the value of lambda. In addition, a trade-off should be made here between lower estimation error, on the one hand, and greater variance persistence, on the other hand.

Finally, the choice of the weight of a variable in the construction of the FCI poses a problem in practice. Plašil et al. (2015) apply equal weights, given that they are multiplied by the correlation matrix, which ultimately determines the weights. Hájek et al. (2017) consider the possibility of setting the weights by estimating the development dynamics of NPLs (non-performing loans). As the authors of the paper assert that NPL dynamics signals the materialisation of systemic risk, which can be detected only with a time lag, NPL dynamics can be used to calibrate the weights in the FCI. The variable measuring the presence or the absence of a crisis, as in the case of the early warning model (see Section 6), is not used here, since the authors claim that the limited sample of the available data includes only a single crisis, and that thus the estimates could be biased. After a final list of variables that will make up the FCI indicator has been made, vectors of weights are generated, by limiting the minimum weight of each variable to 5%. If the selected variable is important for the construction and the interpretation of the FCI, this should be reflected in its weight. In the next step, all the FCI variants are calculated based on the generated vectors of weights, while the change in NPLs, signalling the materialisation of cyclical risks, is regressed to the FCI value, taking into account a lag of 2, 3 or 4 years (depending on the time span of the FCI indicator in predicting the change in NPLs). The best combination of weights is then selected based on the lowest RMSE measure. However, this approach might be problematic in the case of short time series, where the sample includes a single cycle of significant NPL growth related to the global financial crisis, and where the specificities of that period may result in weights that would otherwise not be valid if the entire process is to be repeated by taking into account longer time series.

4.3 Transformation[19] of variables

Once the variables for the construction of the indicator have been selected, they have to be transformed to the same measurement unit to make the values of the variables comparable. To be more precise, although each relevant variable measures the cyclicality of risk, they may be expressed in different measurement units. For example, if gaps from statistical filtering are considered along with rates of growth, variables must be transformed to make them comparable. In determining the FCI, standardisation based on the first two distribution moments is not recommended in the literature, as this implicitly assumes a normal distribution of variables to be standardised, which is rare in practice. Results could be distorted, and their robustness to outliers could be reduced. This is why a transformation is carried out based on the empirical cumulative function of distribution and ranking (order statistics). The original dataset presented as $x = (x_1, x_2, \ldots, x_N)$ is ranked from the lowest to the highest value: $(x_{[1]}, x_{[2]}, \ldots, x_{[N]})$, $x_{[1]} \leq x_{[2]} \leq \ldots \leq x_{[N]}$, where $[r]$ denotes the rank assigned to value $x_{[r]}$. The transformed values z_t are then calculated based on an empirical cumulative distribution function as follows:

$$z_t = \begin{cases} \frac{r}{N}, if\ x_{[r]} \leq x_t < x_{[r+1]} \\ 1, if\ x_t \geq x_{[r+1]} \end{cases}, \tag{4}$$

for $t = 1, 2, \ldots, N$. The sequence z_t obtained in (4) now takes values within the interval of (0,1]. This transformation allows the value of the FCI to be within the interval between 0 and 1, which will facilitate its interpretation. The values of individual variables and those of the FCI that are closer to 0 will mean a smaller build-up of systemic risks, while higher values (closer to 1) will point to higher risk[20].

[19] See details and sources in Holló et al. (2012).

[20] When choosing the variables to be transformed, the variables should be carefully interpreted in order to discern whether the increase in the value of a variable can be interpreted as the build-up of systemic risk or not. The rest of this paper contains indication of the variables that were multiplied by -1 for this interpretation to be valid.

4.4 Results of the calculation and the construction of the FCI

In the light of the above discussion, Table 2 shows the variants of individual categories of measures used as indicators in the construction of the FCI. Several of these variants are considered below. The variables have been selected based on the discussion in Plašil et al. (2015) and the selection of variables therein, but account has also been taken of the specificities of Croatian data. This paper proceeds to analyse two variants that prove to be the best match for the case of Croatia. All the variables will be expressed as 2-year changes or growth rates, for the sake of better smoothness of the series and the composite indicator. One variant will take note of five risk categories, as was the case in the original paper in which the FCI was developed (excluding the "strength of bank balance sheets" category), while the second variant will include all six categories. These two variants are being compared because in the original paper, the authors did not consider the category of the strength of bank balance sheets. This will provide us with additional information on the potential effects of the inclusion of this category on the value of the composite indicator. In addition, the dynamics of current account trends for Croatia is specific in comparison to some other countries (Figure D.3) and so because of the greater stationarity of a composite indicator changes are considered and not levels as in the original paper.

As the correlation between the variables is very important for the FCI, we aimed to reduce the number of variables covered by a risk category in case they were highly correlated. Otherwise, they would contribute to the dynamics of the composite indicator. For example, with regard to the category of measures relating to overvaluation of property prices, we did not include the trends in property prices and the price-to-income ratio at the same time. Within the scope of this approach to constructing the indicator, variables have been selected based on the above discussion, without specific testing of the statistical properties of these variables or the early warning model. Furthermore, the choice of variable transformations was arbitrary, depending on whether the variables were expressed as levels, changes or growth rates. 1-year and 2-year transformations result in greater volatility relative to the HP gap, with a large smoothing parameter. However, some variables should reflect a somewhat slower dynamics than others, given that they are more related to the credit cycle than the business cycle.

Table 1 Summary of the described variables considered for the FCI

Abbreviation	Variable transformation	Variable	Category	Indicator variant
ΔHPI	1-year growth rate	House price index	Overvaluation of property prices	(1-a)
A. 2ΔHPI	2-year growth rate			(2-a)
Δ (I / Inc)	1-year growth rate	Residential real estate price-to-disposable income ratio		(1-b)
A. 2Δ (I/Inc)	2-year growth rate			(2-b)
ΔHL	1-year growth rate	Bank loans to households	Credit developments	(1)
A. 2ΔHL	2-year growth rate			(2)
ΔLNFC	1-year growth rate	Bank loans to non-financial corporations		(1)
A. 2ΔLNFC	2-year growth rate			(2)
Δ(LR)	1-year change	Capital-to-assets ratio (multiplied by -1)	Strength of bank balance sheets	(1)
A. 2Δ(LR)	2-year change			(2)
Δ(LTD)	1-year change	Loan-to-deposit ratio		(1)
A. 2Δ(LTD)	2-year change			(2)
Δ(H/Y)	1-year growth rate	Total household debt-to-disposable income ratio	Private sector debt burden	(1)
A. 2Δ(H/Y)	2-year growth rate			(2)
Δ(NFC/GOS)	1-year growth rate	Corporate debt-to-gross operating surplus ratio		(1)
A. 2 Δ(NFC/GOS)	2-year growth rate			(2)
ΔCROBEX	1-year growth rate	CROBEX, stock exchange equity index	Mispricing of risk / financing conditions	(1)
A. 2 ΔCROBEX	2-year growth rate			(2)
Δ margin H	1-year change	Difference between interest rates on new household loans and EURIBOR (multiplied by -1)		(1)
A. 2 Δ margin H	2-year change			(2)
Δ margin NFC	1-year change	Difference between interest rates on new loans to non-financial corporations and EURIBOR (multiplied by -1)		(1)
A. 2 Δ margin NFC	2-year change			(2)
ΔRN	1-year change	Share of the current account in GDP (multiplied by -1)	External imbalances	(1)
A. 2 ΔRN	2-year change			(2)

Note: the dynamics of all variables is described and shown in Appendix 1. Both the variants with and without the “strength of bank balance sheets” are analysed, see Appendix 4.

Source: prepared by the author based on discussion in the previous sections.

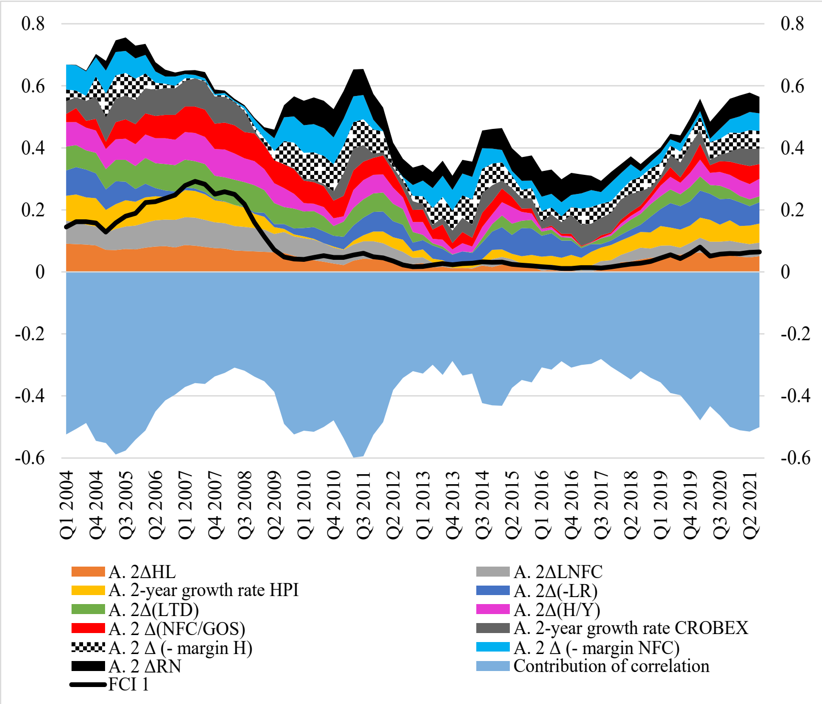
The difference between the two variants considered below is the number of categories included (one of them includes five, and the other six categories), while both of them analyse 2-year changes or growth rates, and the category pertaining to overvaluation of property prices includes the HPI. Other variants in Table 1 concern 1-year changes and growth rates, and consider an alternative measure of property price overvaluation in the form of residential real estate price-to-disposable income ratio. Alternative composite indicators are presented in Appendix 4. For example, in the case of a variant of the indicator (1) in Table 1, this means that all variables in 1-year growth rates or changes will be used for its calculation, while in the category pertaining to property price overvaluation, one variant will include house price index, while the other will include the residential real estate price-to-income ratio. Other possible combinations (8 in total, according to Table 1, see Appendix 4 for a more detailed description) are similarly interpreted. In addition, during the preparation of variables, it has been observed that 2-year changes or growth rates were aligned with HP gaps, with a smoothing parameter of 1,600 or 25,600. In these cases, changes or growth rates were selected in order to avoid problems occurring with the statistical filter (see the introductory part of this research). In addition, some transformations were selected because one-sided gaps did not provide the best information: for example, while the two-sided gap cannot be used because decisions are made based on the inflow of the available information in a given quarter, in the case of property price overvaluation, the one-sided gap did not provide full information at the beginning of the sample due to the method of its calculation (see figures in Appendix 2), while 2-year changes and growth rates provided more accurate information.

Figure 2 shows the two mentioned FCI indicator variants, and the variables included in the calculation. Looking at the dynamics on panel c, the FCI indicator with lambda parameter in the formula (3) of 0.94 shows a considerable increase in the FCI value prior to the last global financial crisis, from the already elevated levels predominantly resulting from heavy lending to the private sector, the rise in property prices, and the changes in the strength of bank balance sheets (visible from the structure on panel a). As this indicator is calculated by applying the formula that also includes a correlation matrix for all variable pairs, Figure 2 also shows the contribution of the average correlation to the decrease in the value of the indicator. In other words, although the increase in individual values of all variables contributes to the increase in the FCI value, if they do not indicate an increase or decrease in the same period, the negative correlation will contribute to the reduction of the indicator. As a result, the FCI values from 2018 to the end of the observed period are not as high as in the beginning, given that, other than the fact that the changes in the values of individual variables are not so large, the lower correlation of the variables reduces the final value of the indicator. After the indicator reached its maximum value at the beginning of 2007, it dropped drastically as a result of the crisis, when the values of all the variables decreased, which was accompanied by price change in the residential real estate market, but also the reduction of external imbalances. A mild recovery that started in 2017 is still ongoing. However, even though, at first sight, it can be said that in the last three years the FCI values have been much lower than the growth recorded before the financial crisis (due to the specificities of the period), this does not mean that, given the distribution of the FCI and the variables it includes, such values do not point to a moderate level of risk (see chapter on the calibration of the CCyB).

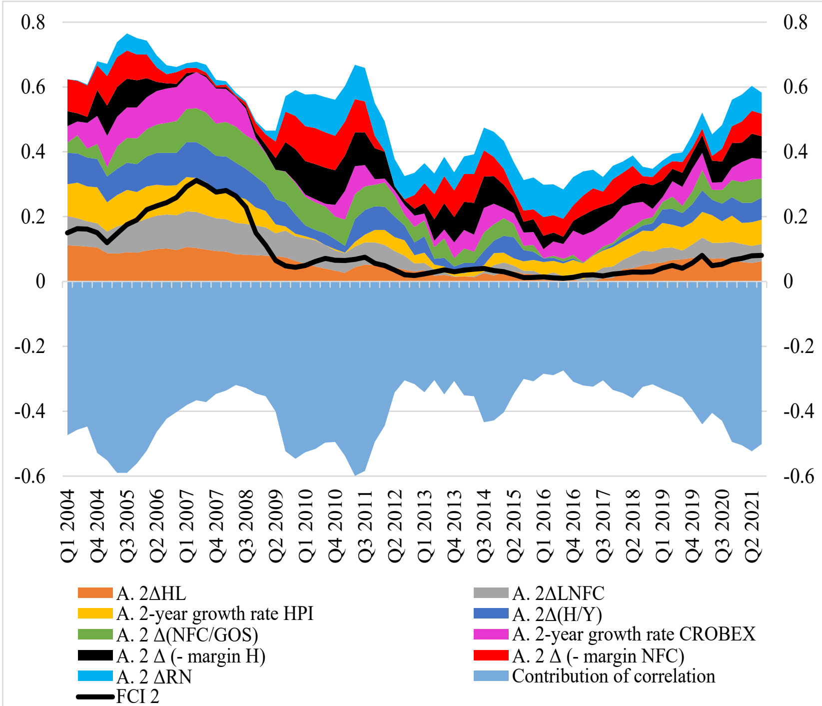
The remaining indicators shown in Figure 2, panels c and d, pertain to the testing of the robustness of this indicator. To be more precise, the change in the value of the smoothing parameter in formula (3) will result in a more or less volatile series of FCI values. FCI_85, FCI_94 and FCI_97 show variations of the initial indicator, depending on whether lambda has been set to 0.85 (its minimum value taken from the literature) or up to 0.97 as its maximum value. In the calibration of the CCyB, it is important that the indicator is smooth, which justifies the higher value of lambda, and that there are no significant quarter-on-quarter changes in the majority of variables comprising it (persistence). This is why utilising a higher value of lambda in the construction of the FCI makes more sense and is more justified. The FCI, as the composite measure of the build-up of cyclical risks, can be easily interpreted: a higher value is interpreted as larger build-up, while the dynamics in the movement of individual categories comprising the indicator can also be analysed. The usefulness of this indicator is evident from Figure 2 (panels a and b), showing the sources of the increase in cyclical risks. Finally, comparing the dynamics of FCI 1 and 2, with and without the “strength of bank balance sheets” category, it can be seen that these indicators show very similar trends, even though the values are slightly more elevated if the category is excluded (panel b and d on Figure 2), which results in an increase in the FCI value, meaning that no excessive behaviour likely to contribute to the increase in systemic risks was recorded in this risk category. However, since this risk category provides important information, further monitoring is also recommended as part of the calculation of the composite indicator.

Figure 2 Selected FCI indicators and their dynamics

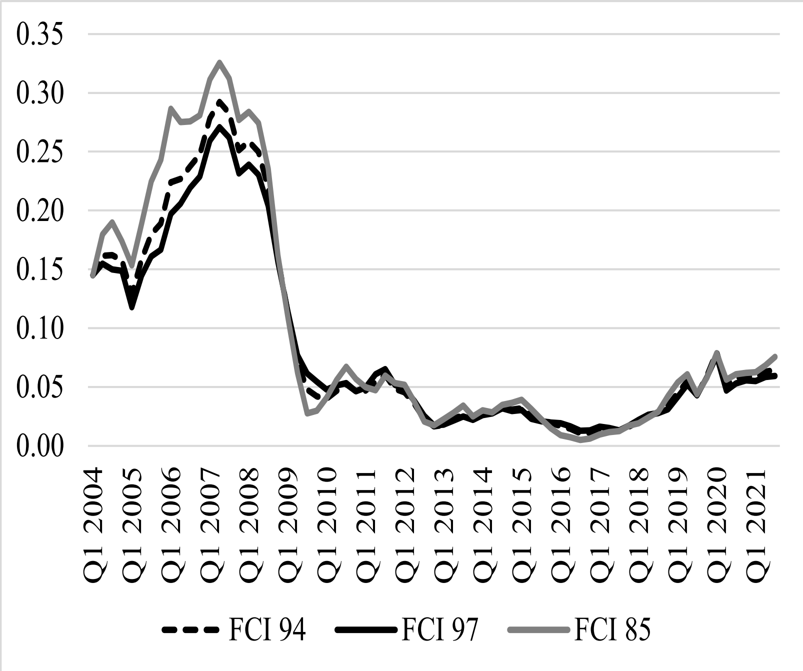
a. FCI, variables from variant (2) in Table 1, six categories of risk measures



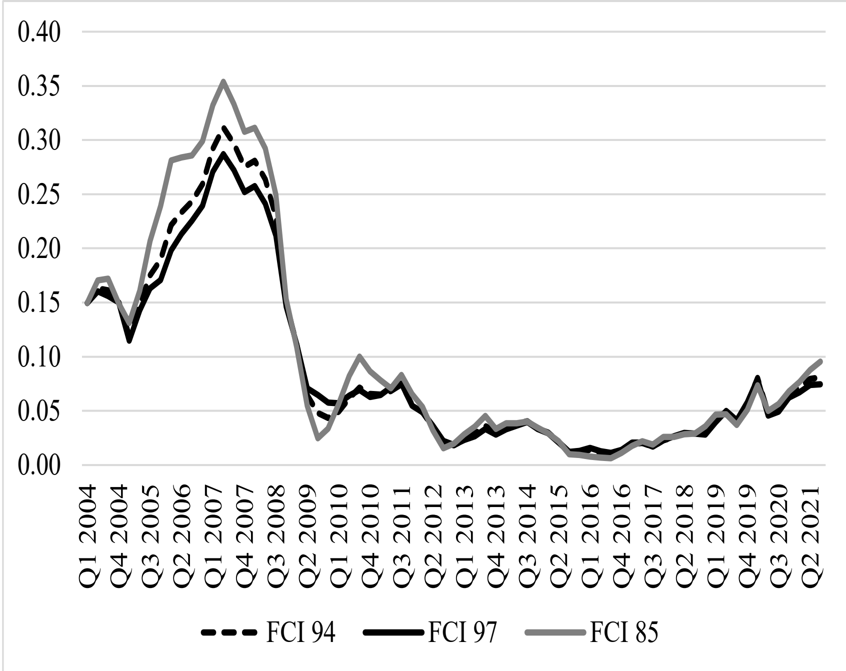
b. FCI, variables from variant (2) in Table 1, five categories of risk measures



c. FCI indicator from a, different lambda values in formula (3)



d. FCI indicator from b, different lambda values in formula (3)



Note: 85, 94 and 97 denote lambda values in formula (3) when estimating the FCI. The abbreviations are explained in Table 1.

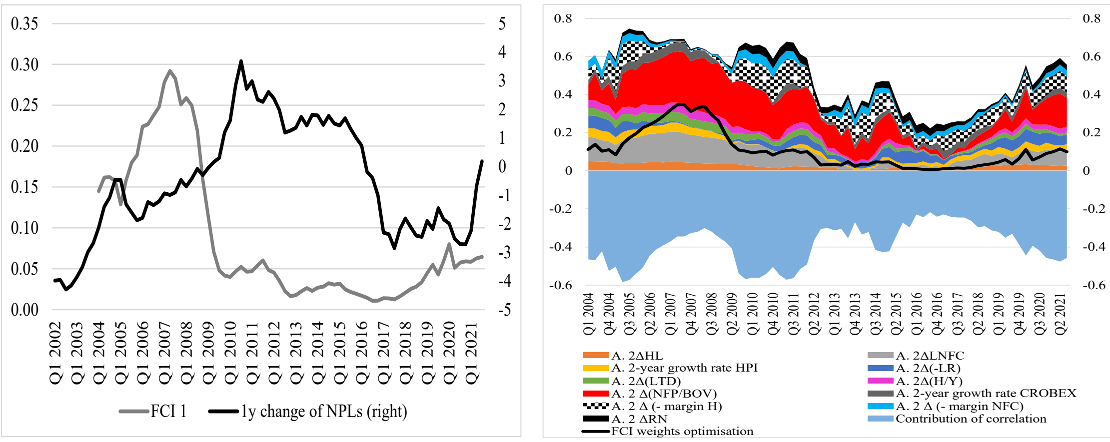
Source: CNB, author's calculation.

4.5 Possible calibration of weights for the FCI

Finally, the construction of the new variant of FCI 1 follows Hájek et al. (2017), and is based on the assignment of weights to individual variables by assessing the model in which 1-year change in the share of NPLs is predicted on the basis of 100.000 FCI variants and selecting the model with the lowest RMSE value.

Figure 3 Comparison of FCI and NPL dynamics and the new FCI indicator based on weights in Table 2

a. Comparison of FCI 1 and change in NPLs b. FCI obtained by optimising weights



Note: FCI dynamics on panel b has been increased in Figure 4.b to allow for comparison with other indicators.

Source: CNB, author's calculation.

Figure 3 (left panel) shows the dynamics of the FCI movement from Figure 2 (panel a), and the 1Y change in the share of NPLs are observed. It can be noticed that there is a certain lagged reaction of NPLs relative to the FCI dynamics[21] related to the events following the global financial crisis. However, given the specific nature of the crisis, in the period up to 2011, the FCI was relatively successful in predicting the change in

[21] Twelve quarters have been selected for the optimisation, because maximum values of the FCI from Figure 3, panel a, and the changes in NPLs have been compared.

NPLs, which is not the case for the rest of the observed period. Figure 3 (right panel) shows a comparison of the FCI obtained by optimising the weights (contained in Table 2). Certain differences can be observed, given that the largest weights, based on results, are assigned to the variable pertaining to corporate sector debt burden, as well as loans to corporates, but also the interest rate spreads on new loans to households. Appendix 5 contains a comparison between FCI 1 and the new FCI shown in Figure 3 (panel b), in order to make the differences in their dynamics more apparent. The problem here is the interpretation of the weights obtained. To be more precise, their values are affected not only by the dynamics of individual variables, but also by the entire changing correlation structure, which contributes to the final assessment of the RMSE measure.

Table 2 Variable weights in the FCI based on optimisation

Variable:	A.2ΔHL	A.2ΔLNFC	A.2 HPI growth rate	A.2Δ(-LR)
Weight:	5%	15.98%	5%	6.94%
Variable:	A.2Δ(LTD)	A.2Δ(H/Y)	A.2Δ(NFC/GOS)	A.2 growth rate CROBEX
Weight:	5%	5%	28.5%	5%
Variable:	A.2Δ (- margin K)	A.2Δ (- margin NFC)	A.2ΔRN	-
Weight:	13.58%	5%	5%	

Note: abbreviations are included in Table 1.

Source: CNB, author's calculation.

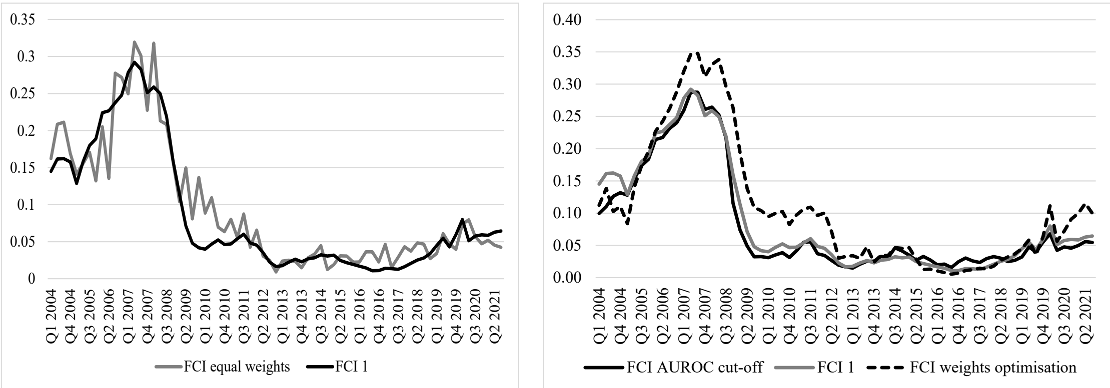
4.6 Proposed calibration of the weights in the FCI

In addition to the approach mentioned above, two more approaches could be employed for the purpose of assigning weights to the variables to be included in the calculation of the FCI: in the first approach, equal weights are assigned to each category of variables included in the indicator, while the second approach utilises the results of the early warning model (see Section 6.2) to select the structure of weights that enabled the FCI to best signal the past GFC. Since the literature offers no consensus on how to assign weights to the variables for the calculation of the indicator and as the differences in results can be large, the first approach reduces the subjectivity of such decisions. To be more precise, if it is important to monitor all six categories of the measures of sources of systemic risk, they should be assigned equal weights. However, the drawback of such an approach is that it is not country-specific. On the other hand, assigning weights based on expert judgement might be influenced by the events related to the past crisis, which also has an impact on the final result. The second approach is complementary, to a certain extent, to the methodology described in Chapter 6, where the choice of variables is based on signalling future crises. Although this may also make the results somewhat biased, it is important to know how certain variables "behaved" in the pre-crisis period.

Figure 4 Comparison of alternative FCIs with FCI 1 shown in Figure 2

a. FCI equal weights assigned to all categories of measures

b. FCI obtained within the scope of an early warning model



Note: panel b also compares the FCI dynamics based on the optimisation shown in Figure 3.

Source: CNB, author's calculation.

Figure 4 shows a comparison between the two variants of FCI 1 (with original values from Figure 2). The left panel shows that the volatility of indicator increases if equal weights are assigned to the six categories of measures[22], while the right panel shows minor differences between the original series and the series obtained with the use of an early warning model. These approaches may serve as an additional check of the robustness of the results when choosing the approach to be used for the purpose of monitoring cyclical systemic risks. It should be noted that the comparison of the

[22] Given that higher weight is now assigned to some variables included in a particular category, such as the change in residential real estate prices, such volatility is largely mapped in the final value of the FCI.

weights in Table 3 with those in Table 2 points to major differences, meaning that the choice of the approach to the model this problem can have a significant impact on the results and consequently on the calibration of the CCyB value. For example, even though the dynamics of CROBEX prior to the GFC was very similar to that in other countries, where stock markets play a much more important role, and was thus assigned a weight of almost 21% in the calculation, given the very weak dynamics of this indicator in the last 15 years, the question is raised as to whether it is still justified to continue assigning such a weight to this variable[23]. Appendix 6 contains a more detailed description of the structure of both FCIs from Figure 4, in order to make it easier to detect differences relative to the structure of FCI 1.

Table 3 Weights of variables in the FCI based on the early warning model

Variable:	**A.2ΔHL**	**A.2ΔLNFC**	**A.2 HPI growth rate**	**A.2Δ(-LR)**
Weight:	5%	5%	5%	14.1%
Variable:	A.2Δ(LTD)	A.2Δ(H/Y)	A.2Δ(NFC/GOS)	A.2 growth rate CROBEX
Weight:	10.13%	6.68%	11.33%	20.69%
Variable:	A.2Δ (- margin K)	A.2Δ (- margin NFC)	A.2ΔRN	-
Weight:	9.38%	7.61%	5%	

Note: abbreviations are explained in Table 1.

Source: CNB, author's calculation.

[23]In carrying out all the analyses for the purpose of this paper, a certain portion of time was devoted to the question of whether or not the CROBEX dynamics should be included in all the analysed indicators, given that the majority of approaches and empirical studies also included the equity price dynamics, as such dynamics was not "subdued" in other countries, but also because of the interpretation of mispricing of risk by investors in this category of measures dealing with risk cyclicality. As comparison of the majority of analysed indicators involved different combinations by including and excluding certain "problematic" variables, CROBEX included, it has been observed that there were no major changes in the final indicator and its dynamics. In addition, flexibility should be allowed concerning the inclusion and exclusion of variables in all the categories of measures of cyclical risk.

5 Cyclogram

5.1 The cyclogram in general

A cyclogram is a graphical representation of the composite indicator of systemic risk, developed in Rychtarik (2014, 2018) and applied in Slovakia. The main idea behind the cyclogram is the aggregation of information about the trend dynamics of a larger set of relevant variables in the form of a chart, in order to make a better assessment of where the economy is positioned in the financial cycle.

