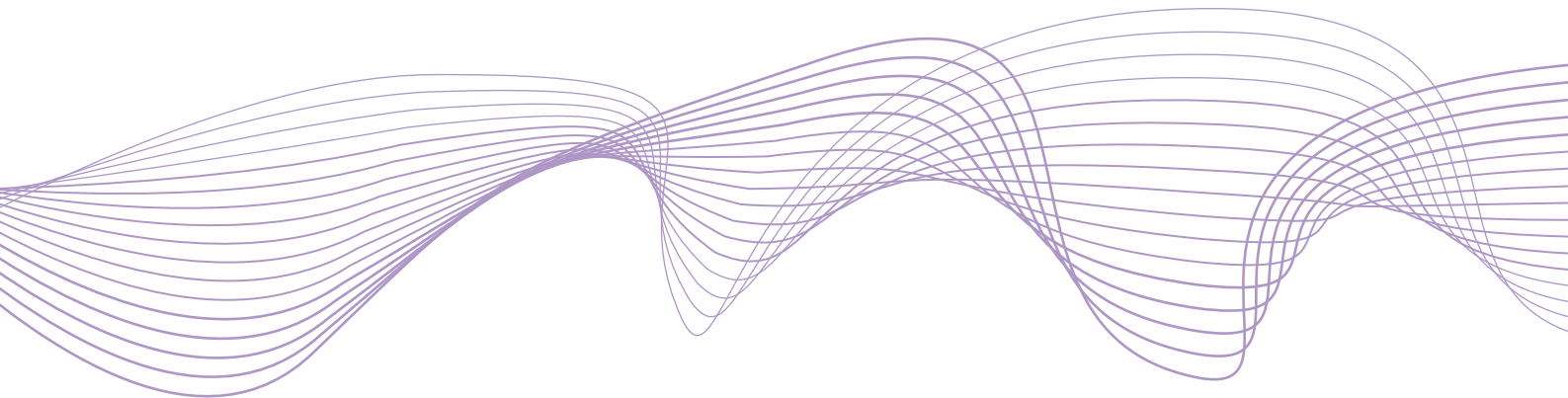


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A profit-to-provisioning approach to
setting the countercyclical capital
buffer:
the Czech example

by
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European Systemic Risk Board

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Abstract: Over the last few years, national macroprudential authorities have developed different strategies for setting the countercyclical capital buffer (CCyB) rate in the banking sector. The existing approaches are based on various indicators used to identify the current phase of the financial cycle. However, to our knowledge, there is no approach that directly takes into consideration banks' prudential behavior over the financial cycle as well as cyclical risks in the banking sector. In this paper, we propose a new profit-to-provisioning approach that can be used in the macroprudential decision-making process. We construct a new set of indicators that largely capture the risk of cyclicity of profit and loan loss provisions. We argue that banks should conserve a portion of the cyclically overestimated profit (non-materialized expected loss) in their capital during a financial boom. We evaluate the performance of our newly proposed indicators using two econometric exercises. Overall, they exhibit good statistical properties, are relevant to the CCyB decision-making process, and may contribute to a more precise assessment of both systemic risk accumulation and risk materialization. We believe that the relevance of the profit-to-provisioning approach and the related set of newly proposed indicators increases under IFRS 9.

JEL Codes: E58, G21, G28

Keywords: Financial stability, macroprudential policy, countercyclical capital buffer, profit-to-provisioning approach, banking prudence indicators

1 Introduction

The global financial crisis (GFC) highlighted the problem of procyclical banking regulation. The post-crisis period therefore saw significant reform efforts. A new economic policy pillar emerged in the form of macroprudential policy aimed at reducing the vulnerability of the financial system through careful implementation of preventive tools. The countercyclical capital buffer (CCyB) was to be the main macroprudential instrument aimed at addressing cyclical risks stemming from excessive growth in credit to the private non-financial sector. The CCyB rate, expressed as a percentage of total risk exposure, takes values between 0% and 2.5%.² The set of regulatory rules formulated by the Basel Committee on Banking Supervision (BCBS, 2010) and the European Systemic Risk Board (ESRB, 2014) also requires national authorities to publish their buffer rate decisions quarterly. The decision to set the CCyB is based mainly on the position of the economy in the financial cycle, often expressed by the benchmark credit-to-GDP gap, calculated as the deviation of the total credit-to-GDP ratio from its long-term trend.³ However, the use of the credit-to-GDP gap has turned out to be problematic for either purely statistical (Hamilton, 2017) or economic reasons (Edge and Meisenzahl, 2011; Geršl and Seidler, 2015). Geršl and Seidler (2015) show that the credit-to-GDP gap may give rise to wrong recommendations, especially in converging economies. Therefore, countries often use other cyclical risk indicators to identify the current phase of the financial cycle.

The BCBS (2010) defines the CCyB as a “buffer of capital to protect [the financial system] against future potential losses.” In other words, the primary objective of the CCyB is to strengthen the banking sector’s resilience during the cyclical risk accumulation period. Most countries also note a secondary purpose in leaning against the build-up of excess credit (BIS, 2017). In this spirit, the capital buffer should be created in times of systemic risk build-ups to be then released in periods of financial stress to reduce the transmission of shocks from the financial sector to the real economy through the mitigation of credit crunches. Naturally, the existing approaches are configured to identify the current phase of the financial cycle. However, there is no indicator (to our knowledge) that directly also takes into consideration banks’ prudential behavior over the financial cycle. A very important factor in the financial cycle is thus omitted. The level of potential losses may reduce prudent provisioning when cyclical risks are accumulating, but loan loss provisions are largely linked to the volume of problem assets and thus have a procyclical bias. Jimenéz and Saurina (2006) find robust evidence that loans granted during economic boom periods have a higher probability of default than those granted during periods of low credit growth. This means that lending policy mistakes occur during economic booms, so the prudential response from the supervision authority should take place at the same time. In fact, Banco de España put dynamic provisioning into force back in July 2000.⁴ This measure has a similar countercyclical effect to the CCyB. The capital buffer (or in the Spanish case the dynamic provision fund) is built up from retained profits during a financial boom to cover realized losses during a subsequent period of financial stress (Saurina, 2009).

In this paper, we propose a profit-to-provisioning approach that is based on the logic of dynamic provisioning and can be used as a supplement in the macroprudential decision-making process for setting the CCyB rate. While Spain based its provisioning system on the evolution of loan loss provisions and their impact on profit, we propose to use the evolution of these variables for the purposes of the CCyB rate decision-making process. Specifically, we construct a new set of indicators that are based on comparing profits and provisioning for loans. We assert that during a financial boom, the observed provisioning is below the average through-the-cycle level, while profits are higher

² The legislation also allows a rate higher than 2.5% in specific cases.

³ Following the BCBS and ESRB recommendation, the trend is computed recursively for each quarter using a Hodrick-Prescott (HP) filter with a smoothing coefficient of 400,000.

⁴ Spain is the only country in which dynamic provisioning was in place over the whole financial cycle.

than average (not only because of lower provisioning, but also due to strong loan growth). A financial boom is the ideal period to create capital reserves to be released during a subsequent period of financial stress when the non-performing loan ratio rises and bank profits are biased downward. Throughout this paper, we refer to these indicators as banking prudence indicators (BPIs), as they are based largely on the evolution of expected losses in the banking sector.

Furthermore, we believe that the importance of the proposed profit-to-provisioning approach for the CCyB decision-making process should increase with the introduction of IFRS 9, which has been in place since January 2018. A new expected credit loss (ECL) approach to measuring loan loss provisions is a key element of the new IFRS 9. The ECL approach is a response to the “too little, too late” IAS 39 provisioning critique. The previous IAS 39 allowed banks to postpone the deterioration of a loan portfolio so it was reflected in profit over a longer period, which could ultimately prolong the financial stress. Under the new IFRS 9 accounting framework, banks should determine the amount of loan loss provisions in a forward-looking manner (i.e., considering the evolution of the financial cycle and macroeconomic indicators). Although the introduction of IFRS 9 should ideally limit the procyclical bias of the provisioning procedure, Abad and Suarez (2017) argue that the ECL approach may actually increase procyclicality in the banking sector, as banks may underestimate their expected losses, especially during financial boom periods. So, the effectiveness of the ECL approach depends on banks’ ability to forecast the future materialization of credit risk. If banks are able to predict credit risk, they will create provisions during a financial boom. This should reduce the potential losses when risks materialize. If banks do not generate provisions when cyclical risks are accumulating, their profit will be cyclically overestimated and the potential loss when risks materialize will be higher due to the “cliff effect.”⁵ Our proposed BPIs should basically evaluate how successful banks were in forecasting future credit risk materialization while drawing attention to the risk of underestimating the expected loss in the banking sector. We evaluate the performance of the proposed indicators using Czech banking sector data. To this end, we use two econometric exercises to show the favorable statistical properties of the BPIs in relation to the task of setting the CCyB.

The rest of the paper is organized as follows. Section 2 offers a brief literature review. Section 3 explains why a new approach is required in the decision-making process for setting the CCyB rate. Section 4 describes the construction of each BPI. Section 5 presents the results of a simple forecasting model and a non-linear Markov-switching model, which we use to assess the BPIs’ ability to identify systemic risk build-up periods. Section 6 provides a brief discussion of the relevance of the profit-to-provisioning approach under IFRS 9 and Section 7 concludes.

2 Literature Review

Financial crises are a recurrent phenomenon coming after periods of strong credit growth (Kindleberger and Aliber, 1978) with damaging effects on the economy (Reinhart and Rogoff, 2009). Macroprudential policy is set to limit the vulnerability of the financial system through the careful deployment of the instruments at the authorities’ disposal. The countercyclical capital buffer (CCyB) is the main macroprudential policy instrument aimed at addressing cyclical risks resulting from excessive credit growth. The existing methodology for setting the CCyB rate was formulated by the Basel Committee (BCBS, 2010) and described in more detail in a European Systemic Risk Board Recommendation (2014/1 on guidance for setting CCyB rates), which is based mainly on the use of the deviation of the credit-to-GDP ratio from its long-term trend, estimated using a Hodrick-Prescott filter. The recommended approach is further elaborated in the *ESRB Handbook on Operationalizing Macroprudential Policy in the Banking Sector* (in a separate chapter on the CCyB). According to Aikman

⁵ A significant hike in loss provisions which may put a bank into loss and result in a need to absorb capital.

et al. (2015), the credit-to-GDP gap should correlate with the emergence of banking crises. However, practice shows that the recommended methodological approach to setting the CCyB rate often gives rise to wrong recommendations, especially in converging economies (Geršl and Seidler, 2015). Macroprudential authorities may also use other methods for setting the CCyB. The Bank for International Settlements (BIS, 2017) has evaluated current practices and lists the systemic risk indicators used to set the CCyB in individual countries. It is clear from its overview that indicators measuring credit activity predominate. Credit standards, the indebtedness of households and businesses, and real estate prices are also widely used. Some countries have also published a set of indicators and described national methodologies. For instance, the Czech National Bank (CNB) uses a wide set of indicators for setting the CCyB rate (as described in Hájek et al., 2017). One of its main indicators is a Financial Cycle Index (Plašil et al., 2015), which combines signals of cyclical risks from various segments of the economy. The National Bank of Slovakia (Rychtárik, 2014) also uses a composite cyclical risk indicator (the “cyclogram”). The Bank of England’s Financial Policy Committee bases its framework on the results of stress tests (BoE, 2015). The German Bundesbank uses indicators related to credit granted to the private non-financial sector (Tente et al., 2015). Banco de España uses indicators of credit activity, private debt sustainability, real estate prices, and external imbalances (Castro et al., 2016; Mencía and Saurina, 2016).

