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What is the Sustainable Level of Banks' Credit Losses and Provisions?

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Abstract: In this paper, we estimate the sustainable level of lifetime expected credit losses and provisions and assess the procyclicality of banks' credit losses and provisions in the Czech Republic. Further, we discuss the implications of the results for provisioning in stage 3 under the IFRS 9. Based on the estimation results, we can identify periods of insufficient provisioning when the actual values were below the sustainable levels. Additionally, we show that credit losses and provisions behave procyclically (i.e., decrease with a rising output gap and increase with a falling output gap) while banks recognize impaired credit losses and create provisions with a delay of three to four quarters after the output gap starts shrinking. Such a delay may result in a sharp increase in lifetime expected credit losses and provisioning in response to a deterioration in economic conditions under the IFRS 9 regime.

Keywords: Credit losses, IFRS 9, procyclicality, provisions.

JEL Classification: C22, E32, G21

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Introduction

The impact of the global financial crisis (GFC) led to a rise of attention to the research on the sources of procyclicality in the financial cycle as not only credit quality of exposures but also approach to the provision creation are important. Provisioning may be viewed differently. Before 2018 when the IAS 39 was effective, it should have reflected incurred losses. Since 2018 when the IFRS 9 was implemented, provisions should work as a buffer created in good times for use in bad times. This transition from a backward to a forward-looking approach has an important impact on the profitability of banks, their capital adequacy and lending capacity. The IFRS 9 implementation was motivated by the procyclicality of the IAS 39 accounting approach that was criticized for a large 'cliff effect' in losses recognition when exposure was transferred from performing to non-performing and the provision was created. This provisioning creation accumulated in the economic downturn and threatened the stability of credit institutions. The provisions under IFRS 9

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should be created in advance. During the economic upturn, the provisioning of performing exposures lowers the profit and creates a buffer that might be used in the economic downturn.

In this paper, we estimate 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. Afterwards, we use these estimates to assess the procyclicality of banks' credit losses and provisions in the Czech Republic with potential implications under the IFRS 9. The 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).

The remainder of this paper is organized as follows. Section 2 describes the empirical framework used. Section 3 reports the estimation results and section 4 concludes.

1. Literature review

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.

Until 2018, banks created provisions under the IAS 39 approach. This accounting approach was backward-looking and banks were allowed to create provisions only after the occurrence of a loss event. The IAS 39 approach has been criticized for this fact (see, for example, Restroy et al. 2017, ESRB 2019) and found to be highly procyclical. During the upturn, banks created only low provisions, and during the downturn, provisions grew significantly and amplified the impact of the crises on the banking sector (see, for example, Huizinga et al. 2019, Laeven et al. 2003).

The shortages of the IAS 39 approach to the provisioning led some countries to implement alternative approaches such as dynamic provisioning (adopted in Spain, Peru, or Colombia) and the IFRS 9. Under the dynamic provisioning, banks are expected to create a buffer in 'good times' that would be released in 'bad times' when credit risk materializes (Wezel et al. 2012). The new International Financial Accounting Standard 9 (IFRS 9) came into force on 1 January 2018, however, it is still being criticised for procyclicality. IFRS 9 is based on the expected credit loss (ECL) model, i.e., a forward-looking model that allows banks to create provisions in advance. ECLs 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; in stage 1 the 12-month PIT PD is used; in stage 2 and stage 3 the lifetime PIT PD is used for calculation. ECLs are discounted to present value using an appropriate discount rate. It was believed that this approach should smooth cyclical fluctuations and limit the additional increase of provisions during the downturn. IFRS 9 provides a set of basic principles that need to be fulfilled when ECL modeling, but does not provide a particular model or methodological approach, and thus there is space for discretion at the level of individual banks. The ECL modeling should reflect: '*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). In other words, the ECLs should be set as a weighted average of credit losses where the weights are the respective risks of default occurring in a given time period. GPPC (2016) provides a discussion on different aspects of the IFRS 9 impairment requirements implementation by individual banks. Thus, despite the original intention, some studies suggest that due to the discretion the procyclicality of banks' behavior may be even higher compared to the IAS 39 approach (ESRB 2017, 2019). The procyclicality may be exaggerated due to four main reasons.

