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Banks' Credit Losses and Provisioning over the Business Cycle: Implications for IFRS 9

Simona Malovaná and Žaneta Tesařová *

Abstract

We examine the procyclicality of banks' credit losses and provisions in the Czech Republic using pre-2018 data and then discuss the implications of the findings for provisioning in stage 3 under IFRS 9. This is possible because the majority of banks seem to have aligned their accounting definitions of default with the regulatory definition prior to the implementation of IFRS 9. We find significant asymmetries in banks' behavior over the cycle. Firstly, provisioning procyclicality is strongest in the later contractionary phase and early recovery phase, while it is non-existent in the early contractionary phase. Secondly, banks with higher credit risk behave more procyclically than their peers. If this behavior persists under IFRS 9, it may lead to delayed transfer of exposures between stages and exaggerate cyclical fluctuations.

Abstrakt

V tomto článku zkoumáme procykličnost úvěrových ztrát a opravných položek bank v České republice na základě dat za období před rokem 2018 a zabýváme se implikacemi našich zjištění pro tvorbu opravných položek ve stupni 3 podle IFRS 9. Umožňuje nám to skutečnost, že většina bank před implementací IFRS 9 zřejmě sladila své účetní definice selhání s regulatorní definicí. V chování bank během cyklu nacházíme značné asymetrie. Zaprvé, procykličnost tvorby opravných položek je nejsilnější v pozdější fázi kontrakce a počáteční fázi oživení, ale během počáteční fáze kontrakce není přítomna. Zadruhé, banky s vyšším úvěrovým rizikem se chovají procykličtěji než ostatní banky. Jestliže toto chování bude pokračovat i v režimu IFRS 9, může vést k opožděnému přesunu expozic mezi jednotlivými stupni a nadměrně zesilovat cyklické výkyvy.

JEL Codes: C22, E32, G21.
Keywords: Credit losses, IFRS 9, procyclicality, provisions.

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1. Introduction

The global financial crisis (GFC) has increased the interest of many regulators in the mechanisms reinforcing the inherent procyclicality of banks' behavior. It has become evident that attention has to be paid not only to the quality of credit exposures, but also to the adequacy of provisioning over the cycle. Provisioning is of crucial importance to the resilience of the banking sector. It serves as a buffer against expected credit losses and significantly influences banks' profitability, which, in turn, may have an impact on their capital adequacy and lending capacity.[1] Consequently, the question has arisen of how much the regulatory and accounting framework itself contributes to the procyclicality. In fact, numerous studies have found that the accounting framework effective before 2018 (i.e., the incurred loss approach in impairment models under International Accounting Standard IAS 39) is highly procyclical. The new International Financial Reporting Standard (IFRS) 9, which came into force on 1 January 2018, was implemented as a response to this criticism. However, some studies indicate that under certain assumptions, provisioning under IFRS 9 may remain procyclical or even exaggerate the procyclicality relative to IAS 39 (ESRB, 2019).

In this paper, we examine the procyclicality of banks' credit losses and provisions in the Czech Republic using pre-2018 data and then discuss the implications of banks' behavior for provisioning in stage 3 under IFRS 9. We consider to be procyclical such credit losses and provisions that are negatively correlated with the business cycle, i.e., that tend to decrease when the real economy is growing faster than its sustainable growth level and increase when it is growing more slowly than its sustainable growth level or falling. Accordingly, we distinguish between the sustainable level and cyclical component of lifetime expected credit losses and provisions in stage 3 by establishing their relationship with the output gap and potential output. Potential output represents the highest level of real GDP that can be sustained over the long term given the economy's resources and other constraints. As such, the estimated sustainable level of credit losses and provisions should not contribute to the amplification of business cycle fluctuations. On the other hand, credit losses above or below this level may be viewed as over- or undervalued, and provisions above or below it may be considered excessive or insufficient, ultimately amplifying business cycle fluctuations. This view is in line with another approach to procyclicality, which may be understood not only as a purely empirical relationship, but also as a mutually reinforcing mechanism through which the financial system can amplify business cycle fluctuations (see, for example, FSF, 2008).

Distinguishing between the sustainable level and the cyclical component is a novelty of this paper relative to the existing literature. Beyond that, we examine asymmetries in banks' procyclicality over the different stages of the business cycle and in different quantiles, an approach which, to our knowledge, has not been applied yet. Finally, we discuss the potential implications of our empirical findings with respect to the new provisioning mechanism under IFRS 9. We argue that if the effects identified persist under IFRS 9, they may exaggerate banks' procyclicality and lead to a cliff effect, i.e., a sharp increase in expected credit losses and provisions in response to a deterioration in economic conditions.

The remainder of this paper is organized as follows. Section 2 provides a literature review. Section 3 presents an empirical approach. Section 4 reports the estimation results and section 5 discusses the implications for provisioning procyclicality under IFRS 9. Section 6 concludes.

[1] The impact on banks' lending capacity is influenced, among other things, by the stringency of capital regulation (Malovaná and Kolcunová, 2019).

2. Provisioning Procyclicality under IAS 39 and IFRS 9

High procyclicality of provisioning is undesirable from the financial stability perspective because it may negatively affect banks' capitalization during economic downturns, when capital is usually most needed. Consequently, it may lead to, or exacerbate, the procyclicality of bank credit supply, feed back to the real economy, and amplify macroeconomic fluctuations. Although procyclicality is inevitable and inherent in economic activity, we need to restrain it, since it can lead to large financial fluctuations and endogenous financial cycles.

There are two approaches to credit risk – the regulatory approach and the accounting approach. Under the regulatory approach, we distinguish between performing and non-performing exposures.[2] The regulatory definition of default has implications for the calculation of risk-weighted exposure amounts and the related capital requirements, which are intended to cover the risks stemming from unexpected losses. Under the accounting approach, impairment losses have been recognized and provisions created differently under different accounting approaches (IAS 39, the dynamic provisioning mechanism, IFRS 9[3]). Until 2018, banks calculated loan loss provisions using an incurred loss model under IAS 39 (issued in March 1999). This accounting standard was backward oriented: banks could create provisions only after a loss event had occurred and the loan had become impaired.[4]

The inability of banks to create provisions in advance of a loss event under IAS 39 was criticized for being "too little, too late" (see, for example, Restroy and Zamil, 2017; ESRB, 2019). As a result, IAS 39 was found to be strongly procyclical, as provisions grew significantly during economic downturns when banks' earnings and capital came under pressure from large losses (see, for example, Bikker and Metzemakers, 2005; Huizinga and Laeven, 2019). Additionally, some studies indicate there may be possible non-linearity over the cycle, providing evidence that banks provision more, the deeper they are into an economic downturn (Laeven and Majnoni, 2003; Bouvatier and Lepetit, 2008, 2012).

The provisioning procyclicality under IAS 39 led some countries to adopt a dynamic provisioning mechanism[5] and eventually motivated the implementation of IFRS 9. IFRS 9 builds on an expected credit loss (ECL) model which requires banks to set credit impairment allowances for all loans since their inception rather than just for already impaired loans. As such, the ECL model should use forward-looking information to recognize a significant proportion of credit losses well in advance and to determine the amount of provisions which should be set aside. This should limit an additional increase of provisions to the moment of credit default, helping to smooth cyclical fluctuations and ease capital pressures. The mechanism works as follows. Credit exposures are divided into three stages. At the inception of the loan, the exposure is immediately categorized as stage 1 and an impairment allowance is set to cover losses at the 12-month horizon. Once a significant increase in

[2] An exposure is non-performing (in default) when the obligor is unlikely to repay its credit obligations or is past due more than 90 days on any material credit obligation, or both (see Article 178, CRR (EU) 575/2013.)
[3] In the Czech Republic, banks were allowed use two other approaches: the coefficients method and a statistical model (see Decree No. 123/2007 Coll. as amended by Decree No. 89/2011 Coll. of 16 March 2011, which stipulates prudential rules for banks, savings and credit cooperatives, and securities traders).
[4] The loss event could be a result of one particular event or combination thereof leading to the impairment of assets. The conditions for a loss event are described in IAS 39, paragraphs 58–59. Generally, it must become probable that the obligor will not repay its credit obligation in full.
[5] The logic behind dynamic provisioning was to create a buffer in "good times" that would be released in "bad times" when credit risk materializes. A comprehensive review is provide by, for example, Wezel et al. (2012).

credit risk occurs,[6] the exposure is transferred to stage 2 and a credit impairment allowance is set to cover the credit losses that are expected to materialize over the lifetime of the asset. The transfer to stage 3 is triggered by the occurrence of a loss event whose definition is expected to be closely aligned with the regulatory definition of default (see footnote 6). At this stage, credit impairment allowances should still cover lifetime expected credit losses. Stage 3 under IFRS 9 is conceptually the most similar to the incurred loss approach under IAS 39, which already required estimation of lifetime expected credit losses for impaired loans.[7]

Despite the original intention of the new accounting standard, the amount of discretion under IFRS 9 may lead to higher procyclicality of banks' behavior relative to IAS 39, as suggested by some studies (ESRB, 2017, 2019).[8] There are a few core limitations which may prevent ECL models from correctly determining the amount of provisions which should be set aside.

Firstly, the forward-looking information fed into ECL models must be accurate and properly incorporated. In other words, macroeconomic projections must be valid and modeling techniques must be adequate. However, the difficulty that standard macroeconomic models have in predicting downturns is well known (see, for example, Tovar, 2008; Trichet, 2010; Negro et al., 2015). The models used for forecasting are usually highly stylized and necessarily abstract from many important economic linkages and transmission mechanisms. Therefore, they cannot be expected to accurately forecast an abrupt change in economic conditions. In response to the GFC, some important aspects have been partially incorporated into these models, but in practice the "post-crisis" models remain very similar to the "pre-crisis" ones.

Secondly, there may be a lack of sufficient loss data on the cyclical sensitivity of certain asset classes; this may lead to inadequate modeling, a delay in the transfer of exposures from stage 1 to stage 2 and 3, and reinforced procyclicality (ESRB, 2019).

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[6] IFRS 9 provides only general guidance on a significant increase in credit risk triggering the transfer of an exposure from stage 1 to stage 2; significant space is left for discretion at the level of individual banks (see paragraphs 5.5.9–5.5.12 of IFRS 9). As suggested by EBA (2017), the indicators that can be used to assess a significant increase in credit risk include (but are not limited to) a downgrade of a borrower by a recognized credit rating agency, a significant deterioration of relevant determinants of credit risk (future cash flows, turnover, profitability), a significant decrease in collateral value, or the exceeding of a certain limit on days past due (the limit is usually set to 30 days). Each institution's own internal definition of default, i.e., an event triggering the transfer of an exposure between stages 2 and 3, may be critical in setting the threshold for a significant increase in credit risk. IFRS 9 does not define the term "default" either, but it does require each institution to do so. Such definition should be consistent with the definition used for internal credit risk management purposes (see paragraph B5.5.37 of IFRS 9). BCBS (2015) recommends that the definition of default be guided by the definition used for regulatory purposes, i.e., Article 178, CRR (EU) 575/2013.