With regard to the FCI, the aggregation of information is based on a linear function, without correlations between variables. The cyclogram shows the average value of the evolution of cyclical risk in the economy. Core variables are defined first, such as credit gap, GDP gap, credit growth, NPL dynamics and private sector debt burden, which is followed by the definition of supplementary variables, offering a more complete picture: unemployment rate, property market trends, default rates, lending conditions, consumer confidence, etc. The original publication from 2014 considers a more limited set of variables, whereas the 2018 publication introduces cyclogram+, which is based on a wider set of variables than the original indicator. While the original cyclogram is based on the same transformation of variables as for the FCI (formula (4)), cyclogram+ is based on a slightly different transformation (see Section 5.2). The cyclogram is essentially a chart, showing the presence or the absence of the build-up of cyclical risk in the system as a whole, as well as in individual components (e.g. risks in the household sector). As mentioned in Rychtarik (2014, 2018), the idea and the definition of such indicator is based on the experience of the Slovak economy, especially before the global financial crisis, backed by common sense. The choice of variables is not based on theoretical evidence and explanations as in the previous case. Instead, decisions on the choice of variables are based on monitoring the actual experience in the economy, other experience and findings in the literature and the behaviour of individual variables before crises, as well as on the availability of data. In addition, Rychtarik (2014) argues that the choice of variables is based on monitoring cyclical movements of variables relevant for Slovakia over the last ten years. The problem with this type of research and analysis is that it is very difficult to determine a single indicator, the approach to its calculation and all the details to be taken into consideration in its construction, which would be applicable for all countries. It is thus hardly surprising that there are many approaches to quantifying cyclical systemic risks.

5.2 Indicator methodology

The cyclogram value is a linear combination of the values of individual variables that are included in the calculation, while the weights can be assigned in two ways. The first way is to assign equal weights to all the variables, which would result in the following function:

$$CYCLOGRAM_t = \frac{\sum_{i=1}^{N} z_{i,t}}{N}, \tag{5}$$

where $z_{i,t}$ denotes the transformed value of variable i in period t, while N denotes the number of variables. The other way is to assign equal weights to categories of variables comprising the indicator. The variables can be grouped in the six categories set out in the mentioned ESRB Guidelines or categorised as follows: “cycle”, “banks” and “clients”, according to Rychtarik (2014). In this case, the weight within each category is further divided by the number of variables. The smaller the number of variables in a category, the larger the weight assigned to such variables. This serves to prevent cases in which the dynamics of a larger number of variables in a category would become predominant, thus significantly affecting the cyclogram. Generally, the value of the cyclogram in both sub-cases can be expressed as follows:

$$CYCLOGRAM_t = \sum_{i=1}^{N} w_i z_{i,t}, \tag{6}$$

where w_i denotes the weight of variable i. The present case concerns a linear combination of transformed variables. Their cross-correlations have not been taken into account as they have in the case of the FCI. The problem of setting the weights of individual variables persists here as well. Either equal weights can be assigned or the optimisation procedure can be carried out, as in the case of the previous indicator. Cyclogram+ variant introduced a uniform number of variables in each category of measures in order to mitigate the problem of assigning weights. The papers defining the cyclogram do not propose any specific models to be used in assigning weights, as in the case of the FCI.

5.3 Transformation of variables

Rychtarik (2014) transformed the variables for the cyclogram as follows. First, the ranking of each variable is determined, but instead of using the transformation as in formula (4), where the ranking of individual value is divided by the highest ranking, scores from 1 to 9 are assigned based on the respective ranking. Rankings up to the 10th percentile of the distribution of individual variables take the value of 1, those from the 10th to the 20th percentile take the value of 2, etc., up to the maximum values (equal to or exceeding the 80th percentile) which take the value of 9:

$$z_{i,t} = \begin{cases} 1,\ if\ ranking_{i,t} < x_{i,t}^{10\%} \\ 2,\ if\ x_{i,t}^{10\%} \leq ranking_{i,t} < x_{i,t}^{20\%} \\ \dots \\ 9, if\ ranking_{i,t} \geq x_{i,t}^{80\%} \end{cases}. \quad (7)$$

As the cyclogram is a linear combination of variables from (7), it will also take values from 1 to 9. Cyclogram+ (Rychtarik, 2018) involves modification of the transformation of variables, by computing the max-min transformation:

$$z_{i,t} = \frac{x_{i,t} - x_{min}}{x_{max} - x_{min}}, \quad (8)$$

where $x_{i,t}$ is the value of variable i in quarter t, while x_{min} and x_{max} denote the corresponding minimum and maximum value throughout the period. The values of the transformed variables will thus be within the interval of [0,1]. Additionally, transformation in (8) can also be carried out in such a way that the new variables take values within the interval of [-1,1][24]. This working paper recommends the latter transformation, so that the result relating to the composite indicator can take both positive and negative values, which are easier to perceive and link to the expansionary and contraction phases of the cycle.

5.4 Selection of variables for the cyclogram

Rychtarik (2014, 2018) lists five categories of variables comprising the cyclogram, with a large number of them overlapping with the variables related to the FCI. The description is almost identical to that for the FCI. Depending on the number of variables included in the analysis, both cyclogram and cyclogram+ are considered. The issue of applying this approach to Croatian data is that some time series are not sufficiently long (e.g. economic sentiment index (ESI), corporate bankruptcy rate), while others do not exist (e.g. LTV ratios).

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[24] This results in the following formula: $z_{i,t} = \frac{2(x_{i,t} - x_{min})}{x_{max} - x_{min}} - 1$.

Generally speaking, the choice of variables in this approach is also based on the preferences of decision makers. The list varies, in terms of the combination of the variables making up the cyclogram and their definition (level, ratio, growth rate, etc.). Appendix 7 contains a detailed description of the variables used in Slovakia. There are several problems concerning the choice of variables for Slovakia. First, levels, gaps and changes are used simultaneously in terms of variables. Analysis of the cyclical behaviour of an indicator requires the extraction of a cycle (either by means of a statistical filter, growth rate, etc.), so it remains unclear why both a level of an indicator and its transformation are observed, while the original research also does not provide any explanation of why both the level of a variable and its transformation are considered. Although one variable may display cyclical behaviour in terms of its levels, and another in terms of its changes, the papers do not present individual movements of such variables, and therefore it remains only to be assumed that the variable's behaviour was such that it did not require any additional transformations. NPLs pose another problem. In the previous approach (FCI), NPLs are considered as risk materialisation, while here they are included as one of the variables to be monitored in order to detect the build-up of risk.

Finally, it should be noted that although it is useful to consider indicators of uncertainty, sentiment indicators and similar metrics, as these are variables that contribute to nowcasting, they do not display cyclical behaviour, but rather (heavily) depend on one-off economic, political, climate and similar shocks. Even though these shocks influence the stability of the financial system, the mentioned variables do not signal the cyclical behaviour of risks. This is why this paper argues that such variables are not to be included in composite indicators utilised in the calibration of the CCyB, but should nevertheless be monitored in order to have a more complete picture when decisions are being taken.

This is why several cyclogram variants will be considered below, as shown in Table 4, where variant (1) contains all the variables used for FCI 1 from Table 1, showing their 2-year changes or growth rates; while in the second variant the selected variables are considered as HP gaps[25], given that the credit dynamics is slower than in the case of some other variants. In addition to these two variants, their extended versions will also be considered, including the trends in GDP and unemployment rates, in order to allow

[25] The selection is based on the results of the analysis contained in the following section. For more details on selection, see the following section. Table 4 shows the variables in gaps.

for a full comparison relative to the original research[26]. Each variable group will be assigned a weight of 1/6 or 1/7 if the macroeconomic variables are included as well. First, a transformation is carried out by applying formula (7) (results are shown in the next section). The max-min transformation is selected in such a way that the variables take values within the interval of $[-1,1]$. The results of these calculations are shown in Appendix 8, with a dynamics that is more intuitive for interpretation, given that the dynamics of variables in the original form (reflecting the cycle) varies between positive and negative values.

Table 4 Cyclogram variants in the case of Croatia

Cyclogram	Cyclogram components	Additional information
Variant 1	Variables as annualised 2-year growth rates and changes	Variant without and with GDP and unemployment rate dynamics
Variant 2	Combination of variables as annualised 2-year growth rates or changes and HP gaps with a smoothing parameter of 125,000[27]	Gaps for credit developments and private sector debt burden, variant without and with GDP and unemployment rate dynamics

Note: NPL means non-performing loans. The abbreviations of other variables are explained in Table 1. Taking into account the variants that include GDP and unemployment dynamics, there are 4 variants in total.

Source: prepared by the author based on the discussion in this paper.

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[26] As this concerns the realisation of negative trends that lag behind the trends of variables that should signal the build-up of risks, using such indicators can reduce the predictive power of the composite indicator that is intended to measure the build-up of risk before its materialisation. The values of NPLs and their dynamics will not be included, following the original working paper, given that, according to Berti et al. (2017), NPLs may also be viewed as a structural problem in the euro area, which is more related to the business cycle, thus lagging behind the changes in the financial cycle, similar to GDP and unemployment.

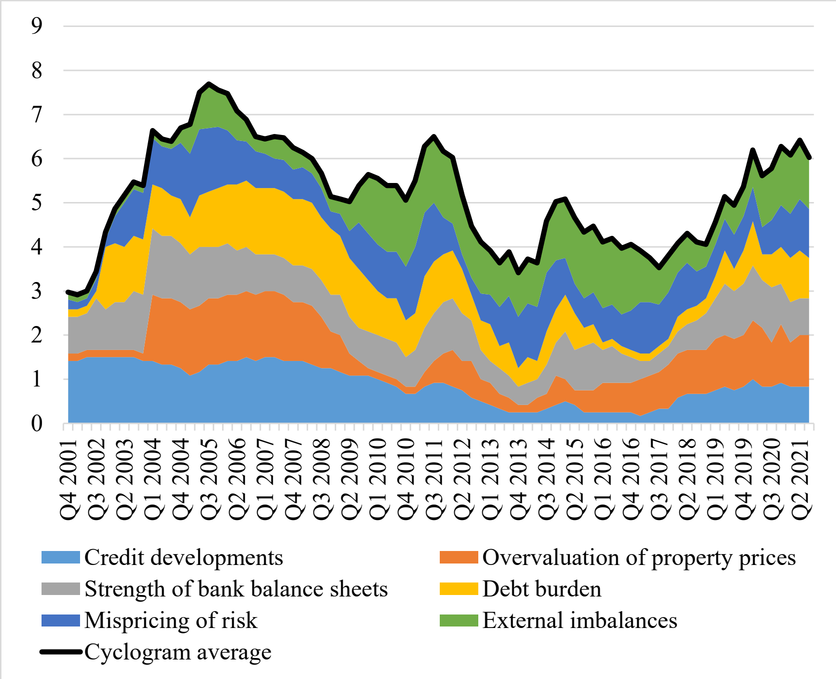
[27] Since the duration of financial cycle in Croatia is unknown, setting the smoothing paragraph at 125,000 means that the financial cycle is assumed to last about three times longer than the business cycle, i.e. around 22.5 years. Choosing a value of 400,000 would mean that the cycle lasts for 30 years. However, the problem of a gap closure that is too slow has been dealt with in the literature on credit gap. For more details see Valinskytė and Rupeika (2015) or Galán (2019).

5.5 Results of the calculation and the construction of the cyclogram

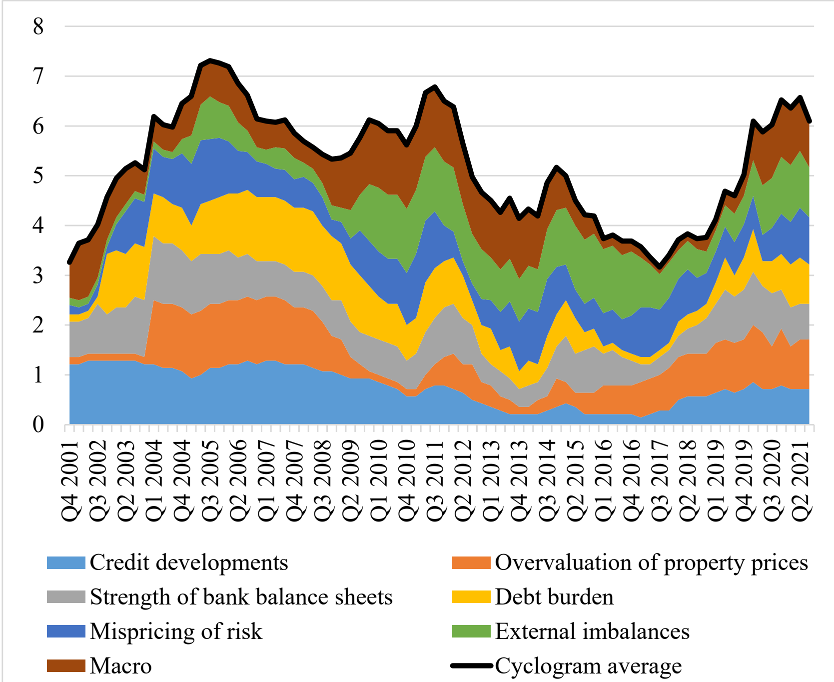
In the construction of the cyclogram, equal weights have been assigned to all the risk categories for each of the cyclograms. The results of the calculated cyclograms from Table 4 are shown in Figure 5. As the variables have been transformed by applying formula (7), all the values are positive. The higher the value, the higher the build-up of risk in a given category. In addition, all the calculations were repeated for the purpose of max-min transformation, as shown in Appendix 8. The positive and negative values of the movements of variables allow for easier and more intuitive interpretation than shown in Figure 4. Although the present case, like the FCI, also involves the build-up of risk at the beginning of the observed period, before the GFC, as well as at the end of the observed period, the correlation structure is not included here. This is why, on average, the build-up of systemic risk in the last few years appears to have already reached the levels from the 2000s. It is therefore advisable to use max-min transformation in practice. Despite allowing for more intuitive interpretations, the publicly available publications dealing with the cyclogram do not employ this approach. This approach to presenting results is something worth considering in the future. Looking at the interpretations presented in Figure 5, the values of some risk categories are always positive, because of transformation in (7), with each of the categories taking a value from 1 to 9. However, for easier consideration of the results, the values have been rescaled, being divided by the number of categories (six or seven). Such a dynamics is more difficult to interpret, as there is the problem of how to set the limits for a particular risk category. Although this approach also captures risk reduction in a recessionary period, due to the way in which the variables are chosen or transformed, the 2-year growth rates capture a mild recovery in 2011 and 2014, due to the low preceding basis. This is why the result shown in Figure 5 may wrongly indicate the build-up of risk.

Figure 5 Structure of the cyclogram shown in Table 4, based on the variables contained in Table 1

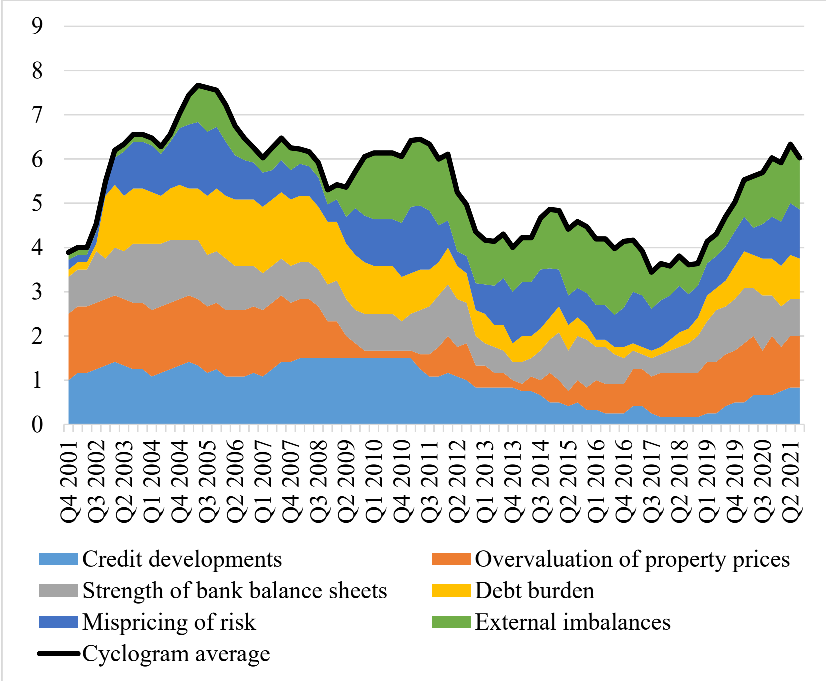
a. Variables of variants (2) in Table (1)



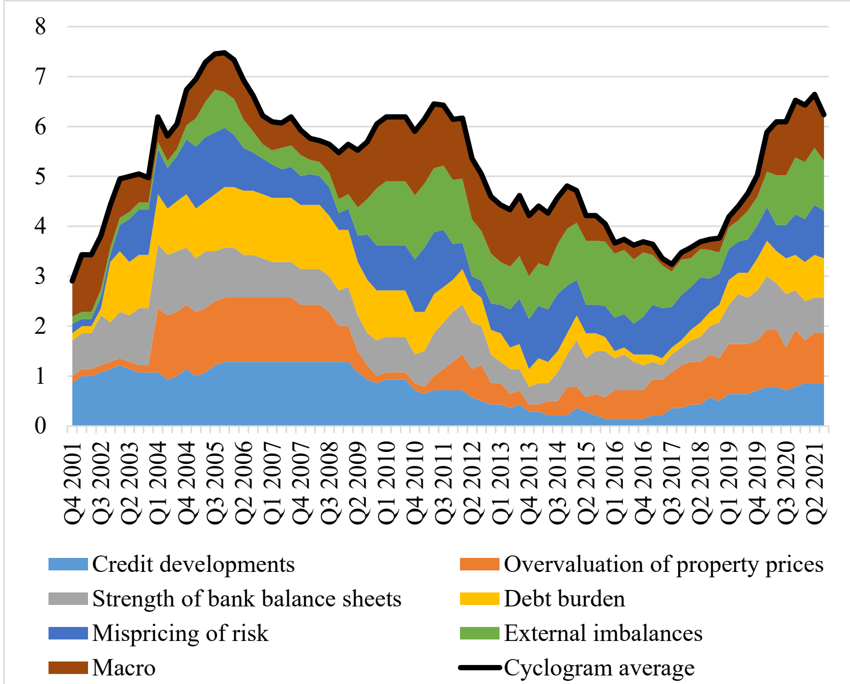
b. Variant from a. with macroeconomic variables



c. Variant (2) of the cyclogram in Table 4



d. Variant from c. with macroeconomic variables



Note: the “macro” category contains negative GDP gap with a lambda of 1,600 and annualised 2-year unemployment rate change.

Source: CNB, author’s calculation.

6 Composite indicator of cyclical systemic risk (d-SRI)

6.1 General observations on the d-SRI

The composite indicator of cyclical systemic risk was developed in Lang et al. (2019) and is referred to as d-SRI (domestic systemic risk indicator). It is based on the selection of variables included in early warning models with the best power to predict a crisis, and covers five of the six categories[28] of measures set out in the ESRB Recommendation. The main difference between this indicator and the previous two approaches is that the selection of variables and their transformations is based on the results of the early warning model. The idea is to use the experience from previous crises and choose those variables that best predicted these crises as a starting point in monitoring the build-up of systemic risks.

The research of Lang et al. (2019) was driven by the problems in utilising the credit gap (as already mentioned in the introductory part). Recognising the importance of other categories of measures as well, this paper also considers other variables. In addition, authors have been motivated by previous papers testing the power to signal future crises and claiming that cyclical trends in property prices or external imbalances can predict future crises. The paper concerned employs an empirical approach to constructing the composite indicator, based on the findings of previous empirical papers, and covers five categories of measures. While the previous two indicators (the FCI and the cyclogram) are based on one crisis (GFC) and the country for which they were first developed, this approach is based on a panel[29] of countries and covers several decades and a number of systemic crises in order to assess the importance and the signalling power of individual variables. Several variants of variable transformation are considered in order to identify the one that gives best results of estimations. Individual theoretical approaches are not considered. As opposed to the FCI and the cyclogram, the choice of variables here is based on empirical research on crisis signalling, where variables have been ranked according to the best power to predict future crises.

6.2 Indicator methodology

Like the cyclogram, the d-SRI indicator is constructed as a linear combination of transformed variables, with assigned weights w_i and values of transformed variables $z_{i,t}$:

[28] The only rationale provided in the paper for considering 5 out of 6 categories of measures (excluding "strength of bank balance sheets" category) is included in one of the footnotes, stating that the category concerned does not measure the build-up of cyclical risk, but only the resilience of the banking system.

[29] Euro area countries, UK, Denmark and Sweden.

$$d\text{-}SRI_t = \sum_{i=1}^{N} w_i z_{i,t}, \tag{9}$$

where the indicator takes values indicatively, ranging from -2 to 2, depending on the transformation of variables (see next section), and is interpreted as the average deviation of aggregated cyclical risk from the median value. What is relevant in relation to the methodology utilised for the purpose of this indicator is the early warning model[30], as described below. The idea behind the model is that the movement of an indicator variable occurs well before the movement of the vulnerability variable linked to the dates of the financial or banking crisis. In this approach, it is necessary to specify the dates when a crisis occurred, for they are used for the definition of a binary vulnerability variable. As the dynamics of the indicator variable should signal the occurrence of a crisis ahead of time, the vulnerability variable is determined as follows, according to ECB (2017):

$$vulnerability_t = \begin{cases} 1, \ for\ 12\ to\ 5\ quarters\ before\ the\ crisis \\ omit\ data, for\ the\ period\ from\ 4\ \ to\ 1\ \ quarter\ prior\ to\ crisis\ and\ crisis\ period \\ 0, otherwise \end{cases} \tag{10}$$

taking also account of the variants including pre-crisis horizons of 16-5 quarters (see Gálan, 2019), 12-7 quarters (Behn et al., 2013) and 20-3 quarters (see Financial Stability No 13, CNB, 2014). In the period preceding the crisis, the indicator should display higher values than the long-term trend or average (the indicators are usually defined in such a way that a higher value means higher risk), while in the non-crisis period the indicator should display lower values. Furthermore, the formal dates of crises are based on a comprehensive analysis of previous crises in ESRB (2018b), ECB (2017), Duprey et al. (2017) and Dimova et al. (2016). In accordance with these sources, the analysis in this paper covers the period from October 2008 to June 2012 as the formal period of the crisis.

The variables whose indicators are being tested to determine their signalling performance are then analysed by looking into the percentiles of the distribution of the variable, in order to determine the reference level τ denoting the level at which the indicator assumes the value of 1 (if in a given quarter the value is greater than τ) or 0 (if the value is lower). The analysis looks at the value of indicators in the periods for which vulnerability is defined in formula (10). The idea is that the indicator should display values of 0 or 1 in as many cases as possible when the vulnerability displays the values of 0 or 1. For this purpose, cases where

[30] See Kaminsky and Reinhart (1999), Borio and Drehmann (2009), Drehmann et al. (2010, 2011) or Alessi and Detken (2011).

both vulnerability and indicator display the value of either 0 or 1, and combinations where one value is 0 and the other is 1, are counted.

For this reason, a confusion matrix is formed (as shown in Table 5), in order to estimate Type I errors (T1, missed vulnerable states, false negative) and Type II errors (T2, false alarms, false positive). A denotes the total number of true positives, B denotes the total number of false positives, C denotes the total number of false negatives, and D denotes the total number of true negatives. Type I and II errors are calculated as $T1 = \frac{C}{A+C}$ i $T2 = \frac{B}{B+D}$.

Table 5 Confusion matrix

Signal/vulnerability	Crisis	No crisis
Indicator signals a crisis	A	B (Type II)
Indicator does not signal a crisis	C (Type I)	D

The following function may be considered the first objective function that can be optimised in order to identify the optimum level τ:

$$\arg\min_{\tau}[\theta T1 + (1-\theta)T2] = \arg\min_{\tau}[\theta \frac{C}{A+C} + (1-\theta)\frac{B}{B+D}], \qquad (11)$$

where the goal is to minimise the proportion of Type I and Type II errors, whereby the errors are assigned weights of θ and (1 – θ), taking into account macroprudential policy preferences, $0.5 < \theta < 1$[31]. Another frequently used objective function is the following:

$$\arg\max_{\tau} J = \arg\max_{\tau}[\frac{D}{D+B} + \frac{A}{A+C} - 1], \qquad (12)$$

where weights of θ and (1 – θ) may also be assigned. Where longer time series are available, covering more crises analysed, the weights θ and (1 – θ) can vary, in order to reflect the preferences of decision makers with regard to the failure to signal crises that occurred or false alarms (since both Type I and Type II errors involve certain costs). The area under the receiver operating characteristic curve (AUROC) is the value used to evaluate the early warning model. A curve obtained by considering the value of Type II error on x-axis, and by considering the signal ratio on y-axis (i.e. 1 – T1) can be shown in a coordinate system. For different values of τ from the baseline distribution of the indicator being analysed, a receiver operating characteristic (ROC) curve can be constructed, plotting the cumulative distribution function, calculating the surface value below this curve. As the AUROC takes values within the interval of [0.5,1], the values closer to 0.5 mean that the selected indicator randomly gives

[31] See Alessi and Detken (2009, page 12) explaining how the global financial crisis influenced the change in preferences and the increase in the value of θ.

an accurate signal of a future crisis, while values closer to 1 mean that there are almost no Type I and Type II errors, meaning that the selected indicator accurately signals a future crisis or its absence. Within each category of measures, Lang et al. (2019) select those measures with the maximum AUROC value.

Finally, after selecting variables comprising d-SRI, Lang et al. (2019) assign weights by using the vulnerability variable from (11) in the panel of countries whose indicators are being estimated, regressing the variable concerned to the best individual crisis signals. The variables with the highest estimated parameters in the model are assigned higher weights in the d-SRI. The estimated parameter values are then transformed into weights by dividing each parameter by the sum of all parameters, ensuring that the sum of weights is equal to 1. The only additional limitation imposed is that the minimum weight of a variable in the composite indicator is at least 5%. As the authors state, the advantage of this approach over others is that the panel analysis takes into consideration common patterns of behaviour of specific variables around crises, and reduces the bias of country-specific estimates.

6.3 Transformation of variables for the d-SRI

Once the indicators to be incorporated in the d-SRI are identified, they should be transformed to make them comparable, as in the case of the previous indicators. This involves standardisation, subtracting the median from the value of an indicator and dividing the difference by the standard deviation of the indicator concerned. This will result in an indicator that will be interpreted as an average deviation from the median value of the composite indicator. As Lang et al. (2019) perform their analysis with the use of panel data, the standardisation is based on the properties of data across countries and periods included in the analysis:

$$z_{i,k,t} = \frac{x_{i,k,t} - x_{med,k}}{\sigma_{x_k}}, \qquad (13)$$

where i denotes a country, k represents a variable selected for the purpose of the composite indicator, t denotes quarter, x denotes the initial value of the variable, $x_{med,k}$ and σ_{x_k} represent median value and standard deviation across all countries and quarters for the selected variable k. Median is chosen as it is more robust to outliers, even though the standardisation also depends on the trends in the values for other countries covered by the analysis, not only on the properties of the country being analysed. As for the calculation of this indicator for a single country, the transformation depends only on its own distributions, reducing its comparability with those countries using the results of calibrations and estimates included in Lang et al. (2019). However, the analysis enables the comparison of those countries included in the research.

6.4 Selection of variables for the d-SRI

This indicator aims to cover five[32] categories of measures already mentioned above. For greater comparability with countries included in the research sample, this research follows the description provided in Lang et al. (2019), with the selection of the following variables and the corresponding weights:

1. annualised 2-year change in credit-to-GDP ratio (NDC, narrower definition of credit, see Appendix 2) (36%);
2. annualised 2-year real credit growth rate (BDC, broader definition of credit, see Appendix 2) (5%);
3. annualised 3-year change in real estate price-to-income ratio (17%);
4. current account[33]-to-GDP ratio (20%);
5. annualised 2-year change in debt service-to-income ratio (5%);
6. annualised 3-year change in real stock market index (17%);

which, according to empirical findings, have proven to be the best signals of previous crises. The problem here is that the data normalisation was performed only for Croatian data. This means that the results are not fully comparable to other countries, but nevertheless provide a starting point.

6.5 The results of the d-SRI calculation

This approach to constructing the composite indicator allows no room for changing between the combinations of variables as permitted in the previous two approaches. However, the weights or transformations of variables can vary in the light of past experience or the properties of variables. Figure 6 shows the indicator obtained according to Lang et al. (2019). All indicator variants captured crisis periods and risk build-up in the last few quarters.

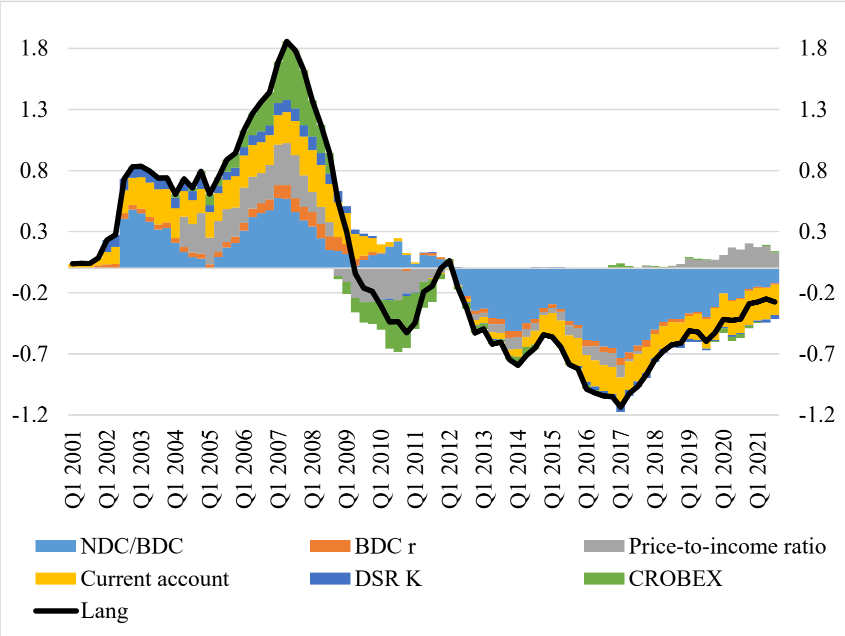
All indicators reached their peaks in the period of economic upswing preceding the global financial crisis, which was supported by all the indicators included. Once the global financial crisis began and the Croatian economy fell into a several-year long recession, the value of both indicators began to fall sharply as a result of the slowdown in credit growth, the decline in residential real estate prices and the decrease in external imbalances. The lowest indicator value was recorded at end-2016, after which it began to recover, a trend continuing, with certain interruptions, until today. The upward trend of both indices indicates the recovery in the credit and the financial cycle characterised by low risk perception and systemic risk

[32] Lang et al. (2019) only briefly indicate that their research does not include the category of "measures of the strength of bank balance sheets" because they measure the resilience of the banking system rather than risk build-up.