Firstly, the inputs of the ECL models are forward-looking information that must be accurate. This means that the macroeconomic projections must be valid, however, the difficulty of the standard macroeconomic models in predicting downturns is well known (see, for example, Tovar 2008, Trichet 2010, Negro et al. 2015). Secondly, the modeling may suffer from a lack of sufficient loss data of different asset classes that may lead to a delay in transfer of exposures between stages[3,4] and procyclicality. Thirdly, the incentives of the bank managers, for example, to smooth banks' results, attain internal profitability and capital targets, may prevent new relevant information from being reflected in time. This behavior may reinforce the cyclical fluctuations. Fourthly, the criteria of the transfer of exposure between stages should be set adequately. A relatively high threshold for a

[3] IFRS 9 distinguishes three stages of exposures. Performing loan without significant increase of credit risk is categorized as stage 1 and the allowance is calculated to cover losses at the 12-month horizon. Significant increase of credit risk leads to a transfer to stage 2 where the allowance is set to cover the lifetime losses. A loss event triggers the transfer to stage 3 and conceptually is very similar to the incurred loss approach under IAS 39. The allowance at stage 3 should cover the lifetime expected credit losses.

[4] For a general guidance on a significant increase in credit risk triggering the transfer of an exposure from stage 1 to stage 2 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 should be guided by the definition used for regulatory purposes, i.e., Article 178, CRR (EU) 575/2013.

significant increase in credit risk could lead to a delayed recognition. The deterioration in economic conditions may lead to an abrupt increase in provisions, i.e. a cliff effect. On the contrary, a lower threshold may limit the cliff effect but also lead to a deterioration in banks' profits affecting their capitalization and lending.

2. Data, Hypothesis and Methodology

We estimate the sustainable level of banks' credit losses and provisions, and examine banks' procyclicality, with an emphasis on potential heterogeneity among banks. 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). The cyclicality of real economic activity and the financial sector is well documented in the literature (among recent studies, see, for example, Egert et al. 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. The 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. The relationship is estimated on the aggregate level and the individual bank level to explore heterogeneity among banks.[5]

$$LLPL_{i,t} = \alpha_1 + \beta_1 OutputGap_{t-p} + \gamma_1 OutputTrend_{t-p} + \upsilon_{1,i} + \epsilon_{1,t} \qquad (1)$$

$$NPLL_{i,t} = \alpha_2 + \beta_2 OutputGap_{t-p} + \gamma_2 OutputTrend_{t-p} + \upsilon_{2,i} + \epsilon_{2,t} \qquad (2)$$

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 percentages of the output trend (potential output) and the output trend expressed in annual percentage changes[6]; p is the number of lags or leads determined in section 3; v_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.

[5] 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).

[6] 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.

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 should 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 follows the dynamics of changes in non-performing loans in the Czech Republic relatively nicely (see Figure A2 in Appendix A). It seems that it works 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).

To account for a possible effect of the financial cycle, we extend the baseline specification by two additional variables – a proxy variable for the credit cycle and a proxy variable for the property price cycle:

$$LLPL_{i,t} = \alpha_1 + \beta_1 OutputGap_{t-p} + \gamma_1 OutputTrend_{t-p} + \delta_1 CreditGap_{t-p} + \delta_2 PPriceGap_{t-p} + \upsilon_{1,i} + \epsilon_{1,t} \quad (3)$$

$$NPLL_{i,t} = \alpha_2 + \beta_2 OutputGap_{t-p} + \gamma_2 OutputTrend_{t-p} + \delta_3 CreditGap_{t-p} + \delta_4 PPriceGap_{t-p} + \upsilon_{2,i} + \epsilon_{2,t} \quad (4)$$

where $CreditGap_{t-p}$ and $PPriceGap_{t-p}$ are the credit gap and the property price gap estimated using the Hodrick-Prescott filter.

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 et al. 2012, Borio 2012).

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 percentages of potential output. 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 percentages 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 et al. 2012); the estimation results should be interpreted with respect to this limitation. Both gaps are depicted in Figure A4 in Appendix A.