[7] Expected credit losses are calculated as the product of the point-in-time probability of default (PIT PD), the loss given default (LGD), and the exposure at default; ECLs in stage 1 are calculated using the 12-month PIT PD; ECLs in stages 2 and 3 are calculated using the lifetime PIT PD. ECLs are discounted to present value using an appropriate discount rate.

[8] There is significant space for discretion at the level of individual banks in the modeling of ECLs. IFRS 9 provides a set of basic principles that need to be fulfilled, but does not provide a particular model or methodological approach. The ECL should be measured in such a way that reflects: *"a) an unbiased and probability-weighted amount that is determined by evaluating a range of possible outcomes; b) the time value of money; and c) reasonable and supportable information that is available without undue cost or effort at the reporting date about past events, current conditions and forecasts of future economic conditions"* (paragraphs 5.5.17–5.5.20 of IFRS 9). This means that ECLs should be measured as a weighted average of credit losses, with the respective risks of default occurring in a given time period used as the weights. A detailed discussion of different aspects of the implementation of the IFRS 9 impairment requirements by banks is provided by GPPC (2016).

Thirdly, all new relevant forward-looking information should be reflected in a timely manner despite bank managers' biases and incentives. However, banks' managers may have incentives to use their discretion with respect to provisioning, for example, to smooth banks' results, meet market expectations, attain internal profitability and capital targets, or to improve disclosed results over time. When improper incentives are coupled with a bias to over-weight more recent economic conditions, delayed or too early provisioning may result, reinforcing cyclical fluctuations.

Fourthly, the criteria that trigger the transfer of exposures from stage 1 (12-month expectations) to stage 2 (lifetime expectations) and further into stage 3 should be set adequately, i.e., neither too high nor too low. Setting a relatively high (less strict) threshold for a significant increase in credit risk, coupled with the limitations discussed above, could lead to delayed recognition of credit losses and the transfer of exposures between stages 1 and 2; once the economic conditions deteriorate, the transfer between stages may be abrupt and lead to a pronounced cliff effect (ESRB, 2019). On the other hand, setting a relatively low (stricter) threshold, provided that ECL models are capable of using forward-looking information to recognize credit losses well in advance, may mitigate the cliff effect. However, it would lead to a significant deterioration in banks' profits, potentially affecting their capitalization and creating excessive restrictions on lending (Abad and Suarez, 2017; Krüger et al., 2018; Plata et al., 2017).[9]

3. Empirical Framework

3.1 Model Specifications

We first estimate the sustainable level of banks' credit losses and provisions, and then examine banks' procyclicality, with an emphasis on potential asymmetries. To distinguish between the sustainable level and the cyclical component, we estimate the relationship containing potential output and the output gap as indicated in equations (1) and (2). Potential output represents the highest level of real GDP that can be sustained over the long term given the economy's resources and other constraints, and it is therefore used to determine the level of credit losses and provisions that are sustained over the long term. The output gap represents the cyclical component of the economy and is closely linked to the cyclical component of banks' credit losses and provisions.[10] The relationship is estimated on the aggregate level and the individual bank level to explore heterogeneity among banks.[11]

$$LLPL_{i,t} = \alpha_1 + \beta_1 OutputGap_{t-p} + \gamma_1 OutputTrend_{t-p} + \nu_{1,i} + \varepsilon_{1,t} \tag{1}$$

$$NPLL_{i,t} = \alpha_2 + \beta_2 OutputGap_{t-p} + \gamma_2 OutputTrend_{t-p} + \nu_{2,i} + \varepsilon_{2,t} \tag{2}$$

where $LLPL_{i,t}$ is the ratio of loan loss provisions to total loans and $NPLL_{i,t}$ is the ratio of non-performing loans to total loans; $OutputGap_{t-p}$ and $OutputTrend_{t-p}$ are, respectively, the output gap expressed in percent of the output trend (potential output) and the output trend expressed in

[9] These studies simulate hypothetical scenarios of the behavior of ECL models under IFRS 9; they do not use actual data, as these are still very limited.

[10] The cyclicality of real economic activity and the financial sector is well documented in the literature (among recent studies, see, for example, Egert and Sutherland, 2014). Potential output is a well-established measure of the output level that can be sustained over the long term. Correspondingly, the output gap is a well-established measure of the cyclicality of real economic activity.

[11] We opted to use a relatively simple model which is easy to interpret and allows us to incorporate expert information already available at the central bank (i.e., the decomposition of output into its gap and trend components) rather than some alternative methodology (such as the error correction model).

annual percentage changes;[12] p is the number of lags or leads determined in section 4; ν_i are fixed effects and ε_t is an error term.

Estimated elasticities are used to decompose $NPLL_{i,t}$ and $LLPL_{i,t}$ into the sustainable level and the cyclical component. The sustainable level of $LLPL_{i,t}$ is indicative of the sustainable level of lifetime expected credit losses and provisions in stage 3. The difference between the sustainable levels of $NPLL_{i,t}$ and $LLPL_{i,t}$ is then indicative of the sustainable amount of impaired loans which can be expected to be recovered in the future.

Changes in non-performing loans may be understood as a proxy for changes in lifetime expected credit losses in stage 3. This is possible because the regulatory definition of default is conceptually very similar to the accounting definition of loss event under IFRS 9. Even though IFRS 9 does not define the term "default," it requires each institution to do so and specifies a rebuttable presumption that default does not occur later than when a financial asset is 90 days past due. Moreover, BCBS (2015) recommends that the definition of default be guided by the definition used for regulatory purposes. Therefore, the transfer of credit exposures to stage 3 should be triggered by the same events as the recognition of non-performing loans.

The conditions for a loss event under IAS 39 did not specifically include a "90 days past due" presumption; however, the dynamics of impaired credit losses follow the dynamics of changes in non-performing loans in the Czech Republic relatively nicely (see Figure A2 in Appendix A). It seems that internationally as well, the majority of banks have aligned their accounting definitions of default with the regulatory definition, as suggested by EY (2018). After the transition to the new standard, the provisions in stage 3 remained fairly stable compared to the provisions for impaired loans under IAS 39. Therefore, the analysis of provisioning procyclicality under IAS 39 may be indicative of provisioning procyclicality in stage 3 and of potential triggers for a cliff effect under IFRS 9.

We use two proxy variables for the output gap and trend, the first estimated by the CNB using a small structural model (see, for example, CNB, 2019) and the second estimated using the Hodrick-Prescott filter with lambda equal to 1,600 and sample period 1996 Q1–Q4 (both gaps and trends are depicted in Figure A3 in Appendix A).

Next, the specifications are extended to include other cyclical variables and bank-specific variables potentially explaining the procyclical behavior of $NPLL_{i,t}$ and $LLPL_{i,t}$:

$$\begin{aligned} LLPL_{i,t} = {} & \alpha_1 + \beta_1 OutputGap_{t-p} + \gamma_1 OutputTrend_{t-p} + \delta_1 CreditGap_{t-p} + \delta_2 PPriceGap_{t-p} \\ & + \omega_1 X_{i,t-1} + \nu_{1,i} + \varepsilon_{1,t} \end{aligned} \tag{3}$$

$$\begin{aligned} NPLL_{i,t} = {} & \alpha_2 + \beta_2 OutputGap_{t-p} + \gamma_2 OutputTrend_{t-p} + \delta_3 CreditGap_{t-p} + \delta_4 PPriceGap_{t-p} \\ & + \omega_2 X_{i,t-1} + \nu_{2,i} + \varepsilon_{2,t} \end{aligned} \tag{4}$$

where $CreditGap_{t-p}$ and $PPriceGap_{t-p}$ are the credit gap and the property price gap estimated using the Hodrick-Prescott filter.[13,14] The vector of bank-specific control variables $X_{i,t}$ includes a proxy

[12] We assume that the level of credit losses and provisions sustainable in the long term will be governed by changes in potential output; in other words, changes in credit losses and provisions which are lower or higher than changes in potential output are considered to be short-term fluctuations and not to be sustainable in the long term.

[13] Credit and property prices have been shown to best capture financial cycles (Drehmann et al., 2012), whose peaks are closely associated with the subsequent drops, i.e., corrections of the deviation from sustainable levels (Schularick and Taylor, 2012; Borio, 2012).

[14] The credit gap is estimated using bank credit for the private non-financial sector and the Hodrick-Prescott filter with lambda equal to 26,000 and sample period 2003 Q1–2018 Q4; it is expressed in percent of potential output.

for gross profitability (banks' profits before tax and loan loss provisions over total assets; ROA), a proxy for banks' capitalization (equity over total assets), and a proxy for bank size (the logarithm of total assets). Bank-specific control variables are included in lags in order to eliminate the potential endogeneity problem.

A positive relationship between banks' profitability and capitalization on the one hand and loan loss provisions on the other would be indicative of potential earnings management and capital management, i.e., bank managers using their discretion with respect to loan loss provisioning to smooth banks' results, meet market expectations, attain internal profitability or capital targets, or improve disclosed results over time. Empirical evidence generally supports the idea that earnings management and capital management are an important motive in provisioning decisions. This includes both the earlier evidence on US data (see, for example, Greenawalt and Sinkey, 1988; Scholes et al., 1990; Beatty et al., 1995; Ahmed et al., 1999; Koch and Wall, 2000) and more recent research studies (see, for example, Hasan and Wall, 2004; Bouvatier and Lepetit, 2008; Leventis et al., 2011). Examining these two hypotheses would require a more comprehensive analysis, which is not the aim of this paper. A proxy for bank size is included because larger banks may be more diversified and better able to withstand shocks.

Finally, to explore potential asymmetries in the relationship, we introduce interaction dummies for a positive output gap (*dPositive*) and a rising output gap (*dRising*):

$$Y_{i,t} = \alpha_1 + [\beta_1^1 dRising + \beta_1^2 (1 - dRising)] OutputGap_{t-p} + \gamma_1 OutputTrend_{t-p} \omega_1 X_{i,t-1} + \varepsilon_{1,t} \tag{5}$$

$$\begin{aligned} Y_{i,t} = \alpha_1 + [&\beta_1^1 dPositivedRising + \beta_1^2 dPositive(1 - dRising) + \beta_1^3 (1 - dPositive) dRising \\ &+ \beta_1^4 (1 - dPositive)(1 - dRising)] OutputGap_{t-p} + \gamma_1 OutputTrend_{t-p} \omega_1 X_{i,t-1} + \varepsilon_{1,t} \end{aligned} \tag{6}$$

where $Y_{i,t}$ is either $LLPL_{i,t}$ or $NPLL_{i,t}$.

As such, we are able to analyze the relationship in different phases of the business cycle: recovery (early expansionary phase; negative and rising gap), prosperity (later expansionary phase; positive and rising gap), recession (early contractionary phase; positive and falling gap) and depression (later contractionary phase; negative and falling gap).