[33] Multiplied by -1 for the direction of movement of this indicator to be consistent with other indicators and the overall score.

accumulation. Since 2017, the most significant contribution to the increase in broad d-SRI has come from growing residential real estate overvaluation and the accelerating credit activity.

Figure 6 The d-SRI indicator according to Lang et al. (2019)



Source: CNB, author's calculation.

The calibration of the CCyB value based on this approach is ultimately complemented by a decision that can be based on the consideration of the trend of individual variables relevant for making such a decision. For example, if there is a subdued credit dynamics in the economy, and the other variables included in the calculation of the d-SRI contribute to the build-up of cyclical risks, a zero CCyB rate can be imposed where a positive rate would additionally hamper credit growth. It should be noted that in the case of normalisation according to Lang et al. (2019), the d-SRI indicator is interpreted as an average deviation from median risk level[34], meaning that negative values of this indicator can also indicate the need for introducing a positive CCyB rate. To be more precise, the d-SRI value of 0 would mean that on average the economy is at the median level of cyclical risks, i.e. the combination of selected variables and their current levels in a linear combination may result in a median level of total risk.

[34] In Lang et al. (2019), this means the average deviation from the median risk level for the whole panel of countries, while in a country-specific analysis, such as the one performed in this research, this concerns deviation from the median value for the country concerned.

6.6 Extension of the d-SRI indicator (1): the FSRI indicator

The financial stability risk indicator (FSRI) is elaborated in ECB (2018) and extends d-SRI by including measures covering the degree of interconnectedness of the financial system, spillover of shocks within the financial system, as well as contagion shocks. The authors argue that an indicator constructed in such a way has a good near-term predictive power for recessions. This indicator measures both the cyclicality of the financial system and the looming recession, and also includes measures relating to cross-sectional information. The idea is to also cover the risks relating to the interconnectedness within the financial system and the economy as a whole. In addition to the existing indicators used for the d-SRI indicator, indicators measuring co-movement within the financial system are also defined, especially in terms of the realisation of the accumulated cyclical risks. First, the data are divided into four buckets, concerning the movement of measures related to risk appetite, non-financial sector imbalances, financial sector vulnerabilities and the spillover and contagion measures (as this includes several dozen measures, a detailed list is provided in Table A2 here). The first three buckets mostly include the variables that have already been analysed in the above sections. The fourth bucket complements the first three, providing information on the interconnectedness of the financial system and mutual exposure. The fourth bucket measures sectoral interconnectedness, shock amplification, systemic illiquidity and “contagion” among banks (providing information about the extent to which the problems of one bank in the system will affect and spill over to other (connected) banks). Given the large number of individual indicators, after all data have been collected, a factor analysis is conducted, meaning that for each of the four buckets one factor is estimated, and then the factors are averaged into the FSRI indicator.

A quantile regression is used to predict the left tail of the GDP growth density over the short term (next quarter). The results of the analysis for the euro area show that this indicator is a good predictor of the negative GDP trends. In this regard, this indicator can be problematic for the calibration of the CCyB. To be more precise, the d-SRI indicator is constructed on the basis of an early warning model, where the crisis is predicted in the period from several years to several quarters preceding the crisis. In addition to the risks associated with the spillover of shocks, the construction of the FSRI indicator results in a measure forecasting the economic growth or downturn in the next quarter. In this context, this indicator is not the best choice for the calibration of the CCyB. However, it proves useful for an indicative assessment of the overall economic situation in the country, in the light of useful information concerning the interconnectedness of the system, given that it considers as many as 11 different approaches[35] in modelling the spillover of different shocks.

[35] Measures and models such as CoVaR, delta CoVar, SRISK, etc. See details and interpretations in the publication concerned.

6.7 Extension of the d-SRI indicator (2): the CSRI indicator

The publication of the ECB (2018) dealing with the FSRI also defines the cyclical systemic risk indicator (CSRI), which is a combination of the d-SRI (see Chapter 6) and the e-SRI ("e" as exposure) measuring risk cyclicality associated with a country's foreign exposures. The d-SRI and e-SRI indicators are constructed first as described in Chapter 6. These indicators are then combined into the CSRI indicator. As the d-SRI has already been described in detail, we will now consider the e-SRI indicator. The e-SRI indicator is constructed as a weighted average of the d-SRI of those countries to which the banking system of the country of interest is most exposed. The weights depend on the extent of exposure. For example, if the financial system of a country is significantly exposed to other countries, weights are assigned to their domestic cyclical risk indicators (d-SRI) based on the size of exposures by country, and the average thus obtained represents the e-SRI of the first country. Weights vary over time, based on the direct asset-side exposure to other banking systems. This approach is relevant for those countries whose banking systems are largely exposed to other countries. Finally, the CSRI is obtained as a weighted average of the d-SRI and the e-SRI. The ECB (2018) says that the weights are assigned according to the results of the early warning model. The indicator that produces better results from the use of this model will be assigned larger weight. This indicator requires data on the exposure of a country to other countries, but also data from all the variables across all countries, in order to construct their d-SRI, and ultimately to construct the CSRI. Given that many countries, Croatia included, still have only very short time series, the calculation of this indicator remains problematic. Therefore, it is not surprising that this indicator is rarely applied in practice.

One variant of the combination of the FSRI and the d-SRI is applied in Sweden (see Krygler and van Santen, 2020), where the same variables as in the case of the d-SRI are considered. The e-SRI is not estimated, and the composite indicator includes the global government debt to 21 countries[36]. As for the interconnectedness within the financial system (linked to the FSRI), several measures to estimate tail-dependencies across several largest banks and generally exposure to individual sectors are used. Uncertainty indicators (domestic, global, political, economic uncertainty) are also included. The variable transformations include moving averages and gaps from statistical filtering and the resulting measure is a hybrid between an indicator that signals future system changes sufficiently in advance (such as the d-SRI) and an indicator forecasting only one quarter ahead (such as the FSRI). In this approach, all variables are normalised by average and standardised (whereas median is used for other related indicators mentioned above). In practice, such a hybrid approach would be problematic for the calibration of the CCyB as it is difficult to interpret the results of the

[36] In this research, no examples have been found of countries calculating the e-SRI as described in this section. The best example in this regard would be the case of Sweden in terms of global government debt.

indicator thus obtained in order to signal crises in a timely manner. However, it provides a lot of useful information for the purpose of obtaining an overview of the situation in the economy and the financial system over the short term.

7 Comparison and selection of indicators for Croatia

7.1 Advantages and drawbacks of individual indicators

From the above detailed descriptions, a brief comparison can be made of the advantages and drawbacks, as well as the applicability of individual indicators for the case of Croatia. In general, all the composite indicators prove useful in terms of combining more information in one number, as it is more difficult to monitor the dynamics and complementarity of all individual variables at the same time, especially when deciding on the CCyB value. In addition, some of the indicators mentioned can be quite easily interpreted given that they are all constructed in such a way that the higher value indicates higher cyclical risk. However, there are some differences.

Some approaches involve arbitrary choice of variables, meaning that there is a broad freedom of choice in terms of the composition of categories of measures. For example, in the case of the FCI and the “private sector debt burden” category of measures, there is an option to arbitrarily choose either a 1-year or a 2-year change/growth rate of a variable. This means that the decision maker may be subjective and consider different variants in the selection of variables and their transformation in order to match a particular narrative, while the further development of cyclical risks in the future can have a different dynamics than the one presented for a previous period. Within the scope of other approaches, the decision on the choice of variables to be used in an indicator and their form is based on early warning models. This primarily concerns the d-SRI[37], which has been developed based on a panel analysis by examining the power to signal crises over the long term, covering several crises. This reduces bias in results linked to specific crises or countries. As the analysis does not cover Croatia, the only option is to map the results as accurately as possible, in the light of the currently available data. Furthermore, looking at the comparability of indicators by country, the indicator should preferably be based on a methodology allowing for full comparability across countries. This provides an insight into both the phase of the financial cycle of a country and its position relative to other countries. In addition, if the exposure of a country to the financial system of another country is analysed, the composite indicators should be comparable. Calculation of the d-SRI allows for such comparability, while this is

[37] And some approaches to aggregation to be discussed in the next section.

not possible in the case of the cyclogram due to the lack of uniform guidelines. In addition, balance should also be sought in terms of the number of variables to be included in the indicator. Too few or too many variables can generate problems: too few variables could create bias in the trend of the composite indicator, the purpose of which is to summarise more information in a single piece of information. Too many variables could lead to capturing “noise” rather than true signals preceding the crisis. This is why a balance should be struck, as in practice there is no formula capable of helping to identify the optimal number of variables. This problem can to a certain extent be alleviated by assigning equal weights across categories of measures of riskiness of variables, rather than at the level of a particular variable.

Concerning the advantages and drawbacks of individual indicators, the following can be concluded: one of the advantages of the FCI indicator is the way it is constructed, as the information about the correlations between individual variables is included in its calculation. If several categories of measures point to an increase or decrease in cyclical risks, this will result in additional rise or fall in the FCI values. However, this complicates the interpretation of the results, as it is a non-linear function that is difficult to communicate to the public. Although the contribution of the average correlation is illustrated graphically, the value of the indicator depends on the varying correlation structure, and the movement of the FCI value, which either drops or increases in a given period, cannot be directly interpreted by increasing risk in a category of risk measures. Instead, its interpretation also depends on correlations, the number of which increases[38] as the number of variables in the indicator grows. Furthermore, the movement of the FCI depends on the choice of variables, constant variable weights are used in the calculation (due to short time series and the lack of information about the variables that require larger weights and the reasons for larger weights), while adding new data leads to revisions of the previous FCI values (due to the change in the distribution properties of some variables). However, the latest criticism of the weights and data revisions relate essentially to all indicators, meaning that over time all approaches would need to be revised.

On the other hand, the cyclogram allows for a graphic illustration of the movements of both the composite indicator and the variables comprising it, even though most of the other indicators can also be presented and monitored in this way. The advantage of the cyclogram and other indicators that do not include gaps from statistical filtering is that the calculation does not implicitly include problems associated with statistical filtering (e.g. the problem of the last point in the HP filter, see details in footnote 4). On the other hand, the selection of variables, although based on previous findings in the literature, is still arbitrary in terms of

[38] The total number is equal to the binomial coefficient n over k, where n denotes the number of variables included in the indicator, while k equals 2.

transformations, and the results can therefore vary significantly, which can affect the calibration of the CCyB value. In addition, the use of 1-year changes or growth rates results in excessive oscillations of the composite indicator (this is also true for the FCI), which is why empirical research also uses annualised 2-year or 3-year changes or growth rates, to be smoothed by the final series. However, this is not consistent with the descriptions of the selected variables provided in papers dealing with this type of composite indicator.

The problem of arbitrary choice of variables and their transformations in the analysis is reduced in the d-SRI indicator, as it includes all the possible variants of measuring the cyclicality of the behaviour, finding the one that best signalled the past crises. The problem here is the lack of data when only one country is being analysed. However, this indicator still provides better comparability among countries if the described methodology involving a panel of countries is followed. Generally speaking, it is difficult to identify the best transformation of variables used for the calculation of indicator. In the case of short time series, it is difficult to determine their statistical properties such as their stationarity and method of distribution, all of which affects the final calculation of the indicator. An indicator should ideally be stationary because for such series it would be less difficult to assess the moments of distribution. Its variables should be normally distributed, and the transformation by normalisation would thus be unquestionable. Table 5 summarizes the comparison of all the approaches described.

In conclusion, in terms of the advantages and drawbacks of various approaches, the d-SRI enables easy interpretation and communication with the public, and the choice of variables is based on greater objectivity compared to the other two approaches. It must be noted that, unlike the previous two composite indicators, there is a model that ranks the best variables that pointed to problems before the onset of the financial crisis. For these reasons, use of the d-SRI is currently recommended in the case of Croatia. While the choice of variables to be included in the calculation and their transformations are open to discussion in the case of the FCI and the cyclogram, meaning that the result will depend on the subjectivity of the decision maker, the d-SRI is based on the properties and behaviour of variables prior to the crisis, taking into account various transformations and choosing the one that best signals a crisis. The next section deals with the d-SRI that is adjusted to enable repeated crisis signalling testing, for Croatian data.

Table 5 Summarized description of the approaches considered for the construction of composite indicator

Indicator	Transformation of variables	Information condensing method	Choice of variables	Advantages	Drawbacks
FCI	Order statistics	Non-linear function (from portfolio theory)	Financial cycle theory, previous literature, without empirical evaluation of the properties of variables before crisis	Takes into account variable correlations, graphic representation, no problems associated with statistical filtering, robustness due to scaling of values at interval (0,1]	It is not based on the properties of variables prior to previous crises, the choice of variables is prone to major changes, it is more difficult to communicate the aggregation of variables, volatility of results given the choice of variables, there is no way to evaluate results
Cyclogram	Based on the percentile of distribution or max-min	Simple average / weighted average	Past trends in variables during country-specific crises	Graphic representation, no problems associated with statistical filtering, simple aggregation	It is not based on the properties of variables prior to previous crises, the choice of variables is prone to major changes, volatility of results given the choice of variables, there is no way to evaluate results
d-SRI	Normalisation based on median and standard deviation of a series or max-min	Simple average / weighted average	Early warning models and ranking of the best variables according to predictive power	Based on the properties of variables prior to previous crises, simple aggregation, robust indicator	Correlations between variables are not taken into account, the possibility of biased results in the case of country-specific analysis

Note: The second column “Transformation of variables” includes variables that have already been defined as statistical gaps, growth rates, changes or otherwise. Furthermore, the hybrid composite indicator can be defined by applying the transformation of variables different from that applied in the original research papers.

Source: prepared by the author based on the previous chapters.

7.2 Selection of the best indicator – ICSR

Taking into account the advantages of the d-SRI indicator, its extended variant is further considered, where the procedure described in Lang et al. (2019) is repeated for all the six categories of risk measures, for all the collected data and variables in Appendix 2. Instead of mapping the variables in a narrower variant (the variant is referred to as narrow due to the smaller number of variables that make up this indicator), variables that best signalled the past crisis in Croatia are used. The construction of the ICSR (*indicator of cyclical systemic risk*) takes into account all the variables described in Chapter 3 and presented in Appendix 2, together with all the transformations. The values of the smoothing parameter in the case of

HP gaps are based on the findings in the previous literature[39] about the greater power to signal future crisis depending on the parameter used, but also about the lack of information on how long the cycle of each group of variables could be. Due to the large number of variables, this research deals only with the variables that ultimately proved best in their category of measures[40].

The procedure for selecting variables was as follows. Having performed all the relevant transformations, the AUROC value was estimated for all the variables, which was followed by the identification of the variables with the highest value within each category of measures. Given that some AUROC values within a category of measures were within a very narrow range, all the best variables in a category were selected. Table 6 shows the variables in each of the categories that best signalled the previous crisis. Although the analysis involves a single crisis in only one country, which can make the results biased, it nevertheless gives an indication of the variables that best signalled the build-up of cyclical risks, at least in the pre-crisis horizon of 16-5 quarters. Equal variable weights were assigned to each of the categories and equal weights were then allocated within each category, meaning that the weights were assigned objectively. In addition, in the cases analysed above, where weights are assigned based on the early warning model that was valid for the previous crisis, it can be argued that the weights might be biased due to the specific behaviour of some variables in the period of several quarters preceding the global financial crisis. Future analyses should also consider alternative ways of assigning weights, other than equal weights and those based on early warning models.

Table 6 Best indicators for the construction of the ICSR

Risk categories	Indicator abbreviation	Description of indicators
Measures of credit developments	HL 125k	HP gap[41] for the broader definition of household loans, smoothing parameter of 125,000
	LNFC 125k	HP gap for the ratio between the narrower definition of credit and the sum of GDP in the current quarter and in the previous 3 quarters, smoothing parameter of 125,000

[39] For details on the choice of the smoothing parameter in the HP filter, see Detken et al. (2014), Drehmann et al. (2010) or Wezel (2019).

[40] The full list with the results of the early warning model are available upon request.

[41] In future research, this approach will be complemented by HP gap corrections by using out-of-sample forecasts, which will require a separate detailed analysis and comparison of the underlying forecasting models used. Given the satisfactory results of the ICSR indicator in this paper, in view of the interpretations and the timely calibration of the CCyB value in Chapter 9, for now HP gap corrections is something to be considered in the future.

	NDC 125k	HP gap for the ratio between the narrower definition of credit and the sum of GDP in the current quarter and in the previous 3 quarters, smoothing parameter of 125,000
Measures of credit institution financing risk	- Cap / Assets 2y	A. 2-year change of the negative capital-to-asset ratio of credit institutions
	- Dep / Cred 2y	A. 2-year change of the private sector negative deposit-to-credit ratio
Measures of potential overvaluation of property prices	HPI 2y	A. 2-year growth rate in the house price index
	P / I 2y	A. 2-year growth rate in the residential real-estate price-to-disposable income ratio
	VICW 2y	A. 2-year growth rate in the volume index of construction works
Measures of private sector debt burden	DNFC / GOS 125k	HP gap for the ratio between corporate debt and the sum of gross operating surplus in the current quarter and previous three quarters, smoothing parameter of 125,000
	HD / Inc 125k	HP gap for the ratio between household debt and disposable income, smoothing parameter of 125,000
	DSR H 125k	HP gap for household debt service ratio, smoothing parameter of 125,000
	DSR NFC 125k	HP gap for corporate debt service ratio, smoothing parameter of 125,000
Measures of external imbalances	- NX / GDP 2y	A. 2-year change in the negative share of net exports of goods and services in GDP
	- CA /GDP 2y	A. 2-year change in the negative share of current account balance in GDP
Measures of potential mispricing of risk	CROBEX 2y	A. 2-year growth rate in CROBEX
	- margin H 2y	A. 2-year change in the negative interest margin on new loans to households relative to the 3-month EURIBOR
	- margin NFC 2y	A. 2-year change in the negative interest margin on new corporate loans relative to the 3-month EURIBOR

Note: 2-year changes are annualised and marked with A. Denotation "-" preceding the abbreviations of some variables denote negative value, meaning that the values have been multiplied by -1.

Source: CNB, author's calculation.

Furthermore, some bias may arise in a country-specific analysis, such as the one performed in this research, given that the sample includes a single crisis. However, in terms of the results presented in Table 6, most variables overlap with those included in the previous literature that also examines the power to signal crises, on a wider set of countries and over a longer period of time. The results can thus be considered reliable, but other relevant indicators should also be monitored when deciding on the level of the CCyB. Figure 7 thus shows extended[42] indicators based on the variables from Table 6, on the basis of the standardisation of variables (panel a). For the purpose of comparison with the initial method of variable transformation, panel b considers the indicator with max-min transformations of variables, which better preserves the original trend dynamics, given that the transformation by means of median and standard deviation is more linked to the assumption of normal distribution of variables[43].

In practice, variants of indicators with one or the other form of variable transformation can be considered, given that none of the approaches is ideal. This will provide more information about the position of the economy in the financial cycle. Finally, the interpretation of results in Figure 7 is very intuitive, as the values of both individual risk categories and the final composite indicator move in intervals that include both positive and negative values. As panel a shows transformation based on median and standard deviation, value 0 means that the average deviation from the median risk level is zero standard deviations, i.e. that the economy, given such combination of variables, is at the median level of risk associated with the financial cycle. Panel b is obtained by max-min transformation and offers no direct interpretation like the previous panel, but produces a similar dynamics, alleviating the problem of non-normality of distributions. In addition, although the calculation of this indicator includes 2-year changes or growth rates, unlike the previous two approaches, the increases in 2011 and 2014 remain in the negative territory, meaning that the calibration of the CCyB will not change for those sub-periods.

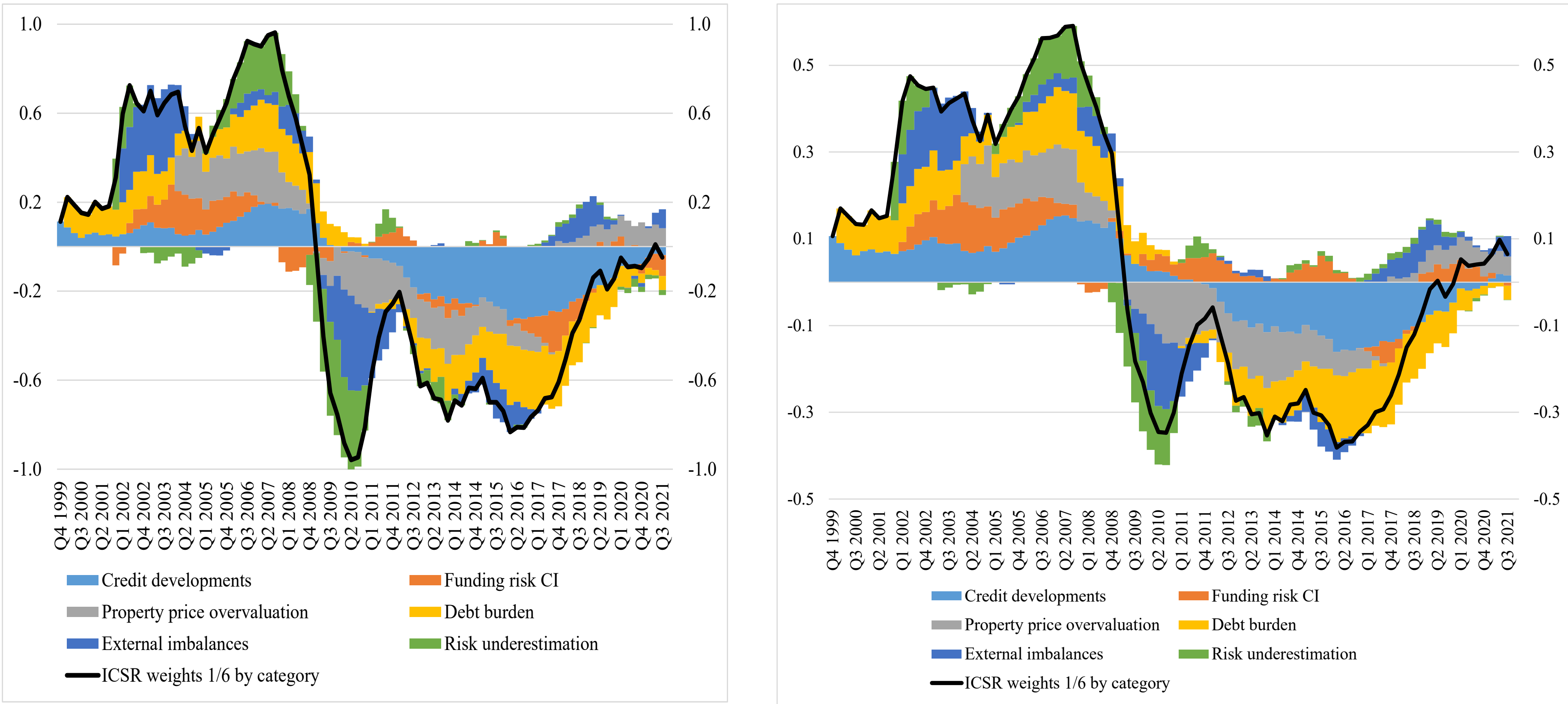
[42] Extended in terms of the number of variables compared to the original research contained in Lang et al. (2019).

[43] Normality of the distributions of variables has been tested and the zero hypothesis was discarded for most variables. In view of this fact, max-min transformation is recommended.

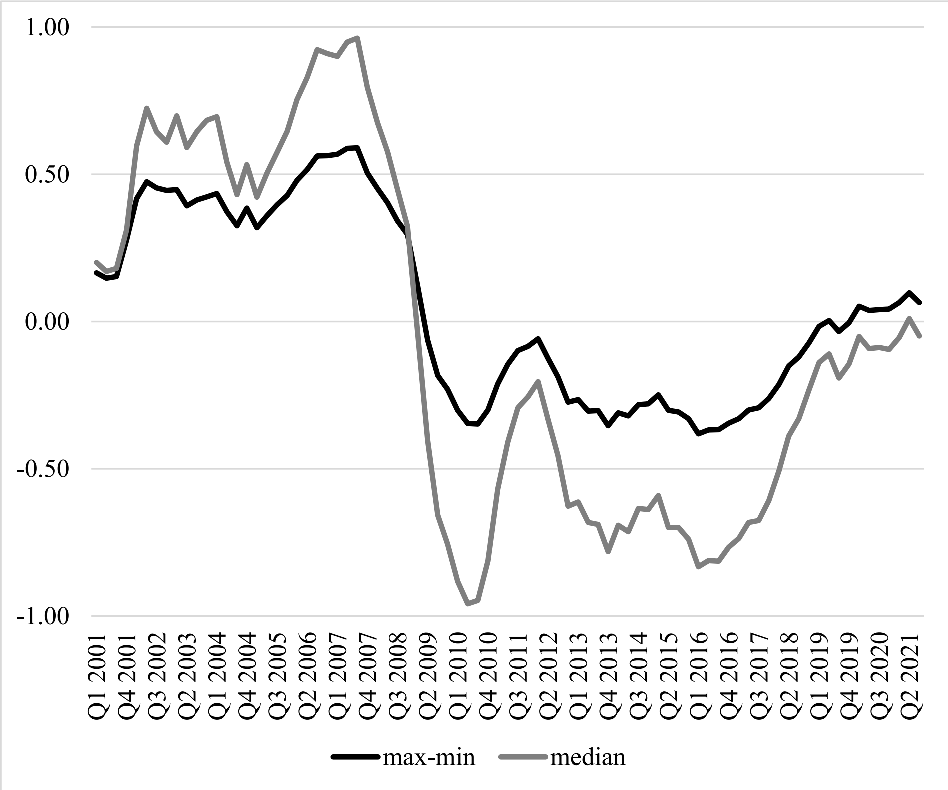
Figure 7 Cyclical systemic risk indicators for Croatia

a. Extended cyclical systemic risk indicator

b. Extended indicator from panel a, max-min transformation



c. Comparison of indicator trends from panel a and panel b



Note: Table 6 contains the list of variables used in panel a.

Source: CNB, author's calculation.

8 Additional data aggregation approaches

Several other approaches to calculating the composite indicator found in the literature and related to the subject of this paper are presented below. They concern individual data aggregation models or methods, where in the first part of the research the authors present previous papers dealing with similar topics, and then proceed to select the variables that are relevant for a particular country and that were identified in the previous literature as the best signals of crises. Where possible, methodology should be adjusted in order to match Croatian data better, reduce the bias of estimates and enable easier interpretation of results. Three additional approaches are analysed. Their application is relatively simple, and some of them could be used to complement the main analysis by using some of the composite indicators discussed above.

These are not complete indicators with the description of the selection of variables, transformations or aggregations. Instead they relate to a part of the whole approach. For example, principal component analysis is one of the possible ways of selecting the weights to be assigned to the variables constituting the composite indicator. The selection of variables and their prior transformation are not relevant, meaning that this is not a complete composite indicator, but an indicator that forms a part of the methodology. As the ICSR has been selected as the best indicator in the previous sections, the variables and their transformations are based on this approach, while some modifications to the choice of weights or aggregation methods are discussed below.

8.1 Principal component analysis

Principal component analysis (PCA) is used in the analysis of a large number of correlated variables, whereby the original set of variables is transformed into a new set of uncorrelated variables (referred to as "principal components"), which are linear combinations of the original variables. The variances of the obtained principal components have certain properties. For example, the first principal component accounts for the maximum possible proportion of the variance of original data. The PCA methodology proves useful where the initial set of variables is made up of a large number of variables, in order to reduce the dimensionality of the analysis[44]. This

[44] For details of PCA, see, for example, Tabachnick and Fidell (1996).

approach is used in Karamisheva et al. (2019), where individual variables selected for the construction of the composite indicator are first normalised, and then filtered in order to extract the cyclical component. Then the PCA analysis is carried out and one variant is selected for the composite indicator of the financial cycle. However, certain assumptions the PCA entails must be met here (linearity of variable interrelations in the analysis, the first two moments of distribution of variables are sufficient to describe the whole distribution, the larger variance of the resulting component has a more significant dynamics than others; see details in Jackson, 1991).

Karamisheva et al. (2019) deal with the construction of the financial cycle variable, even though the authors also include the cyclical movement of GDP in the analysis. However, the duration of the business and financial cycles is not the same, as already discussed in the literature (see Drehmann et al., 2010). This is why below we focus on the methodology and variables belonging to the categories of measures already mentioned above, following the recommendations of the ESRB[45]. The choice of variables can follow any of the approaches. Our choice of variables below follows the one made in the case of the above composite indicator ICSR (Table 6). After statistical filtering of variables, the PCA is carried out, where the analysis is limited to one principal component. The two core variants analysed in this section are presented in Table 7.