However, financial stability in the banking sector is affected not only by the evolution of systemic risks, but also by the prudence of banks over the cycle. According to some authors, the previous methodology for setting loss provisions (IAS 39) supports procyclicality of the banking sector (Laeven and Majnoni, 2003; Beatty and Lio, 2011; Pool et al., 2015). In general, loan loss provisions are very low in long periods of economic boom, when loan portfolio quality improves. Banco de España therefore put dynamic provisioning in place in July 2000. Dynamic provisioning was based on the notion that banks should provision at the average provisioning rate (the across-the-cycle average) and thus build up a capital buffer from retained profits in economic booms to cover losses in periods of financial stress (Saurina, 2009; Lis and Garcia-Herrero, 2012). Jiménez et al. (2017) show that dynamic provisioning mitigates Spain’s credit supply cycles.

In a similar way, the evolution of provisions can be used to set the CCyB, in particular under the new International Financial Reporting Standard IFRS 9. In direct response to the GFC, the European Union has adopted IFRS 9, which contains a new expected credit loss (ECL) approach for measuring provisioning (mandatory from January 2018). The new ECL approach should ensure that bad loans are written off substantially earlier, which, in turn, should limit the risks related to forbearance (Cohen and Edwards, 2017). IFRS 9 should therefore be countercyclical, provided banks are able to predict the materialization of credit risks in advance. However, some studies argue that the ECL approach may actually increase procyclicality in the banking sector because of the existence of model risk related to the absence of a precise definition of a “significant deterioration in credit risk” and the use of the point-in-time method.⁶ Similarly, Abad and Suarez (2017) point out that the introduction of IFRS 9 may lead to a situation in which the impact of credit losses will be concentrated at the onset of financial stress (i.e., a cliff effect related to a sudden and sharp increase in loan loss provisions). At the same time, however, they state that a certain level of capital reserves should usually be sufficient to cover the additional shock. Also, the ESRB (2017, p. 36) states that the impact of the incremental increase in loss provisions during a financial stress period can be mitigated by a higher set of capital buffers in normal times. Two of the existing macroprudential capital reserves can be released and used to absorb losses, namely, the capital conservation buffer and the countercyclical capital buffer.

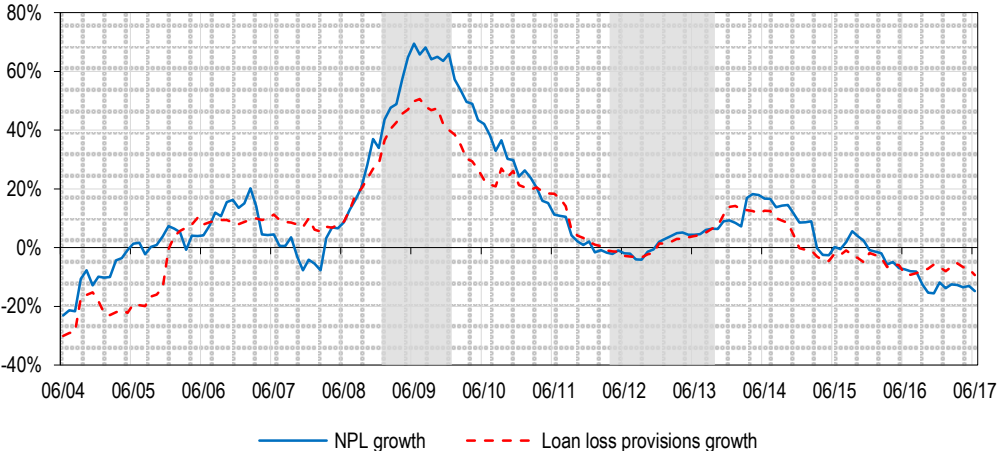
⁶ Model risk can be understood as the space of the model providing inconsistent results (Danielsson et al., 2016). Its existence, in the case of the IRB approach, is often justified by the complexity and lack of clarity of credit risk management models (Haldane, 2011; Montes et al., 2016). The point-in-time methodology in the ECL approach may produce a significant hike in loss provisions if aggregate economic indicators unexpectedly deteriorate.

However, only the CCyB rate is set according to the evolution of the cyclical component of systemic risk. In fact, Agénor and Silva (2017) state that cyclically adjusted provisioning and the CCyB are substitutes. Similarly, Jiménez et al. (2017) highlights the compatibility of the countercyclical capital buffer with countercyclical provisions.

3 Time Mismatch of Cyclical Risk and Loan Loss Provisions

During an economic boom, credit growth accelerates and loan portfolio quality generally improves. This results in a drop in loss provisions (**Figure 1**). The improving loan portfolio quality is also positively reflected in banks’ profit. Furthermore, the drop in provisioning leads to a decrease in the risk premium, a significant component of the interest rate on loans. However, if there is a low amount of non-performing loans at the top of the cycle, then banks also receive a cyclically overestimated profit (as the default rate included in the risk premium does not materialize during repayment of the loan during the boom). This non-materialized expected loss (in simple terms, the difference between the risk premium and portfolio defaults) is the cyclically overestimated interest income. Therefore, the appropriate moment for raising the CCyB rate is during the financial boom period, when the cyclical underestimation of the expected loss and the risk premium, the cyclical overstatement of profit, and the likelihood of a crisis naturally grow. Therefore, banks’ resilience to unexpected losses should be increased. On the contrary, during a period of financial stress, when provisioning and the risk premium are rising, the CCyB rate should be reduced. A reduced capital requirement should help banks maintain space for providing credit to the economy, which, in turn, should reduce the amplitude of the financial cycle.

Figure 1 Dynamics of non-performing loans and loan loss provisions (y-o-y change in %)

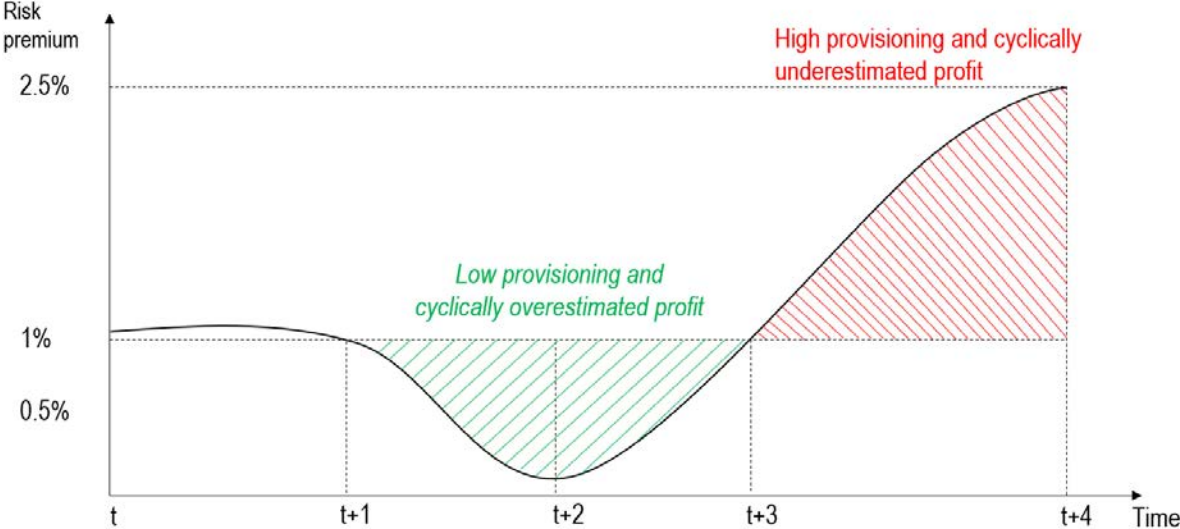


Source: CNB data
 Notes: The shaded areas denote periods of negative GDP growth.

One of the most important issues a bank faces is to determine the right price to charge for a loan, considering many economic factors. A significant part of the interest rate is the risk premium, which is usually lower during economic booms due to more relaxed credit standards and overconfidence. This can result in an inadequate loan pricing and lending mistakes that will become apparent during subsequent financial stress. **Figure 2** shows the dynamics of the risk premium for a loan portfolio for which we set the risk premium initially at 1% (when the loan is provided at time t). During a favorable phase of the financial cycle, loans are repaid and the default rate thus goes down. The risk premium decreases from 1% to 0.5% (bottoming out at $t + 2$). However, when the loan was granted at time t , the interest rate comprised the risk premium of the given loan portfolio of 1%. The difference represents

the non-materialized expected loss, which leads to a decrease in depreciation costs and growth in profit. Profit is therefore overestimated for cyclical reasons.⁷ The bank will report a cyclically overestimated profit if our credit portfolio (provided at time t) is repaid between periods $t + 1$ and $t + 3$, because the risk premium is below the long-run average. Such profit should not be allotted wholly to dividends. Banks should conserve a portion of their profit (the non-materialized expected loss) in the CCyB during the financial boom, because future financial stress (growing impairment allowances) may have a negative impact on their profit and capital.

Figure 2 A loan portfolio with a risk premium of 1%



From the measurement of a financial cycle, it is possible to anticipate the adverse evolution and subsequent materialization of credit risk over time. Assume that at $t + 2$ the economy is at the peak of the cycle. Suddenly, asset quality deteriorates. The risk premium will gradually increase to 2.5% at time $t + 4$. This is significantly higher than the bank assumed when it provided the loan (in period t). The impact of the cycle on both provisioning and profit is now reversed. Profit will be cyclically underestimated if the credit portfolio is repaid at $t + 3$ until the default rate falls to 1%. High losses can result in the need to absorb capital. Therefore, banks should use the cyclically overestimated profit (the non-materialized expected loss) to increase their countercyclical capital buffer during the financial boom. This is required particularly under the ECL approach, which will push for a quick write-off, potentially causing the above-mentioned cliff effect to occur.

4 Construction of the Banking Prudence Indicators (BPIs)

We construct three banking prudence indicators (BPIs) that address the above-mentioned risks of cyclically underestimated provisioning and cyclically overestimated bank profit. The newly proposed set of simple, yet powerful, indicators is largely based on comparing profits and provisioning over the cycle. It illustrates the extent of cyclical understatement/overestimation of loss provisioning and the risk premium by banks (as described in Section 2 of this paper) and can be used as a complement to the existing approaches to the decision-making process for setting the CCyB rate. A description of the construction of each BPI follows.

⁷ In addition, the credit boom increases profit due to the growing volume of lending.