3.2 Estimation Techniques

We use three estimation techniques. On the aggregate level, we estimate the relationship using simple OLS. On the individual bank level, we employ a weighted least-squares dummy variables model to estimate mean effects and penalized quantile regression to examine how the response differs along the distribution of the dependent variable. As the weight we use the market share defined as the share of the bank's financial assets in the total financial assets of the whole sample in each period.[15] We implement the penalized quantile regression as proposed by Koenker (2004)

The property price gap is estimated using transaction prices of older apartments from a CZSO survey and the Hodrick-Prescott filter with lambda equal to 26,000 and estimation period 1999 Q1–2018 Q4; it is expressed in percent of potential gross disposable income (GDI), which is estimated using GDI in nominal prices and the Hodrick-Prescott filter with lambda equal to 1,600 and estimation period 1999 Q1–2018 Q4. The sample period is still relatively short given that the average length of the financial cycle is estimated to be 16 years in advanced countries (Drehmann and Gambacorta, 2012); the estimation results should be interpreted with respect to this limitation. Both gaps are depicted in Figure A4 in Appendix A.

[15] We use weighted regression in order to account more for banks whose impact on the banking sector is larger and whose data are generally of better quality and to account less for banks whose impact on the banking sector is limited and whose data are generally of worse quality.

because of the large number of "fixed effects" introduced, which significantly increases the variability of the estimates of the covariate effects. The penalty parameter helps shrink the fixed effects toward a common value (i.e., zero) and reduce the variability. The degree of this shrinkage is controlled by a penalty parameter λ (for more details, see Koenker, 2004).[16]

3.3 Data

We examine the proposed relationships using a sample period running from 2004 Q1 to 2017 Q4. We exclude data from January 2018 onward in order to estimate the effects consistently and to prevent IFRS 9 transition bias.[17] As of the end of 2017, the Czech banking sector consisted of 19 banks, 5 building societies, and 21 foreign bank branches.[18] The final sample covers 43 banks and 56 quarters, giving an unbalanced panel of 1,530 observations in total.[19] Summary statistics of bank-specific variables are presented in Table A1 in Appendix A.

The Czech banking sector is mostly foreign owned (92.1% of its total assets were managed by foreign owners as of 2017 Q4). Most of the banks operate under a universal business model; only two banks can be categorized as investment banks. Within the group of universal banks we can further distinguish a sub-group of building societies and mortgage banks; most of these banks, however, are part of larger banking groups. Seven consolidated groups were designated as other systemically important institutions for 2017 (the designation remained similar for 2018 and 2019).[20] The Czech banking sector is characterized by high liquidity stemming from its strong client deposit base and growth in exposures to the central bank.[21] This provides banks with sufficient resources to ensure a stable and/or increasing credit supply.

[16] The estimation methods are implemented using the R package *lm* for OLS, *plm* for LSDV, and *rqpd* for QR (Koenker and Bache, 2011).

[17] The period in which IFRS 9 is effective is too short to be used in the estimation exercise; it may introduce unnecessary noise into the data sample connected with the implementation period. It may take some time for banks to converge to some stable solution, i.e., to develop and properly calibrate adequate ECL models (for further discussion, see section 5).

[18] ICBC Limited, Trinity, and Creditas were excluded from the analysis due to their very short data history. Further, the Czech Export Bank and the Czech-Moravian Guarantee and Development Bank were excluded as well, as they are wholly owned by the Czech state (which provides implicit state guarantees for their liabilities) and have different business models.

[19] The bank-level data are from the Common Reporting (COREP) and the Financial Reporting (FINREP) standardized reporting frameworks issued by the European Banking Authority for Capital Requirements Directive (CRD) reporting. We use data on a solo basis.

[20] For more information, see the CNB's website.

[21] At the end of 2017, the ratio of quick assets to total assets was 41.6%, the liquidity coverage ratio was 182.8%, and the net stable funding ratio was 126% (well above the regulatory requirements). For more details, see CNB (2018).

4. Empirical Results

4.1 Sustainable Level of Credit Losses and Provisions

We first estimate the relationship in equations (1) and (2) with up to four lags and leads of the output gap and trend, and then explore the explained variance and the strength of the effect. For specifications at the aggregate level, we report adjusted R^2; for panel data specifications, we report within R^2 and overall R^2.

The estimation results indicate that banks recognize impaired credit losses and create provisions with a delay of three to four quarters after the output gap starts to decrease. In other words, most of the variability of both dependent variables is explained by three to four lags of the explanatory variables, regardless of the estimation technique or filtering technique used to identify the output gap and trend. The explained variance decreases significantly with fewer lags and more leads (see Table B1 in Appendix B).[22] Some delay in impaired loss recognition and provisioning is generally expected given price and wage stickiness: it takes some time for worsening economic conditions to feed into price and wage contracts, which then may eventually result in debt-servicing difficulties. Additionally, a usual trigger for categorizing a loan as non-performing or impaired is for the obligor to be past due more than 90 days (see section 2); this adds one more quarter to the transmission, i.e., before the deteriorated economic conditions are reflected in impaired credit losses and provisioning.[23] Such a delay is therefore not surprising, but it may potentially reinforce banks' inherent procyclicality. In what follows, we use the fourth lag of the explanatory variables (Table 1).

Table 1: Regression Results – Mean Effect

Dependent var.:	LLPL				NPLL			
Data:	Aggr.	Panel	Aggr.	Panel	Aggr,	Panel	Aggr.	Panel
Constant	**3.225*** **	**2.36*** **	**3.179*** **	2.674	**5.226*** **	**5.89*** **	**5.045*** **	6.073
	(0.09)	**(0.089)**	**(0.086)**	(0.135)	**(0.188)**	**(0.155)**	**(0.157)**	(0.233)
Output gap (t-4)	**-0.17*** **	**-0.268*** **	**-0.181*** **	**-0.26*** **	**-0.353*** **	**-0.414*** **	**-0.375*** **	**-0.38*** **
	(0.024)	**(0.018)**	**(0.02)**	**(0.018)**	**(0.051)**	**(0.034)**	**(0.036)**	**(0.034)**
Output trend, gr. (t-4)	**-0.104*** **	**0.053** **	**-0.081** **	-0.014	**-0.163** **	0.013	-0.085	-0.017
	(0.033)	**(0.024)**	**(0.031)**	(0.027)	**(0.069)**	(0.047)	(0.056)	(0.053)
Credit gap (t-4)			**0.052* **	**-0.138*** **			**0.166*** **	**-0.081* **
			(0.028)	**(0.024)**			**(0.051)**	**(0.047)**
Prop. price gap (t-4)			0.001	**0.004* **			-0.001	-0.007
			(0.003)	**(0.002)**			(0.005)	(0.004)
Within R^2		0.036		0.063		0.067		0.104
Overall R^2		0.876		0.883		0.791		0.799
Adjusted R^2	0.827		0.891		0.802		0.905	

Note: The output gap and trend are estimated using a small structural model. Regression results with the output gap and trend estimated using the Hodrick-Prescott filter are given in Appendix B, Table B2.

The estimation results show that there is a negative relationship between our proxy for impaired credit losses and provisions on the one hand, and the output gap and trend on the other hand. This indicates that (i) the sustainable level of credit losses and provisions is negatively related to potential output, and (ii) credit losses and provisions behave procyclically, i.e., decrease with a rising output gap and increase with a falling output gap. The provisioning procyclicality is not surprising and has been found by others (see, for example, Laeven and Majnoni, 2003; Pain, 2003; Bikker

[22] A simple correlation analysis confirms the results: the correlation is highest at the third and fourth lags (about 90%) and decreases with fewer lags.

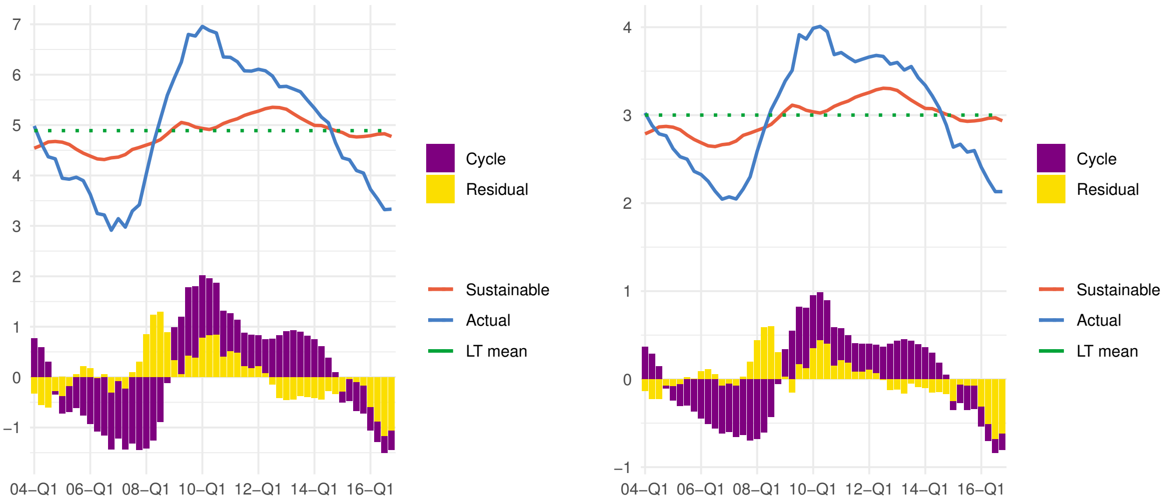
[23] Some credit exposures may become impaired earlier if, for example, the obligor is unlikely to repay in full (for more details, see section 2).

and Metzemakers, 2005; Bouvatier and Lepetit, 2008, 2012; Huizinga and Laeven, 2019). The procyclicality is stronger when estimated using bank-level panel data as compared to the aggregate-level estimates. This suggests that heterogeneity among banks plays an important role and that, on average, individual banks behave more procyclically than indicated by the aggregated data.

In order to assess the contribution of variables related to the financial cycle, we extend the specification to include the credit gap and the property price gap, as indicated by equations (3) and (4). The relationship with the business cycle remains negative, while the effect of additional variables differs across specifications (see Table B2 in Appendix B). Specifically, the relationship between the dependent variables and the credit gap is negative and statistically significant in the panel data regressions, but it is not significant in the majority of the specifications at the aggregate level. This supports the view that the bank-level perspective is more suitable for assessing procyclical behavior than the aggregate-level one. The contribution of the property price gap is not economically significant.

Figure 1: Sustainable Level and Cyclical Component – Aggregate-Level Estimates

Panel A: Non-performing loans ratio Panel B: Loan loss provisions ratio



Note: Aggregate regression results; the output gap and trend are estimated using a small structural model. The decomposition with the output gap and trend estimated using the Hodrick-Prescott filter is given in Appendix B, Figure B1.