Furthermore, it should be noted that in Karamisheva et al. (2019), the authors first normalise the variables, which is followed by the extraction of cyclical components, although it is more customary to first extract the cyclical component, and then normalise or transform the variables. The paper provides no justification for such approach, but it can be assumed that the authors wanted to reduce/increase the cyclicality of individual variables prior to the extraction of the cycle, because they implicitly assume that the length of the cycle is the same for all the variables. As the composite indicator needs to be estimated, it is assumed that the first principal component in the PCA is the one defining it. After estimating the weights for each of the variables by correlating each variable with the first principal component by dividing each correlation with their sum, the composite indicator is defined as the sum of the multiples of such weights and the normalised values of all the variables[46]. Using the PCA as the basis for determining the weights and the dynamics of cyclical risks proves

[45] The list of variables used in Karamisheva et al. (2019) is included in Appendix 8.

[46] Appendix 10 contains weights of variables used in the variants of the PCA indicator from this chapter.

problematic here. Variable weights are corrected without economic interpretation, and it is hard to communicate such corrections to others. This may lead to wrong conclusions when calibrating the CCyB.

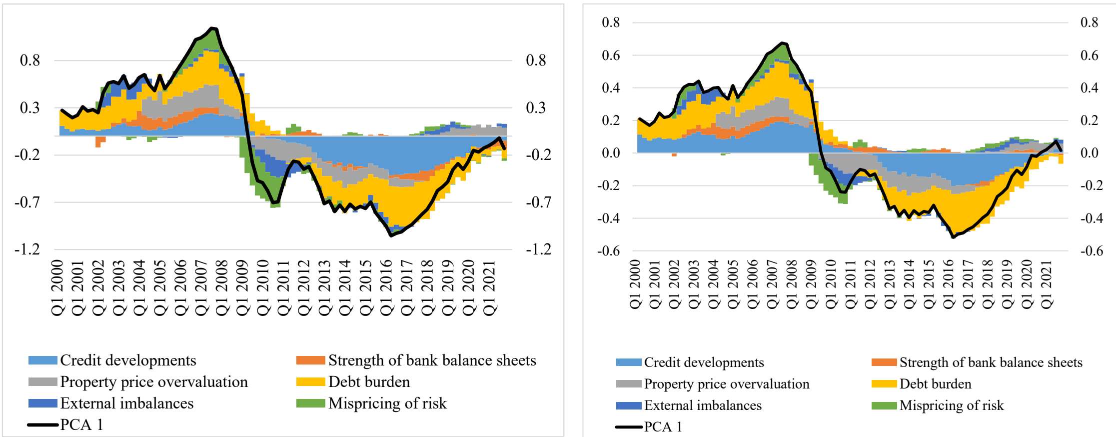
Table 7 Variants of the set of variables considered in the analysis

Indicator variant	Description
Variant 1	Variables from Table 6, normalisation by median and standard deviation of individual variables.
Variant 2	Variables from Table 6, normalisation by max-min transformation.

Figure 8 Composite indicators based on the PCA[47]

a. Variant 1 from Table 7

b. Variant 2 from Table 7



Note: weights for each of the variables in the indicators are included in Appendix 11.

Source: CNB, author's calculation.

Figure 8 compares the dynamics in the movement of the obtained composite indicators, which is very similar to that in the previous section. However, this approach proves problematic also in terms of clarifying the weights of the variation of the initial dataset based on the first principal component. A very small weight of this variation is explained in both cases, 50.16% and 48.68% for variant (1) and (2) respectively.

[47] Appendix 10 contains a comparison between the ISCR and the PCA in the case of max-min transformation and variants including variable gaps and changes.

Finally, it is questionable whether the assumption of constant correlations between variables, which is relevant for the PCA analysis, has been met, given that in most variable pairs significant changes were recorded in the values of correlation, which in some cases undergoes considerable changes, ranging from almost -1 to 1. This raises the question of whether it is valid to use this analysis. Although the results shown in Figure 6 correspond to those in the previous chapter, this is explained by the fact that the larger number of variables making up the indicator in the PCA leads to the allocation of almost equal weights. This is why use of this approach calls for caution. Finally, the interpretation of the dynamics shown in Figure 8 is identical to those shown in Figure 7, with the only difference being in how the weights of individual variables making up the composite indicator are selected.

8.2 Overheating index

Chen and Svirydzenka (2021) define the overheating index (OI), based on the preliminary analysis of the signalling performance of individual variables belonging to the categories of measures pertaining to credit developments, property price overvaluation and other typical indicators that have already been discussed in this paper as well. On a sample of 59 advanced and emerging economies, the authors first identify the variables that best predict financial crises, and then include the best indicators in the index. Special consideration is given to a panel of advanced economies (where stock exchange index and GDP gaps are identified as the best signals of crises) and a panel of emerging economies (credit gap, stock exchange index gap and property price gap). Based on the results of the early warning model, the authors define the overheating index as the following linear combination:

$$OI_t = \sum_{i=1}^{N} w_i I_t^i, \tag{14}$$

where w_i denotes weights of a variable i, while the variable I^i is the indicator variable, assuming the value of 1 if the value of its corresponding gap breaches the threshold, or 0 otherwise. Thresholds are set by estimating the two-sided gap in the year before the crisis[48] and by calculating the average level of gap for that year. Weights w_i are set by calculating Type I errors and Type II errors from the early warning model that has been

[48] The paper provides no explanation of why a two-sided gap in the year before the crisis is considered. Given that there are few available data, we have considered all the available data and the corresponding thresholds from individual early warning models for individual variables.

carried out, and using the obtained values to assign higher or lower weights, in the light of the errors concerned.

As no details concerning the allocation of weights based on these errors have been provided, the following will be assumed here. Type I and Type II errors will be added up for the variables included in the *OI* and based on the lower of the sums obtained; higher weight will be added to individual variables in formula (14). The drawback of this approach is the method of allocating weights based on Type I and Type II errors where the sample includes a single crisis, as in the case of Croatian data[49]. As the *OI* is a combination of variables taking the values of 0 or 1, it will be within the interval of [0,1], with the higher value indicating higher risk, similar to some of the above composite indicators. It should be noted that the positive value of this index means that there is already a combination of variables that breached the threshold, which are already interpreted in the early warning models as variables pointing to a crisis in the near future. However, the interpretation of the *OI* is different here relative to the previous indicators. For example, while the FCI remains at the interval of (0,1], the positive values of the FCI up to a certain level are interpreted to mean that the build-up of risk is not such that it would lead to its possible materialisation in the near future.

The results for the variables that best signalled the previous crisis in the case of the ICSR (see Table 6) are shown below, even though the results should be treated with caution as the analysis involves one crisis underlying the calculation of Type I and Type II errors. The results would be more reliable in the case of longer time series. Table 8, based on the results obtained for the ICSR, shows the calculated weights by applying the *OI* approach. Binary variables *I* for formula (14) are now defined, by comparing the movements of individual variables in each quarter with the threshold from the early warning model. Finally, the *OI* is constructed based on binary variables and the weights in Table 8, as shown in Figure 9, panel a. The largest weights based on the early warning model were assigned to the real estate price-to-income ratio, deposit-to-credit ratio, house price index and loans to households (column "weight"). Taking into account the mentioned problem of a single crisis in the sample analysed, the OI with equal weights of all variables is considered together with these weights in order to

[49] Some variables had negligible Type I and Type II errors and were thus assigned the majority of weights in the final indicator. However, as this concerned only two variables (dynamics of CROBEX and VICW), the weights were adjusted so that all the other variables were first assigned a corresponding weight based on the results of the early warning model, and then the weights for each of the variables were decreased by one percentage point, and assigned to CROBEX and VICW.

reduce the bias of estimates. The results of the composite indicator thus obtained are shown in Figure 9 (panel b). Both indicators on panels a and b can be interpreted as an average overheating value, depending on whether certain variables breached the threshold or not. As the transformed variables can take the value of 0 or 1, low values of the final indicator in the post-GFC period mean that only a few of the variables breached the threshold, possibly those that had small weights in Table 8 (in the case presented on panel a). However, the dynamics is similar to the FCI and the d-SRI, even though the reliability of these thresholds is questionable, having regard to the fact that they relate to the past crisis.

Table 8 Assigning weights to variables for the OI based on Type I and Type II errors

Indicator abbreviation	T1	T2	Sum	Weight
HL 125k	0,08	0,08	0,16	8,84%
LNFC 125k	0,08	0,21	0,29	4,47%
NDC 125k	0,00	0,41	0,41	2,84%
- Cap / Assets 2y	0,50	0,00	0,50	2,15%
- Dep / Cred 2y	0,00	0,09	0,09	15,82%
HPI 2y	0,00	0,13	0,13	11,09%
P / I 2y	0,00	0,09	0,09	17,14%
VICW 2y	0,00	0,00	0,00	8,00%
DNFC / GOS 125k	0,00	0,22	0,22	6,10%
HD / Inc 125k	0,00	0,49	0,49	2,24%
DSR H 125k	0,00	0,49	0,49	2,24%
DSR NFC 125k	0,00	0,33	0,33	3,73%
- NX / GDP 2y	0,00	0,61	0,61	1,57%
- CA /GDP 2y	0,08	0,45	0,53	1,95%
CROBEX 2y	0,00	0,00	0,00	8,00%
- margin H 2y	0,33	0,16	0,49	2,22%
- margin NFC 2y	0,25	0,19	0,44	2,60%

Note: the abbreviations of the variables are included in Table 6.

Source: CNB, author's calculation.

Greater volatility of individual variables leads to an increased oscillation of the *OI* in both variants at the beginning of the observed period. When all the variables are assigned equal weights (right panel), slightly higher values of the OI are recorded in the last period observed, even though the dynamics is similar to that for the previously analysed indicators. Panels c and d in Figure 9 show the structure of the OI: panel c shows the structure of the index from panel b, providing information about the variables that cause the increase in cyclical risks, while panel d shows the number of variables breaching the threshold in a given quarter. This information is also relevant for taking decisions on the level of the CCyB, as the OI can be positive in a given quarter, but, e.g., if only two variables from Table 8 breached the threshold, this does not necessarily point to a build-up of cyclical risks and the need to set a positive CCyB value. However, the dynamics of all movements should continue to be monitored.

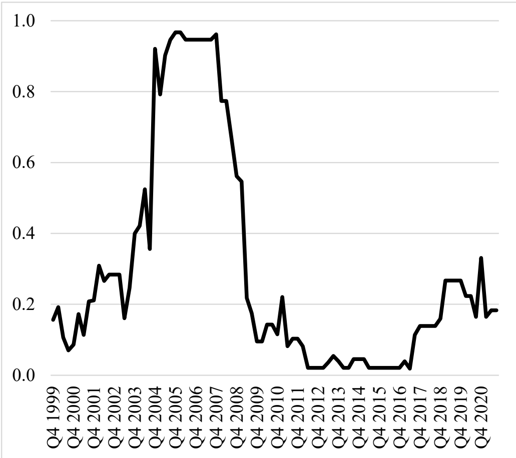
An indicator constructed in such a way would prove useful in practice as an additional indicator in monitoring the build-up of cyclical systemic risks, as it provides additional information on top of the information obtained from the previously analysed composite indicators: it provides information on the structure of indicator which, when positive, indicates what the value of risk build-up is. However, this can also be a drawback in analyses that, for example, involve Croatian data, given that such an analysis covers a single crisis, and thus the thresholds are under the influence of the specific developments of the GFC.

This is why the following adjustment of this indicator is proposed. Instead of the threshold from the early warning model, the analysis should focus on whether each of the variables is above or below the median level. As the median level means that the variable is at the median level of cyclical risks, the information about whether the movements are above or below this risk level can be of relevance to decision makers. Figure 10 therefore shows the OI and its structure relevant for the calculation of binary variables taking the value of 1 where a variable exceeds its median level or the value of 0 otherwise.

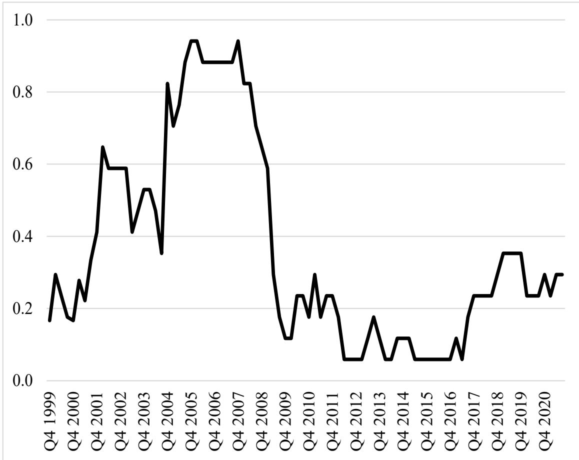
What can now be seen in Figure 10 is that since 2018, almost half of the variables in this period had values that exceeded their medians, which can prove useful in taking decisions on the level of the CCyB. As already mentioned, this approach would be useful in practice because it could serve to complement the main analysis of the position in the financial cycle. It also provides additional information about how many variables exceed the threshold and when such a threshold is exceeded, which is also important to decision makers.

Figure 9 Comparison of the OI based on the variables contained in Table 8

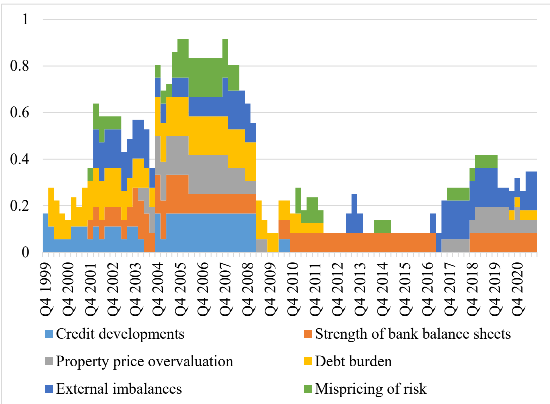
a. OI, weights in Table 8



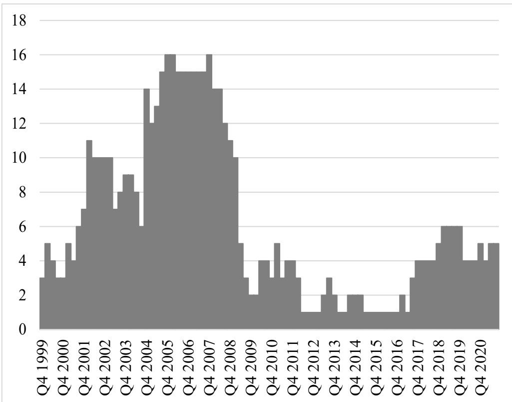
b. OI, equal weights of all the variables



c. Structure of the OI, equal weights



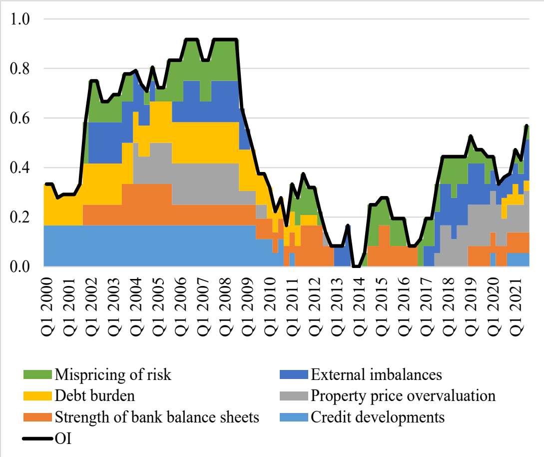
d. Number of variables breaching their threshold



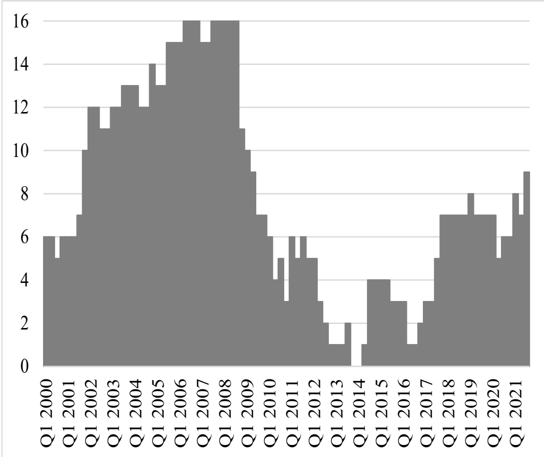
Source: CNB, author's calculation.

Figure 10 Proposed adjustment of the OI

a. Movements and structure of the OI



b. Number of variables exceeding the median level in a given quarter



Source: CNB, author's calculation.

8.3 Approach developed by Aikmann et al. (2015)

The paper by Aikmann et al. (2015) published by the FED presents several approaches to the aggregation of cyclical risks into a single indicator, with a focus on the US financial system. The choice of variables will not be further elaborated, given the wide set of variables discussed in the paper, many of which are not available for Croatian data (e.g. the change in lending standards from the Senior Loan Officer Opinion Survey (SLOOS) or FICO scores for mortgages sold to government-sponsored enterprises). Instead, variables from Chapter 6 will be used.

It should be noted that the choice of variables in Aikmann et al. (2015) is based on the results of the previous related research and US experience, with some variables being considered in levels, but others as changes or growth rates (without further specifying the reason for such differences and without them being based on e.g. early warning models). Several variants of variable transformations and aggregations used are described below. The variables are transformed by means of normalisation and standardisation (the normality of distributions is implicitly assumed), using rolling windows for such transformations (considering the availability of data relating to the US economy). The second transformation variant is based on the estimation of the quantile of distribution of the original variable and mapping to the interval (0,1), the same as in the case of the FCI. Furthermore, as the paper considers a large number of variables, after their transformation they are grouped into sub-indicators by calculating a simple average for each of them. The mentioned sub-indicators include "risk appetite" or "non-financial imbalances". The transformed variables, i.e. the obtained sub-indicators are then aggregated by applying the following formula:

$$V_t = \left[\sum_{i=1}^{N} w_i (v_{i,t})^r\right]^{\frac{1}{r}}, \qquad (15)$$

where V is the value of the cyclical risk or vulnerability indicator, obtained as a linear combination of sub-indicator v_i, i denotes a sub-indicator, $i \in \{1,..., N\}$, w_i denote their weights, while due to the assumption of the constant elasticity of substitution of sub-indicators, parameter r and its reciprocate value are introduced, and thus $1/(1-r)$ denotes the elasticity of substitution of sub-indicators[50]. Several variants are considered in the definition of the indicator by applying formula (15):

1. The assumption that $r = 1$ and that all weights w_i are equal results in a simple average.
2. Disregarding exponent r, assignment of equal weights w_i, and assuming that $1/r = 1/N$ will result in a geometric average. The paper incorrectly states that $r = 0$, due to the division in $1/r$, and fails to assert the assumption that $1/r = 1/N$, while the result is referred to as geometric mean. The description has been modified here to be consistent with the definition of geometric average. The usefulness of the geometric average in the context of financial stability is important because the multiple results in the amplification of shocks if the majority of sub-indicators move in the same direction. However, the problem arises where the final multiple is negative and we calculate its even root. This is not discussed in the paper.
3. The assumption that $r = 2$ and that all the weights are equal results in the root mean square (RMS) measure. In this case, the trends in only a few components of the indicator will be sufficient to ascertain the build-up of cyclical risks. This is because the weights of sub-indicators are squared, meaning that high values

[50] The authors provided no explanation of why they opted for this approach. If interpretation of constant elasticity of the substitution of production factors from microeconomic theory is applied in the context of cyclical risk indicators, this means that the ratio of the percentage limit contributions of the change in the indicator for each sub-indicator pair will always remain constant, with the increase in the ratio of such sub-indicators by 1%. This is a rather restrictive assumption.

will become even higher, while those indicating the absence of risk (very small values) will take an even lower squared value. This can be both an advantage and a drawback: a small number of variables pointing to the build-up of cyclical risks is enough to support the assertion that there is an actual build-up of such risks, in particular where a large number of variables within an indicator is considered. On the other hand, if only some variables indicate the build-up of cyclical risks, while others do not, it cannot be claimed that the measure covers different aspects of the economy, especially if the set of variables pointing to the potential build-up of risks changes over time.

4. One approach considered is the PCA analysis already discussed above.

The variable multiples and roots (even roots) pose a particular problem, while the majority of variables included in the composite indicators, either as growth rates or filtering gaps, also take negative values. In this case, the combination of the multiples of the positive and negative values may vary greatly depending on the number of negative values, it is more difficult to interpret the result obtained, and there could be an even number of variables whose multiple is a negative number, for which the corresponding even root cannot be calculated.

The results of aggregation in the second and the third[51] case and the variables used for the ICSR indicator are presented below. We propose that the variables be transformed as in the case of the FCI, where percentiles of distribution are considered, meaning that the variables will be within the interval of (0,1), eliminating the problem of a negative multiple under even root. The left panel of Figure 11 shows the trend in geometric average, while the right panel shows the RMS indicator. Given the multiplication of the values of individual variables within the six categories of risk measures, the structure on panel a is hard to interpret, while the structure on panel b allows for a more intuitive interpretation.

Although the definitions of composite indicators differ from those previously analysed, the indicators in Figure 11 also capture the increase in cyclical risks since 2018. The interpretation of the results is difficult compared to the above cases that involved the calculation of simple or weighted average. To be more precise, the geometric average is the result of the multiplication of trends in the values of variables by risk category,

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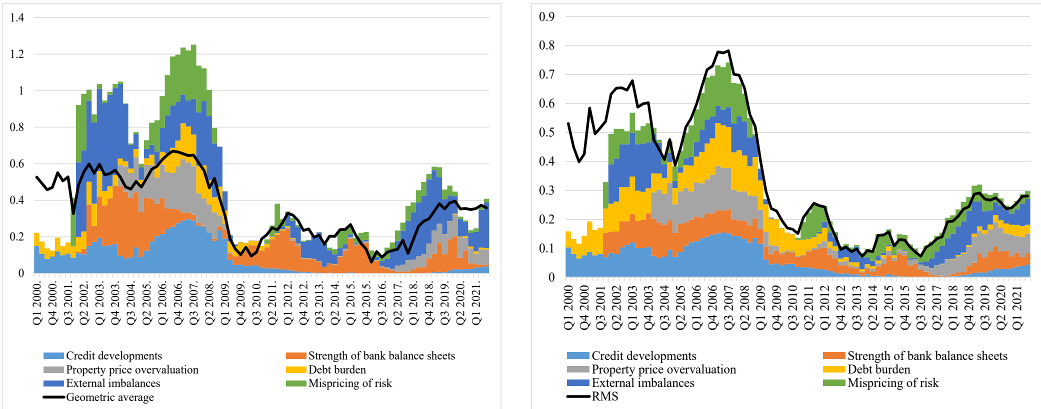
[51] The first case has already been discussed in the section dealing with the d-SRI, while the fourth case has been analysed in the section dealing with the PCA.

where the results are then multiplied to obtain the final value of the indicator. What proves to be useful in this case is observing the values of individual categories on panel a of Figure 11, showing that a higher multiple will result in larger weight of a category of risk measures in forming the final value of the indicator. However, communication to the public appears to be problematic. The case of the RMS indicator on panel b is somewhat simpler, but it involves squaring of values before their averaging, meaning that it does not allow for a direct interpretation as the d-SRI indicator.

Figure 11 Geometric average and the RMS as composite indicators

a. Geometric average

b. RMS indicator



Source: CNB, author's calculation.

In practice, these indicators could be considered as auxiliary indicators, given that their communication and interpretation are more difficult due to the non-linear calculation method. In addition, the non-linearity of function in (15) makes it hard to calibrate the CCyB rate, while in practice, the approach taken needs to be informative, but at the same time easier to use.

8.4 Comparison of approaches in 8.1 – 8.3

The following section deals with the advantages and drawbacks of the approaches discussed in the above sections. It should be borne in mind that the PCA focuses on the selection of the weights of variables included in the indicator, while the geometric average and the RMS concern the method of variable aggregation, whereas the OI primarily focuses on the additional transformation of variables included in the composite indicator.

The PCA is characterised by the simplicity of its approach, but does not involve a specific way of designing a new indicator. Rather, it is deemed to be one of the possible statistical approaches to condensing information into a single series, namely one principal component. However, this approach creates more problems than benefits. The problem with the PCA is that it is hard to test the validity of the assumptions of the PCA and factor models in general if only short time series are available, as in the case of Croatia. Furthermore, the factor models assume a linear correlation between variables, which is not necessarily the case in practice. Even though the PCA is relatively simple relative to some other approaches, statistical weighting is hard to explain in the context of macroprudential policy and objectives. Another drawback of the PCA is the assumption that the correlation between the variables is constant, which also does not have to be the case.

The geometric average and the RMS as aggregation methods are problematic when variables with negative values are used, making the interpretation of results more difficult. This gives priority to the simple average applied in the ICSR, given that the part concerning the communication with the public also must be taken into account.

Finally, the OI provides a solid basis for further upgrading of the ICSR indicator, but only where more data and several crises are included in the sample, enabling more reliable results. Since the OI is based on thresholds from the early warning model, it is not fully applicable in the case of Croatia due to the specific growth of certain variables before the GFC. This means that the variables might not breach some of the thresholds again. This is why other thresholds should be considered for future analyses. Table 9 below gives an overview of some advantages and drawbacks of all the approaches analysed in this section.

Table 9 Brief description of the approaches considered for aggregation

Approach	Variable transformation	Information condensing method	Choice of variables	Advantages	Drawbacks
PCA	Normalisation based on average and standard deviation of a series	Weighted average based on correlations from the first principal component	Description as for the FCI, the cyclogram or the ICSR (or their combination)	Simple aggregation	PCA assumptions, volatility of correlations in analysis, poor explanatory power of the first principal component

Geometric average	Normalisation based on average and standard deviation of a series	Geometric average formula	Description as for the FCI, the cyclogram or the ICSR (or a combination of them)	Simple aggregation	Information condensing method is difficult to justify economically, correlations between variables are not taken into account, if the choice of variables is based on the description for the FCI, there is no way to evaluate results, the problem of negative values of variables in the calculation
RMS	Normalisation based on average and standard deviation of a series	The second positive root of the sum of the squares of variable values	Description as for the FCI, the cyclogram or the ICSR (or their combination)	Simple aggregation	Information condensing method is difficult to justify economically, correlations between variables are not taken into account, if the choice of variables is based on the description for the FCI, there is no way to evaluate results, the absence of risk in a sector is compensated by another sector due to the squaring of variable values.
OI	Binary variable taking into account the results of the early warning model	Simple average / weighted average	Description as for the FCI, the cyclogram or the ICSR (or their combination)	If it is based on the choice of variables as the ICSR, it takes into account the properties of variables before previous crises, simple aggregation	Correlations between variables are not taken into account, if the choice of variables is based on the description for the FCI, there is no way to evaluate results

Note: The second column “Transformation of variables” includes variables that have already been defined as statistical gaps, growth rates, changes or otherwise. Furthermore, a hybrid composite indicator can be defined by applying the transformation of variables different from the one applied in the original working papers.

Source: prepared by the author according to the previous chapters.

9 Calibration of the countercyclical capital buffer based on composite indicators

The composite indicators analysed above are a starting point in setting the level of countercyclical capital buffer, the purpose of which is to alleviate cyclical systemic risks that may arise from the excessive growth of credit to the private non-financial sector, while during economic downturns it helps the banks to absorb potential losses and to preserve their credit activity. The main principle guiding the modelling of the level of the CCyB rate is based on the linear function of the credit gap value, where the CCyB becomes positive if the credit gap exceeds the lower threshold L, the linear growing function extends from the lower threshold *L* to upper threshold *H*, after which the CCyB takes the value of 2.5%. The interval from *L* to *H* is a functional form of a linear equation from two points. As composite indicators are a linear or non-linear combination of variables that have been transformed for the sake of comparability, the formula for the calibration of the CCyB cannot be directly applied to composite indicators.

Possible ways of calibrating the lower and upper thresholds *L* and *H* as for the calibration of the CCyB are as follows, focusing most on the ICSR indicator, given that it has been chosen as the most appropriate indicator for the case of Croatia. The first way is to observe the indicator and the properties of the distributions of variables included in the indicator, in order to assess the values these variables take when the risk is moderate or just begins to build up. The second way is to identify thresholds based on the results of the early warning models for each of the variables, while the third way is linked to the first approach based on distributions, but is further expanded in order to include the so-called neutral positive rate. Descriptions and calculations of them are presented below, after some general remarks.

Given that the choice of thresholds for the calibration of the CCyB values in most approaches is based on the distribution of these values and on the properties of indicators before the GFC, a certain level of bias is included in the modelling. The information on the average values of the indicator before the crises cannot be obtained if time series are short, as in the case of Croatia. If the analysis were to focus only on the values before the single crisis included in the sample, future movements of indicators could be such that they no longer reached the lower threshold, as required for the timely activation of the CCyB. Even though certain percentiles of indicator distributions are discussed below, these values are also influenced by the dynamics prior to the GFC. On the other hand, in the publications of the Czech National Bank (see discussion in Hájek et al., 2017 and the references mentioned there), where the time series are of the same length as in the case of Croatia, it is argued that the series include both the peak and the trough values, representing the maximum and minimum values that the indicator reached in the past, and are included in the analysis to determine the starting point for the range of the CCyB value. In any case, in future analyses it should be borne in mind that the thresholds for the calibration of the CCyB will need to be revised in view of the properties of future phases of the financial cycle in Croatia.

9.1 Approach based on the distribution of variables

First, the properties of the distribution of the ICSR indicator are considered. If the transformation of max-min variables with the variable interval of (-1,1) is considered, the ICSR indicator can also take values within that interval as their linear combination. Regardless of the variable transformation method for the calculation of the composite indicator, the distribution of the resulting indicator serves as a starting point in determining the values of the lower and upper threshold for the calibration of the CCyB. The lower and upper thresholds of the ICSR are determined, which will be interpreted as the lower and upper thresholds in the formula applied for the calibration of the CCyB. Values as shown in Table 10 are considered, for which the calculated value of the ICSR is such that the lower threshold is set at the 40th or 45th percentile of distribution of the indicator, while the upper threshold is set at a maximum of the 90th percentile.