BPI A: The formula shows the ratio of the total interest margin⁸ to loss provisions per unit of private loans (i.e., loans to households and non-financial corporations). The interest margin contains information about the risk premium of the given loan portfolio. In the denominator, we use loss provisions per unit of private loans to get information about banks' prudential behavior. We use only client loans because they make up a substantial part of the credit portfolio which generates the overwhelming majority of loan loss provisions. We use the stock of client loans and loan loss provisions. This is because we want to show the evolution of loan loss provisions against the entire loan portfolio from which the bank has interest income for the year. BPI A monitors whether sufficient provisions are created in relation to the risk premium contained in the interest rate on private loans. If not, then BPI A is increasing and banks should conserve a portion of their profit (the non-materialized expected loss) in the CCyB during financial booms.

$$\text{BPI A} = \frac{\text{interest margin}}{\left(\frac{\text{loss provisions}}{\text{private loans}} \right)}$$

BPI B: The formula shows the ratio of the total interest profit to loss provisions per unit of private loans. Interest profit (net interest income) can be expressed as the product of the interest margin and client loans. We use interest profit as a flow variable because banks can only use the profit for the year (before the payment of dividends) for loss absorption. Thus, BPI B is calculated as flow indicator divided by a stock indicator, like other bank profit indicators (RoA, etc.). BPI B increases with increasing loan volume (i.e., potential losses in the banking sector) and as such is more self-supporting as an indicator of the financial cycle than BPI A. Regarding the numerator, we use total interest profit, which includes information about the evolution of the volume of loans and deposits and information about the interest margin. Granting a loan may manifest itself in a profit or a loss. In general, credit losses and provisioning are low during financial boom periods, as most loans are repaid, but this may result in a cyclically overestimated profit. If banks, for any reason, underestimate provisioning during a financial boom, the indicator increases and banks should be advised to increase their resilience to unexpected losses. Ideally, this would be done through cyclically overvalued profits, which are higher than average during financial booms not only because of lower provisioning, but also due to strong loan growth.

$$\text{BPI B} = \frac{\text{interest profit}}{\left(\frac{\text{loss provisions}}{\text{private loans}} \right)}$$

BPI C: This indicator expands BPI A by incorporating banking sector leverage, i.e., the ratio of client loans to capital (the overall capital requirement⁹ plus the capital surplus).¹⁰ Taken as such, this indicator should also reflect the procyclicality of risk weights. Brož et al. (2018) show that the risk weights of exposures under the internal ratings-based approach are procyclical with respect to the financial cycle. The cyclicity of risk weights leads to a decrease in the absolute level of the capital requirement at a time of systemic risk accumulation and an increase in banks' vulnerability. BPI C would increase in this situation – signaling a need to compensate for the decrease in the capital requirement by increasing the CCyB rate.

⁸ The interest margin is the difference between the average client loan rate for the sector and the average client deposit rate.

⁹ The overall capital requirement comprises the sum of Pillar 1 requirements, additional Pillar 2 requirements, and capital reserves. The main risk in the Czech banking sector is credit risk (which accounts for more than 85% of the Pillar 1 capital requirement), because the sector is based on the traditional model (accepting deposits and granting loans).

¹⁰ It may be relevant to include banks' capital surplus, because banks might be willing to hold higher capital due to a planned credit expansion or changes in asset structure toward riskier assets.

$$\text{BPI C} = \left(\frac{\text{interest margin}}{\left(\frac{\text{loss provisions}}{\text{private loans}} \right)} \right) * \left(\frac{\text{private loans}}{\text{capital}} \right)$$

Note that all the proposed indicators can be modified to account for individual types of loans (loans to non-financial corporations, mortgages, and consumer loans). However, the existing data are by no means granular enough to be successfully incorporated into an empirical framework. Still, they can be used for a descriptive analysis.

Table 1 provides a list of the input variables together with a description of each of them (time series are also shown in Appendix A). We do not make any adjustment to the data, i.e., they enter the ratios in levels. Note that we also tried to calculate the indicators using flow variables only, by replacing the loss provisions in the denominator with risk costs and impairment losses. However, the flow indicators turned out to be extremely volatile and therefore do not enter our empirical exercises. For details, please consult Appendix C.

Table 1 Description of the variables used

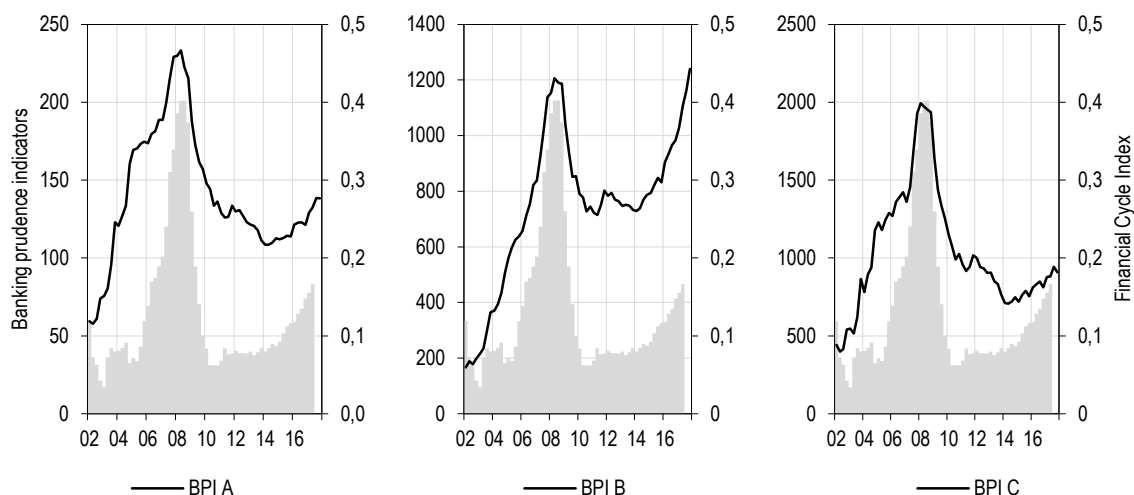
Variable	Description	Stock or flow
Interest margin	Difference between the average client loan rate for the sector and the average client deposit rate	Stock
Loss provisions	Loss provisions by non-credit institutions from claims	Stock
Private loans	Loans to households (consumer and housing) and non-financial corporations – the non-financial corporations item does not include revolving loans and credit cards	Stock
Interest profit	Total net interest income	Flow (quarterly contributions)*
Capital	Overall capital requirement (OCR)** + capital surplus	Stock

* Interest profit exclusively from loan contracts is not available in a sufficiently long time series.

** The overall capital requirement comprises the sum of Pillar 1 requirements, additional Pillar 2 requirements and capital reserves.

Figure 3 plots the newly proposed BPIs together with the Financial Cycle Index (Plašil et al., 2015) to show their possible complementary character. The indicators for the Czech banking sector all exhibit a gradual increase over the 2005–2007 period prior to the GFC outbreak. After the crisis, the risks expressed by the BPIs do not fall to the pre-crisis level at all. As the GFC did not have a significant impact on the Czech banking sector, there was no significant deterioration in loan portfolio quality, which would have led to growth in loss provisions and thus a decrease in the value of the BPIs. This shows that crises do not just come and go, but the associated risks have a persistent character and tend to stick around. The risks expressed by the BPIs stagnated during 2010–2014 (at the 2005 risk levels) and started to grow again in 2015. By mid-2017, the values are close to those at the top of the previous cycle in mid-2008. This shows that the volume of lending increased significantly, while the ratio of loss provisions to private loans decreased. Hence, banks' cautiousness regarding expected losses in relation to the underlying risks declined. Also, banks maintained relatively high profits. The CNB behaved cautiously in this respect, setting the CCyB rate at 0.5% in December 2015 (effective January 2017) and raising it to 1% in May 2017 (effective July 2018) and 1.25% in December 2017 (effective January 2019).

Figure 3 Banking prudence indicators (BPIs) and the Financial Cycle Index

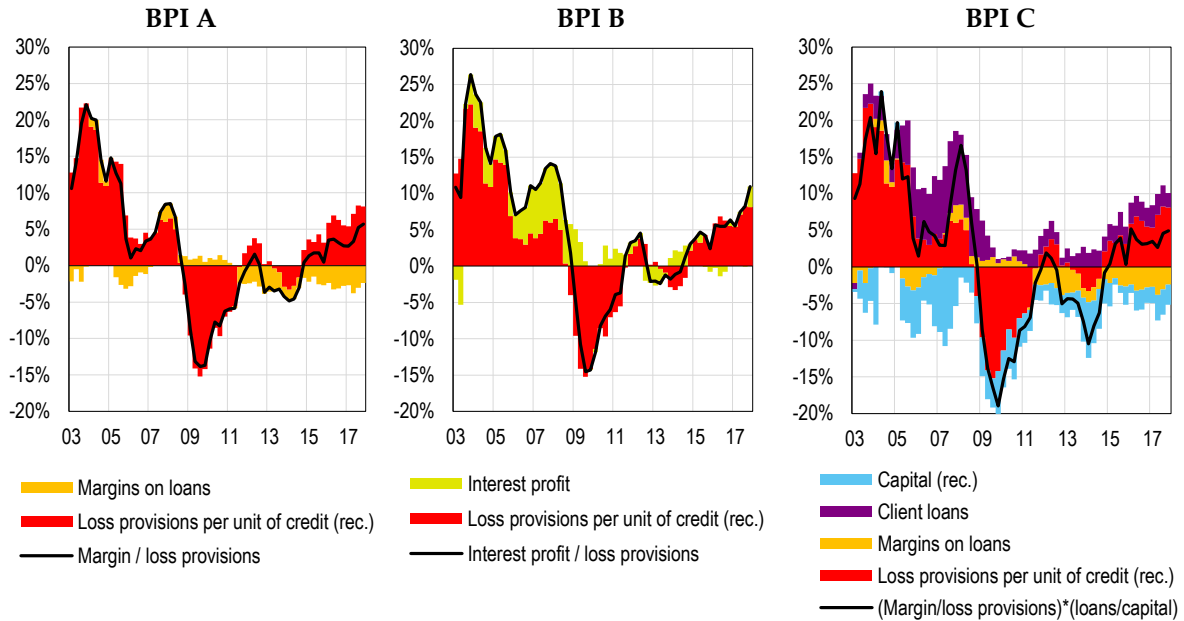


Source: CNB and authors

Notes: The indicators are reported in base units. The grey area depicts the Financial Cycle Index (right-hand scale).