The decomposition of the two dependent variables is shown in Figure 1 for the aggregate level regression and in Figure 2 for the panel data regression.[24] The decomposition shows that the sustainable levels of the non-performing loans ratio and the loan loss provisions ratio oscillate around their long-term averages of 5% and 3%, respectively. The difference between the two indicates that the sustainable amount of impaired loans which can be expected to be recovered in the future is about 2% of total loans. In the specifications with the output trend estimated using the Hodrick-Prescott filter, the sustainable levels are more volatile, while in the specifications with the output trend estimated using the small structural model, the sustainable levels are relatively stable with only small deviations from the long-term perspective. The small structural model provides consistent estimates of the output gap and trend by employing a set of equations describing the whole real economy, so it provides a more reliable estimate of the business cycle than the simple

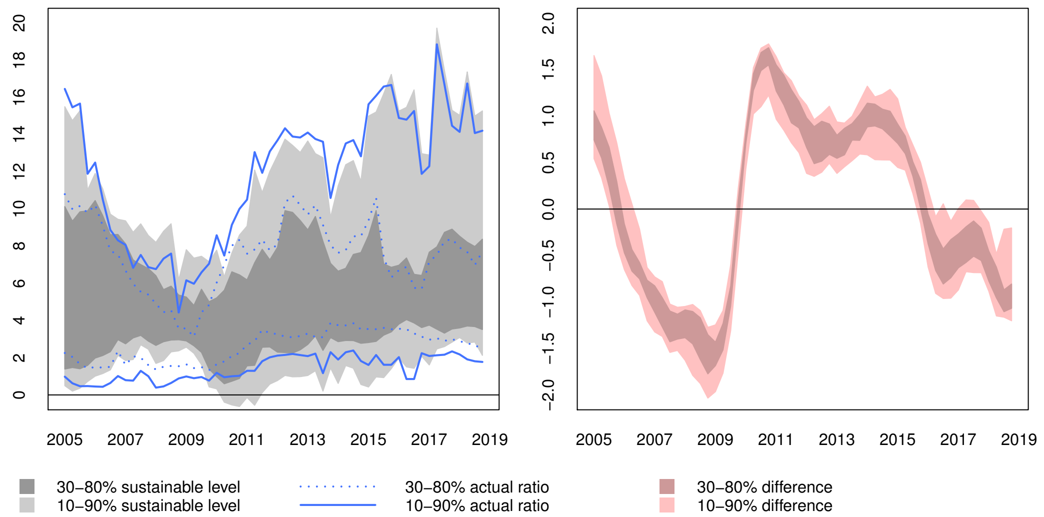
[24] Analogously, the estimated coefficients from Table B2 are used to decompose the ratios into the sustainable level and different cyclical components (see Figure B2 in Appendix B).

Hodrick-Prescott filter. According to the decomposition, the pre-crisis period of 2006–2008 was characterized by undervaluation of non-performing loans and insufficient provisioning (the actual values were below the sustainable levels). This was followed by a sharp correction during the crisis, leading to high non-performing loans and excessive provisioning. At the end of 2017, the situation seemed to be very similar to the pre-crisis period. Most of the deviation from the sustainable levels between 2004 and 2014 can be explained by the cyclical component (the output gap), while the recent deviation is mainly attributed to the unexplained variance (see Figure 1); this is not surprising, because determining the output trend and gap usually suffers from end-point bias, i.e., it is difficult to estimate correctly the trend and gap values at the end of the sample period. Additional cycle variables (the credit gap and the property price gap) help explain some of the unexplained variance between 2004 and 2014; the most recent period, however, remains mostly unexplained (see Figure B2 in Appendix B) because the additional cycle variables suffer from the same end-point bias as the output gap. Therefore, when analyzing the main contributors to the deviation from sustainable levels, it is better not to rely on the latest observations; this may help identify historical behavioral patterns.

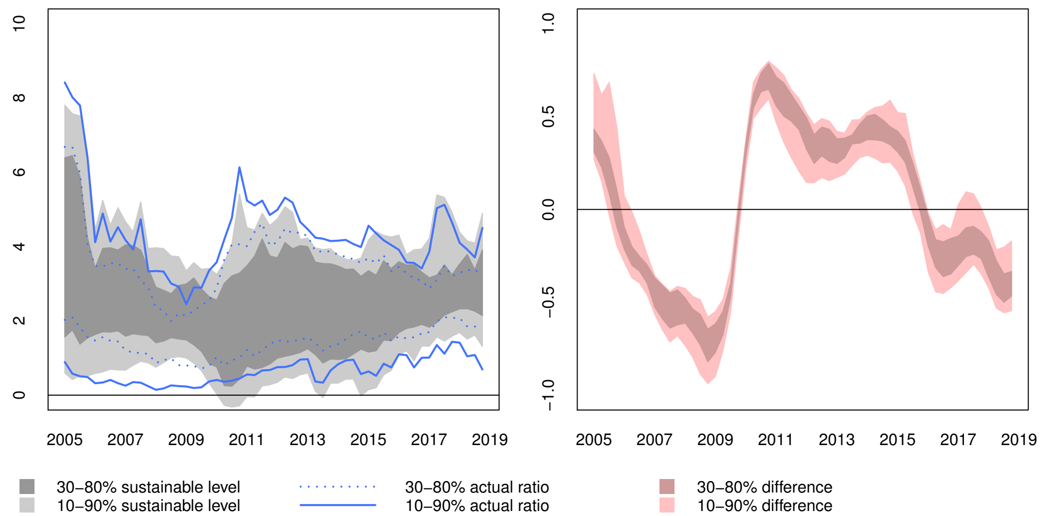
The decomposition based on estimates from panel data regression shows significant heterogeneity among banks, while the overall picture remains similar (see Figure 2). The heterogeneity in the cyclical component is mostly subdued, but it increases at the end of the sample; again, this may be due to end-point bias as discussed above.

Figure 2: Sustainable Level and Cyclical Component – Panel Data Estimates

Panel A: Non-performing loans ratio



Panel B: Loan loss provisions ratio



Note: The output gap and trend are estimated using a small structural model. The decomposition with the output gap and trend using the Hodrick-Prescott filter is given in Appendix B, Figure B3.

4.2 Asymmetry in the Procyclicality of Credit Losses and Provisions

In this subsection, we examine potential asymmetries in the relationship by employing panel data quantile regression and interaction dummy variables as described in section 3.[25] The mean regression results of equations (5) and (6) are reported in Table 2. For the sake of brevity, only the coefficients on the output gap and trend and 90% confidence intervals are reported for the quantile regression results; the mean effects are shown in red (Figure 3). Complete estimation results are presented in Appendix B.[26]

Firstly, the mean effect of the output gap and trend is negative in all specifications. The effect is stronger in periods of a rising output gap than in periods of a falling output gap (columns 2 and 5). In other words, banks react on average more weakly to business cycle contractions than to expansions. The estimation results with additional dummy variables for a positive output gap indicate that the effects are strongest in the later contractionary phase (depression) and the recovery phase (columns 3 and 6). This finding is in line with some studies providing evidence that banks provision more, the deeper they are into an economic downturn (Laeven and Majnoni, 2003; Bouvatier and Lepetit, 2008, 2012). Such an asymmetric effect with respect to the business cycle phases may have negative consequences in terms of pronounced provisioning procyclicality (for further discussion, see section 5).

Secondly, the quantile regression reveals that the procyclicality is more pronounced in higher quantiles of loan loss provisions and non-performing loans, i.e., the procyclicality is strongest when loan loss provisions and non-performing loans are highest. This indicates that banks with the highest credit risk are the most sensitive to changes in the business cycle. The effect of the output trend, on the other hand, does not change in different quantiles. The asymmetry in the procyclicality is present regardless of the phase of the business cycle (Figure 3). This indicates that the most vulnerable banks (with the highest credit risk) profit the most from improving economic conditions, but they are also the most affected by worsening economic conditions.

Thirdly, the effect of banks' profitability and capitalization on loan loss provisions is positive and statistically significant, while the effect of banks' size is negative and statistically significant. The negative relation with banks' size indicates that larger banks create less loan loss provisions in relation to their loans than smaller banks; this lower provisioning cannot be explained by lower credit risk, because the relation between bank size and non-performing loans is not statistically significant. Therefore, larger banks may behave less prudently than smaller banks in terms of provisioning, because larger banks may be more diversified and better able to withstand shocks. The positive relation with profitability and capital suggests that bank managers may use loan loss provisioning to smooth banks' results, meet market expectations, attain internal profitability or capital targets, or improve disclosed results over time (see section 3).

[25] The normality of both dependent variables can be rejected based on the Shapiro-Wilk normality test and QQ plot. Both dependent variables are positively skewed (with mean > median > mode and skewness higher than 1) and leptokurtic (kurtosis higher than 3). There is also significant heterogeneity in the estimated distributions among different bank groups. The distribution is estimated using Epanechnikov kernel density estimation. The results are not reported but are available upon request.

[26] In the next two subsections we use only the output gap and trend estimated using the small structural model (output gap and trend B). The regression with the output gap and trend estimated using the Hodrick-Prescott filter provides similar results; we therefore do not report them, but they are available upon request.

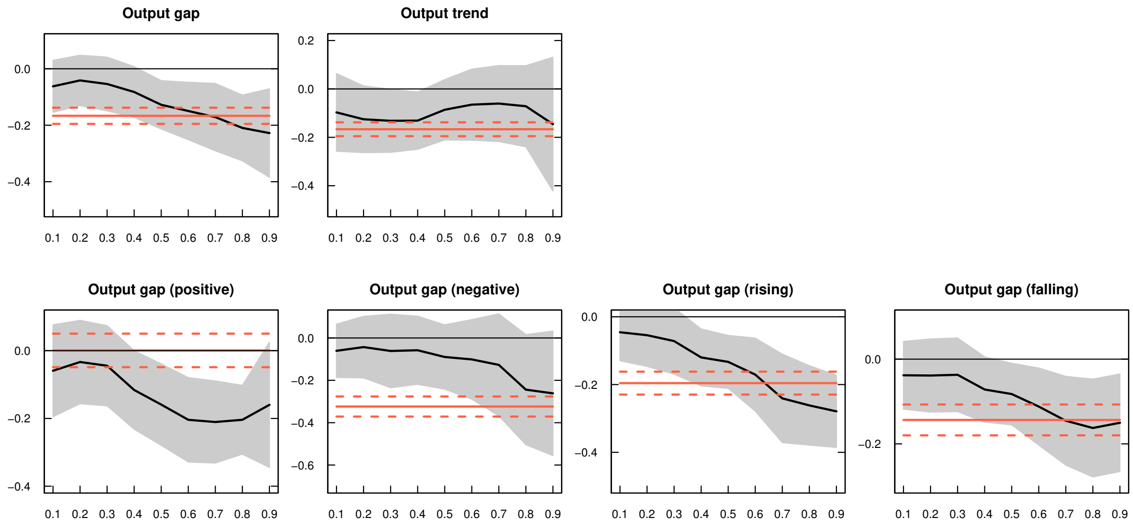
Table 2: Panel Data Regression Results with Additional Controls and Interaction Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var.:		LLPL			NPLL	
Output gap (t-4)	**−0.160*****			**−0.391*****		
	(0.017)			**(0.035)**		
Output gap (t-4)*dRising		**−0.191*****			**−0.433*****	
		(0.021)			**(0.041)**	
Output gap (t-4)*(1-dRising)		**−0.132*****			**−0.343*****	
		(0.022)			**(0.044)**	
Output gap (t-4)*dPositive*dRising			−0.031			**−0.217*****
			(0.036)			**(0.072)**
Output gap (t-4)*(1-dPositive)*dRising			**−0.357*****			**−0.667*****
			(0.033)			**(0.066)**
Output gap (t-4)*dPositive*(1-dRising)			0.057			−0.057
			(0.035)			(0.071)
Output gap (t-4)*(1-dPositive)*(1-dRising)			**−0.286*****			**−0.586*****
			(0.033)			**(0.066)**
Output trend (t-4)	**−0.120*****	**−0.116*****	**−0.128*****	−0.040	−0.042	−0.048
	(0.026)	**(0.028)**	**(0.029)**	(0.053)	(0.055)	(0.058)
ROA (t-1)	**0.076*****	**0.075*****	**0.060****	**0.235*****	**0.228*****	**0.205*****
	(0.024)	**(0.024)**	**(0.023)**	**(0.048)**	**(0.047)**	**(0.047)**
Equity to assets (t-1)	**0.044*****	**0.037*****	**0.049*****	0.040	0.020	0.038
	(0.014)	**(0.014)**	**(0.014)**	(0.028)	(0.028)	(0.028)
Bank size (t-1)	**−0.179***	**−0.226****	**−0.176***	0.320	0.229	0.304
	(0.100)	**(0.103)**	**(0.102)**	(0.203)	(0.206)	(0.204)
FE included	Y	Y	Y	Y	Y	Y
Observations	1,360	1,324	1,324	1,360	1,324	1,324
Within R^2	0.155	0.148	0.145	0.105	0.098	0.093
Overall R^2	0.914	0.916	0.919	0.841	0.849	0.852