In the final exercise, we extend the specifications to include bank-specific variables potentially explaining the dynamics of $NPLL_{i,t}$ and $LLPL_{i,t}$ and heterogeneity among banks:

$$LLPL_{i,t} = \alpha_1 + \beta_1 OutputGap_{t-p} + \gamma_1 OutputTrend_{t-p} + \omega_1 X_{i,t-1} + \upsilon_{1,i} + \epsilon_{1,t} \quad (5)$$

$$NPLL_{i,t} = \alpha_2 + \beta_2 OutputGap_{t-p} + \gamma_2 OutputTrend_{t-p} + \omega_2 X_{i,t-1} + \upsilon_{2,i} + \epsilon_{2,t} \quad (6)$$

The vector of bank-specific control variables $X_{i,t}$ includes a proxy 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 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 important motives in provisioning decisions. This includes both the earlier evidence on US data (see, for example, Greenawalt et al. 1988, Scholes et al. 1990, Beatty et al. 1995, Ahmed et al. 1999, Koch et al. 2000) and more recent research studies (see, for example, Hasan et al. 2004, Bouvatier et al. 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.

We use two estimation techniques. On the aggregate level, we estimate the relationship using simple OLS. On the individual bank level, we employ a weighted fixed-effects model to panel data. The fixed-effects model assumes that differences between institutions can be accumulated into intercepts, thus the effects are fixed and only the intercepts differ (Brüderl et al, 2015). The decision between fixed and random effects was based on the results of the Hausman test[7]. As the weight, we use the market share defined as the share of the bank's financial assets in total financial assets of the whole sample in each period.[8]

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 containing data

[7] The results of the Hausman test will be provided by the authors upon request.

[8] 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.

before the implementation of IFRS 9; our results are therefore indicative mostly of the provisioning procyclicality of exposures in stage 3, and potential delays in the recognition of credit losses, bank management biases, and asymmetries.

The proposed research question will be examined using a sample from 2004 Q1 to 2017 Q4. The reason for the exclusion of data after the end of 2017 is that we aim to estimate the effects consistently without the IFRS 9 bias as the period in which the IFRS 9 is effective is too short.[9] As of the end of 2017, the Czech banking sector consisted of 19 banks, 5 building societies, and 21 foreign bank branches.[10] The final sample covers 43 banks and 56 quarters, giving an unbalanced panel of 1,530 observations in total.[11] Summary statistics of bank-specific variables are presented in Table A1 in Appendix A.

In the Czech banking sector, 92.1% of total assets were managed by foreign owners as of 2017 Q4. Most of the banks operate under a universal business model and 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).[12] The Czech banking sector is characterized by high liquidity stemming from its strong client deposit base and growth in exposures to the central bank.[13] This provides banks with sufficient resources to ensure a stable and/or increasing credit supply.

3. Results and Discussion

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

[9] The period when banks develop and properly calibrate the ECL model may take some time.

[10] 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.

[11] 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.

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

[13] 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).

significantly with fewer lags and more leads (see Table B1 in Appendix B).[14] 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; this adds one more quarter to the transmission, i.e., before the deteriorated economic conditions are reflected in impaired credit losses and provisioning.[15] 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).

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 et al. 2003, Pain 2003, Bikker et al. 2005, Bouvatier et al. 2008, 2012, Huizinga et al. 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.

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.

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.[16] 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 that 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

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

[15] Some credit exposures may become impaired earlier if, for example, the obligor is unlikely to repay in full.

[16] Analogously, the estimated coefficients from Table B2 are used to decompose the ratios into the sustainable level and different cyclical components (see Figure B1 in Appendix B).

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 Hodrick-Prescott filter.