To see what drives the dynamics of each of the indicators considered, we break them down into individual factors and calculate the factors' contributions to the growth of the indicator (**Figure 4**). First, we take the log of the entire indicator and second, we calculate its annual change, expressing the contributions as log changes of the contributing factors. For the sake of clarity, we report the elements of the denominator in reciprocal values. From an inspection of the decompositions of the individual BPIs, we see that loan loss provisions are the main driving force behind their cyclicity. Loan loss provisioning contributed to the growth of the indicators especially in the years prior to the GFC and again since 2014. In those periods, the BPIs would support activation and gradual increases of the CCyB rate. Taking a closer look, we can spot several more interesting patterns in each of the BPIs. First, BPI A signals that during several episodes (e.g., 2004–2005 and 2007–2008) loan loss provisions fell even when banks' interest margins and risk premium increased. This indicates that sufficient provisions were not created in relation to the risk premium contained in the interest rate. So, banks' expected losses may have been underestimated and banks should have increased their resilience to unexpected losses and increased the CCyB rate. Second, BPI B shows a mostly inverse relationship between loan loss provisions and interest profit, supporting the notion that banks tend to overestimate profit during times of underestimated loan loss provisions (e.g., 2004–2007). Therefore, banks should have increased their resilience to unexpected losses and increased the CCyB rate. Third, BPI C depicts increasing leverage in the financial sector prior to the GFC period (excluding 2005–2007). Risk weights increased during the financial stress period, deepening the decline in BPI C. Also, there is a visible impact of the capital requirement increase due to the introduction of a capital conservation buffer in the full amount of 2.5% as from 2014 and a systemic risk buffer for domestic systematically important institutions of 1%–3% as from November 2014. Leverage has increased since 2015, so the absolute level of the ratio of capital to client loans has decreased. This, together with a low level of loan loss provisions, may serve as an impulse to increase the CCyB rate.

Figure 4 Decomposition of the proposed BPIs' annual growth rates



Notes: rec. denotes variable in reciprocal values. Variables are expressed as y-o-y growth rates in percent.

5 Evaluation of the Proposed BPIs

We argue that the main strength of the profit-to-provisioning approach and the BPIs as financial cycle measures is their explicit foundation on banks' management, which allows them to encompass banks' reaction to the cycle rather than just relying on measuring credit activity or asset price developments. Taken as such, the BPIs form a simple, yet accurate, set of financial cycle indicators. The postulated conceptual superiority of the BPIs notwithstanding, this section attempts to evaluate empirically whether the BPIs measure what they are supposed to measure sufficiently accurately.

We are aware that evaluating the performance of any financial cycle indicator is inherently complicated. This stems from the fact that financial crises are rare events, giving the econometrician only a handful of historical episodes of financial stress or even crises and thereby limiting the statistical reliability of empirical analyses. The fuzziness of the concept of systemic risk, the complexity of modern-world financial systems, and spillover effects from the rest of the economy do not help either. In general, it is difficult to assess whether the indicator considered is "good" or even "better than others." Against the background of these caveats, we evaluate the performance of the indicator using two econometric exercises. First, we use a simple forecasting exercise to evaluate the predictive performance of the BPIs. This modeling strategy of ours is based on Plašil et al. (2015), who state that the predictive content of a financial cycle indicator may be a positive side effect to its main purpose. Similarly, Ng (2011) argues that one way to assess the usefulness of a particular financial cycle measure is to assess its predictive power. Second, we estimate a nonlinear Markov-switching model to see whether the proposed indicators are able to identify levels of risk which may undermine the resilience of a financial sector. Franta (2016) analyzes the link between credit/financial markets and the real economy and shows that nonlinearities play an important role in predicting future economic developments. Similarly, Abdymomunov (2013), Dumpyrey and Klaus (2017), and Brave and Lopez (2017) use a Markov-switching modeling framework to assess the ability of various financial cycle measures to identify low or high financial stress periods.

5.1 A Simple Forecasting Exercise

In this section, we test the predictive performance of the proposed BPIs with respect to the accumulation and future materialization of credit risk. Even though the main purpose of the proposed indicators is different from guessing future values of other variables, we can use this simple forecasting exercise to ascertain their merits. First, we mimic the forecasting exercise in Plašil et al. (2015) and analyze the predictive performance of the three versions of the indicator with respect to growth in non-performing loans (NPLs), which serve as a representative of the materialization of systemic risk. Second, we test whether the inclusion of the BPIs yields useful information regarding systemic risk accumulation. Therefore, we evaluate whether they can capture the early stages of house price growth, which is a typical financial cycle variable that behaves very nicely across the cycle, with increases during financial booms and decreases during episodes of financial stress.¹¹ Note that we are not interested in obtaining the best possible predictor of growth in house prices or NPLs. We only aim to show the favorable statistical properties of the proposed indicator in relation to the task of setting the CCyB. To this end, we employ a simple single-equation prediction model that takes the following form:

$$Y_{t+h} = \beta_t M_t + \delta_t X_t + \varepsilon_t, \quad (1)$$

where Y_{t+h} is the predicted variable (growth of house prices or NPLs) predicted at horizon h using information up to time t , M_t holds the three BPIs (added one-by-one), and X_t is a set of additional regressors. In our application, we only use the lags (up to the fourth lag) of the variable Y as additional regressors. When estimating the model forecast of house prices, we set the forecasted horizon h to one quarter. Keeping the estimated relationship close to a contemporaneous one might generate interesting results in relation to pre-crisis systemic risk build-ups. In the case of the model forecast of NPL growth, we set h to six quarters, which corresponds to the pre-announced activation of the CCyB by up to 12 months (BCBS, 2010). Prior to the estimation, we scale the data by taking logs and then calculate the year-on-year change (see Appendix A). We make no seasonal adjustment of the raw data.

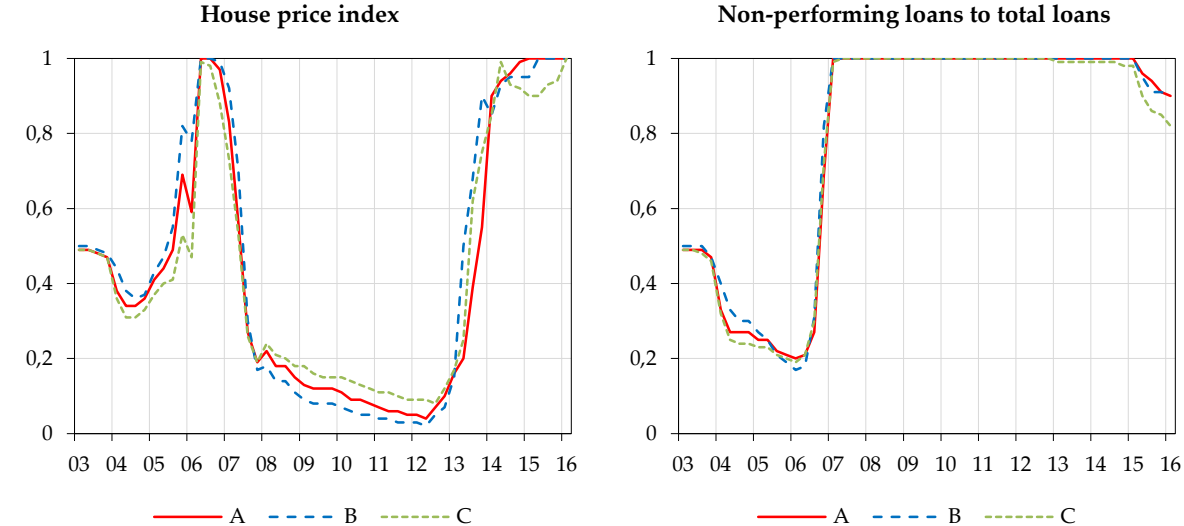
Since we want the BPIs to provide policy-makers with useful information regarding the evolution of the financial cycle, we assess the out-of-sample fit. For this purpose, we use the dynamic model averaging (DMA) method of Raftery et al. (2010).¹² The method considers all possible combinations of the variables of interest as potential predictors at various lags. The key output of this method is the posterior inclusion probability (PIP), which shows the probability that the measure M_t is included in the “best” model given the available data. It works in a time-varying framework, meaning that the estimated parameters β_t and δ_t may change over time. It also has another feature important to us: in the prediction, it only uses the information available up to time t instead of taking into account the whole sample period. This is much closer to reality, where policy-makers only know the real-time data at best. In our application, we use CNB data for the entire banking sector available to us from 2002Q1 to 2017Q4 and use the first 40 observations as a training sample (for data sources and a description, please consult Appendix B). To provide the reader with some basic comparison, we also report the results of this exercise for the Financial Cycle Index and the credit-to-GDP gap in Appendix B.

¹¹ Geršl and Jašová (2018) show for emerging markets that simple market variables such as credit growth may outperform the credit-to-GDP gap in terms of early warning ability.

¹² The code we used to estimate the DMA model is based on Koop and Korobilis (2012), who apply it to an inflation-forecasting exercise. They find that dynamic model averaging leads to substantial forecasting improvements over simple benchmark regressions and more sophisticated approaches such as those using time-varying coefficient models.

Figure 5 sheds light on which predictors are important at each point in time for growth in house prices and NPLs. The two graphs show the evolution of the PIP associated with each BPI. This is the total probability attached to models that include that particular financial cycle measure. Equivalently, it is the weight used by DMA attached to models that include a particular predictor. The left-hand graph depicts the assessment of models predicting growth in house prices. That is, it shows whether our proposed BPIs may improve the house price forecast. Again, we stress that our goal is not to anticipate the actual evolution of house prices, but to point out that cyclical risks increase at par with increasing residential property prices (coupled with relatively high profits on new mortgage contracts). Therefore, banks should create reserves and increase their capital and thus their resilience to unexpected future losses. The main point worth noting is that the inclusion probabilities vary over time, indicating that DMA attaches different weights to different predictors over time t . Our results show that models containing any of the BPIs considered contain useful information for the prediction of house prices in the pre-crisis period, when the PIP gradually increases and jumps to near one in the first quarter of 2007, indicating the BPI as the dominant predictor. During an expansionary phase of the financial cycle, the BPIs would call for more prudent behavior by banks with respect to the increasing amount of mortgage contracts and rising house prices, which would manifest in increasing interest profit and decreasing loan loss provisions. By contrast to the pre-crisis period, the BPIs perform rather poorly during the GFC and its aftermath. In other words, they do not show any comparative gains. The PIP values further show that the models with BPIs gain significance again at the end of the period analyzed. This may be explained by gradually increasing house prices and mortgage contracts, which are reflected in banks' profits and loss provisions. Overall, these results suggest that BPIs might bear useful information for policy-makers, as they could provide them with some early warning signals in relation to house price developments, which are responsible for a large portion of the financial cycle. By contrast, in the case of NPL growth (the right-hand graph), the PIP exhibits a different pattern, as it rises abruptly at the end of 2007 and remains high for most of the remainder of the sample. In particular, the high PIP for NPL growth in 2007Q4 suggests that models containing the BPIs may generate a better prediction for this period (remember that the model uses information lagged by six quarters, i.e., information up to 2006Q2). This shows that models containing the BPIs dominate their competitors over most of the sample and may serve as good predictors of future changes in credit risk in expansionary as well as recessionary phases of the cycle.

Figure 5 Time-varying posterior inclusion probabilities for the proposed BPIs



Notes: The time axis corresponds to the forecasted variable. The figures show how good predictions may be obtained by models containing the three versions of the proposed BPI.