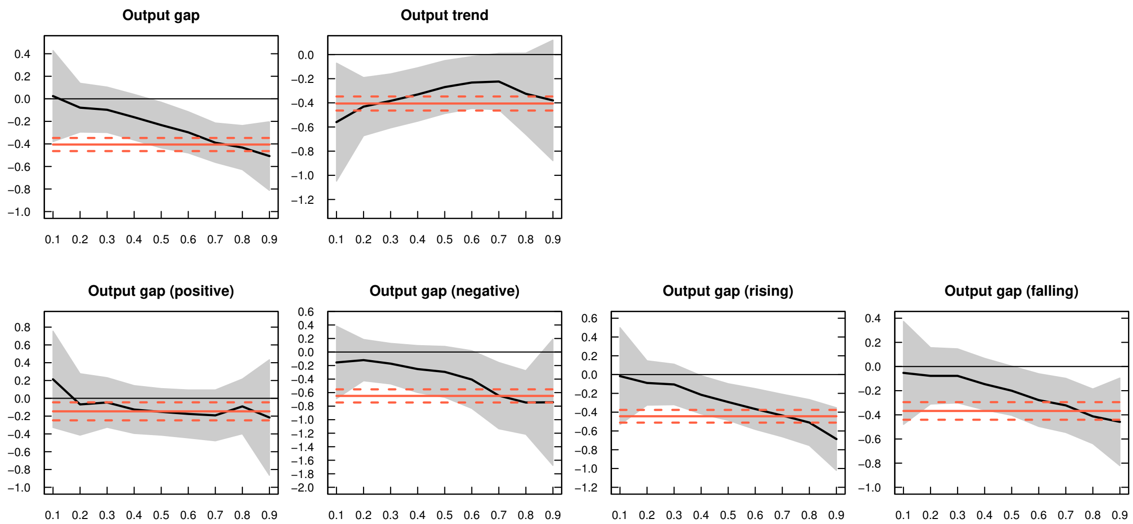
Note: The output gap and trend are estimated using a small structural model. The regression with the output gap and trend estimated using the Hodrick-Prescott filter provides similar results; we therefore do not report them, but they are available upon request. Specifications include fixed effects and are estimated using the LSDV estimator. Standard errors reported in parentheses; ***, **, and * denote the 1%, 5%, and 10% significance levels.

Figure 3: Effect of an Increase in the Cycle Variable (pp)

Panel A: Dependent variable – loan loss provisions ratio



Panel B: Dependent variable – non-performing loans ratio



Note: X-axis – quantiles, y-axis – coefficient size; red lines refer to the mean effect; 90% confidence intervals reported. The output gap and trend are estimated using a small structural model. The regression with the output gap and trend estimated using the Hodrick-Prescott filter provides similar results; we therefore do not report them, but they are available upon request.

5. Implications for Provisioning Procyclicality under IFRS 9

In what follows, we are going to discuss the potential implications of our empirical findings with respect to provisioning procyclicality under IFRS 9. Firstly, it is important to note that banks have only been applying IFRS 9 since the beginning of 2018, which limits the assessment of its potential effects. A full evaluation will be possible once banks gain experience in provisioning according to IFRS 9 and data become more available and reliable. We perform our analysis on the sample prior to the implementation of IFRS 9; our results are therefore indicative mostly of the provisioning procyclicality of exposures in stage 3, as explained in section 3, and potential delays in the recognition of credit losses, bank management biases, and asymmetries.

As discussed in section 4, we identified significant asymmetries in banks' provisioning over the cycle; the main results are summarized in Table 3. In particular, banks seem to recognize credit losses and create provisions with a delay with respect to worsening economic conditions: the increase in credit losses and provisions is concentrated mostly in the later rather than the early stage of an economic contraction. Such asymmetry, if it persists under IFRS 9, may have negative consequences and potentially reinforce the inherent procyclicality of banks' provisioning. Banks are generally less profitable in "bad times." Postponing the recognition of credit losses and provisioning toward the later stages of a recession intensifies the pressures on profitability and, consequently, may be reflected in banks' capital and lending capacity.[27] A slowdown in credit growth would feed to the real economy and back to the banking sector, potentially deepening and prolonging the recession.

Another factor potentially exaggerating provisioning procyclicality is the stronger reaction in higher quantiles, indicating that banks with the highest credit risk (as proxied by the NPL and LLP ratios) are the most sensitive to changes in the business cycle. This reaction is apparent in both the upturn and the downturn of the business cycle and may therefore increase the overall amplitude of business cycle fluctuations.

The delayed transfer of exposures between stages and the pronounced impact in higher quantiles may result in a sharp increase in lifetime expected credit losses and provisions in response to a deterioration in economic conditions. As discussed in section 2, ECL models rely heavily on forward-looking information about future macroeconomic developments produced by models which tend to underestimate the probability and severity of recessions. These models are usually able to predict some degree of mild economic slowdown, but not a severe deterioration. Macroeconomic projections are usually revised only after the economic downturn has already occurred, i.e., once it is too late, which may trigger a cliff effect of potentially larger magnitude relative to IAS 39. The actual magnitude of this cliff effect would depend largely on how banks implement the new standard, especially their definition of a significant increase in credit risk. If the significant increase in credit risk is linked to the ability of projection models to predict at least a mild economic slowdown, banks might transfer exposures between stages 1 and 2 already in the early contractionary phase. This will mitigate the cliff effect once the projection is significantly revised down and exposures are transferred between stages 2 and 3. However, it might take some time for banks to identify a set of suitable indicators triggering transfers between stages. It might even be impossible for them to come up with an adequate modeling approach appropriately incorporating inherently inaccurate macroeconomic projections and more-or-less accurately estimating expected credit losses while mitigating the potential for a cliff effect. It is therefore

[27] Banks with relatively low capital surpluses (regulatory capital above the capital requirements) are especially likely to restrict their credit supply (see, for example, Malovaná and Kolcunová, 2019).

likely that the delay under IFRS 9 will persist in the near future, leading to a significant increase in both incurred and expected credit losses once the economy enters a downturn, which, in turn, would exacerbate cyclical fluctuations.

Table 3: Summary of Estimated Effects

	Credit losses	Provisioning
later expansionary phase (positive and rising output gap)	moderate effect (−0.217)	no significant effect
early contractionary phase (positive and falling output gap)	no significant effect	no significant effect
later contractionary phase (negative and falling output gap)	strong effect (−0.586)	strong effect (−0.286)
early expansionary phase (negative and rising output gap)	strong effect (−0.667)	strong effect (−0.357)

Note: Based on estimation results presented in Table 2, columns 3 and 6.

6. Conclusions

We estimated the sustainable level of lifetime expected credit losses and provisions which should be attainable in the long run given the economy's resources and other constraints. We also examined banks' procyclicality using pre-2018 data, with an emphasis on potential asymmetries. Finally, we discussed the implications of this behavior for provisioning in stage 3 under IFRS 9.

The sustainable level is the level to which credit losses and provisions are supposed to revert in the long term. Credit losses above or below this level should be understood as over- or undervalued, and provisions above or below it should be viewed as excessive or insufficient. Insufficient provisioning may justify the implementation of stricter prudential policies, for example, a higher countercyclical capital buffer rate or additional Pillar 2 capital requirements (in the case of idiosyncrasies between banks). Credit losses that are not covered by provisions will be covered by imposed capital add-ons. Similarly, excessive provisioning may signal the need to implement less strict prudential policies, i.e., to release the existing countercyclical capital buffer or reduce Pillar 2 add-ons.

Regarding banks' procyclicality, we found significant asymmetries. Firstly, provisioning procyclicality is strongest in the later contractionary phase and early recovery phase, while it is non-existent in the early contractionary phase. Secondly, banks with higher credit risk behave more procyclically than their peers. If this behavior persists under IFRS 9, it may lead to delayed transfer of exposures between stages and to a pronounced cliff effect, which will exaggerate cyclical fluctuations. The magnitude of the cliff effect would largely depend on the implementation of the new standard, which gives banks a significant amount of discretion.

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Appendix A: Data

Table A1: Summary Statistics

Variable	Min	Max	Median	Mean	St.dev.
Non-performing loans to total loans (%)	0.01	39.96	3.87	5.57	5.54
Loan loss provisions to total loans (%)	0.00	29.79	2.14	2.79	3.12
Return on assets (%)	-0.35	97.32	2.57	3.64	5.98
Equity to assets (%)	5.43	63.00	6.53	7.64	7.96
Natural logarithm of assets	0.01	21.06	17.89	17.63	1.80

Figure A1: Ratio of Loan Loss Provisions and Non-Performing Loans to Total Loans (%)

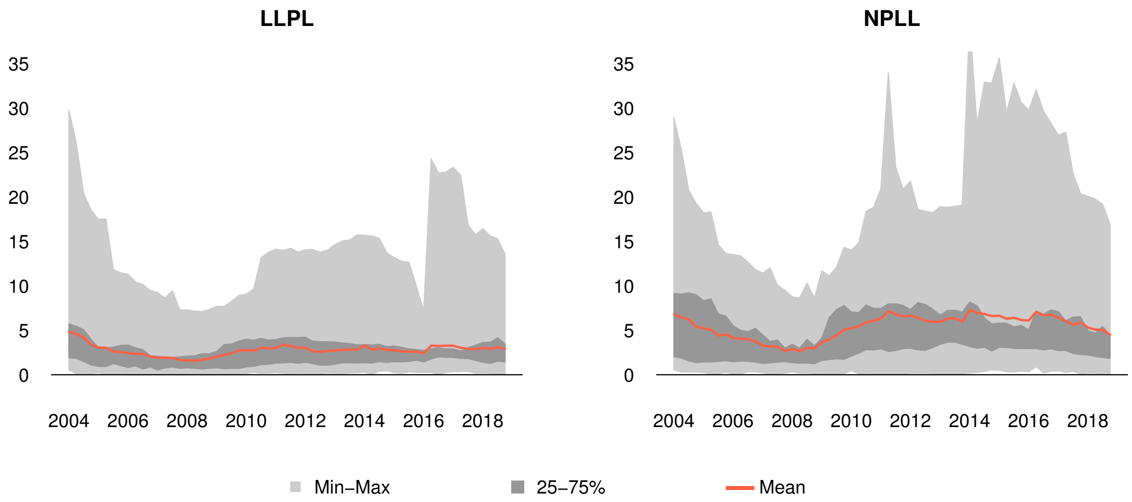


Figure A2: Impaired Credit Losses and Change in Non-Performing Loans (CZK billions)