Table 10 Proposed lower and upper thresholds of the ICSR for the calibration of the CCyB

Lower	Upper
40th percentile of the ICSR	90th percentile of the ICSR
40th percentile of the ICSR	Maximum value of the ICSR
45th percentile of the ICSR	90th percentile of the ICSR
40th percentile of the ICSR	Maximum value of the ICSR

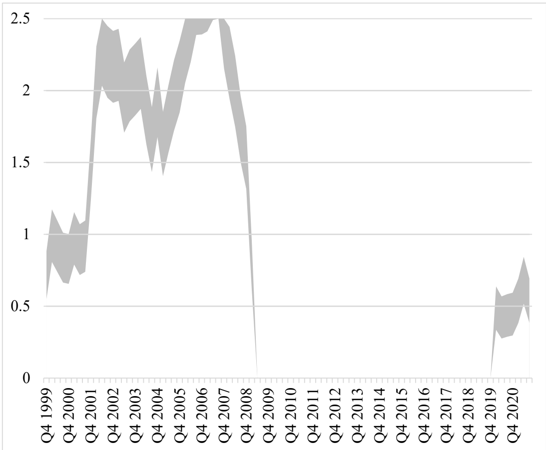
Source: author's discussion in the text

The lower threshold is set at either the 40th or 45th percentile because the 50th percentile or median could be interpreted as the mean level of risk accumulation. If the standardisation of variables (Figure 6) is considered, the ICSR is interpreted as the average deviation of values of all risk categories from the median risk level. In addition, as there is a 12-month CCyB implementation lag, and if the economy faces the build-up of cyclical risks to moderate levels, it is better to consider indicator values leaving enough time to build the capital buffer, meaning those that are below the distribution median. For this reason, several variants are proposed for use as the lower threshold (40-45% percentile of distribution), in order to take into account the tendency to build the CCyB more gradually (or the lack thereof) and to allow more room for decisions on its build-up. Similarly, several options are also considered in terms of the upper threshold, given that the maximum value of the ICSR is the one that was reached prior to the last crisis, meaning that it may be too high for the calibration of the CCyB. This is why the values that account for the 90th percentile of distribution at the time of modelling are also taken into account. After the lower and the upper thresholds have been calculated, they are used as values L and H in the formula applied for the calibration of the CCyB, while instead of considering gaps, the value of the ICSR in a given quarter is taken into account.

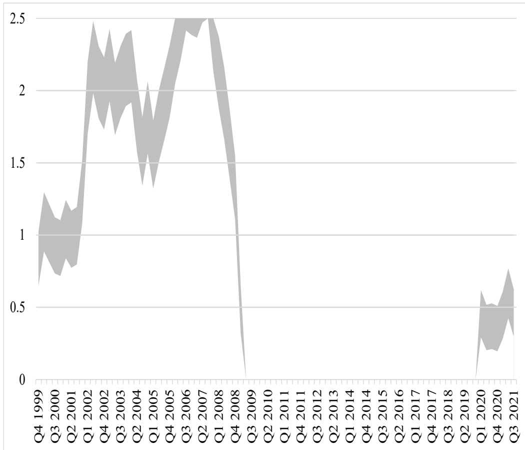
Given that there are four combinations for the calibration of the CCyB according to Table 10, the entire resulting distribution of possible CCyB values in Figure 12 is considered, for both ICSR indicators in Figure 7, the max-min transformation of variables (Figure 6, panel b) and the standardisation (panel a). The resulting distributions of the CCyB are very similar. The increase in all the variables prior to the global financial crisis, causing an increase in the ICSR, largely also resulted in the increase in the CCyB in the period concerned, with the maximum rate of 2.5 reached in 2006. Considering the trends in variables in the last few quarters, the positive values of the CCyB again indicate the build-up of cyclical risks. However, it should be noted that the calibration involves only mechanical mapping of values from one variable to another, and that the definition of such functional relations does not allow for the inclusion of the information about whether the economy is in the upward or downward phase of the cycle, whether lending is subdued or pronounced or other relevant information considered in taking decision on the value of the CCyB. This is why it should be noted that the calibration of the CCyB value based on any measure or indicator is only a starting point for macroprudential policy.

Figure 12 Distribution of the CCyB values for the ICSR indicator according to Table 10

a. Max-min transformation



b. Standardisation



Source: CNB, author's calculation.

The FCI and the cyclogram will also be commented within the scope of the first approach. The choice of variables to be included in the composite indicator can be based on the approach discussed in Lang et al. (2019), even though the synthetisation can also be carried out as described in the case of the FCI and the cyclogram. As the FCI involves a non-linear function, the value of the FCI cannot be directly calibrated as a credit gap. However, an overview of the movements of the CCyB values can be obtained by observing the distribution properties of individual variables, by setting the levels of the CCyB at intervals according to the values of the indicator. This approach is summarised in Table 11, where the lower and the upper threshold denote the values of the indicator observed. It should be borne in mind that the positive CCyB rate refers to those values of composite indicators that are interpreted to mean that the risk has already started accumulating, where the medium risk level already poses a problem, meaning that the positive CCyB rate should have already been introduced. The idea is to gradually build up the CCyB sufficiently in advance in order to avoid sudden increases in the CCyB rate when the economy is already close to the materialisation of risks.

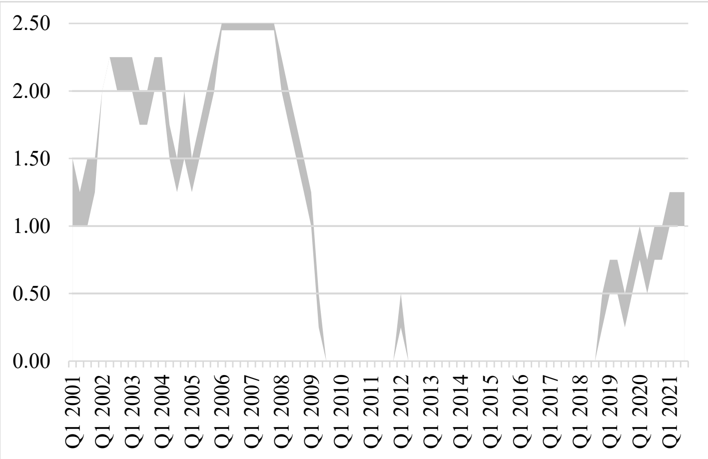
Table 11 Starting point for the potential calibration of the CCyB based on the interval approach

Lower threshold	Upper threshold	CCyB, in %
-	$ICSR_{40}$	0.00
$ICSR_{40}$	$ICSR_m$	0.25
$ICSR_m$		0.50
		0.75
.	.	1.00
.	.	1.25
.	.	1.50
		1.75
		2.00
	$ICSR_{max}$	2.25
$ICSR_{max}$	1	2.50

Source: adjustment according to the CNB (2020) and the author's deliberations.

In Table 11, the ICSR value at the 40th percentile of its distribution has been selected as the lower threshold for the initial activation of the CCyB, even though another value can be selected. This value has been selected in view of what has been discussed above. The decision maker independently determines the limits of the intervals for the ICSR value, assigning them the CCyB rate of 0.50%, 0.75%, etc., up to a maximum of 2.5%. In Table 11, the maximum value of the ICSR indicator has been set for triggering the activation of the rate of 2.5%. Again, please note that the literature provides no specific guideline in this regard and this value depends on the authority performing the calibration and taking the relevant decision. The first interval can be interpreted to mean that there has still been no significant build-up of cyclical risks, and the CCyB rate is set at 0. The next interval would range between $ICSR_{40}$ and the next value of $ICSR_m$, where m denotes percentile chosen based on experience, recalibration based on the available data, while the value of $ICSR_m$ is interpreted as in the case of the previous 40%. In Table 11, the maximum has been set at 1 (the last row), as the maximum value the ICSR could reach in the case of max-min transformation. In the case of transformation as described in the chapter dealing with the FCI, which takes values within the interval of (0,1), the maximum value would be 1, but instead of leaving an empty cell, the lower threshold in the first row of Table 11 would be set at 0 in the case of max-min transformation. The intervals need not necessarily be of the same length. This approach can also be applied to the linear version of the ICSR indicator and to the non-linear function for the aggregation of values of individual variables.

Figure 13 Distribution of the CCyB values for the ICSR indicator



Source: CNB, author's calculation.

Figure 13 shows the distribution of the CCyB for the max-min variable transformation, due to more variants of possible calibrations, where lower and upper thresholds were increased or decreased in order to cover more tendencies to increase the CCyB value (or the lack thereof). Based on Table 11, where the lower threshold for setting a positive value of the CCyB has been set at the 40th and 45th percentile of the composite indicator and where the upper threshold for setting the CCyB at 2.5% has been set at the 90th percentile, the remaining intervals have been arranged in such a way that the difference between the lower and the upper threshold has been equally distributed to the remaining buckets. The dynamics shown in Figure 13 supports that shown in the previous figure, even though the calibration in this case is somewhat more sensitive, because the CCyB values are slightly higher at the end of the observed period relative to Figure 12, panel a.

9.2 Approach based on the early warning model

Another approach that could be applied for the calibration of the CCyB value involves using the lower threshold from the early warning model, where the threshold L is based on the results of the estimation of the reference level τ which minimised the sum of Type I and Type II errors or maximised the Youden index (see Chapter 6). In this way, the corresponding threshold L has been estimated for each of the variables making up the ICSR indicator. As the construction of the ICSR involves the utilisation of transformed values of each of the variables by applying max-min normalisation, their respective L thresholds were first normalised to compare the value of each normalised variable in quarter t with the normalised threshold L. If the value of realisation exceeds L, this value is taken into account; otherwise the value is set at 0. Formally, the following holds:

$$y_{i,t} = \begin{cases} z_{i,t}\ , & if\ z_{i,t} > L_i \\ 0, & otherwise \end{cases}, \tag{17}$$

where $y_{i,t}$ denotes the value of variable i that is included in the calculation of the ICSR in quarter t, $z_{i,t}$ denotes the transformed values of all the variables under consideration, L_i denotes the normalised threshold obtained from early warning models for variable i. A new ICSR indicator is then constructed, obtained in a similar way to the OI index. To be more precise, the OI index takes into account those variables that breached the relevant thresholds L, where the variables took the value of either 1 or 0. In this case, the variables take their values in a given quarter (normalised) where they exceed the threshold L. This transformation has been selected so that the newly obtained composite indicator can be directly reflected in the CCyB value. This "new" ICSR indicator represents the average value of the variables that exceed their thresholds L in a given quarter:

$$\widetilde{ICSR}_t = \sum_{i=1}^{N} w_i z_{i,t} \tag{18}$$

The CCyB value is calibrated on the basis of these values. The positive value $\widetilde{ICSR}_t$ denotes a period in which individual variables signal a crisis. However, the specific behaviour of these variables before the last crisis could mean that the properties of such variables were specific to that period and it is possible that the future build-up of cyclical risk towards levels considered moderate to high can also occur with lower values of thresholds L_i. For instance, in terms of households, the credit gap that best signals the onset of a crisis within the scope of an early warning model is the one at the 75th percentile of the corresponding distribution of the gap. However, this level may already be too high for a decision maker who might not be willing to postpone its reaction until this percentile is exceeded in a given quarter[52]. However, to allow for a full comparison, the values of L_i are used as a starting point in defining the value of the CCyB as follows:

$$PCK_t = \begin{cases} 2.5 \cdot \widetilde{ICSR}_t \, / \, \max\{\widetilde{ICSR}\} \\ 0, \; otherwise \end{cases}, \qquad (19)$$

where $\max\{\widetilde{ICSR}\}$ denotes a maximum value that the indicator in (18) has reached in the observed period. Figure 14 shows the trends in the CCyB in the case of the described calibration, with increased volatility in the movement of the CCyB rate. This means that this approach is unsuitable for Croatian data. To be more precise, as this approach tends to capture the breach of threshold by only one variable, while others can still remain below the threshold, this would mean that the CCyB value might depend on the dynamics of only one variable in a given quarter. This is why peaks in some quarters may be observed in Figure 14. To conclude, this approach is currently not applicable in practice.

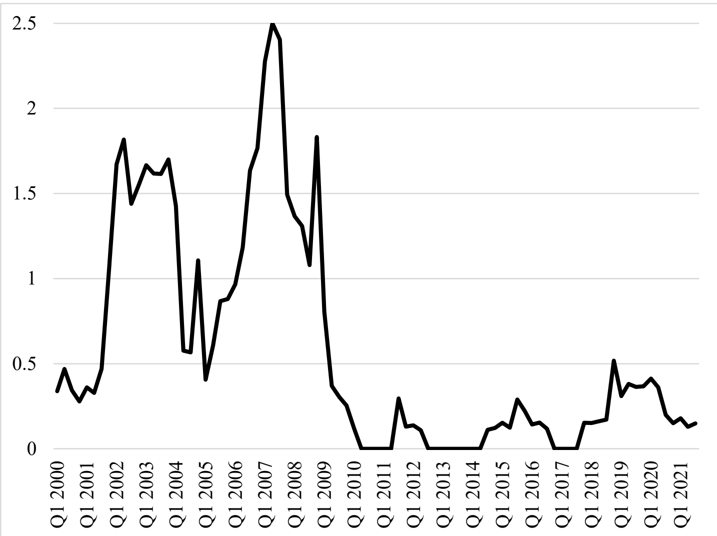
As part of this approach, attention is also drawn to the calibration described in Aikman et al. (2015), where the CCyB is calibrated by taking into account the range between the lower threshold L set at the 65th percentile and the upper threshold at the 85th percentile of the distribution of the aggregated indicator[53]. In their analysis, the authors stress that if the indicator is stationary, they would expect a positive rate of the CCyB one-third of the time, and for it to be at its 2.5% maximum around 15% of the time. This approach cannot be applied to Croatian data due to the very short time series, which, regardless of the approach employed in the construction of the composite indicator, cause the indicator to move in a way that cannot be characterised as a stationary series. Although the stationarity of the indicator is very important to allow for easier modelling, this is still not possible in the case of the Croatian data. Additionally, there is also the question of the choice of the analysed percentiles in Aikman et al. (2015), given that the paper provides no explanation about what constitutes an elevated or moderate level of cyclical risks. Moreover, the authors also calibrate the lower threshold L in such a way that the CCyB switches to a positive rate where at least three variables (from a total of fourteen

[52] There is also the problem of short time series, as in the case of Croatian data, where this percentile could be too high to be used in future calibrations, if it concerns a value that was reached in a specific period, such as in the period of high credit growth in the early 2000s.

[53] The problem with setting such high percentiles is elaborated in the previous footnote.

variables included in the calculation of the composite indicator) cross their 80th percentile. However, there is a problem with this approach. To be more precise, the authors do not explain why it is important for at least three variables to breach the above threshold to trigger the positive CCyB. Furthermore, the authors do not specify what these variables are. Furthermore, in view of the seventeen variables considered as relevant for determining the cyclicality of systemic risk and important in the calibration of the CCyB, the calibration can be problematic if it is necessary to change the number of variables for inclusion in the calculation. Finally, the length of the individual stages of the financial cycle and the strength of the upswing or downswing may change over time. This means that the calibration of thresholds for the CCyB must be changed in time as more data become available to the macroprudential policy maker. In this regard, the principle of guided discretion is very important, meaning that decision-making is based on the results of such quantitative analyses, but also on expert judgement, especially in the case of short time series, as is the case of Croatia.

Figure 14 Trends in the CCyB value for the calibration based on the early warning model



Source: CNB, author's calculation.

9.3 The "positive neutral rate" approach

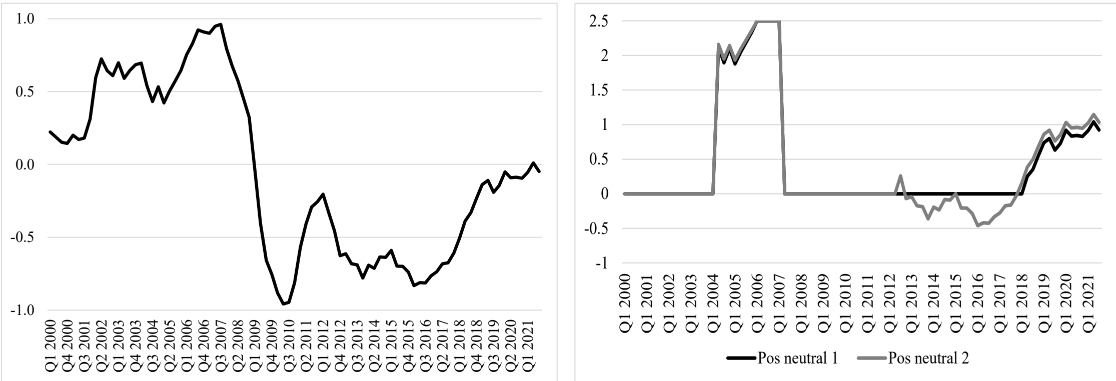
The concept of the "positive neutral rate" has been known for some time; it means that the level of the CCyB is set at a positive rate even when the economy is in the moderate risk phase. On the one hand, according to some opinions, the CCyB should be built in the recovery phase, while on the other hand there are some more prudent stances arguing that the capital buffer should be gradually built up even before such a recovery, as soon as the risks start to build up (see Banque de France, 2019; Babić and Fahr, 2019; ESRB, 2018), even if the systemic risks are not elevated (yet). Since most countries have already surpassed the phase of subdued risks following the last financial crisis, it can be argued that the situation in the past few years has been such that it calls for the introduction of the positive neutral rate (ESRB, 2018). The positive neutral rate strategy offers the advantage of reverting the positive CCyB rate back to zero at any stage of the financial cycle; it involves a number of capital requirements that the credit institutions can utilise when needed and it has the potential to improve capital buffer usability (according to Stojkova, 2020). In contrast to the neutral or natural interest rate within the framework of the monetary policy, meaning the level of interest rate which allows for reaching a zero GDP gap and the inflation target (which can also be negative, as in the case of some countries over the past few years), the positive neutral rate of the CCyB means the adoption of the CCyB rate above zero in those financial systems with insufficient other capital buffers (either voluntary or obligatory), to be applied in the stages of the financial cycle with subdued risks. In other words, the rate will reflect the level of systemic risk acceptable to the macroprudential policy-maker. By definition, the CCyB rate is a rate equal to 0 or above, up to a maximum of 2.5%, meaning that the rate of 0 reflects a neutral level in periods when there is no build-up of cyclical risks. However, as already mentioned, in countries where the total sum of credit institutions' capital buffers barely exceeds the minimum threshold, a positive neutral rate of the CCyB should be considered to ensure sufficient capital in case of a reversal of the financial cycle.

The positive neutral rate approach can also be linked to the theory of financial cycles according to Drehmann et al. (2012, 2013), where the financial cycle in advanced economies lasts about 15 years, with the downward phase from the peak to the trough of the cycle lasting half as much as the upward phase, with the upward phase consisting of two sub-phases: the first phase with subdued risks in the period of post-crisis recovery, and the second phase currently faced by most countries according to ESRB (2018). Both sub-phases are of equal duration, meaning that, if the length of the cycle is approx. 15 years, the upward phase lasts for about 10 years (with the two sub-phases lasting for 5 years each), while the downward phase lasts for about 5 years. In the light of this, given the smoothing parameter of 125,000 for the gaps in the composite indicator, and considering the date marking the official end of the crisis in Croatia (second quarter of 2012, according to Duprey and Klaus, 2017), the period of subdued risks lasted until 2

January 2017, meaning that a positive neutral rate of the CCyB should have been considered after that date. Having regard to the above information, the positive rate of the CCyB is to be considered from the quarter when the ICSR reaches the 40th percentile, in order to avoid setting too high a rate of the CCyB for too low a level of the ICSR.

By way of example, in this case the CCyB is calibrated by setting a positive rate of 0.25 for the value of ICSR in the third quarter of 2018, which can be represented as one point with coordinates (-0.39, 0.25). In order to define the CCyB as a linear function of the trend in the ICSR, it is assumed that the maximum CCyB value of 2.5% is set when the ICSR reaches its 90th percentile, which results in the second point with coordinates (0.72, 2.5). The two points serve to model the linear equation, and the value of the CCyB is set also for the remaining levels of the ICSR. Another assumption is that the CCyB is set at 0 during crisis. The result is the movement of the CCyB as shown in Figure 15 (right panel) in the selected period of crisis and the post-crisis recovery (Figure 14, left panel). Of course, the CCyB can also have a different dynamics, depending on the neutral rate to be defined in a situation where risks are not considered to be elevated. If the approach involving the first sub-phase of recovery is disregarded and a positive rate of the CCyB is calibrated immediately following the end of the crisis period (from the third quarter of 2012 onwards), then the previous point (0.72, 2.5) is used in combination with another point relating to the third quarter of 2012 (-0.46, 0.25). The grey curve in Figure 15 demonstrates such calibration (right panel). The problem here is that the negative values of the CCyB as a result of a further decrease in the ICSR are not usable in the first sub-phase of the financial cycle recovery. In the absence of the public consensus on how to calibrate the CCyB value in the case of the positive neutral rate strategy, the results in Figure 13 should be treated with caution. Future research should focus more on this approach.

Figure 15 ISCR (left panel) and the corresponding CCyB values (right panel)



Note: the vertical lines on the left panel denote formal dates of the end of crisis and the end of the period of subdued risks. Pos neutral 1 and 2 represent CCyB values based on the description of the two strategies in this paper.

Source: CNB, author's calculation.

10 Conclusion

Macroprudential policy calls for a timely and accurate assessment of the position of an economy in the financial cycle. This paper discusses the properties, advantages and drawbacks of several popular approaches to calculating the composite indicators capturing the build-up of cyclical risks over time. Composite indicators are recommended to be used in practice as they provide a more complete picture of other potential sources of risk accumulation, apart from credit dynamics. In view of the analysis provided above, we recommend using the ICSR (indicator of cyclical systemic risk), with the normalisation of values by applying max-min transformation, given the advantages of this indicator relative to the remaining indicators discussed. However, for a more complete picture, the analysis could be complemented by some of the other indicators, providing, for example, information about the number of variables exceeding a threshold in a given quarter.

There are several ways to further improve the composite indicators and their calculation. Longer time series allow for performing transformations of variables in real time. This means that regardless of the chosen method of variable transformation, it can be performed in such a way that the benchmarks used in the transformation change depending on new information. This makes it possible to verify the robustness of the chosen transformation. If a right approach has been chosen, given the data properties, newly added information should not significantly affect the outcome, i.e. the indicator dynamics. Assigning weights to individual variables should also be considered in the context of approaches other than those analysed in the previous sections. To be more precise, if data are scarce or in the absence of a theoretical model that would clarify the importance of a variable in the definition of the composite indicator, the allocation of equal weights to all the six analysed categories of cyclical risk measures at least eliminates the subjectivity of the decision maker based on the results of assessments. If more data become available in the future, assessment could be carried out by utilising a VAR (vector autoregression) model which analyses the dynamics and the interconnectedness between the relevant variables, and the variance decomposition could be used to determine the weights.

It should be noted that the results obtained in this paper ought to be regarded as a starting point for further analysis and application in practice, in particular with regard to the thresholds related to the calibration of a composite indicator or the variables included in such indicator. The analysis also discusses the problem of calibrations based on the past global financial crisis, when certain variables displayed values that might not reappear in the future, given the macroprudential instruments that were introduced following the crisis, aimed at tackling the cyclical risks that built up prior to the crisis concerned. For the purpose of establishing the methodology and initial calibration, the thresholds as described above were considered, given that only one peak and only one trough were covered in the context of the previous financial cycle. Of course, these peak and trough values are specific to the single crisis included in the sample, which is why recalibration should be made based on new information, by considering the distribution properties of indicators, without including the GFC and its specific values. Unfortunately, there is not much practice and there are no guidelines or some other consensus regarding this matter. This is why the decision on the countercyclical capital buffer rate also takes into account the overall economic situation, expectations about future developments, including expert judgement. In any case, this matter should be dealt with in the future.

Furthermore, this paper also touches upon the problem of the GFC and basing the results on this crisis, since this introduces certain bias also with regard to the choice of variables, as shortcomings in monitoring some important indicators of cyclical risks and their potential spillover to the real sector were identified. On a positive note, new sources of risks, such as cyber risk, climate change, cryptocurrency risks, etc., are now being detected in time, and initiatives have already been launched in the EU[54] to create a methodological base for monitoring such risks and performing a comprehensive analysis of these new sources of risk to the financial system. Laying the groundwork for their monitoring seems to be problematic due to the lack of any previous practice in such cases. In addition, the coronavirus crisis has shown that the coordinated policy action helped in addressing this problem, even though it concerned a brand new source of potential materialisation of risk in the financial system. Uncertainties still persist, but some lessons have already been learnt. However, it is evident that new indicators will need to be defined in the future, including new forms of monitoring systemic risks.

The method of synthesising the information into one number should also be considered. Even though the FCI seems to be useful because it includes a correlation structure, the model used for estimating the correlations is not realistic given that it assumes equal dynamics determining all correlation pairs. More complex models such as the aforementioned DCC (dynamic conditional correlation, see section on data aggregation for the FCI) can only be assessed when a sufficient number of observations has been collected, which should be examined in the future. As a result, the current estimated correlations can also distort results to some extent, if the estimates are incorrect. For this reason, the indicators based on the linear combination of the values of individual variables can at the moment only be used as a starting point in identifying the position of the financial system in the cycle. In this respect, the ISCR indicator is recommended in the case of Croatia, given that (despite a single crisis) it provides information about the behaviour of the selected variables prior to the financial crisis, and it does not complicate the interpretation in terms of how the variables are transformed or in terms of their combination in the calculation. Both the broad ICSR indicator and narrower indicators should be monitored, in accordance with the findings contained in Lang et al. (2019).

This paper deals with linking the CCyB rate with the properties of the distribution of the composite indicator or the reference levels of certain variables from early warning models. However, in the future the analysis could also include analysing banks' profitability models (according to Lang and Forletta, 2020) or stress testing (see Couaillier and Scalone, 2021). The main contribution of this paper is the calibration of the CCyB values by considering several approaches, there being little reference in the

[54] In the form of various working groups, cooperation of the European Central Bank with other central banks, etc. More details can be found here: https://www.ecb.europa.eu/paym/cyber-resilience/html/index.en.html .

relevant literature considering the complexity of such analysis. The results of this paper are useful to the macroprudential policy makers because, on the one hand, synthesising more information in the form of a composite indicator facilitates monitoring of the dynamics of the variables comprising it, and on the other hand, the paper provides guidelines for determining the CCyB rate based on the assessment of the level of accumulation of systemic risks in the system, i.e. the assessment of the position of the economy in the financial cycle. Of course, the mentioned problem of the calibration which also depends on the specific values of indicator trends in the pre-crisis period related to the GFC still persists, which is why the results of this research should be understood as a starting point for a future revision of this methodology.

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Appendix 1 – Problems with HP gap

One of the problems is the biased HP credit gap (Hodrick i Prescott, 1997) obtained by filtering as prescribed by the ESRB (2014a), due to the fact that the estimate of the long-term trend also includes the period of credit expansion prior to the global financial crisis, followed by a prolonged period of decreasing gap values (see Lan et al., 2019; Galán, 2019), as in the case of the credit gap in Croatia. Furthermore, the problem of a significant change in the credit gap in the light of the sudden changes in the value of GDP and the resulting change in the CCyB, as in the case of the shock caused by the coronavirus pandemic, does not meet the criterion for to the resilience and the stability of indicators set out in Kauko (2012) and results in arguing that a positive rate of the CCyB should be imposed in times of economic contraction (Repullo and Saurina, 2011; Drehmann and Tsatsaronis, 2014).

There is also the problem of determining the value of the smoothing parameter in the HP filter, whose change depends on the assumption about the length of a country's credit cycle, and the large discrepancy in the value of the credit gap and consequently of the calibrations of the CCyB (see Dell'Ariccia et al., 2012; Rünstler and Vlekke, 2016; Wezel, 2019). Using the HP filter for short time series, as in the case of Croatian data, is also a common problem. To be more precise, the absolute values of credit gap can vary significantly depending on the starting period of the filtering process. This is linked to the first-point problem, as commented in papers by Jokipii et al. (2020) and Drehmann and Tsatsaronis (2014). Depending on the first point of the filtering process, the resulting gaps may vary significantly. The result may vary depending on whether the first point in a sample is set in the build-up phase or at peak or trough of the credit cycle. Charts illustrating this problem can be found in Lang et al. (2019). The end-point problem also needs to be taken into account. Adding new data to the original sample can significantly affect the long-term trend, see Canova (1998), Pedersen (2001), and Edge and Meisenzahl (2011). A good predictor of the financial cycle should be stable and adding new data to a series should not considerably affect the signal. In addition, some papers for certain countries find that the credit gap as set out in Basel has weaker signalling power (Geršl and Seidler, 2012; Rychtarik 2014, Castro et al., 2016 and Plašil et al., 2016). These problems are analysed in more detail in Škrinjarić and Bukovšak (2022).