We hesitate to engage in a direct comparison exercise with other financial cycle measures from a reduced-form forecasting exercise such as ours. Suffice it to say that the Financial Cycle Index performs roughly the same as our proposed BPIs in all the exercises. Turning to the credit-to-GDP gap, it performs rather poorly as a potential predictor of changes in house price dynamics. On the other hand, it exhibits some success in explaining NPL growth prior to the crisis, but follows a downward-sloping path from 2008 on. This is not that surprising, since the one-sided Hodrick-Prescott filter used for the trend estimation, from which the gap is constructed, is very sensitive to the arrival of new data.¹³ It is therefore expected to perform better for ex-post values, but as is evident, its performance decreases in the post-crisis period, which was characterized by rather large data revisions.

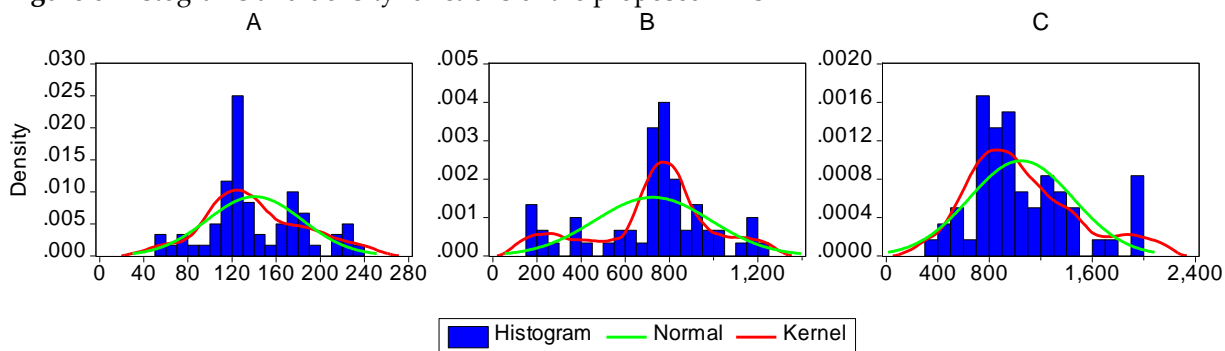
5.2 Regime Classification and Thresholds

Gadea-Rivas and Perez-Quiros (2015) argue that the key question for a policy-maker is to what extent the level of a financial cycle indicator observed in period t increases (or not) the probability of financial instability in $t+1$, or whether it changes the characteristics of future cyclical phases. Bearing in mind that the main purpose of our indicator is to serve as an instrument for CCyB setting, the above-mentioned statement may be rephrased. The main goal of any financial cycle indicator is to properly identify such level of risk that can disrupt the resilience of the banking sector and therefore signal the need for additional capital.

There are two main steps in the task of measuring the financial cycle in general. First, one must identify variables that contain useful information for plotting the course of the financial cycle, and second, one must use those variables in a joint statistical framework. However, the choice of the appropriate model for testing the usefulness of a particular indicator is challenging and deserves closer attention. One possible approach stems from the literature on early warning indicators (EWIs). Using a discrete choice approach, authors transform the variables of interest into crisis probabilities using a logit or probit model (see Bussiere and Fratzscher, 2006, and Babecky et al., 2014, among others). The obvious appeal of discrete choice models lies in their simplicity and flexibility. They take the form of an index that denotes the absence of a crisis with a value of zero and the occurrence of a crisis with a value of one. Using this binary dependent variable allows the econometrician to distinguish between crises and tranquil periods. However, there is a trade-off between the strength of a signal and its value for policy-makers. Early signals tend to be associated with a higher rate of false alarms. Also, such models generally require a large number of data points (in this case crises), which is not applicable to transition economies with short time series. Lastly, such models are not able to model the dynamics of the regimes identified (i.e., they are not able to estimate the probability of moving from one regime to another). Another strand of literature estimates the receiver-operating-characteristics (ROC) curve (AUC) to evaluate the signaling performance of various credit-based variables. While this method provides a simple and easy-to-interpret approach and has been gaining ground in the very recent EWI literature (see Drehmann and Juselius, 2013, and Geršl and Jašová, 2016, for a panel-data analysis and Gerdrup et al., 2013, for a single-country analysis), its application is also limited by the relatively low number of data points in our case. Obviously, the simplest approach is to set some benchmark level for the indicator and classify its level as significant if it exceeds one unit of variance (Illing and Liu, 2006). This approach, however, must explicitly assume that the indicator follows a normal distribution. In many cases, this assumption is not fulfilled. **Figure 6** shows that the distributions of the proposed BPIs cannot be convincingly described as Gaussian. The distribution is skewed toward its right or left tail or is even multimodal. This means that the empirical density function should be represented as a mixture of distributions, each characterizing a separate regime.

¹³ Edge and Meisenzahl (2011) show that the US credit-to-GDP gap has been subject to large ex-post revisions that have lowered its explanatory power.

Figure 6 Histograms and density functions of the proposed BPIs



Notes: “Normal” denotes a Gaussian function and “Kernel” a Kernel density function.

Another approach separates periods of high or extreme financial stress from periods with only moderate or low levels of stress based on the assumption that the time series properties of an indicator are state-dependent. This approach may seem appropriate for us, as it assumes that financial stress is clustered around local attractor levels across different regimes, thereby displaying some intra-regime persistence. Changes in regimes may be modeled by making them dependent on a discrete Markovian process with a given number of states. Unlike in standard threshold models, in the Markov-switching model the state of the process is determined endogenously and the specific state can change from period to period. The process can even be in-between two states in a particular period. Very flexible changes in the model coefficients can thus be accommodated.¹⁴ In this spirit, we use the Markov-switching model to assess the ability of an indicator to identify periods of systemic risk build-up, during which the CCyB rate should be increased to reduce the magnitude of the financial cycle.

5.2.1 A Markov-Switching Framework for the Analysis of the BPIs

The Markov-switching framework we employ is ideal for our purposes for several reasons. First, it provides a way to investigate the presence of nonlinearities. Recently, Franta (2016) showed that in periods of tight credit conditions, nonlinearities play a significant role in the assessment of the economic outlook. Also, Plašil et al. (2015) find some evidence of a potential nonlinear relationship between the Financial Cycle Index and the business cycle. Second, we do not need to make any a priori assumptions about the timing of crisis episodes. And third, we are able to model transitions from one state to another.

We estimate a univariate first-order autoregressive Markov-switching model as per Hamilton (1989). Following Brave and Lopez (2017), we use the model to capture the joint dynamics between real GDP and private credit growth while incorporating the different BPI versions into the time-varying transition probability model proposed by Diebold et al. (1994). The motivation behind this model setting lies in the effort to capture both credit and real economic activity together with the proposed BPIs (again, we also present the results of this exercise for the Financial Cycle Index and the credit-to-GDP gap in Appendix B). The model takes the following form:

$$\begin{aligned}
 Y_t &= \alpha_S + \beta_S Y_{t-1} + \phi_S X_t + \varepsilon_t, \quad \text{for } S = (0,1) \\
 \varepsilon_t &\sim N(0, \sigma^2),
 \end{aligned}
 \tag{2}$$

¹⁴ The MS model has been used extensively in the business cycle literature (Chauvet and Piger, 2008; Bardaji et al., 2009). It has also been widely used together with VAR models. Alessandri and Mumtaz (2014) show that an MSVAR model could have provided a credible warning ahead of the Great Recession in the US.

where Y_t holds real GDP and X_t is the vector of switching regressors containing the lagged dependent variable and loans to the private sector¹⁵ at times t and $t-1$. The variables were scaled by taking logs and enter the model in annual growth rates. The models are assumed to have an ergodic Markov chain with transition probabilities captured in matrix Ω_t with elements p_{01} denoting the transition probability of moving from state 0 to state 1. The probability matrix, inspired by Diebold et al. (1994), is specified as follows:

$$\Omega_t = \begin{bmatrix} \Phi(\delta_0 + \gamma Z_t) & 1 - \Phi(\delta_0 + \gamma Z_t) \\ 1 - \Phi(\delta_1 + \gamma Z_t) & \Phi(\delta_1 + \gamma Z_t) \end{bmatrix}, \quad (3)$$

where $\Phi(\delta_{01}) = p_{01} = \text{Prob}(S_t = 1 | S_{t-1} = 0, X_t, \alpha_s, \beta_s, \phi_s)$ is the cumulative normal distribution and Z_t holds the different versions of the BPI (added one by one).¹⁶ Basically, the model allows the transition probabilities of the first-order Markov process to depend on covariates Z_t . The states of the economy are generally interpreted as low and high financial stability states (see Gadea-Rivas and Perez-Quiros, 2015, and Brave and Lopez, 2017). However, this might be misleading in our case. Since we incorporate predominantly financial cycle indicators in the analysis, we might expect one of the identified regimes to simply be a systemic risk build-up (a systemic risk accumulation period) given that during this period the indicators should grow substantially. The second regime should then capture anything else, including normal times of a relatively stable financial sector as well as crises coupled with risk materialization. Ideally, we would calculate the model with three regimes, but the time series at our disposal are not long enough for such a model to be successfully calculated. On the basis of this shortcoming, we proceed by calling regime 0 a systemic risk build-up and regime 1 simply other times.

First, we take a closer look at the parameter estimates for models using the individual versions of the BPI. The results are summarized in **Table 2**. The top row shows the estimates of the joint transition probabilities. In general, we find that the implied probabilities differ only slightly across the various versions of the BPI. For example, the mean probability of remaining in the systemic risk build-up regime δ_0 is around 30%, in contrast to the 92% calculated for the second regime δ_1 . This indicates lower persistence of the systemic risk build-up regime relative to other states of the economy. For possible extensions to this paper, the procedure described in Brave and Lopez (2017) may be useful. They transform the estimated state probabilities into hazard functions, which they later use in a decision-theoretic framework, as per Khan and Stinchcombe (2015), structured to address the implementation of countercyclical capital buffers. The introduction of the BPI into the modeling framework generates negative γ estimates. This negative coefficient suggests that as the value of the BPIs increases, the probability of transitioning into the systemic risk build-up regime next period increases.¹⁷ Focusing on the regime-dependent dynamics for GDP growth and private loan growth, we find that the estimated parameters vary significantly across the two regimes but are mostly similar across the three models. For instance, we find the coefficients on the lagged real GDP growth rates $\beta^{GDP_{t-1}}$ to be highly positive in the systemic risk build-up regime, but smaller in the other regime, suggesting a faster pace of mean reversion. Further, we find a mostly positive credit growth rate

¹⁵ Throughout this paper, we use the volumes of outstanding loan contracts, as the time series on new contracts are too short and cannot be successfully incorporated into the empirical analysis.

¹⁶ They enter the matrix in levels (in a form used by policy-makers), but we also try to transform them into annualized growth rates and first differences, which yield similar results.