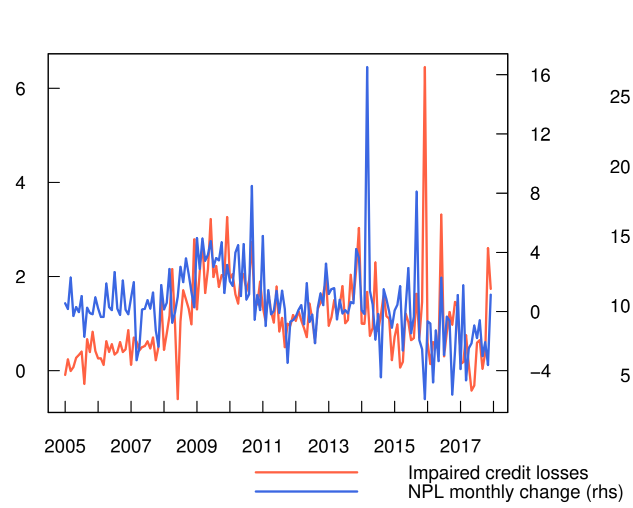


Figure A3: Proxy Variables for Business Cycle and Trend

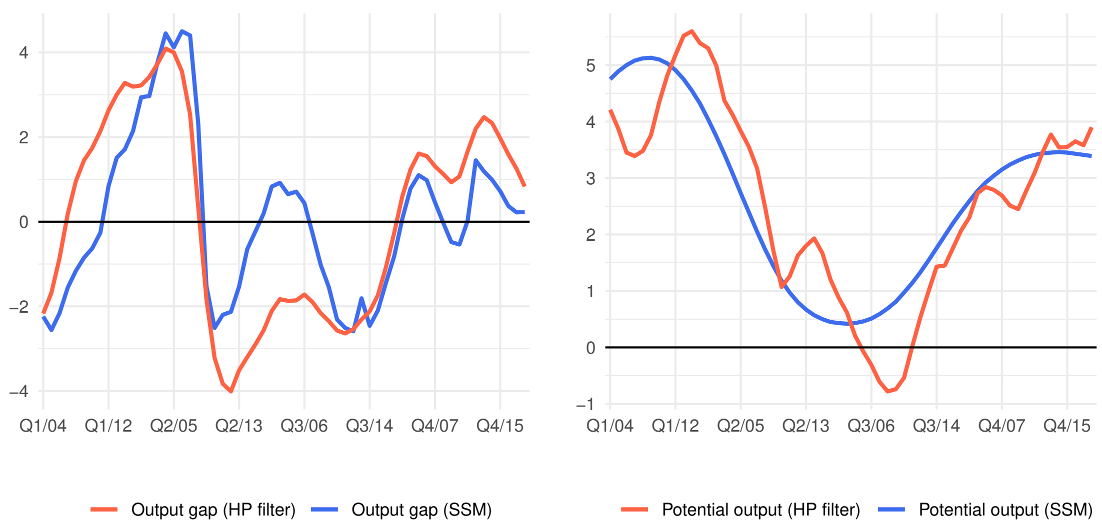
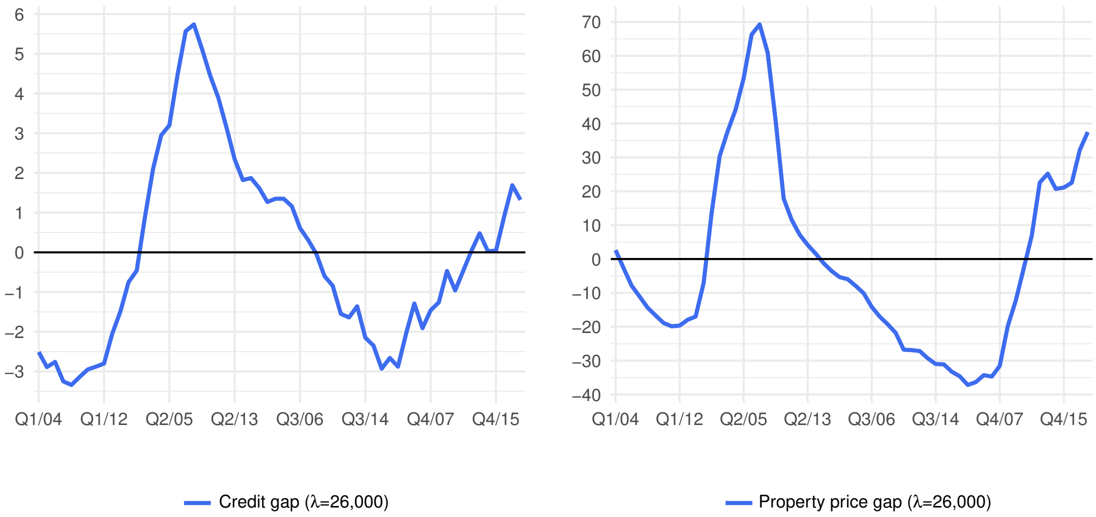


Figure A4: Proxy Variables for Credit and Property Price Cycle



Appendix B: Additional Estimation Results

Table B1: Regression Results – Specifications with Different Lags and Leads

Panel A: Goodness of Fit

Dependent var.:	LLPL						NPLL					
Independent var.:	Output gap and trend (HP)			Output gap and trend (SSM)			Output gap and trend (HP)			Output gap and trend (SSM)		
R^2:	Overall	Within	Aggr.	Overall	Within	Aggr.	Overall	Within	Aggr.	Overall	Within	Aggr.
4 lags	0.911	0.061	0.831	0.91	0.077	0.834	0.831	0.127	0.818	0.835	0.13	0.81
3 lags	0.909	0.053	0.814	0.911	0.069	0.878	0.827	0.116	0.827	0.834	0.121	0.869
2 lags	0.900	0.043	0.745	0.905	0.059	0.862	0.817	0.100	0.804	0.827	0.106	0.878
1 lag	0.886	0.037	0.65	0.894	0.049	0.784	0.802	0.087	0.741	0.812	0.09	0.83
no lag	0.868	0.033	0.542	0.876	0.036	0.65	0.781	0.069	0.635	0.791	0.067	0.73
1 lead	0.87	0.024	0.444	0.873	0.017	0.48	0.784	0.051	0.516	0.790	0.047	0.597
2 leads	0.87	0.015	0.331	0.871	0.005	0.325	0.786	0.032	0.389	0.791	0.031	0.472
3 leads	0.871	0.011	0.247	0.871	0.001	0.229	0.788	0.022	0.277	0.794	0.028	0.393
4 leads	0.872	0.012	0.199	0.872	0.001	0.181	0.789	0.017	0.191	0.797	0.029	0.361

Panel B: Estimated Elasticities on Output Gap Variable

Dependent var.:	LLPL				NPLL			
Independent var.:	Output gap and trend (HP)		Output gap and trend (SSM)		Output gap and trend (HP)		Output gap and trend (SSM)	
	Panel	Aggr.	Panel	Aggr.	Panel	Aggr.	Panel	Aggr.
4 lags	-0.105***	-0.109***	-0.177***	-0.17***	-0.214***	-0.2***	-0.401***	-0.353***
3 lags	-0.137***	-0.138***	-0.207***	-0.197***	-0.266***	-0.25***	-0.439***	-0.387***
2 lags	-0.171***	-0.17***	-0.241***	-0.227***	-0.305***	-0.29***	-0.451***	-0.397***
1 lag	-0.198***	-0.196***	-0.263***	-0.244***	-0.328***	-0.315***	-0.439***	-0.383***
no lag	-0.218***	-0.215***	-0.268***	-0.245***	-0.339***	-0.327***	-0.414***	-0.355***
1 lead	-0.208***	-0.203***	-0.205***	-0.182***	-0.311***	-0.302***	-0.318***	-0.26***
2 leads	-0.19***	-0.184***	-0.11***	-0.09	-0.274***	-0.27***	-0.173***	-0.118
3 leads	-0.174***	-0.169***	-0.013	0.003	-0.242***	-0.241***	-0.008	0.041
4 leads	-0.164***	-0.159***	0.064***	0.074	-0.215***	-0.221***	0.144***	0.182*

Panel C: Estimated Elasticities on Output Trend Variable

Dependent var.:	LLPL				NPLL			
Independent var.:	Output gap and trend (HP)		Output gap and trend (SSM)		Output gap and trend (HP)		Output gap and trend (SSM)	
	Panel	Aggr.	Panel	Aggr.	Panel	Aggr.	Panel	Aggr.
4 lags	-0.317***	-0.3***	-0.103***	-0.104***	-0.52***	-0.589***	-0.056	-0.163**
3 lags	-0.293***	-0.274***	-0.07***	-0.072**	-0.486***	-0.556***	-0.02	-0.132**
2 lags	-0.251***	-0.232***	-0.021	-0.027	-0.435***	-0.506***	0.002	-0.116**
1 lag	-0.199***	-0.181***	0.023	0.012	-0.376***	-0.447***	0.009	-0.112*
no lag	-0.14***	-0.125***	0.053**	0.037	-0.305***	-0.376***	0.013	-0.112
1 lead	-0.102***	-0.085*	-0.001	-0.015	-0.25***	-0.318***	-0.062	-0.185*
2 leads	-0.06***	-0.042	-0.09***	-0.099	-0.188***	-0.253***	-0.193***	-0.313**
3 leads	-0.015	0.003	-0.179***	-0.181**	-0.125***	-0.184*	-0.35***	-0.461***
4 leads	0.034*	0.051	-0.24***	-0.235**	-0.055	-0.11	-0.488***	-0.587***

Note: The output gap and trend are estimated using a small structural model (SSM) and the Hodrick-Prescott filter (HP). Specifications include fixed effects and are estimated using the LSDV estimator. Standard errors reported in parentheses; ***, **, and * denote the 1%, 5%, and 10% significance levels.