Appendix 2 – Graphic representations and descriptions of variables mentioned in Chapter 3

Appendix 2 provides descriptions of variables used in the research for the six categories of risk measures according to the ESRB Recommendation (2014). Given the large number of possible measures and their transformations, taking into account the practices of other central banks and the results in the published literature, the variables and their selected transformations are briefly described below. The description contains the original variables, their 1-year and 2-year changes or growth rates and the gaps obtained by using the HP filter, with smoothing parameters of 1,600 (under the assumption that the business cycle lasts for 7.5 years) and 25,600, 85,000, 125,000 and 400,000, under the assumption that the credit cycle lasts two to four times as long as the business cycle[55]. It can be observed that the 2-year dynamics of some variables is often similar to that of the HP gap in the case of the smoothing parameter of 1,600, which is why a 2-year change is the preferred choice, given that it is smoother than the gap in most cases. This is important for obtaining a more stable indicator, in order to enable a more stable calibration of the CCyB value.

D.1 Measures of overvaluation of property prices

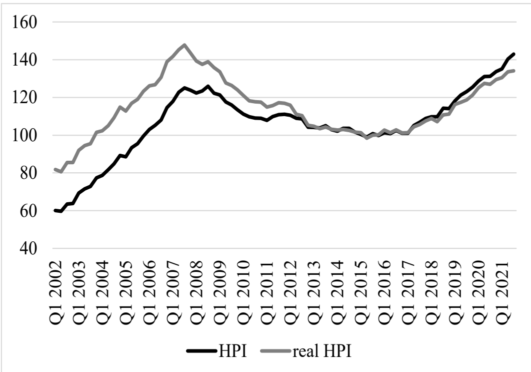
Figure D.1 shows the movement of measures related to the overvaluation of property prices, together with their transformations. Considering, for example, the HPI (house price index), the growth in the index was recorded in the period preceding the last GFC, which was followed by the contraction in the index in the following years, until 2018, where a sharp rise in the index was again recorded, with the value of the nominal HPI in 2020 exceeding the maximum recorded in 2008. The real estate market has been facing price pressures again for several years in a row. A similar dynamics is observed in the remaining measures as well. Due to the higher volatility in 1-year growth rates, the annualised 2-year growth rates and HP filter gaps are taken into account as well. The composite indicator of the divergence in residential real estate prices from fundamentals (panel i, j) also points to the same conclusion, given that it summarises data about the movements from the previous panels and the six indicators they show into a single piece of information.

[55] See details in Drehmann et al. (2010), Rünstler and Vlekke (2016) or Galáti et al. (2016).

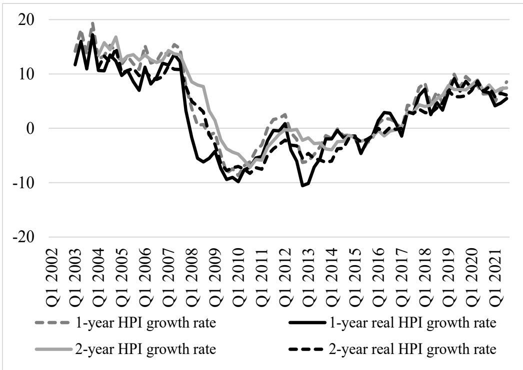
If the variables from this category of risk measures are used, in view of the short time series, the 2-year dynamics provides better information given that the assessment of one-sided HP gaps (panel j) requires setting the initial assessment period, where the dynamics of the variable trends is very close to trends in the values of HP, while on the other hand two-sided gaps (panel i) are not suitable because they are based on the assumption that information about the future is available in the last quarter for which data are available. However, in order to allow for a full coverage, different transformations are included, as in the case of the other measures, in order to make it more clear why a certain transformation is included in the composite indicator and why it had better or weaker power in signalling the previous crisis.

Figure D.1 Variables related to the measures of overvaluation of property prices and their various transformations

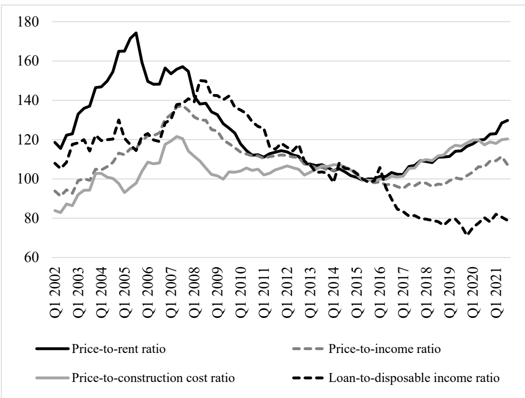
a. Property price indices, in index points



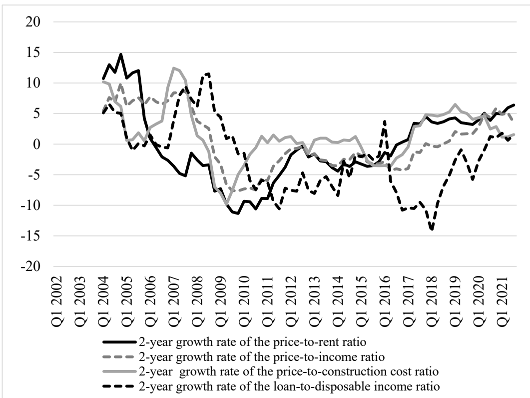
b. Rates of change in the property price indices



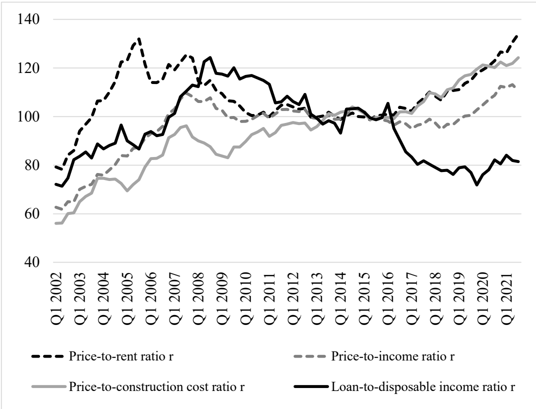
c. Selected ratios related to property prices – real, in index points



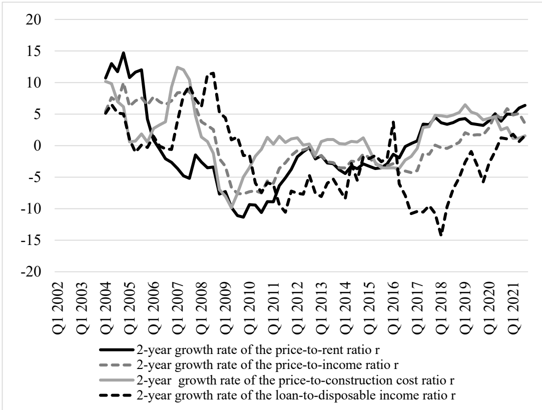
d. Rates of change of the selected ratios in c



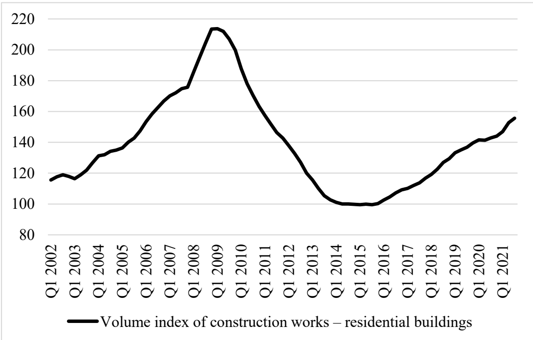
e. Selected ratios linked to property prices – nominal, in index points



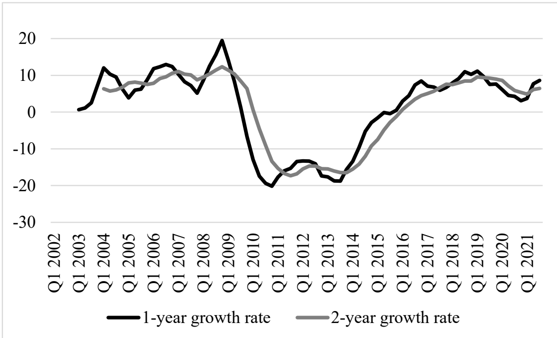
f. Rates of change of the selected ratios in e.



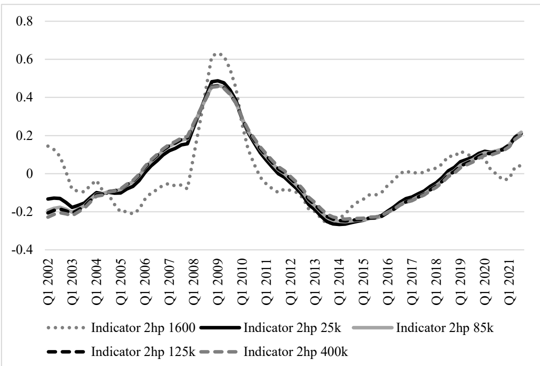
g. Volume index of construction works – residential buildings, in index points



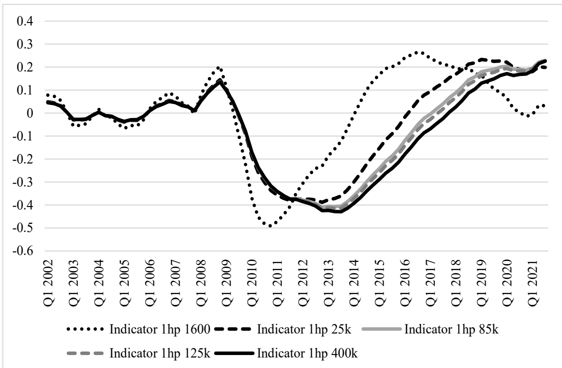
h. Rates of change in the volume index of construction works



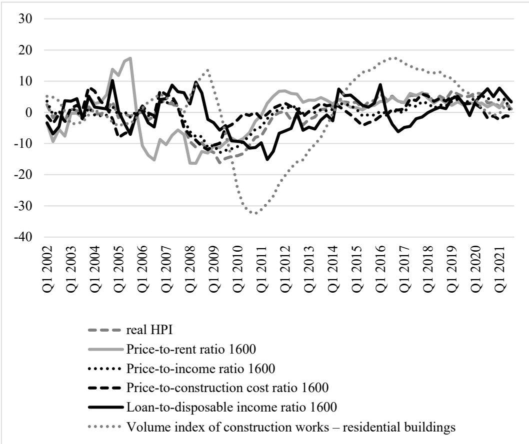
i. Indicator of divergence of real estate prices from fundamentals – two-sided HP gap, various lambdas



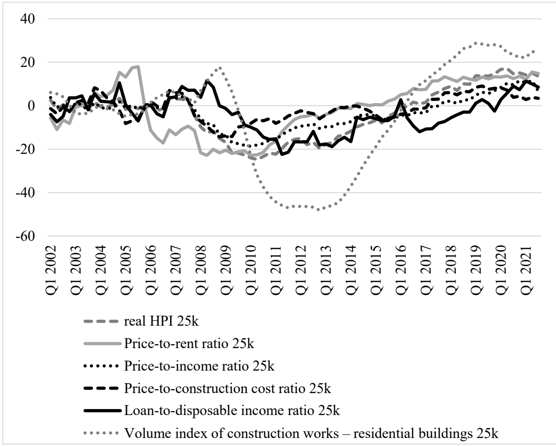
j. Indicator of divergence of real estate prices from fundamentals – one-sided HP gap, various lambdas



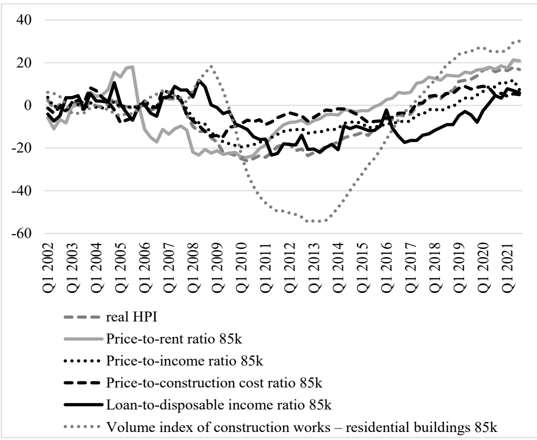
k. HP gaps for the selected measures, lambda of 1,600, one-sided gap



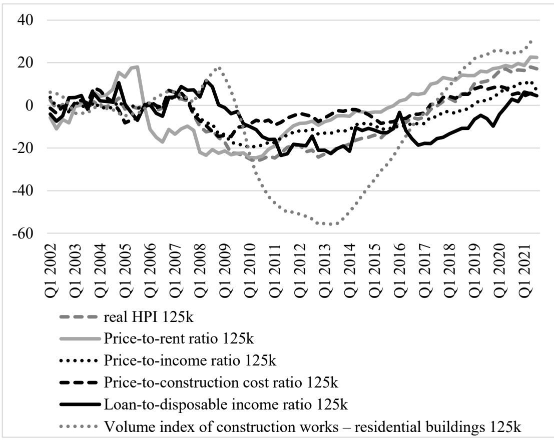
l. HP gaps for the selected measures, lambda of 25,600, one-sided gap



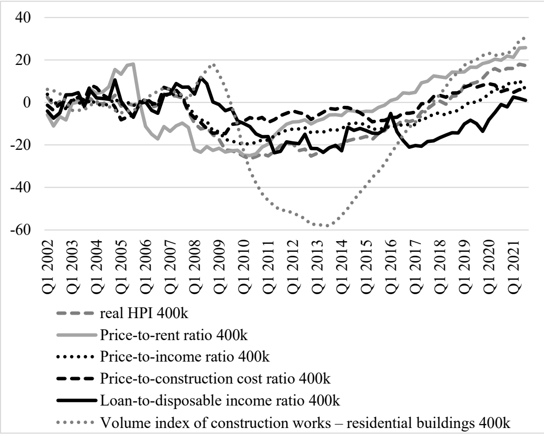
m. HP gaps for the selected measures, lambda of 85,000, one-sided gap



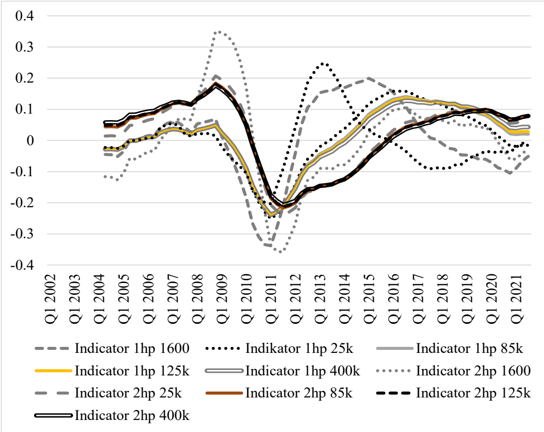
n. HP gaps for the selected measures, lambda of 125,000, one-sided gap



o. HP gaps for the selected measures, lambda of 400,000, one-sided gap



p. Indicator of divergence of real estate prices from fundamentals, 2-year changes



Note: two-year growth rates are annualised. The letter "r" means real "1hp" and "2hp" gap obtained by applying the one-sided and two-sided HP filter, respectively.

Source: CNB, author's calculation.

D.2 Measures of credit developments

Figure D.2 shows credit developments and the intense rise in lending at the beginning of the 2000s, especially to the household sector. A sharp decrease in lending was observed in all the covered measures in 2009, which was followed by several years of subdued growth in lending, especially in the corporate sector. However, the household sector has seen an increase in lending starting from 2017. One-year and 2-year changes in lending have been positive for several years, implying a recovery in credit developments relative to the previous crisis period. In view of such dynamics, credit gaps obtained by statistical filtering of the observed series grow and close at the end of the observed period. Credit developments are characterised by the fact that one-year or two-year changes can have much higher volatility in terms of the correct choice of the HP gap. What seems to be especially problematic with Croatian data is the dynamics of such changes or growth rates at the onset of the 2000s, when the largest credit growth was observed due to financial deepening (panels b, c or d). This is why the composite indicator can be largely biased towards the extremely high values in the observed period, which can pose a problem in the calibration of the CCyB.

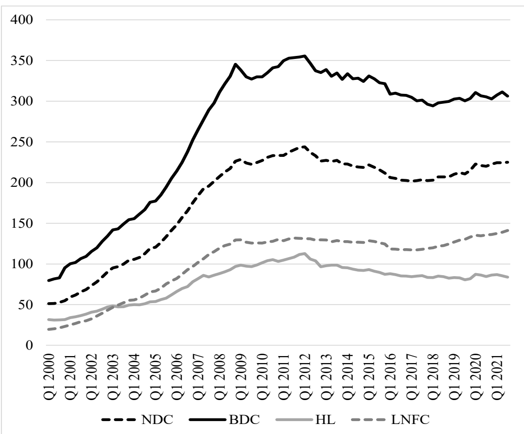
As the credit gap for total loans used for the calibration of the CCyB is based on the HP filter, HP gaps for loans to households and corporates can be used to enable better comparability. This alleviates the mentioned problem linked to the large credit growth, and the composite indicator will not be under such a great influence of credit growth in the given periods.

Some research considers changes in credit ratios, which is why such transformation is also considered in this paper. However, panel j shows similar dynamics in two-year changes in loan value and credit ratios. However, to allow for a full comparison, all transformations in Figure D.2 are considered. The last few panels in Figure D.2 (panels k – s) show credit gaps and credit ratio gaps, given that the statistical gaps obtained by the HP filter are most frequently used in research, but also in practice by central banks.

They allow for different smoothing parameter values, as the duration of the credit cycle in Croatia is not known. The relatively short time series of financial variables make it difficult to estimate the length of the credit cycle in Croatia. In accordance with the findings in the relevant literature, it has been assumed that it is two to four times longer than the business cycle. Different smoothing parameter values (lambdas) are thus used in the HP filter: 25,600, 85,000, 125,000 and 400,000, whereby larger parameter means a longer financial cycle (see the previous footnote).

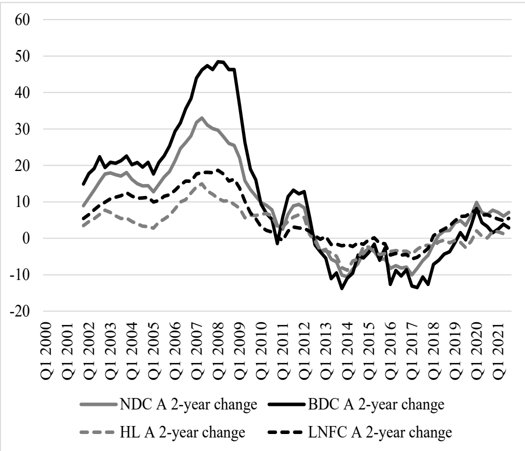
Figure D.2 Credit developments, loan values and various transformations

a. Credit (narrower and broader definition), bank loans to households and non-financial corporations, in billion HRK

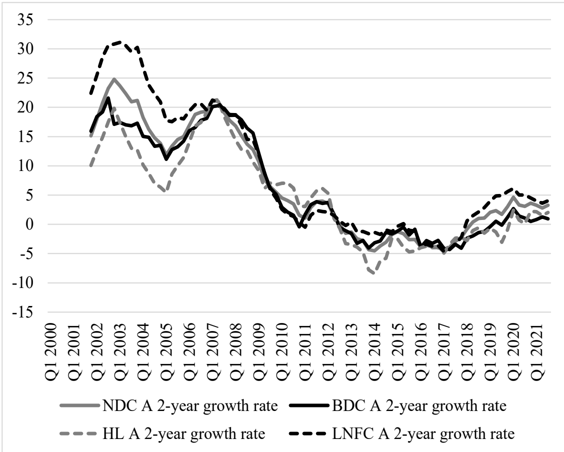


b. 1-year changes in loans under a.

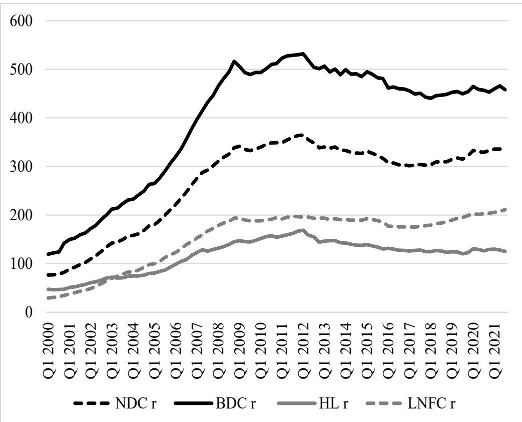
c. 2-year changes in loans under a.



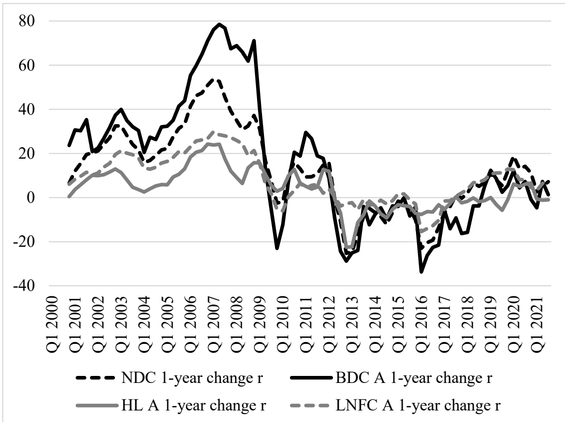
d. 2-year growth rates of loans under a.



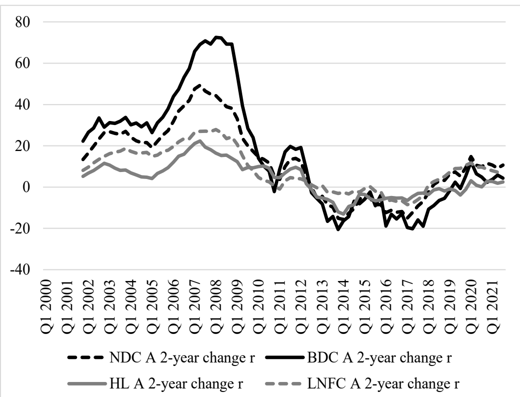
e. Narrower and broader definition of credit, loans to households and non-financial corporations, in billion HRK, real



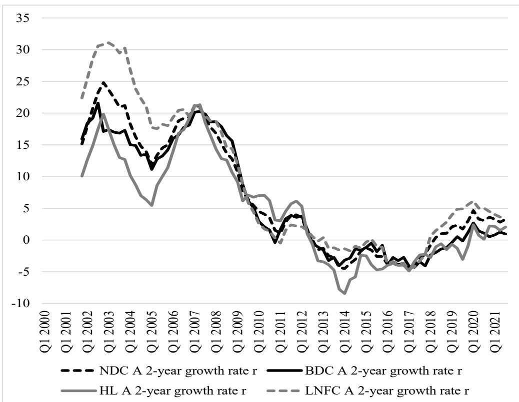
f. 1-year changes in loans under e.



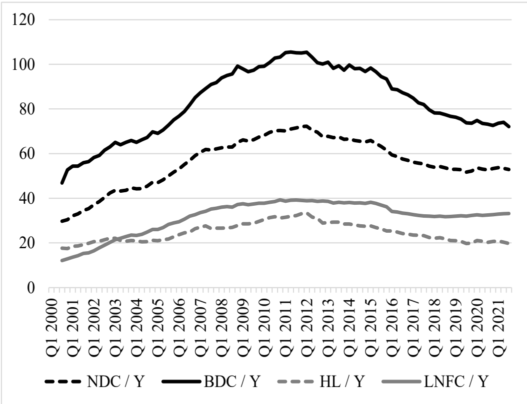
g. 2-year changes in loans under e.



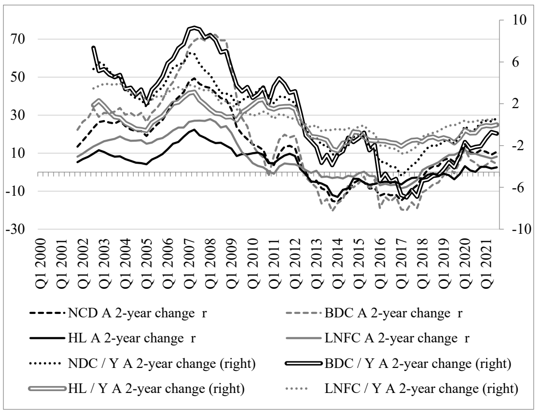
h. 2-year growth rates of loans under e.



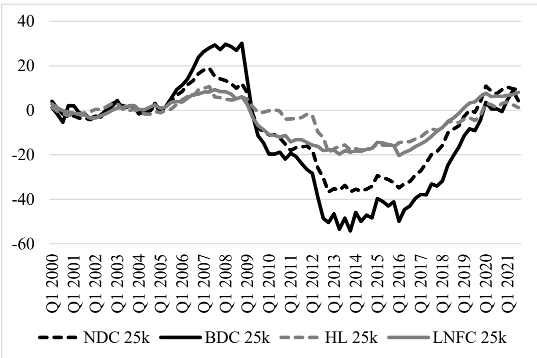
i. Ratio between loans under a. and GDP



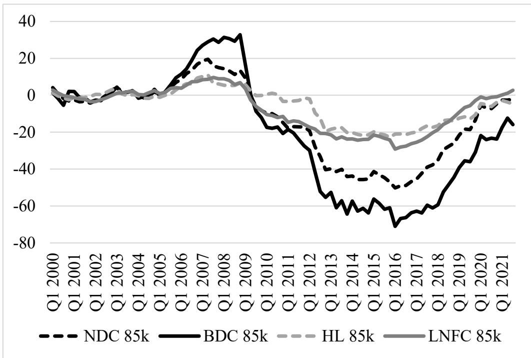
j. Comparison of the 2-year change in loans under a. and ratios under i.



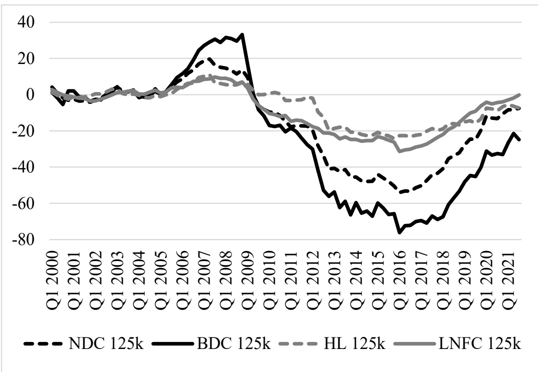
k. Credit gaps for loans under a., lambda of 25,600



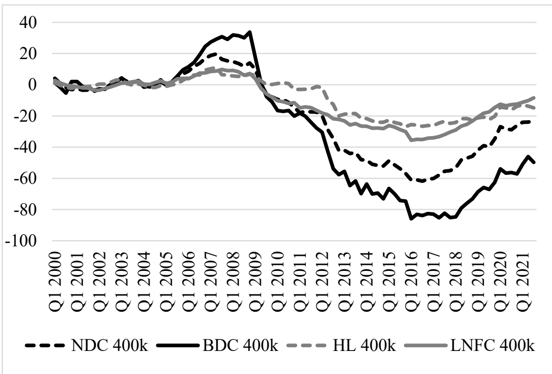
l. Credit gaps for loans under a., lambda of 85,000



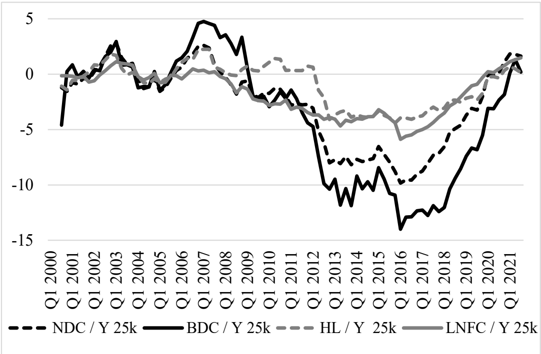
m. Credit gaps for loans under a., lambda of 125,000



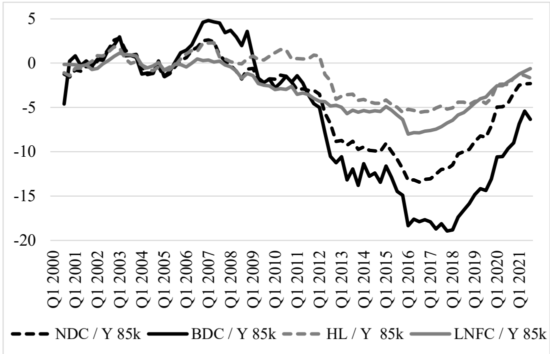
n. Credit gaps for loans under a., lambda of 400,000



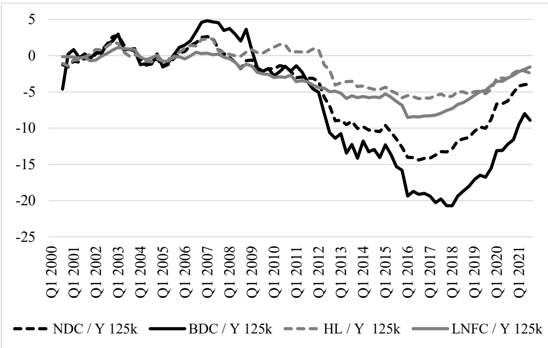
o. Credit gaps for credit ratios, lambda of 25,600



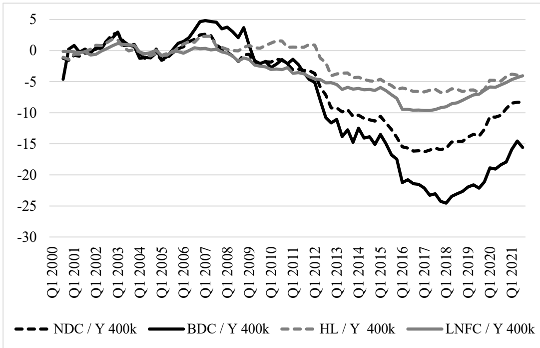
p. Credit gaps for credit ratios, lambda of 85,000



q. Credit gaps for credit ratios, lambda of 125,000



r. Credit gaps for credit ratios, lambda of 400,000



Note: NDC, BDC, HL and LNFC mean narrower definition of credit, broader definition of credit, household loans and loans to non-financial corporations, “A” means annualised, “r” denotes real. Credit-to-GDP ratios are calculated by dividing the value of loans in the current quarter by the sum of GDP from the current and the previous three quarters. Credit ratios under o. and corresponding transformations in p. – s. relate to the described credit-to-GDP ratios.