¹⁷ Note that the parameter γ is found to be insignificant in the model with the credit-to-GDP gap as the leading indicator. This suggests it has lower explanatory power.

coefficient ϕ^{credit_t} in the systemic risk build-up regime, which indicates it has positive effects on the real GDP growth rate. This effect turns around in the other regime (which consists of a recession as well as an antecedent recovery period), where we find negative and statistically significant coefficient values. This shows that past the peak point of the financial cycle, credit growth does not contribute to GDP growth anymore, as the systemic risk materializes and is manifested in a rising number of bankruptcies and delinquencies. In other words, the return to equilibrium and the correction of past lending mistakes are costly not only for the banking sector, but for the entire economy as well.

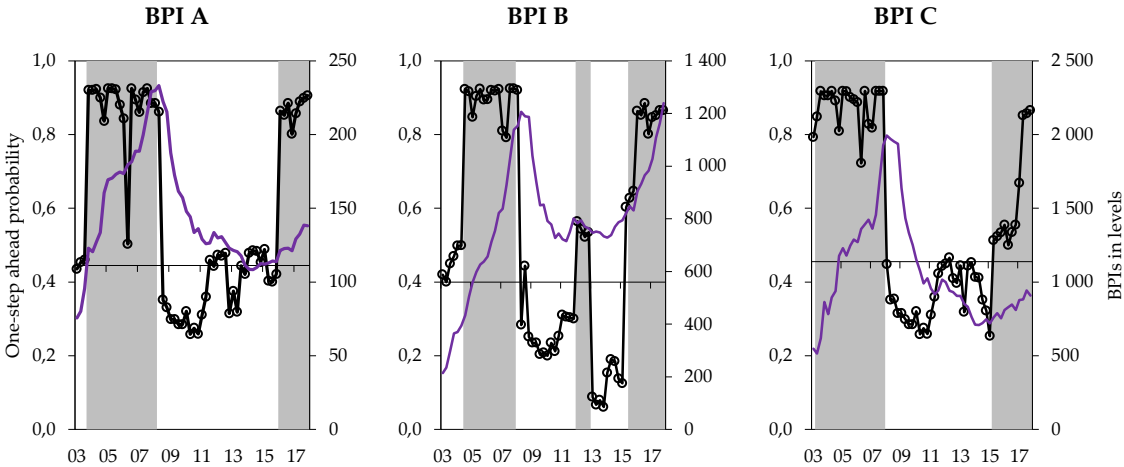
Table 2 Parameters and transition probabilities

Parameters:	BPI A	BPI B	BPI C
<i>Probabilities</i>			
δ_0	0.299	0.314	0.315
δ_1	0.925	0.919	0.917
γ	-0.024* (0.001)	-0.054* (0.024)	-0.047* (0.018)
<i>Regime 0 (systemic risk build-up)</i>			
α_0	0.042* (0.011)	0.032* (0.008)	0.001 (0.003)
$\beta_0^{GDP_{t-1}}$	1.638* (0.250)	1.393* (0.232)	1.396* (0.238)
$\phi_0^{credit_t}$	0.500* (0.143)	0.622* (0.175)	0.617* (0.177)
$\phi_0^{credit_{t-1}}$	0.053 (0.013)	0.060 (0.049)	0.034 (0.014)
<i>Regime 1 (other times)</i>			
α_1	0.003* (0.002)	0.003* (0.002)	0.003* (0.002)
$\beta_1^{GDP_{t-1}}$	0.327* (0.100)	0.393* (0.106)	0.387* (0.109)
$\phi_1^{credit_t}$	-0.138* (0.149)	-0.204* (0.119)	-0.148* (0.155)
$\phi_0^{credit_{t-1}}$	0.028 (0.049)	0.048 (0.052)	0.050 (0.052)

Notes: The table shows the Markov-switching model estimates through the 2003Q1–2017Q4 period. Each column reports the parameter estimates from one of the three model specifications (the model differs by the inclusion of various BPIs). We report the parameter estimates together with their standard deviations. Estimates that are statistically significant at the 10% level or lower are marked with an asterisk and highlighted in bold.

In general, the leading indicator nature of our estimated systemic risk build-up regime is useful for guiding macroprudential policy decisions. To examine the models' properties more closely, **Figure 7** summarizes the probabilities obtained for the two regimes through the sample period of 2003Q1 to 2017Q4. The shaded regions in each panel denote quarters where our filtered probability of the low financial stability state exceeds 50% and the black line with dots shows the one-step-ahead probability. The figures also depict the evolution of the corresponding BPIs. Two periods of systemic risk build-ups (under regime 0) stand out: 2003–2007 and 2015–2017. Each of these periods corresponds to well-known periods of systemic risk accumulation. The first links with the period prior to the GFC outbreak. As is apparent from the results, the BPI sends warning signals way before the crisis outbreak. This conforms nicely with the current CCyB activation logic, as the CCyB usually enters into force a year after it is announced and is expected to be increased gradually. The second period depicts the rising volume of lending and falling cautiousness of banks since 2015. These results support the CNB's decision to increase the CCyB from 0 to 0.5% at the board meeting in December 2015 and then again to 1% in May 2017 and to 1.25% in December 2017.

Figure 7 Smoothed regime probabilities from the three Markov-switching models with different Z_t



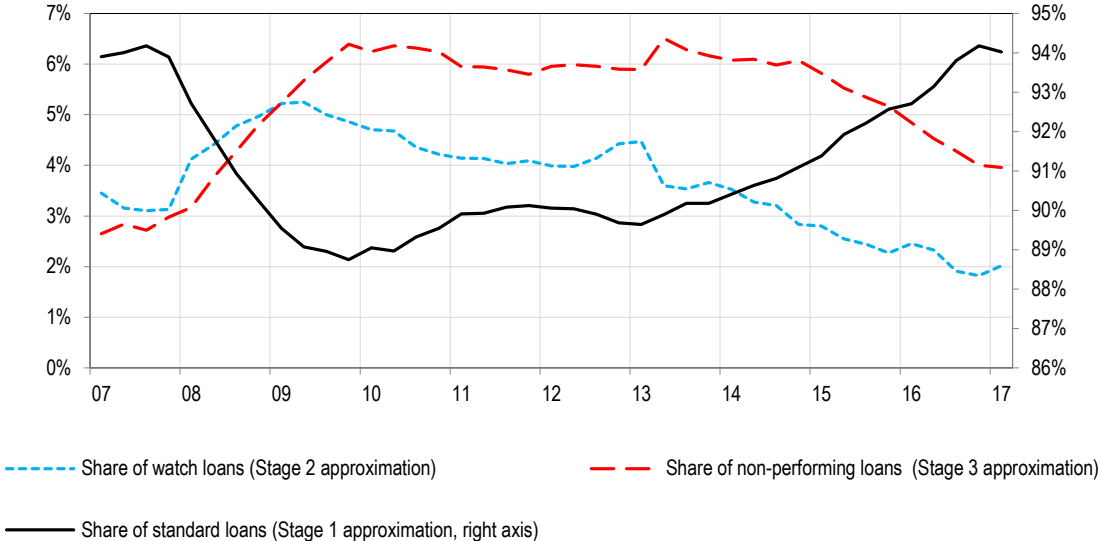
Note: The left-hand vertical axis corresponds to the smoothed probabilities (grey areas) and the one-step-ahead probabilities (solid lines with dots) of the low financial stability regime. The right-hand axis links to the evolution of the BPI, depicted in annual changes of the values in logarithms.

The model containing the Financial Cycle Index also performs reasonably well. It successfully identifies the financial crisis period and antecedent risk accumulation in 2007Q2–2009Q3. In direct comparison to the results of the BPI, it identifies the low financial stability regime a year later. The model with the credit-to-GDP gap as the leading financial indicator identifies up to three periods of low financial stability: 2008Q1–2009Q1, 2012Q3, and 2013Q4–2014Q3. In general, the indicator fails to capture the risk build-ups through 2006–2007.

6 The Profit-to-Provisioning Approach under IFRS 9

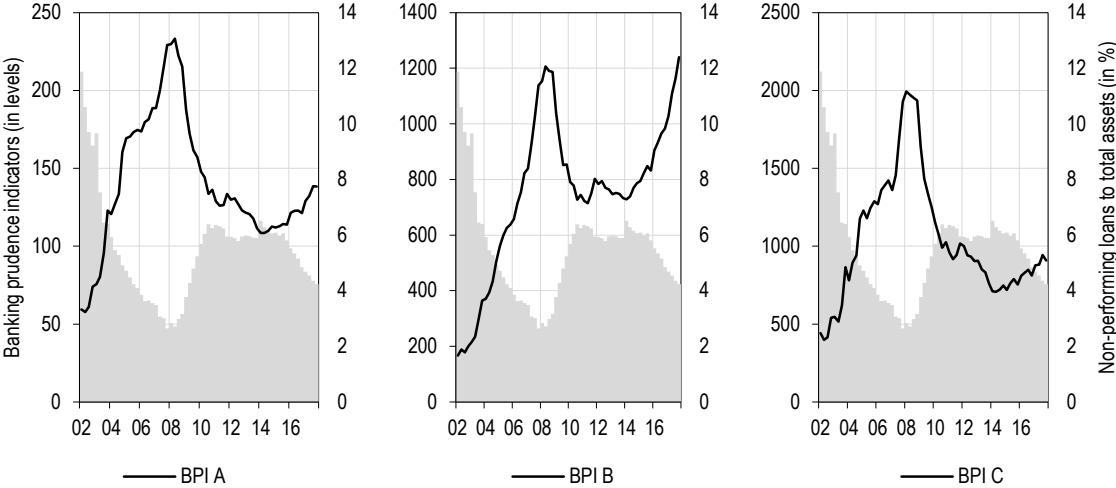
The new ECL approach to loss provisioning by banks under IFRS 9 (in place since January 2018) is forward-looking and its effectiveness depends on banks’ ability to forecast the future materialization of credit risk. Under the new ECL approach, the creation of impairment allowances is based on three stages. Stage 1 contains financial assets that have not significantly increased credit risk since the initial recognition. Standard loans may be an appropriate approximation. In this case, the expected losses are accounted for in the following 12 months. Stage 2 represents assets that have significantly increased credit risk since the initial recognition but have not become impaired yet. This might be described well by watch loans. Expected losses are then charged to the expected lifetime of the financial instrument. Stage 3 represents assets which are already impaired and charged to lifetime (i.e., NPLs). Figure 8 shows the approximate share of exposures in the individual stages before the introduction of IFRS 9.

Figure 8 The approximate share of exposures in the individual stages before IFRS 9



Banks may underestimate the expected losses even under the ECL approach, especially during a financial boom period, when the vast majority of exposures remain in Stage 1. Barclays (2017) states that the shift from a one-year expected loss in Stage 1 to a lifetime loss in Stage 2 may force a sharp increase in provisions in the early stages of a downturn (cliff effect). To determine the expected credit losses, banks may use many in-depth and forward-looking indicators, including macroeconomic measures. However, the threshold for transfer to Stage 2 will depend substantially on how the bank itself interprets the notion of a significant deterioration in credit risk in practice.

Figure 9 Evolution of the banking prudence indicators (BPIs) and the ratio of non-performing loans to total assets



Source: CNB and authors
 Notes: The indicators are reported in base units. The grey area depicts the evolution of NPLs (right-hand scale).