Table B2: Regression Results – Mean Effect (2)

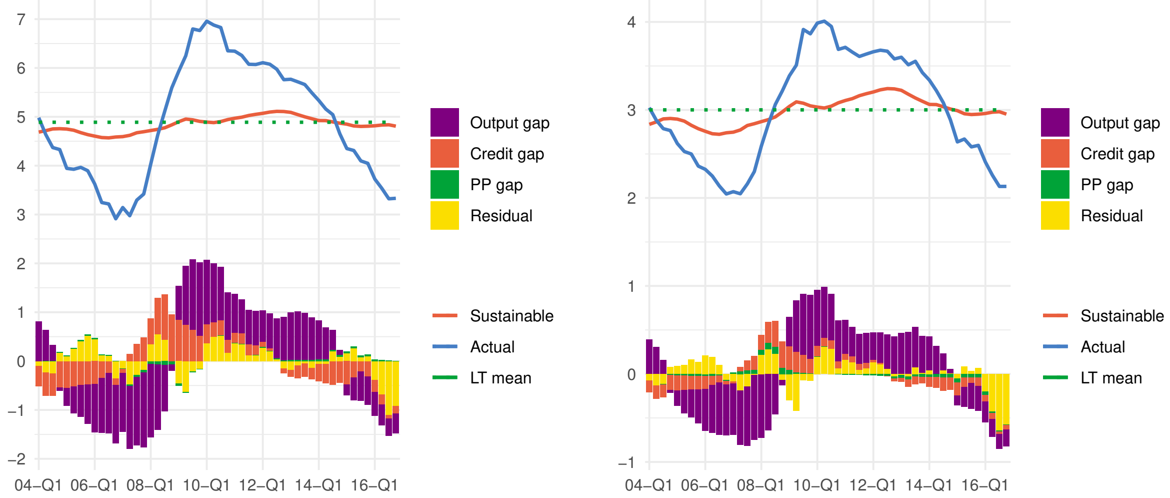
Dependent var.:	LLPL				NPLL			
Data:	Aggr.	Panel	Aggr.	Panel	Aggr,	Panel	Aggr.	Panel
Constant	3.755***	2.633***	3.897***	3.164	6.37***	6.03***	6.397***	7.053
	(0.067)	(0.089)	(0.125)	(0.171)	(0.136)	(0.155)	(0.246)	(0.291)
Output gap (t-4)	-0.109***	-0.218***	-0.145***	-0.154***	-0.2***	-0.339***	-0.295***	-0.197***
	(0.018)	(0.014)	(0.021)	(0.017)	(0.037)	(0.026)	(0.041)	(0.033)
Output trend, gr. (t-4)	-0.3***	-0.14***	-0.341***	-0.341***	-0.589***	-0.305***	-0.576***	-0.549***
	(0.022)	(0.017)	(0.044)	(0.035)	(0.046)	(0.032)	(0.086)	(0.067)
Credit gap (t-4)			-0.064	-0.224***			-0.017	-0.254***
			(0.047)	(0.037)			(0.093)	(0.07)
Prop. price gap (t-4)			0.009**	0.009***			0.013*	0.002
			(0.004)	(0.003)			(0.007)	(0.005)
Within R^2		0.033		0.044		0.069		0.106
Overall R^2		0.868		0.874		0.781		0.79
Adjusted R^2	0.824		0.853		0.81		0.851	

Note: The output gap and trend are estimated using the Hodrick-Prescott filter.

Figure B1: Sustainable Level and Cyclical Components – Aggregate-Level Estimates (2)

Panel A: Non-performing loans ratio

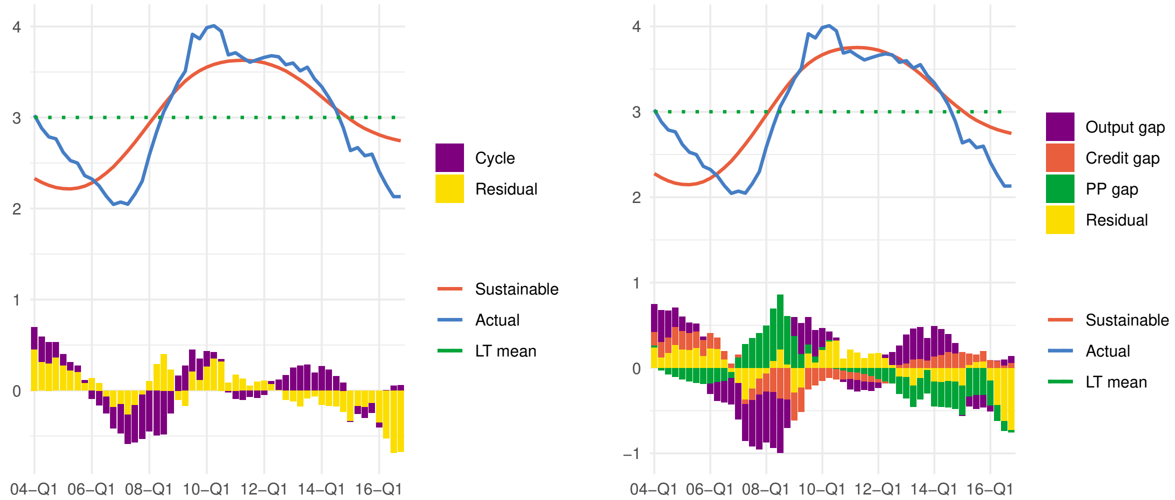
Panel B: Loan loss provisions ratio



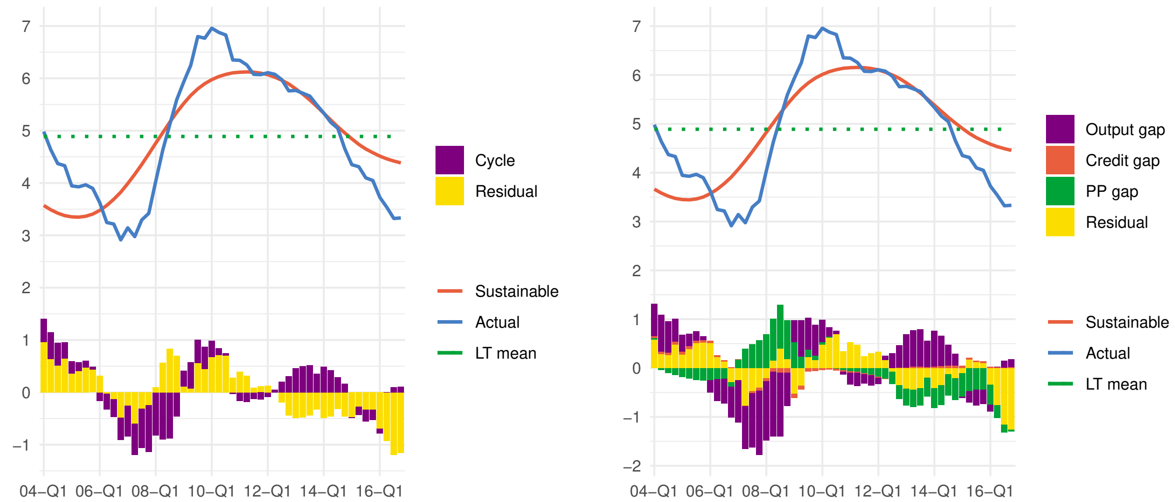
Note: Aggregate regression results; the output gap and trend are estimated using a small structural model.

Figure B2: Sustainable Level and Cyclical Components – Aggregate-Level Estimates (3)

Panel A: Loan loss provisions ratio



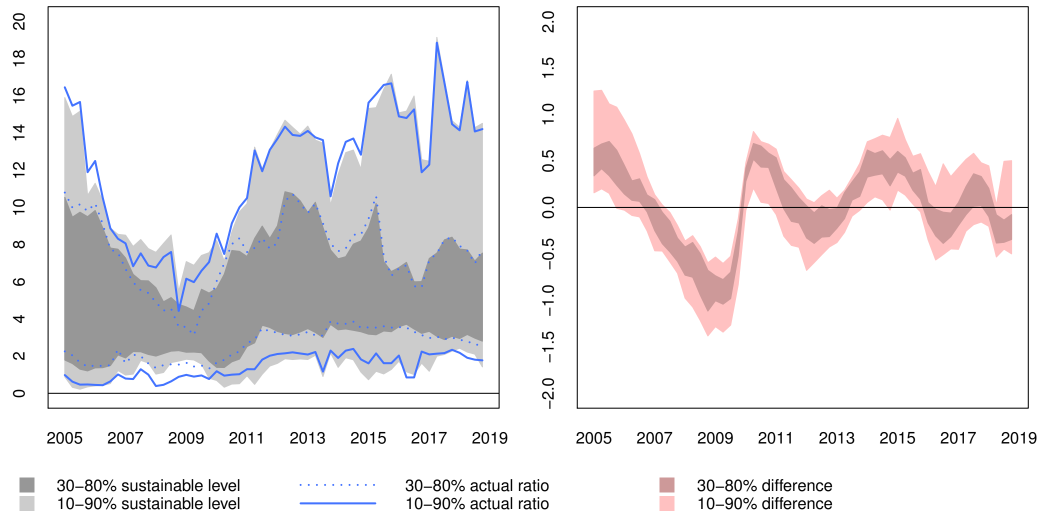
Panel B: Non-performing loans ratio



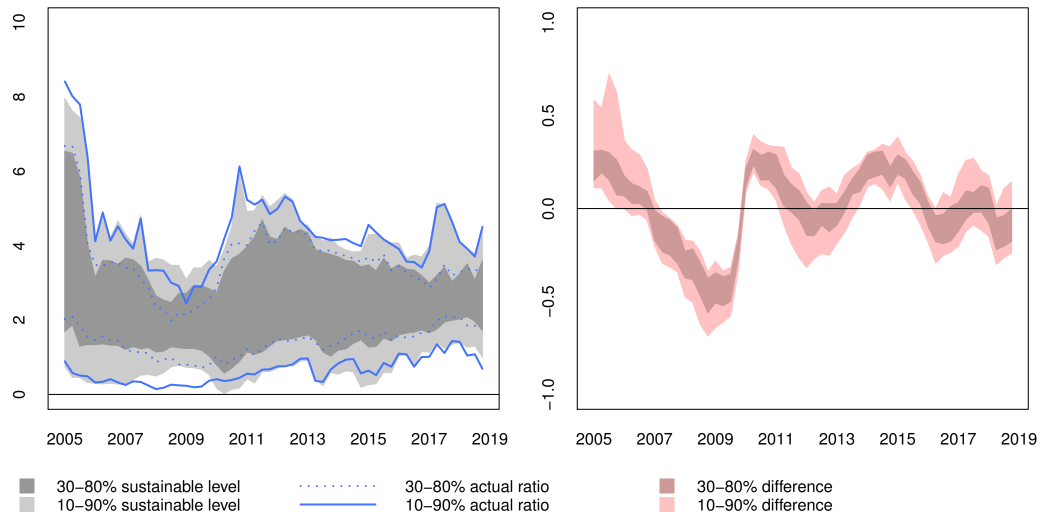
Note: Aggregate regression results; the output gap and trend are estimated using the Hodrick-Prescott filter.

Figure B3: Sustainable Level and Cyclical Components – Panel Data Estimates (2)

Panel A: Non-performing loans ratio



Panel B: Loan loss provisions ratio



Note: The output gap and trend are estimated using the Hodrick-Prescott filter.