Source: CNB, author’s calculation.

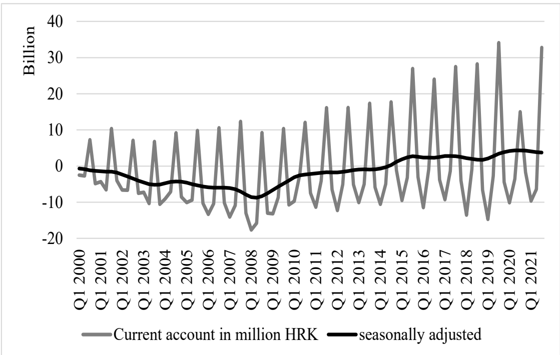
D.3 Measures of external imbalances

Figure D.3 shows the trends in the value of current account, net exports and capital account, terms of trade and their various transformations. Most of the literature focuses on the current account (see Plašil et al., 2014; 2016; Kupkovič and Šuster, 2020), even though some approaches also consider net exports and capital account, as well as gross external debt. This is why this paper considers all the options within the category of measures pertaining to external imbalances. A large current account deficit was recorded in the period up to the peak of economic expansion, which was followed by the GFC and recession in Croatia. The years-long recovery lasted until 2016, when the current account started recording a surplus. The dynamics of the capital account is much more volatile in panel e., which may create analytical problems. This is why changes and statistical gaps are also considered, given that the changes (see panel h. as an example) are characterised by excessive volatility over time, which would contribute to greater volatility of the composite indicator, influencing the calibration of the countercyclical capital buffer. As this category of measures is more linked to the business than to the credit cycle, using HP gaps involves considering lower values of smoothing parameter or changes.

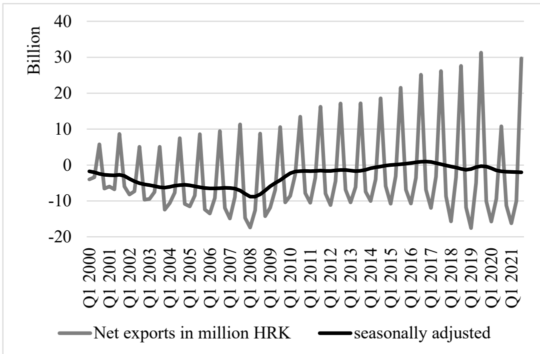
Given that the current account surplus does not indicate a build-up of systemic risks, the balance variable is multiplied by value –1 in the analysis to account for the increase in this indicator (see Karamisheva et al., 2021). Net exports and terms of trade are treated similarly. The series under a high impact of the season have been seasonally adjusted prior to further transformations and use in the analysis.

Figure D.3 Measures of external imbalances and transformations

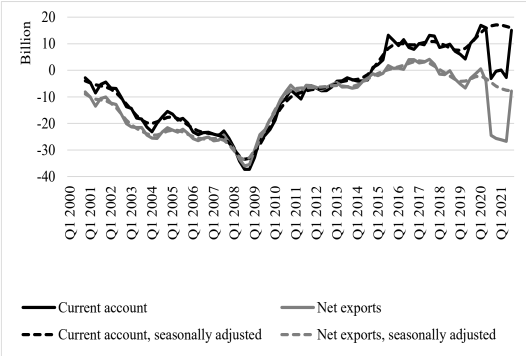
a. Current account trends, in billion HRK



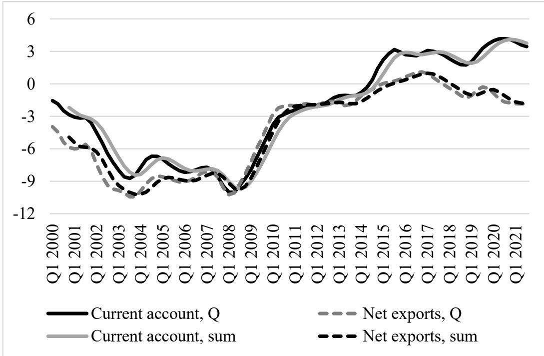
b. Net exports trends, in billion HRK



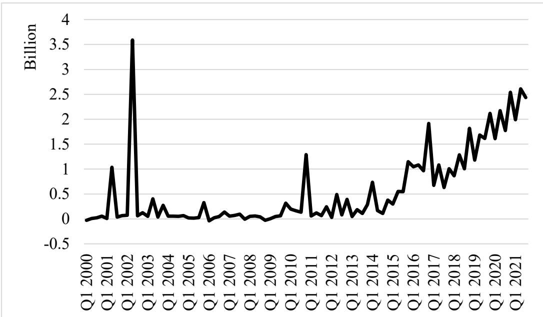
c. Moving sums of values for a. and b. (not seasonally adjusted)



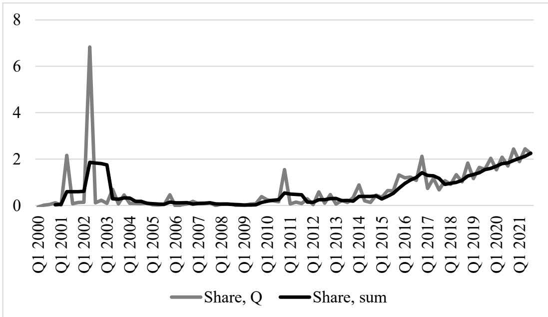
d. The share of current account and net exports in GDP, seasonally adjusted values, in %



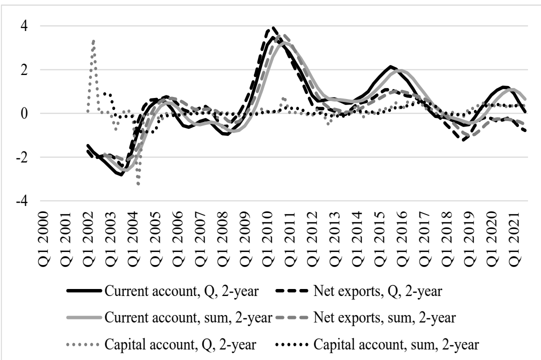
e. Capital account trends, in billion HRK



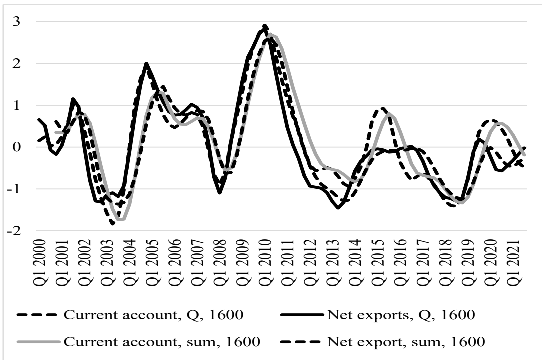
f. The share of capital account in GDP, in %



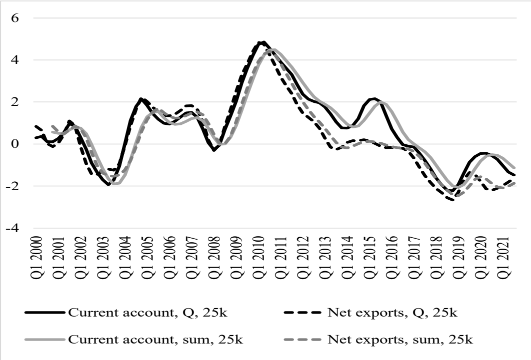
g. Changes in developments of the share of current and capital account and net exports in GDP



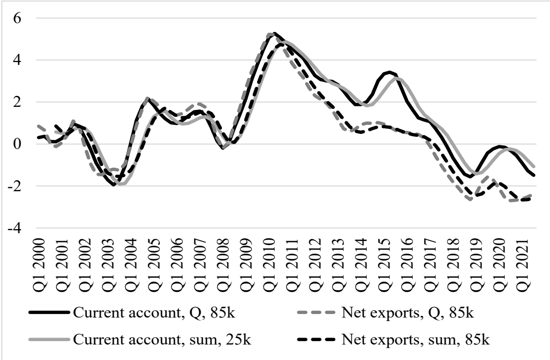
h. Gaps in developments of the share of current account and net exports in GDP, lambda of 1,600



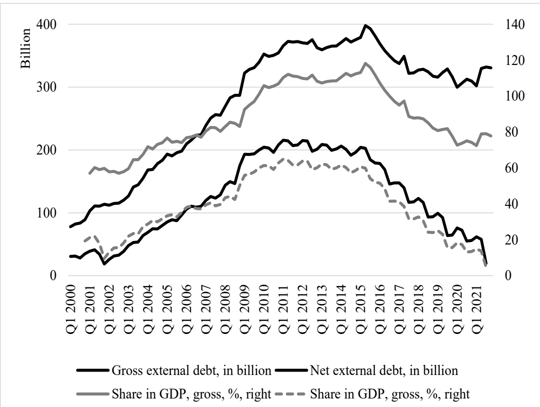
i. Gaps in developments of the share of current and capital account and net exports in GDP, lambda of 25,600



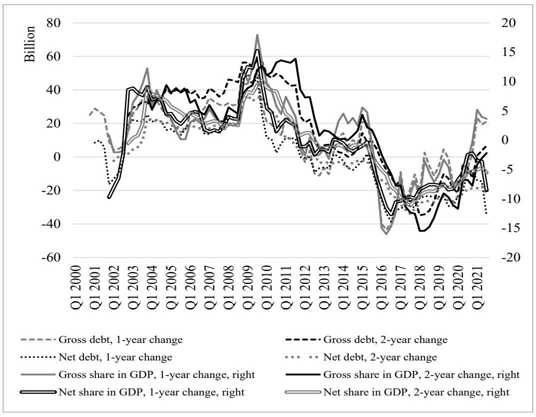
j. Gaps in developments of the share of current and capital account and net exports in GDP, lambda of 85,000



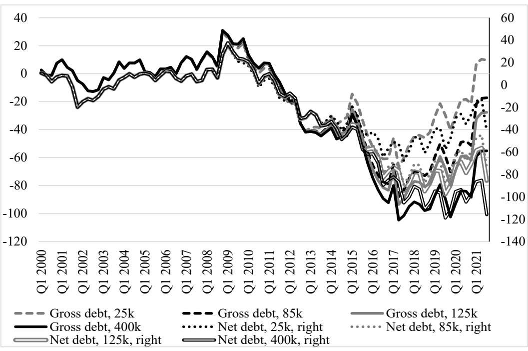
k. Gross and net external debt



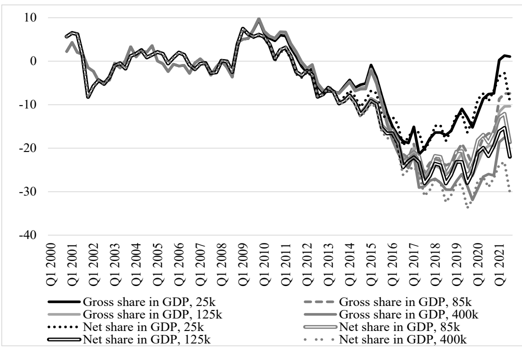
l. changes in debt under k.



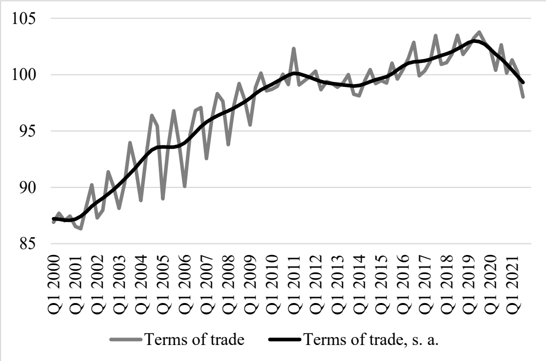
m. Gap between gross and net external debt under k., levels



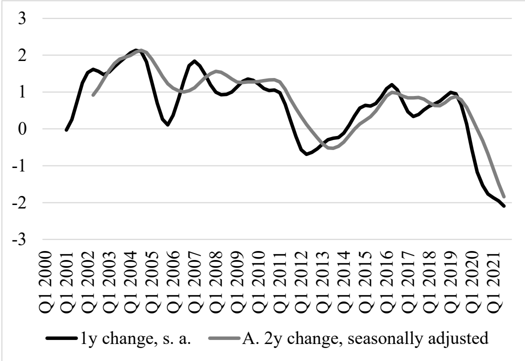
n. Gap between gross and net external debt under k., share in GDP



o. Terms of trade



p. Changes in terms of trade



Note: moving sums under c. refer to the sum of values in the current quarter and in the previous three quarters; “Q” means the calculation of ratio based on the values in the current quarter, “sum” means the calculation of ratios based on moving sums. Terms of trade means the ratio of exports deflator and imports deflator, multiplied by 100%. “s. a.” means seasonally adjusted.

Source: CNB, author’s calculation.

D.4 Measures of the strength of bank balance sheets

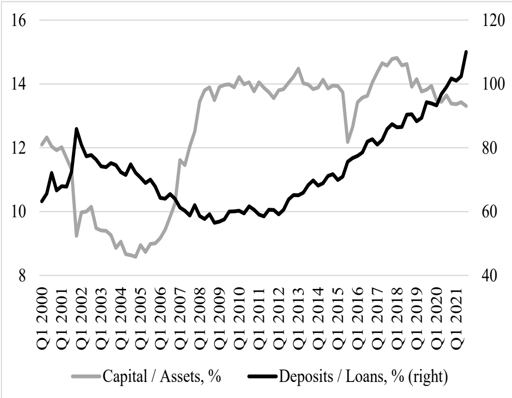
Measures of the strength of bank balance sheets take account of the leverage ratio (LR), calculated as the ratio of a bank’s capital to total assets. Figure D.4 shows the LR and the corresponding changes and growth rates. As the higher LR means that the bank is better prepared to absorb losses, it should be multiplied by -1 prior to its inclusion in the analysis, to allow for the interpretation of the build-up of risks (this has been done in other related papers, see Karamisheva et al., 2019).

Another way to measure the strength of bank balance sheets is by observing the private sector loan-to-deposit ratio (LTD), given that the volatility in the way banks are financed, i.e. their greater reliance on unstable sources of funding, is an additional source of the vulnerability of the financial system (Bank of England, 2014). As deposits are usually considered to be a stable source of funding (Krygier and Santen, 2020), the loan-to-deposit ratio has been examined in the literature dealing with financial cycle forecasting (Alessandri et al., 2015; Drehmann and Juselius, 2014; Giese et al., 2014; Rychtarik, 2014). Figure D.4 also shows the dynamics in the loan-to-deposit ratio and its transformations.

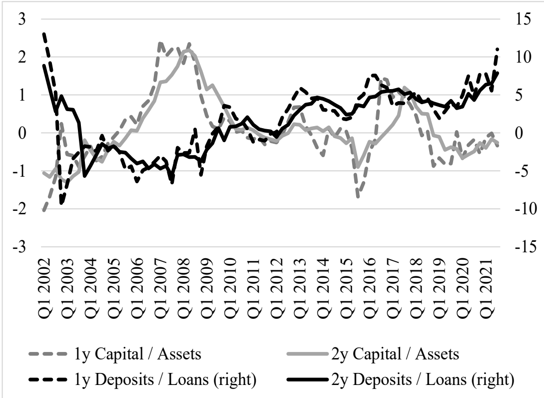
Finally, the share of credit institutions' assets in GDP and the share of non-performing loans (NPLs) in total loans and their transformations are also considered. While the literature brings into correlation the size of the banking sector and the measures of systemic risk in the economy (see details in Kakes and Nijskens, 2018), Berti et al. (2017) find that the NPLs are a structural problem in the euro area related to the business cycle, with a lagging dynamics unsuitable for forecasting the future build-up of systemic risks. This is also evident from Croatian data (panels g and h).

Figure D.4 Measures of the strength of bank balance sheets and their transformations

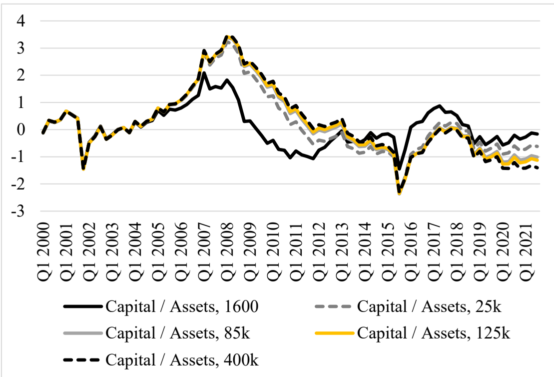
a. Capital-to-total assets ratio and loan-to-deposit ratio in the private sector



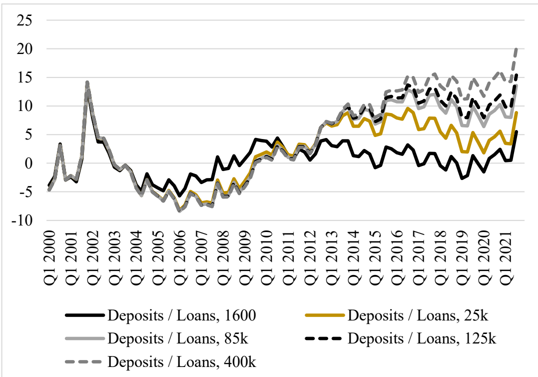
b. Changes in ratios under a.



c. Gaps in ratios under a., capital to assets

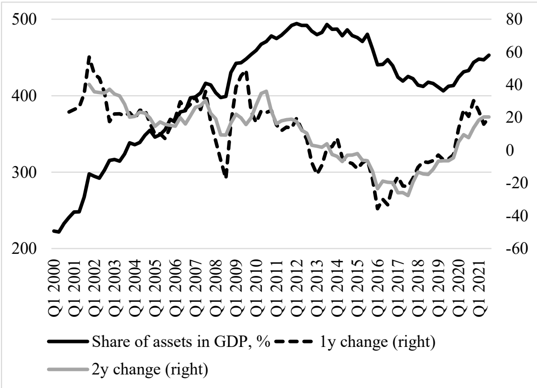


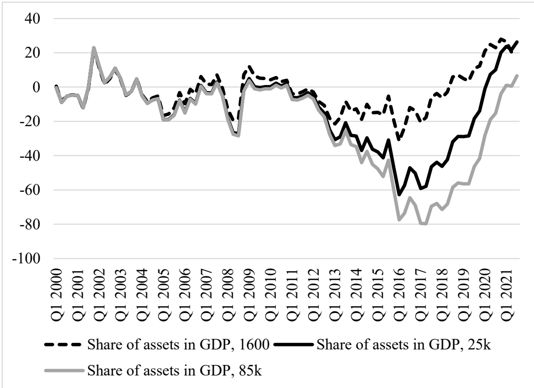
d. Gaps in ratios under a., deposits to loans



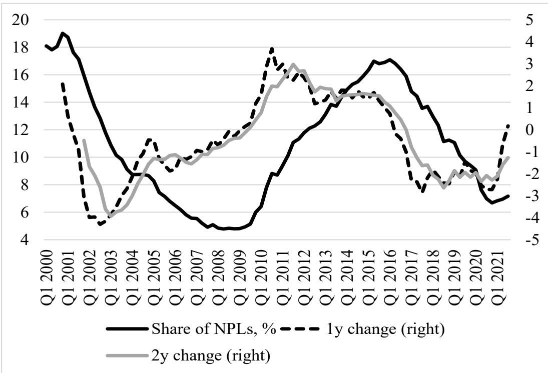
e. Share of assets in GDP, % and changes

f. HP gaps for the share of assets in GDP under e.

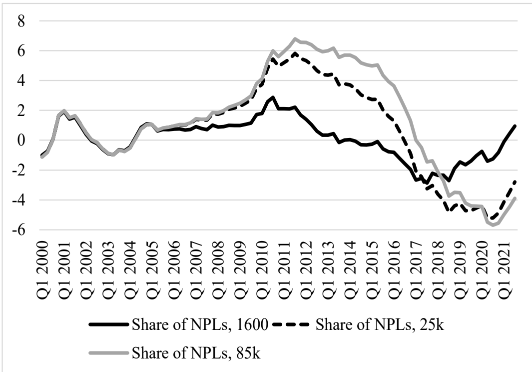




g. The share of NPLs in total loans, % and changes



h. HP gaps for the share of NPLs under g.



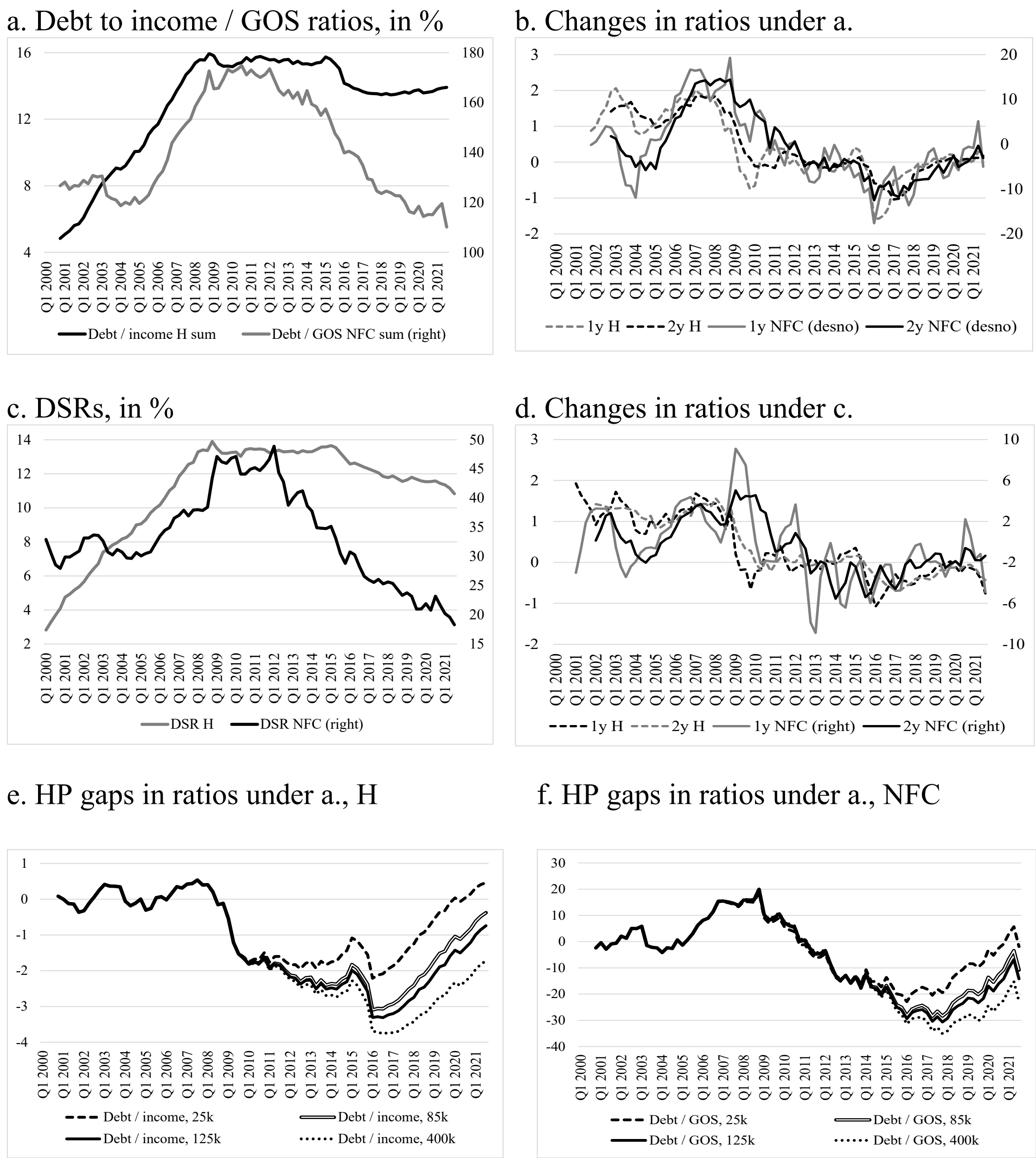
Note: None of the transformations have been multiplied by -1. This was done subsequently, prior to the inclusion in the composite indicators. The 2-year changes have been annualised.

Source: CNB, author's calculation.

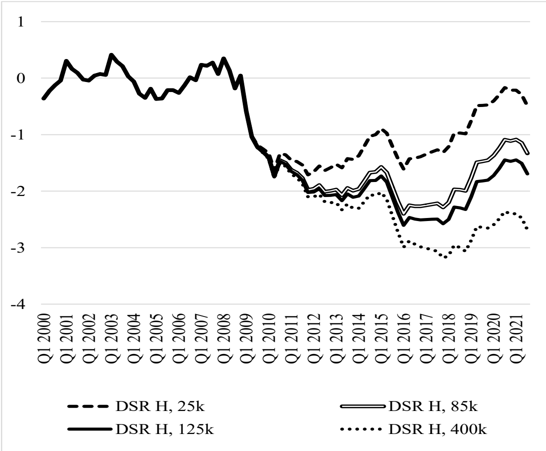
D.5 Measures of private sector debt burden

In view of the above literature, the typical measures of private sector debt burden used (also) in this paper include total debt-to-income ratio for the household sector and total debt-to-gross operating surplus (GOS) ratio for the corporate sector, considering the share of debt in the current quarter and the sum of income or GOS in the current quarter and the previous three quarters. Their values and transformations are shown in Figure D.5, where it can be observed that the dynamics of these variables is more linked to the credit cycle, as the changes (panel b and c) are too volatile, while the gaps obtained by using HP filter result in smoother series. Debt service ratios (DSR) are also considered, especially for the household sector relative to the corporate sector. Figure D.5 also shows the increase in debt burden in both sectors in the pre-crisis period during 2000s, followed by several years of corporate sector deleveraging. A moderate increase in these indicators (panels with gaps, panels e to h) has been recorded in the last few years (right panel).

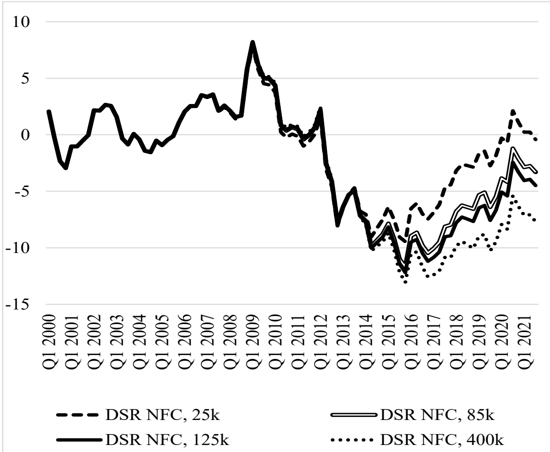
Figure D.5 Measures of private sector debt burden and selected transformations



g. HP gaps in DSR, H



h. HP gaps in DSR, NFC



Note: GOS means gross operating surplus, DSR means debt service ratio, H and NFC mean households and non-financial corporations, "sum" means the ratio between debt and the sum of income or GOS in the current quarter and in the previous three quarters.

Source: CNB, author's calculation.

D.6 Measures of mispricing of risk

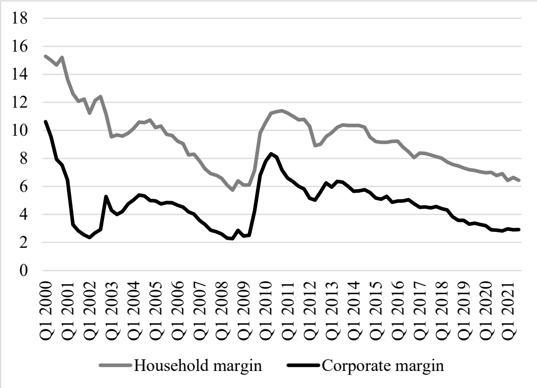
Measures of mispricing of risk include the following variables: interest margins on new loans to households and corporate loans, where the benchmark used to calculate the margin is the quarterly Euribor[56]. Figure D.6 shows margins and their transformations in terms of changes and gaps[57]. Figure D.6 (panels c and d) shows the development of the stock index and its transformations. Accelerated growth is observed before the last financial crisis, followed by a steep decrease in the value of the index, which has been stagnating for nearly 13 years, reflecting weak trading activity.

[56] As ZIBOR no longer exists in Croatia, EURIBOR will be used, as in Pokupovič et al. (2020).

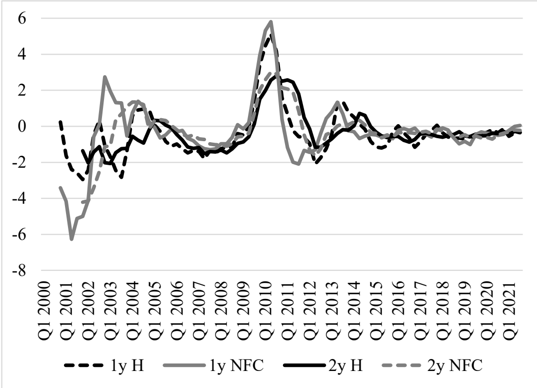
[57] Having regard to the interpretation that the increase in the indicator results in the build-up of cyclical risks, the interest rate spread is also multiplied by -1. To be more precise, in the upward phase of the business cycle, due to the favourable macroeconomic environment, the positive attitude of economic agents, coupled with the growing income and profits, leads to a decrease in risk perception, narrowing the interest rate spread. As the increase in other variables is interpreted as the accumulation of risks, interest margins in Figure D.6 will be multiplied by -1 in calculations.