The BPIs should monitor the forward-looking ability of the ECL approach while drawing attention to the risk of underestimating the expected loss in the banking sector. **Figure 9** depicts the inverse profiles of the BPIs and NPLs, which correspond to their different meanings. While NPLs illustrate credit risk materialization, BPIs should illustrate the accumulation of credit risk or the risk of underestimation of expected losses. Generally, we assume that the relationship between NPLs and BPIs will become looser after the introduction of the ECL approach. The amount of loan loss

provisions will no longer only address the incurred losses (NPLs), but will consider all the available information. Picture a situation in which banks successfully predict the materialization of credit risks in advance. Then the shifts of exposures between Stage 1 and Stage 2 should occur well before the financial stress period. This will increase loss provisions and reduce profit. The BPIs should capture this and their value will decrease (making their relationship with NPLs looser). In this situation, expected losses will not be underestimated, the potential losses on the materialization of risks will be lower, and loan loss provisions should therefore not increase significantly at the start of the financial cycle contraction. The impact of the ECL approach on financial stability would then be positive and the CCyB rate could be adjusted accordingly. Conversely, if banks do not successfully predict the materialization of credit risks, there will not be enough time to move exposures from Stage 1 to Stage 2. In the extreme case, the exposures move directly from Stage 1 to Stage 3. The inverse relationship between the BPIs and NPLs would persist, only with the difference that the increase in loss provisions would be more pronounced during the materialization of credit risk through the use of the point-in-time method (cliff effect). The BPIs should monitor the impact of the ECL approach (positive and negative) on the prudence of banking sector, and this information should be used for setting the CCyB rate. We therefore believe that the relevance of using the BPIs for setting the CCyB rate should increase after the full implementation of the ECL approach.

Conclusion

The banking sector is highly procyclical. However, of all the macroprudential capital reserves, only the countercyclical capital buffer rate (CCyB) is set according to the evolution of the cyclical component of systemic risk. The existing methodologies and prevailing practices for determining the CCyB are mostly based on indicators set to identify the current phase of the financial cycle. However, to our knowledge, there is no approach that directly takes into consideration banks' prudential behavior over the financial cycle as well as cyclical risks in the banking sector.

During a financial boom, loan loss provisioning is below the average through-the-cycle level, while profits are higher than average, not only because of lower provisioning, but also due to strong loan growth. This procyclicality was behind the introduction of the dynamic provisioning system in Spain. Building on the Spanish experience, we propose a new profit-to-provisioning approach to be used in the decision-making process for setting the CCyB rate. In general, during a financial boom banks experience a low default rate, loan loss provisions decrease, and banks receive a cyclically overestimated profit, because the expected loss included in the risk premium does not materialize. This cyclically overestimated profit (non-materialized expected loss) should not be allotted entirely to dividends, but should be conserved in the capital during a financial boom. We construct a very simple yet powerful set of banking prudence indicators (BPIs) which should draw attention to the risks of underestimating the expected loss (and overestimating profit) in the banking sector.

To evaluate the performance of the new set of BPIs, we use Czech banking sector data and two independent parsimonious econometric exercises. First, using a simple forecasting exercise, we show that the BPIs might possess certain predictive ability in relation to house prices and NPLs. Overall, the results suggest that BPIs might bear useful information for policy-makers, as they could provide them with some early warning signals in relation to house price developments, which are responsible for a substantial portion of the financial cycle. Models containing the BPIs could also serve as very good predictors of future credit risk materialization. Second, we test the ability of the individual BPIs to identify historical periods of systemic risk build-ups. During such times, banks should create additional capital reserves to be dissolved during subsequent systemic stress periods. To this end, we estimate a simple Markov-switching model which describes the dynamics between credit and real GDP growth. Our results suggest that the BPIs do a reasonably good job of capturing systemic risk build-up periods in the sample of data considered. In fact, they successfully capture the pre-GFC

systemic risk accumulation period and the most recent period of increased credit activity and house price growth. The results support the CNB Bank Board's decision to increase the CCyB in December 2015, in May 2017, and in December 2017.

Overall, our results confirm that our proposed set of indicators under the profit-to-provisioning approach might serve as good complements to the existing approaches for determining the CCyB in the Czech Republic. Moreover, we believe that profit-to-provisioning is a suitable approach in general for other national banking sectors based on traditional banking. We believe that the relevance of the profit-to-provisioning approach and the related set of BPIs should increase after the implementation of IFRS 9. In addition, we expect that the BPIs may serve for monitoring the forward-looking ability of the new provisioning system on which the ECL approach is based.

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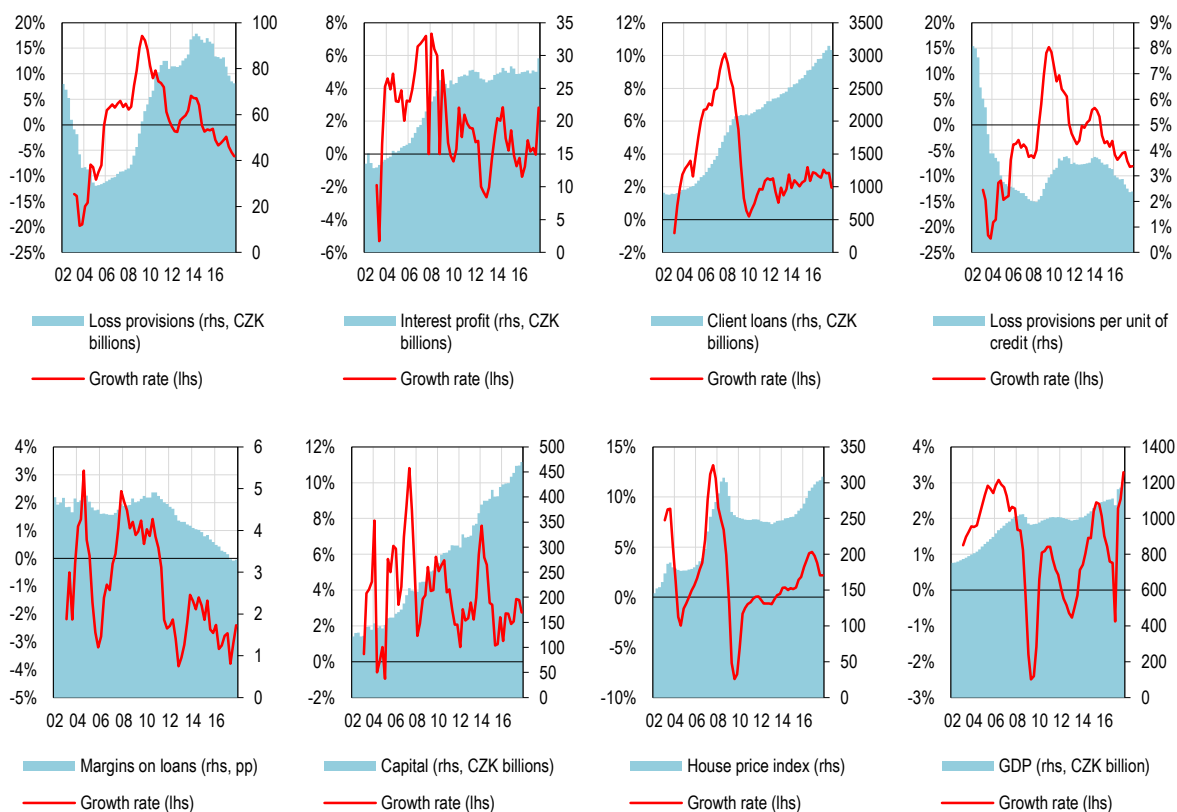
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Appendix A

Table 1A. The following table describes the data used in our empirical exercises through the paper. The data are taken from the Czech National Bank database. All series are seasonally adjusted, where applicable, and run from 2002Q1 to 2017Q4 (this applies to the data in levels). The only exception is the credit-to-GDP gap, for which we use data since 2003Q1. We work with data in quarterly frequency. All the variables are transformed to be approximately stationary. In particular, Tcode shows the stationarity transformation for each variable: Tcode = 1, variable remains untransformed (levels) and Tcode = 5, annual change in logarithmic values. For a description of the construction of the BPIs and the underlying time series, please consult Section 4 of the paper.

Variable	Description	Tcode
BPI A	$A = \frac{\text{margins on the stock of loans}}{\text{loss provisions per unit of client loans}}$	1
BPI B	$B = \frac{\text{interest profit}}{\text{loss provisions per unit of client loans}}$	1
BPI C	$C = \frac{\left(\frac{\text{margins on the stock of loans}}{\text{loss provisions per unit of client loans}} \right)}{\left(\frac{\text{client loans}}{\text{capital}} \right)}$	1
Financial Cycle Index	See Plašil et al. (2015) for details on the construction	1
Credit-to-GDP gap	The gap is estimated using the Hodrick-Prescott with filter $\lambda = 400,000$, see BCBS (2010)	1
House prices	House price index, 2010 = 100	5
Loans to private sector	Loans provided to households and non-financial corporations	5
Gross domestic product	Real gross domestic product, deflated by the GDP deflator 2010 = 100	5

Figure 1A. Input variables in levels (right-hand scale) and in y-on-y percentage change (left-hand scale)



Appendix B

In this appendix, we provide the results of the single equation prediction model described in eq. (1) and the univariate Markov-switching model as in eq. (2)–(3) using the Financial Cycle Index (Plašil et al., 2015) and the credit-to-GDP gap (as recommend by BCBS, 2010, with $\lambda = 400,000$) as alternative financial cycle measures. Both measures are commonly used by the CNB as underlying data for the calculation of parameters for setting the CCyB. More information is available on the CNB website.

Figure 1B. The following graphs depict the estimated posterior inclusion probabilities using the Financial Cycle Index and the credit-to-GDP gap as potential predictors of house prices and NPL growth. The time axis corresponds to the forecasted variable.