Table B3: Full Regression Results – Quantile Regression (1)

Panel A: Dependent variable: Loan loss provisions ratio

	q 1	q 2	q 3	q 4	q 5	q 6	q 7	q 8	q 9
Constant	1.351***	1.492***	1.584***	1.664***	1.725***	1.603***	1.641***	1.768***	1.938***
	(0.336)	(0.295)	(0.303)	(0.334)	(0.383)	(0.404)	(0.416)	(0.441)	(0.596)
Output gap (t-4)	-0.053	-0.035	-0.043	-0.085	-0.122**	-0.155**	-0.183***	-0.221***	-0.245***
	(0.04)	(0.052)	(0.064)	(0.06)	(0.058)	(0.063)	(0.065)	(0.065)	(0.083)
Output trend (t-4)	-0.115	-0.126*	-0.13*	-0.122*	-0.093	-0.043	-0.037	-0.044	-0.132
	(0.087)	(0.071)	(0.074)	(0.073)	(0.077)	(0.082)	(0.083)	(0.091)	(0.139)
ROA (t-1)	-0.023	0.009	0.008	0.005	0.003	0.006	0.021	0.034	0.034
	(0.083)	(0.093)	(0.106)	(0.123)	(0.136)	(0.141)	(0.147)	(0.154)	(0.168)
Equity to assets (t-1)	0.036	0.047**	0.065***	0.083***	0.086***	0.105***	0.124***	0.141***	0.232***
	(0.026)	(0.022)	(0.023)	(0.022)	(0.028)	(0.03)	(0.028)	(0.031)	(0.047)

Panel B: Dependent variable: Non-performing loans ratio

	q 1	q 2	q 3	q 4	q 5	q 6	q 7	q 8	q 9
Constant	4.316***	4.383***	4.573***	4.599***	4.596***	4.831***	5.061***	5.626***	6.489***
	(1.114)	(0.783)	(0.753)	(0.777)	(0.79)	(0.805)	(0.881)	(1.174)	(1.443)
Output gap (t-4)	0.031	-0.082	-0.096	-0.158	-0.229**	-0.294***	-0.386***	-0.439***	-0.534***
	(0.226)	(0.123)	(0.114)	(0.113)	(0.11)	(0.108)	(0.108)	(0.122)	(0.196)
Output trend (t-4)	-0.599**	-0.44***	-0.388***	-0.339**	-0.271**	-0.246*	-0.234*	-0.331*	-0.354
	(0.278)	(0.142)	(0.13)	(0.134)	(0.132)	(0.13)	(0.14)	(0.191)	(0.276)
ROA (t-1)	0.004	-0.003	-0.008	-0.015	-0.021	-0.02	-0.03	-0.048	-0.064
	(0.154)	(0.166)	(0.188)	(0.196)	(0.203)	(0.215)	(0.218)	(0.228)	(0.173)
Equity to assets (t-1)	-0.023	-0.003	0.023	0.057**	0.08***	0.084***	0.117***	0.192***	0.247***
	(0.041)	(0.031)	(0.028)	(0.028)	(0.028)	(0.026)	(0.038)	(0.056)	(0.065)

Note: The output gap and trend are estimated using a small structural model; the regression with the output gap and trend estimated using the Hodrick-Prescott filter provides similar results; we therefore do not report them, but they are available upon request. The regression was implemented using the *rqpd* R function. Specifications include fixed effects. Standard errors reported in parentheses; ***, **, and * denote the 1%, 5%, and 10% significance levels.

Table B4: Full Regression Results – Quantile Regression (2)

Panel A: Dependent variable: Loan loss provisions ratio

	q 1	q 2	q 3	q 4	q 5	q 6	q 7	q 8	q 9
Constant	1.408***	1.483***	1.545***	1.681***	1.77***	1.735***	1.712***	1.707***	1.878***
	(0.321)	(0.307)	(0.333)	(0.367)	(0.407)	(0.427)	(0.432)	(0.441)	(0.687)
Output gap (t-4)*dPositive	-0.061	-0.041	-0.038	-0.083	-0.152*	-0.203***	-0.2***	-0.195**	-0.211*
	(0.082)	(0.079)	(0.091)	(0.089)	(0.082)	(0.078)	(0.07)	(0.077)	(0.119)
Output gap (t-4)*(1-dPositive)	-0.03	-0.036	-0.06	-0.084	-0.099	-0.101	-0.143	-0.257*	-0.3
	(0.091)	(0.07)	(0.098)	(0.097)	(0.089)	(0.107)	(0.133)	(0.154)	(0.199)
Output trend (t-4)	-0.12	-0.121*	-0.126*	-0.123	-0.08	-0.04	-0.042	-0.051	-0.135
	(0.081)	(0.069)	(0.074)	(0.075)	(0.077)	(0.078)	(0.074)	(0.095)	(0.159)
ROA (t-1)	-0.028	0.008	0.008	0.005	0.003	0.006	0.02	0.035	0.031
	(0.079)	(0.1)	(0.118)	(0.132)	(0.137)	(0.139)	(0.142)	(0.141)	(0.148)
Equity to assets (t-1)	0.037	0.048*	0.065***	0.082***	0.085***	0.102***	0.125***	0.142***	0.23***
	(0.029)	(0.025)	(0.025)	(0.024)	(0.028)	(0.031)	(0.03)	(0.033)	(0.05)

Panel B: Dependent variable: Non-performing loans ratio

	q 1	q 2	q 3	q 4	q 5	q 6	q 7	q 8	q 9
Constant	3.876***	4.343***	4.225***	4.399***	4.48***	4.639***	4.567***	5.121***	5.713***
	(1.1)	(0.796)	(0.818)	(0.79)	(0.775)	(0.795)	(0.825)	(1.124)	(1.997)
Output gap (t-4)*dPositive	0.242	-0.06	-0.035	-0.123	-0.164	-0.198	-0.204	-0.074	-0.241
	(0.302)	(0.201)	(0.177)	(0.17)	(0.164)	(0.157)	(0.168)	(0.211)	(0.398)
Output gap (t-4)*(1-dPositive)	-0.185	-0.103	-0.213	-0.241	-0.285	-0.393*	-0.622**	-0.712**	-0.874*
	(0.308)	(0.19)	(0.199)	(0.226)	(0.233)	(0.237)	(0.278)	(0.324)	(0.5)
Output trend (t-4)	-0.603**	-0.434**	-0.365**	-0.322**	-0.293**	-0.268*	-0.235	-0.459**	-0.406
	(0.293)	(0.168)	(0.15)	(0.138)	(0.142)	(0.143)	(0.155)	(0.207)	(0.271)
ROA (t-1)	0.009	-0.002	-0.009	-0.012	-0.021	-0.019	-0.028	-0.045	-0.057
	(0.184)	(0.196)	(0.211)	(0.206)	(0.209)	(0.228)	(0.228)	(0.226)	(0.185)
Equity to assets (t-1)	-0.034	-0.006	0.035	0.057*	0.083***	0.086***	0.122***	0.21***	0.249***
	(0.05)	(0.039)	(0.037)	(0.032)	(0.028)	(0.031)	(0.044)	(0.059)	(0.069)

Note: The output gap and trend are estimated using a small structural model; the regression with the output gap and trend estimated using the Hodrick-Prescott filter provides similar results; we therefore do not report them, but they are available upon request. The regression was implemented using the *rqpd* R function. Specifications include fixed effects. Standard errors reported in parentheses; ***, **, and * denote the 1%, 5%, and 10% significance levels.

Table B5: Full Regression Results – Quantile Regression (3)

Panel A: Dependent variable: Loan loss provisions ratio

	q 1	q 2	q 3	q 4	q 5	q 6	q 7	q 8	q 9
Constant	1.402***	1.503***	1.592***	1.703***	1.771***	1.711***	1.644***	1.769***	2.006***
	(0.394)	(0.358)	(0.366)	(0.401)	(0.459)	(0.501)	(0.511)	(0.521)	(0.574)
Output gap (t-4)*dRising	-0.052	-0.053	-0.077	-0.109*	-0.13**	-0.173***	-0.236***	-0.259***	-0.285***
	(0.041)	(0.055)	(0.067)	(0.062)	(0.054)	(0.066)	(0.075)	(0.075)	(0.099)
Output gap (t-4)*(1-dRising)	-0.041	-0.035	-0.045	-0.068	-0.087	-0.119**	-0.145**	-0.181**	-0.15
	(0.035)	(0.046)	(0.057)	(0.055)	(0.053)	(0.059)	(0.065)	(0.074)	(0.096)
Output trend (t-4)	-0.115	-0.121	-0.114	-0.117	-0.104	-0.049	-0.02	-0.021	-0.112
	(0.086)	(0.082)	(0.084)	(0.079)	(0.082)	(0.095)	(0.099)	(0.108)	(0.141)
ROA (t-1)	-0.048	0.009	0.01	0.006	0.003	0.009	0.022	0.036	0.042
	(0.078)	(0.09)	(0.107)	(0.123)	(0.126)	(0.128)	(0.131)	(0.136)	(0.146)
Equity to assets (t-1)	0.037	0.043	0.058**	0.076***	0.081***	0.091***	0.123***	0.132***	0.207***
	(0.034)	(0.03)	(0.028)	(0.027)	(0.031)	(0.035)	(0.033)	(0.03)	(0.04)

Panel B: Dependent variable: Non-performing loans ratio

	q 1	q 2	q 3	q 4	q 5	q 6	q 7	q 8	q 9
Constant	4.222***	4.366***	4.626***	4.585***	4.61***	4.717***	5.074***	5.603***	6.668***
	(1.092)	(0.757)	(0.722)	(0.725)	(0.728)	(0.773)	(0.859)	(1.122)	(1.407)
Output gap (t-4)*dRising	-0.008	-0.107	-0.12	-0.217	-0.291**	-0.371***	-0.433***	-0.507***	-0.72***
	(0.292)	(0.143)	(0.138)	(0.135)	(0.118)	(0.127)	(0.125)	(0.142)	(0.204)
Output gap (t-4)*(1-dRising)	-0.051	-0.092	-0.079	-0.143	-0.191	-0.283**	-0.32**	-0.415***	-0.488**
	(0.25)	(0.138)	(0.147)	(0.139)	(0.123)	(0.124)	(0.125)	(0.134)	(0.223)
Output trend (t-4)	-0.542*	-0.415***	-0.391***	-0.295**	-0.237*	-0.179	-0.21	-0.266	-0.31
	(0.318)	(0.149)	(0.146)	(0.145)	(0.133)	(0.132)	(0.136)	(0.179)	(0.207)
ROA (t-1)	0.003	-0.003	-0.005	-0.012	-0.02	-0.02	-0.029	-0.044	-0.061
	(0.137)	(0.152)	(0.164)	(0.17)	(0.179)	(0.197)	(0.205)	(0.212)	(0.182)
Equity to assets (t-1)	-0.02	-0.003	0.017	0.047*	0.069**	0.081***	0.107***	0.165***	0.218***
	(0.044)	(0.031)	(0.028)	(0.028)	(0.027)	(0.027)	(0.039)	(0.063)	(0.074)

Note: The output gap and trend are estimated using a small structural model; the regression with the output gap and trend estimated using the Hodrick-Prescott filter provides similar results; we therefore do not report them, but they are available upon request. The regression was implemented using the *rqpd* R function. Specifications include fixed effects. Standard errors reported in parentheses; ***, **, and * denote the 1%, 5%, and 10% significance levels.

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