Figure D.6 Measures of mispricing of risk and their transformations

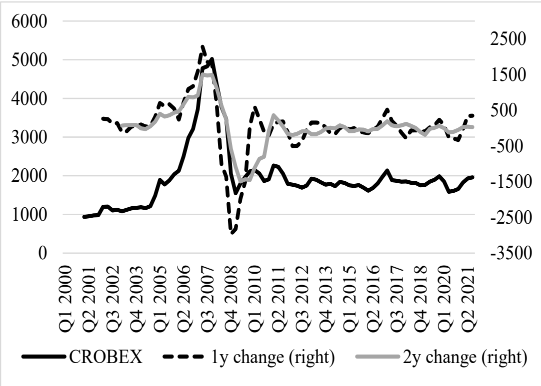
a. Interest margins, in p. p.



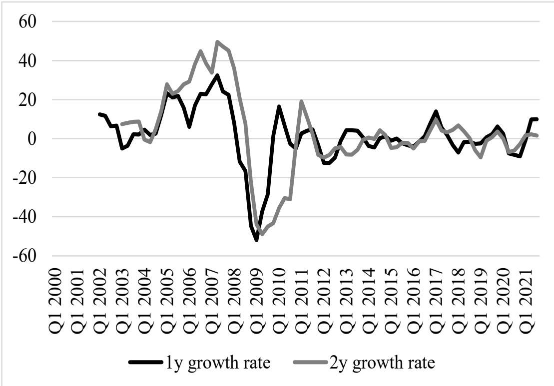
b. Changes in interest margins under a.



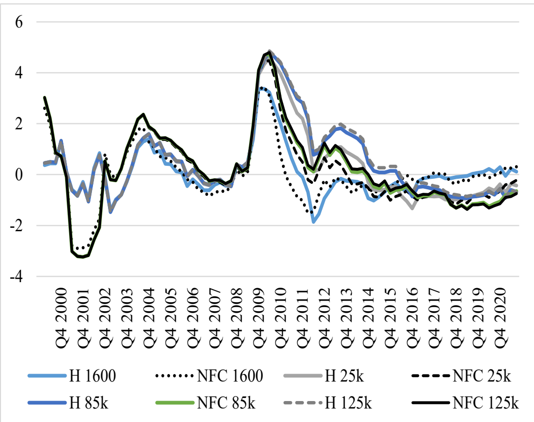
c. CROBEX, in points, and changes



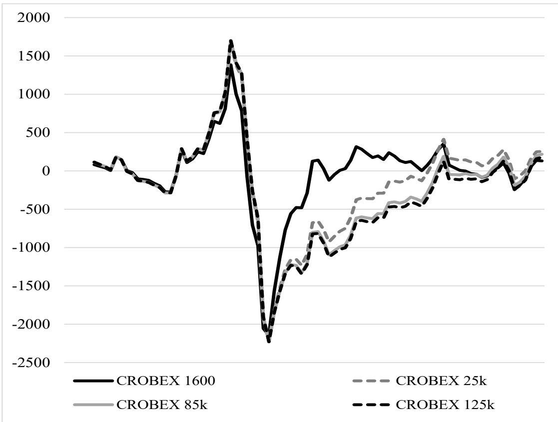
d. Growth rates of CROBEX under c.



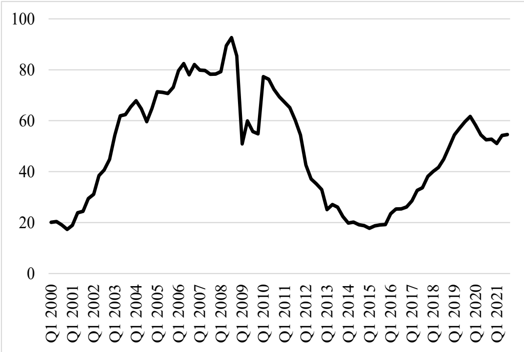
e. HP gaps in interest margins under a.



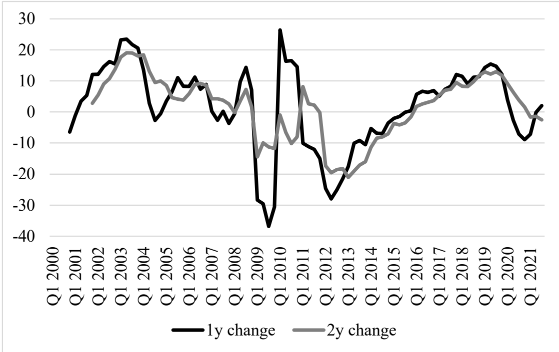
f. HP gaps in index under c.



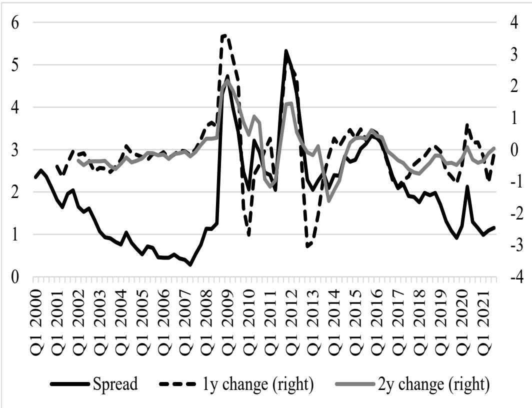
g. BPI and changes



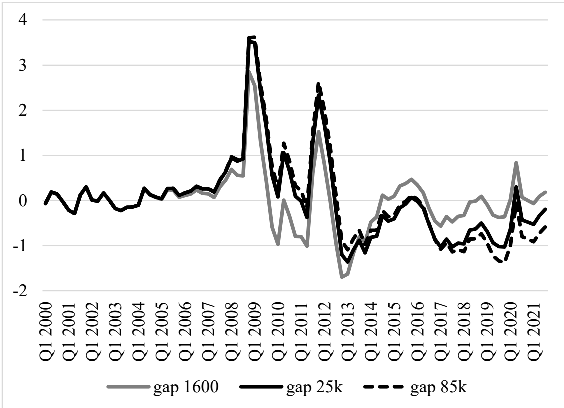
h. HP gaps in BPI under g.



i. Yield spread on government bonds and changes



j. HP gaps in the yield spread on government bonds under i.



Note: H, NFC, 1y, 2y, 1600, 25k and 85k denote households, non-financial corporations, one-year change or growth rate, annualised 2-year change or growth rate and gaps for smoothing parameters of 1,600, 25,000 and 85,000.

Source: CNB, author's calculation.

The BPI indicator described in the main body of this paper is also included in these measures. Panel g. shows the mentioned behaviour of banks with regard to loan provisions also in the case of Croatia in the pre-crisis period, as well as a sharp increase in the BPI. Its value decreased significantly during the recession, but it has fully recovered in the past few years, up to the last few observations in 2020, even though this year was specific due to the coronavirus pandemic. On the positive side, using the BPI measure within the composite index allows for easy calculation and interpretation of the BPI. On the negative side, this indicator provides no information about the properties and the structure of clients to whom the banks lend. Given that Plašil et al.

(2015) and Kupovič et al. (2020) do not consider the BPI variable, and this category of measures is not deemed to indicate the mispricing of risk by banks, this paper analyses combinations with and without the BPI.

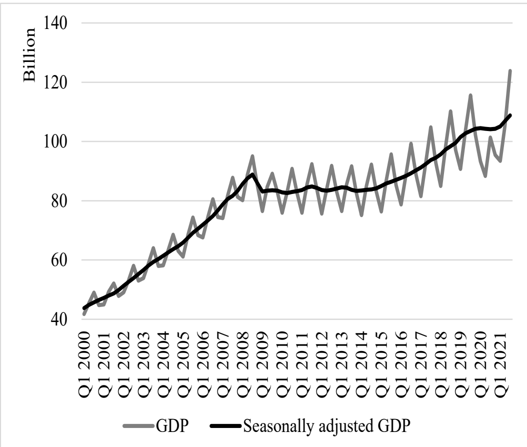
Finally, due to the lack of data on the movements of yields on corporate bonds in Croatia, Venditti et al. (2018) consider the spread in yields on the 10-year generic Croatian and German bond, whose dynamics is shown in panels i and j, in order to approximate the general mispricing of risk for the entire economy.

Appendix 3 – Graphic representations and description of the selected macroeconomic variables

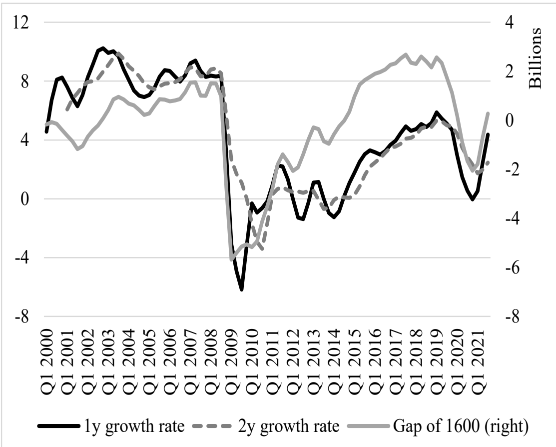
In view of the different approaches and observations concerning risk in the construction of composite indicators, the following selected variables are also considered: GDP and its dynamics, unemployment rate and money trends. Figure D.7 shows that the dynamics of these variables follow the business cycle rather than the financial cycle. This is why the use of such indicators in the construction of the composite indicator is not recommended in the case of Croatia, even though these trends should be monitored as they provide a more detailed insight into developments in the economy.

Figure D.7 Trends in the selected variables

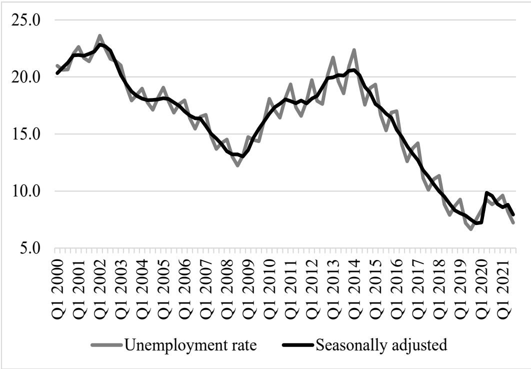
a. Movements in GDP



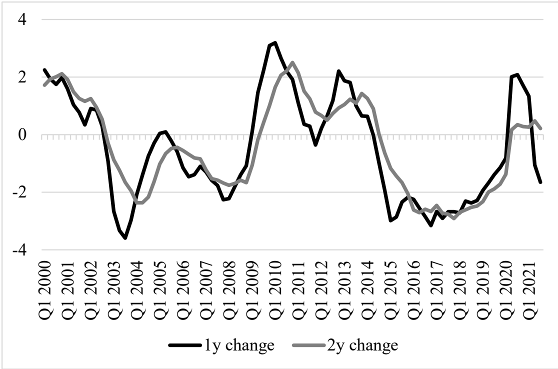
b. Growth rates and the gap in the seasonally adjusted GDP



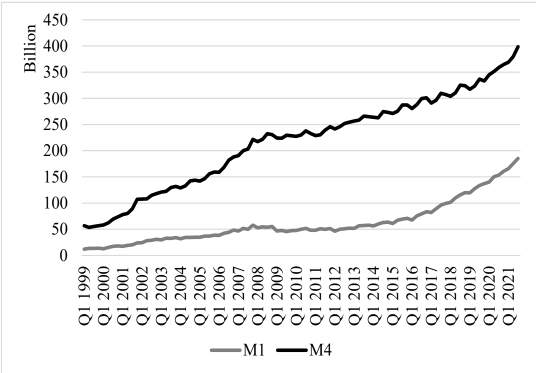
c. Unemployment rate



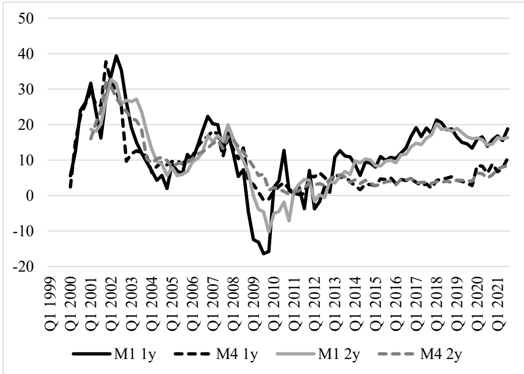
d. Changes and unemployment gap



e. Money trends



f. Money growth rates



Note: 1y, 2y and 1600 mean 1-year growth rate or change, annualised 2-year growth rate or change and gap obtained with a smoothing parameter of 1,600

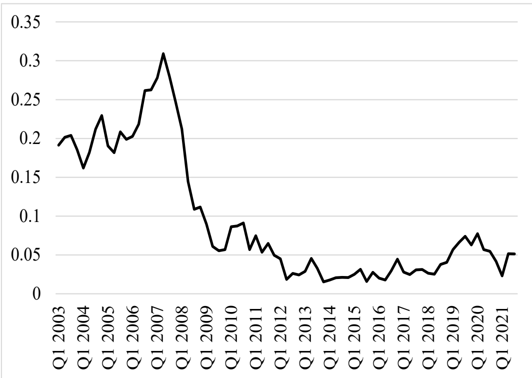
Source: CNB, author's calculation.

Appendix 4 – Description and graphic movement of alternative FCI indicators based on Table 1 in the main body of this paper

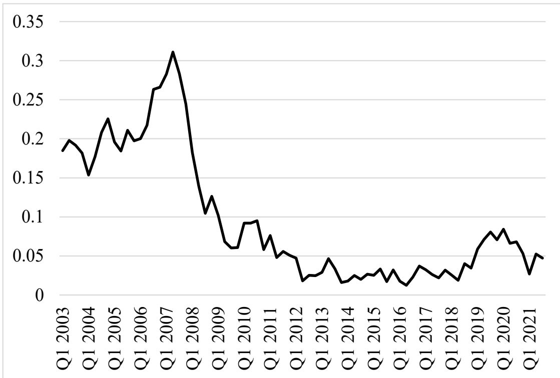
Based on Table 1 in the main body of this paper, a total of 8 FCI variants can be analysed, two of which have already been presented in the main body of the paper. This Appendix contains a description of the remaining six variants and the results of calculations of these alternative FCI indicators. The first variant includes variables under (1) in the column "Indicator variant" using ΔHPI, the second variant includes Δ (I / Inc) instead of ΔHPI, while the third and the fourth are variants of the first two, excluding the category "strength of bank balance sheets". The fifth category includes variables marked with (2) in column "Indicator variant", where the category concerning the overvaluation of property prices involves using A. 2Δ (I/Inc), while the sixth variant again excludes "strength of bank balance sheets" included in the fifth variant. Variants (2) have been analysed in the main body of the paper, with A. 2ΔHPI in the category pertaining to the overvaluation of property prices, with and without the "strength of bank balance sheets" category. In the case of 1-year changes and growth rates, the FCI displays greater volatility relative to other indicators, which is unsuitable for the calibrations of the CCyB rates.

Figure D.8 FCI variants based on Table 1

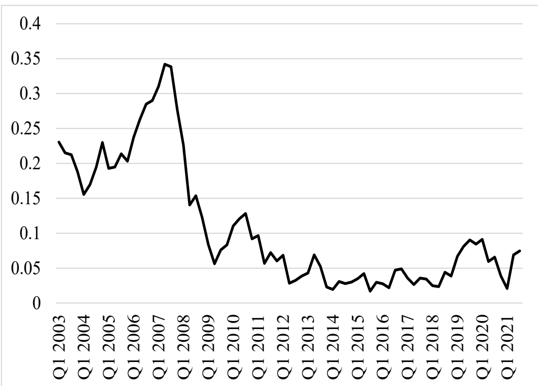
a. Variant (1), with HPI



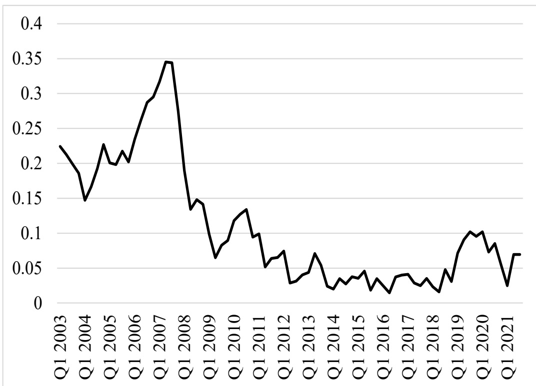
b. Variant (1), with real estate price-to-income ratio



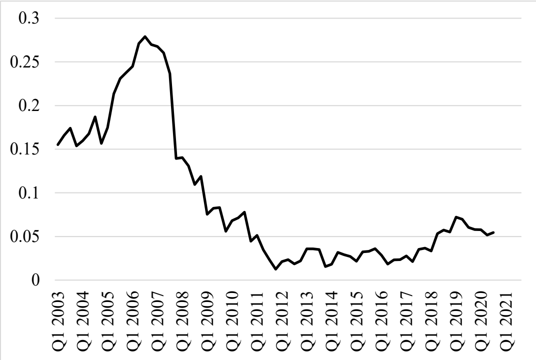
c. Variant from panel a., excluding "strength of bank balance sheets"



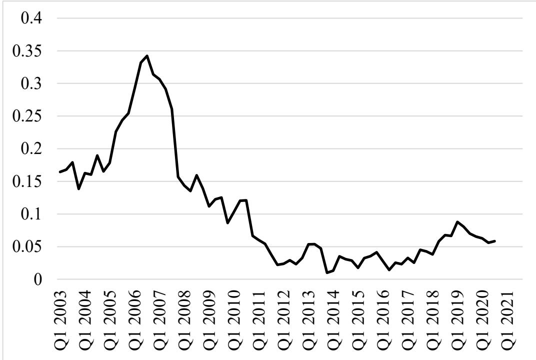
d. Variant from panel b., excluding "strength of bank balance sheets"



e. Variant (2), with real estate price-to-income ratio

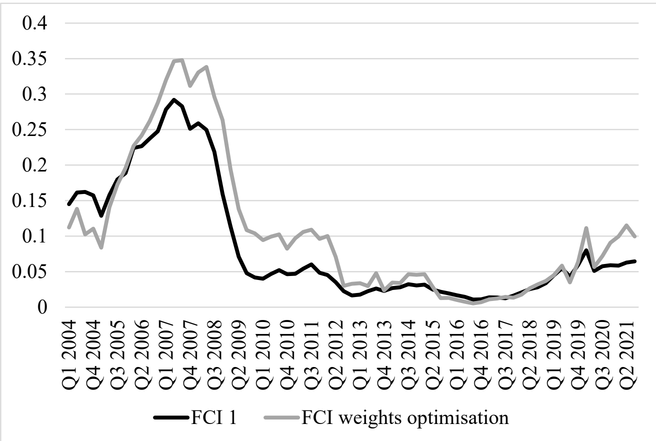


f. Variant from e., excluding "strength of bank balance sheets"



Source: CNB, author's calculation.

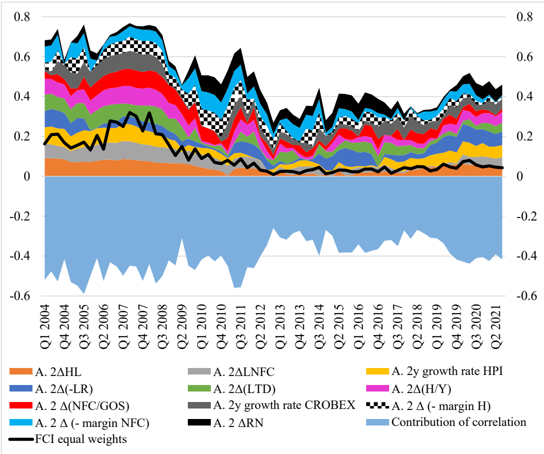
Appendix 5 – Comparison between FCI 1 and the indicator obtained by weight optimisation



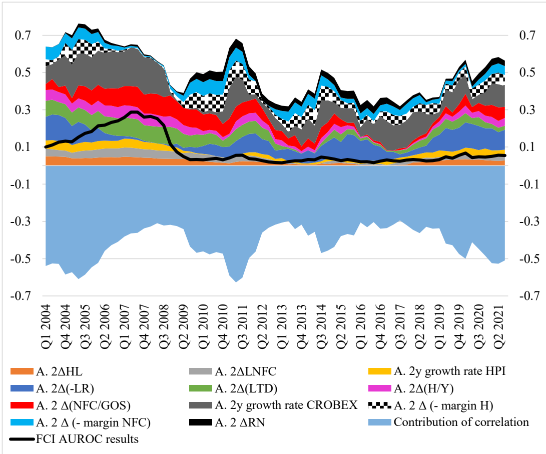
Source: CNB, author's calculation.

Appendix 6 – Structure of the FCI in Figure 3

a. Structure for equal weights by categories of measures



b. Structure for the results of the early warning model



Source: CNB, author's calculation.

Appendix 7 – Description of variables included in the cyclogram and cyclogram+ in Slovakia

The first cyclogram variant (Rychtarik, 2014) includes the following:

1. "Cycle" category: credit gap, GDP gap;
2. "Banks" category: credit growth (absolute change), NPL dynamics (non-performing loans, levels);
3. "Customers" category: debt burden – households, debt burden – enterprises (levels and gaps).

and additional variables in each of the following categories:

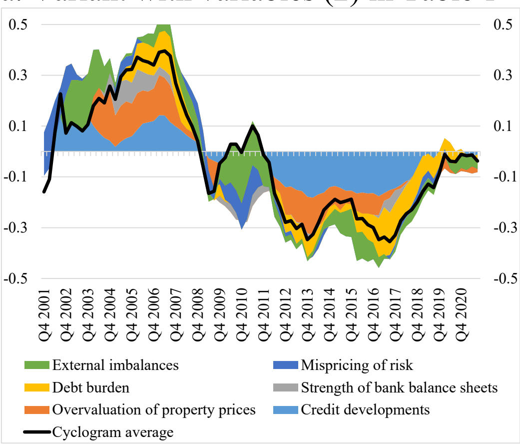
1. unemployment rate and the rise in property prices (relative change);
2. default rate – enterprises, loan-to-value ratios and lending conditions;
3. housing affordability index and consumer confidence.

The new variant (Rychtarik, 2018) includes the following groups of variables used for the cyclogram and the cyclogram+:

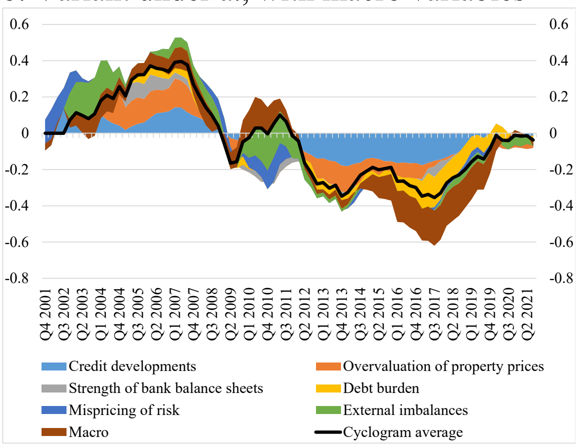
1. Lending market: the credit gap resulting from credit-to-GDP ratio, as in the case of the simple credit ratio; however the gap is observed separately for loans to households and corporate loans; one-year change in bank loans to households and enterprises;
2. Risk appetite: value of non-performing loans (separately for households and enterprises), default rate (enterprises), interest margins (separately on housing loans and loans to enterprises, all in levels);
3. Indebtedness: the level of indebtedness of households and enterprises and the corresponding gaps;
4. Property market: property price growth rate, property price growth rate in Bratislava (or the capital of the country considered in the analysis), property price-to-disposable income ratio, property price-to-rent ratio and flat-to-house price ratio (all in levels);
5. Macroeconomy: Economic Sentiment Indicator (ESI), GDP gap, unemployment rate, revenues gap[58] and the share of current account in GDP.

Appendix 8 – Cyclogram variants with max-min transformations

a. Variant with variables (2) in Table 1

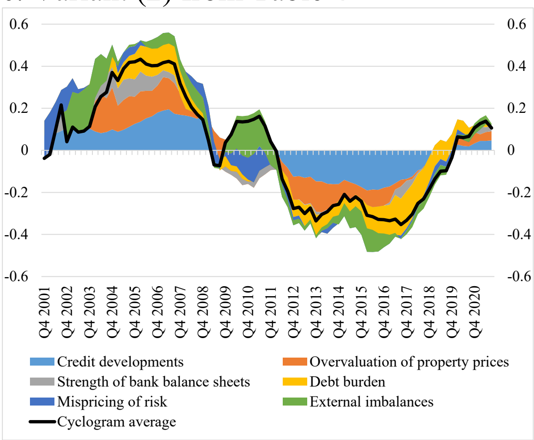


b. Variant under a., with macro variables

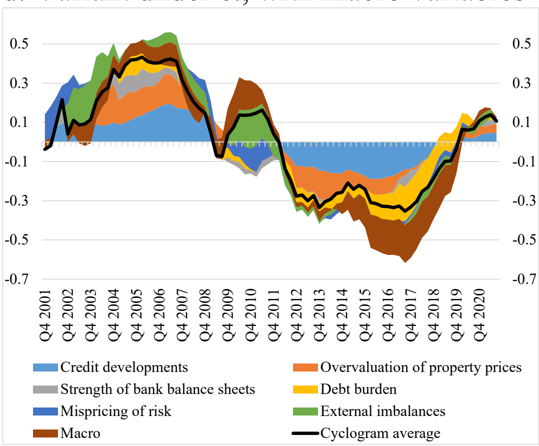


[58] Rychtarik (2018) provides no specification of revenues, and mentions nothing about the value of the smoothing parameter used to calculate the gaps of individual variables, or the elements considered in terms of indebtedness of households or enterprises.

c. Variant (2) from Table 4



d. Variant under c., with macro variables



Note: max-min transformation involved transforming the variables to [-1,1] interval.

Source: CNB, author's calculation.

Appendix 9 – List of variables used in the principal component analysis from Karamisheva et al. (2019)

Karamisheva et al. (2019) analyse the following groups of variables (before moving to a comparison with business cycle and GDP), testing the combinations to identify the one with the best[59] results:

1. measures of credit developments and debt burden: credit gap (separately for households and non-financial corporations), annual credit growth rate (separately for households and non-financial corporations);
2. measures of overvaluation of property prices: annual growth rate of the house price index;
3. measures of external imbalances: current account balance-to-GDP ratio (multiplied by -1);
4. interest rate spreads: spread between interest rates on new loans and EURIBOR (separately for households and non-financial corporations) (multiplied by -1);
5. measures of the strength of bank balance sheets: capital to-assets ratio (multiplied by -1), bank profits to total assets and loan-to-deposit ratio.

[59] The best in the PCA, such that the highest proportion of the variation of original data is explained, with the highest value of concordance index.

Appendix 10 – Variable weights for composite indicator based on the PCA

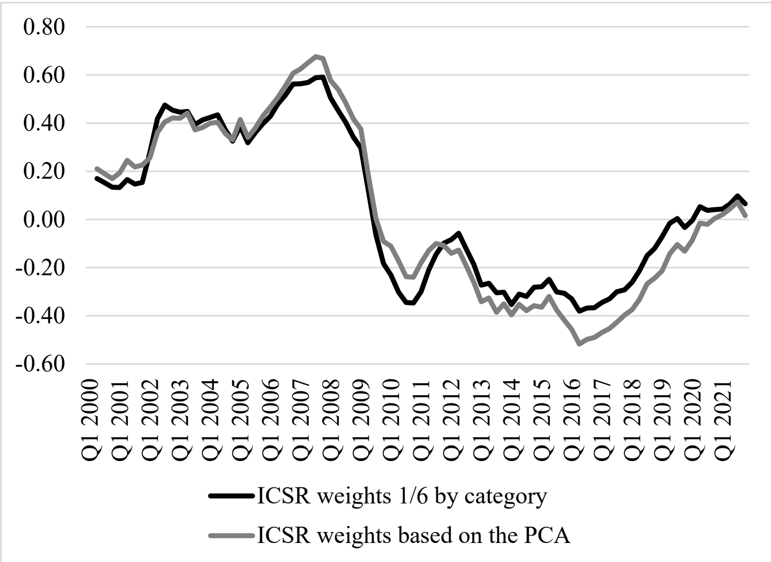
Weights of individual variables in the PCA composite indicators from Figure 6

Variable Variant (1) Variant (2)

Variable	Variant (1)	Variant (2)
HL 125k	0.07	0.07
LNFC 125k	0.07	0.07
NDC 125k	0.07	0.07
- Cap / Assets 2y	0.04	0.04
- Dep / Cred 2y	0.07	0.06
HPI 2y	0.06	0.05
P / I 2y	0.06	0.05
VICW 2y	0.04	0.05
DNFC / GOS 125k	0.07	0.07
HD / Inc 125k	0.07	0.07
DSR H 125k	0.07	0.07
DSR NFC 125k	0.06	0.06
- NX / GDP 2y	0.04	0.04
- CA /GDP 2y	0.05	0.05
CROBEX 2y	0.06	0.05
- margin H 2y	0.05	0.05
- margin NFC 2y	0.05	0.05

Source: CNB, author's calculation.

Appendix 11 – Comparison of ICSR indicators based on equal weights by categories of risk and weights based on the PCA



Source: CNB, author's calculation.

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