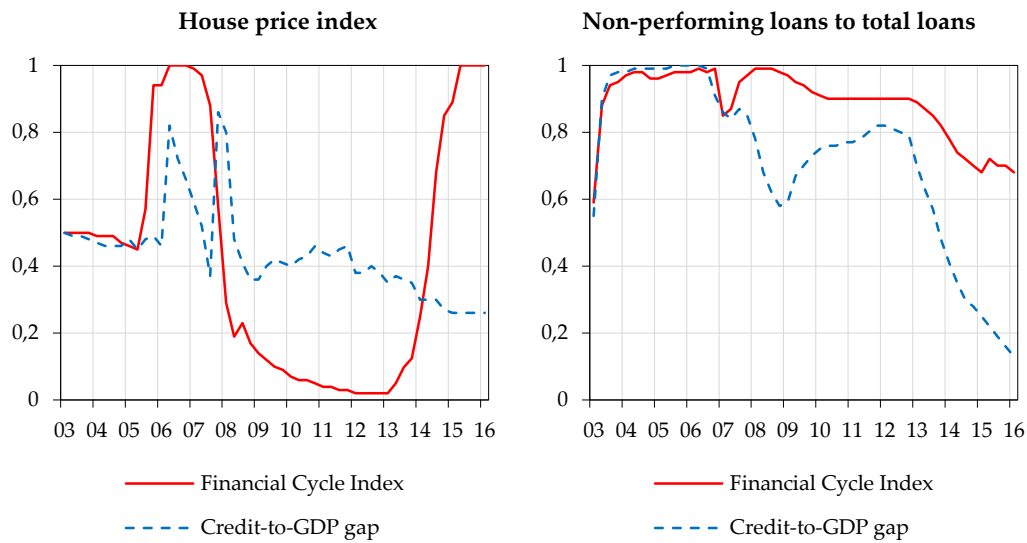
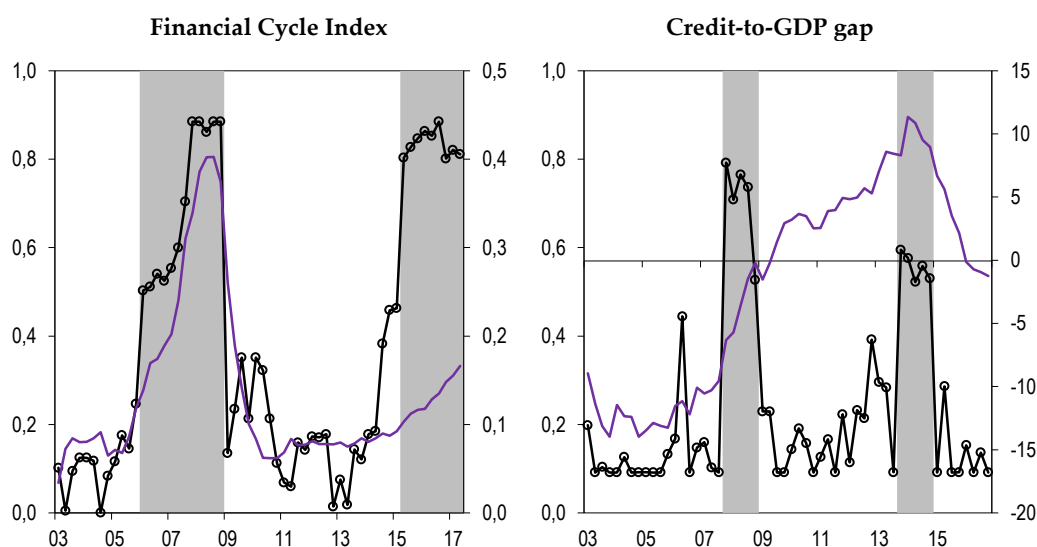


Table 1B. The following table presents the estimated parameters and transition probabilities from the Markov-switching models through the 2003Q1–2017Q2 period where we consider the Financial Cycle Index and the credit-to-GDP gap as measures of the financial cycle. We report the parameter estimates together with their standard deviations. Estimates that are statistically significant at the 10% level or lower are marked with an asterisk and highlighted in bold.

Parameters:	Financial Cycle Index	Credit-to-GDP gap
	<i>Probabilities</i>	
δ_0	0.884	0.899
δ_1	0.116	0.101
γ	-0.037* (0.010)	-0.001 (0.001)
	<i>Regime 0</i>	
α_0	0.005* (0.001)	0.013 (0.010)
$\beta_0^{GDP_{t-1}}$	1.336* (0.155)	1.325* (0.173)
$\phi_0^{credit_t}$	0.149* (0.044)	0.543* (0.153)
$\phi_0^{credit_{t-1}}$	0.092* (0.053)	-0.706* (0.149)
	<i>Regime 1</i>	
α_1	0.006* (0.002)	0.003* (0.002)
$\beta_1^{GDP_{t-1}}$	0.128* (0.078)	0.390* (0.097)
$\phi_1^{credit_t}$	-0.121 (0.125)	0.064 (0.053)
$\phi_0^{credit_{t-1}}$	0.000 (0.121)	0.048 (0.051)

Figure 2B. The following graphs show the smoothed regime probabilities from the Markov-switching models with the Financial Cycle Index and the credit-to-GDP gap. The left-hand vertical axis corresponds to the smoothed probabilities (grey areas) and the one-step-ahead probabilities (solid lines with dots) of the low financial stability regime. The right-hand axis links to the evolution of the financial cycle index and the credit-to-GDP gap.



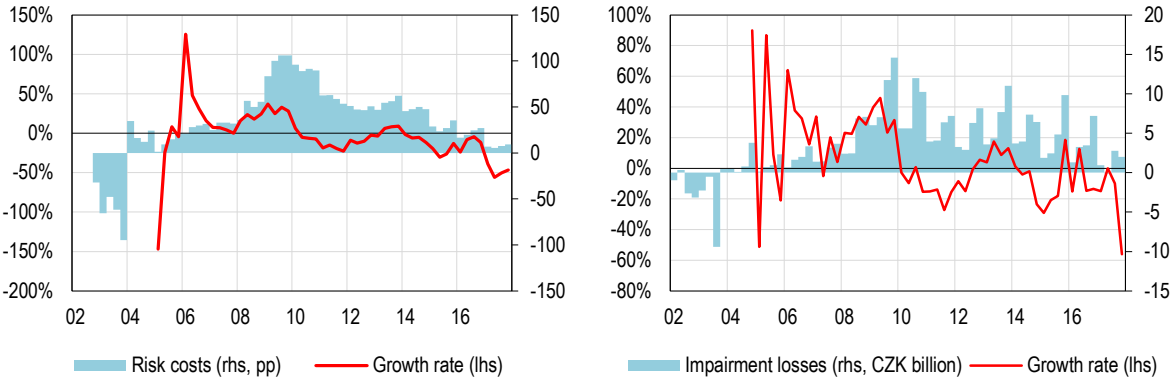
Appendix C

In this appendix, we use two alternative measures as a replacement for loss provisions – impairment losses and risk costs. Impairment losses represent the impact of change in loan loss provisions on the profit-and-loss statement. Risk costs represent the ratio of impairment losses to the 12M average of client loans. By using impairment losses/risk costs and after adjusting other variables, we get flow BPIs.

Table 1C Description of used variables

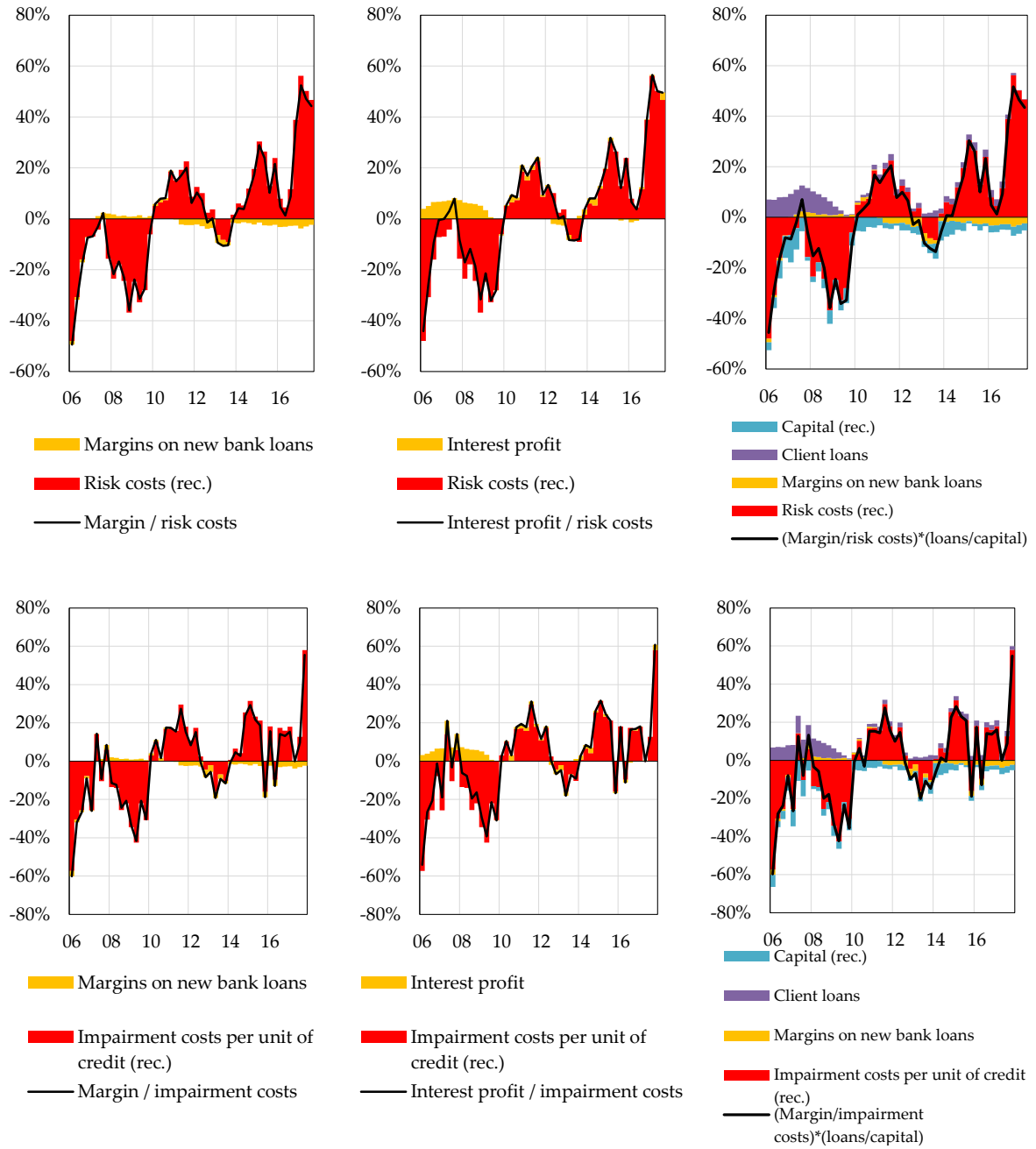
Variable	Description	Stock or flow
Risk costs	Ratio of impairment losses to 12M average of client loans	Flow
Impairment losses	Impairment or (-) reversal of impairment on financial assets not measured at fair value through profit or loss	Flow

Figure 1C. Input variables in levels (right-hand scale) and in y-on-y percentage change (left-hand scale)



We present the decomposition of each indicator since 2006 because of two facts: (i) both time series (risk costs and impairment losses) exhibit negative values at the beginning of the sample (2002Q1–2003Q3), which makes log-based decomposition impossible, and (ii) the time series also exhibit enormous volatility, with annual changes close to 100% (over the 2004–2005 period). One way to address the extreme volatility is to use cumulative flows (over a window of one year or more). However, smoothing the data in this manner leaves us with an insufficient number of observations for the subsequent econometric exercises. Also, one of the disadvantages of using flow indicators is the high volatility of the denominator, which thereafter completely dominates the evolution of the indicators. Moreover, the BPIs in this form (wrongly) signify rising risks already at the time the risks materialized (2008–2009).

Figure 2C Decomposition of the BPIs using alternatives for loss provisions



Notes: rec. denotes variable in reciprocal values. Variables are expressed as y-on-y growth rates in percent.

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