Table 1. Regression Results – Mean Effect

(A) Dependent variable: LLPL

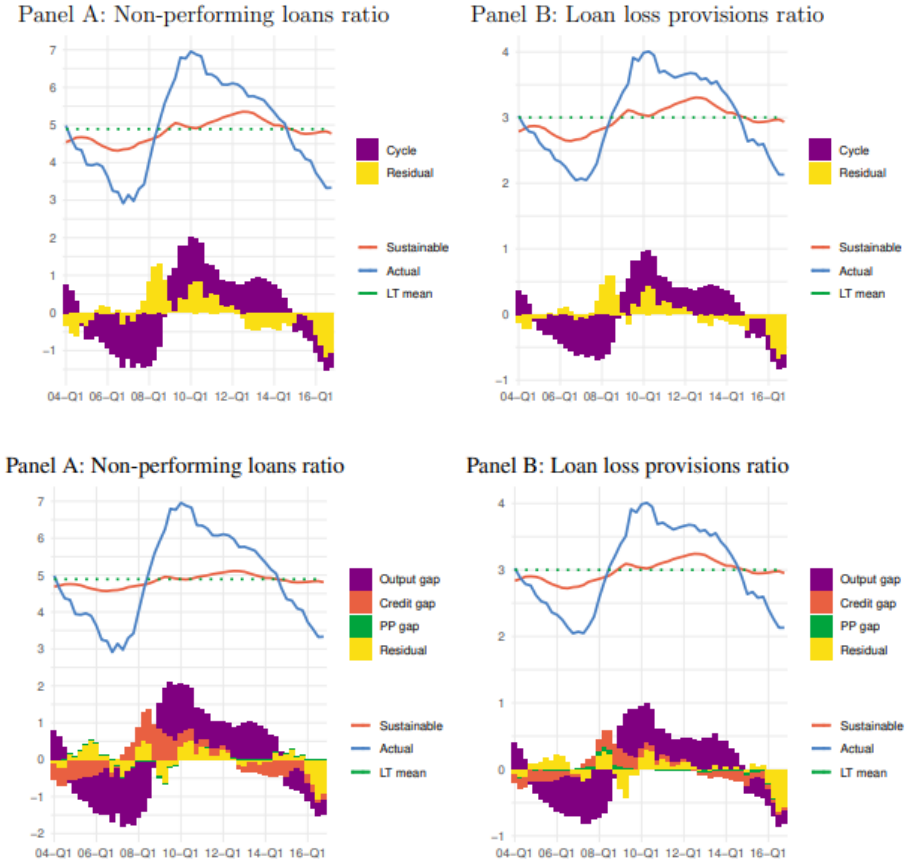
Data:	Aggr.	Panel	Aggr.	Panel
Constant	**3.225*** **	**2.36*** **	**3.179*** **	2.674
	(0.09)	**(0.089)**	**(0.086)**	(0.135)
Output gap (t-4)	**-0.17*** **	**-0.268*** **	**-0.181*** **	**-0.26*** **
	(0.024)	**(0.018)**	**(0.02)**	**(0.018)**
Output trend, growth (t-4)	**-0.104*** **	**0.053*** **	**-0.081*** **	-0.014
	(0.033)	**(0.024)**	**(0.031)**	(0.027)
Credit gap (t-4)			**0.052*** **	**-0.138*** **
			(0.028)	**(0.024)**
Property price gap (t-4)			0.001	**0.004***
			(0.003)	**(0.002)**
Within R2		0.036		0.063
Overall R2		0.876		0.883
Adjusted R2	0.827		0.891	

(B) Dependent variable: NPLL

Data:	Aggr.	Panel	Aggr.	Panel
Constant	**5.226*** **	**5.89*** **	**5.045*** **	6.073
	(0.188)	**(0.155)**	**(0.157)**	(0.233)
Output gap (t-4)	**-0.353*** **	**-0.414*** **	**-0.375*** **	**-0.38*** **
	(0.051)	**(0.034)**	**(0.036)**	**(0.034)**
Output trend, growth (t-4)	-0.163**	0.013	-0.085	-0.017
	(0.069)	(0.047)	(0.056)	(0.053)
Credit gap (t-4)			**0.166*** **	**-0.081***
			(0.051)	**(0.047)**
Property price gap (t-4)			-0.001	-0.007
			(0.005)	(0.004)
Within R2		0.067		0.104
Overall R2		0.791		0.799
Adjusted R2	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.

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



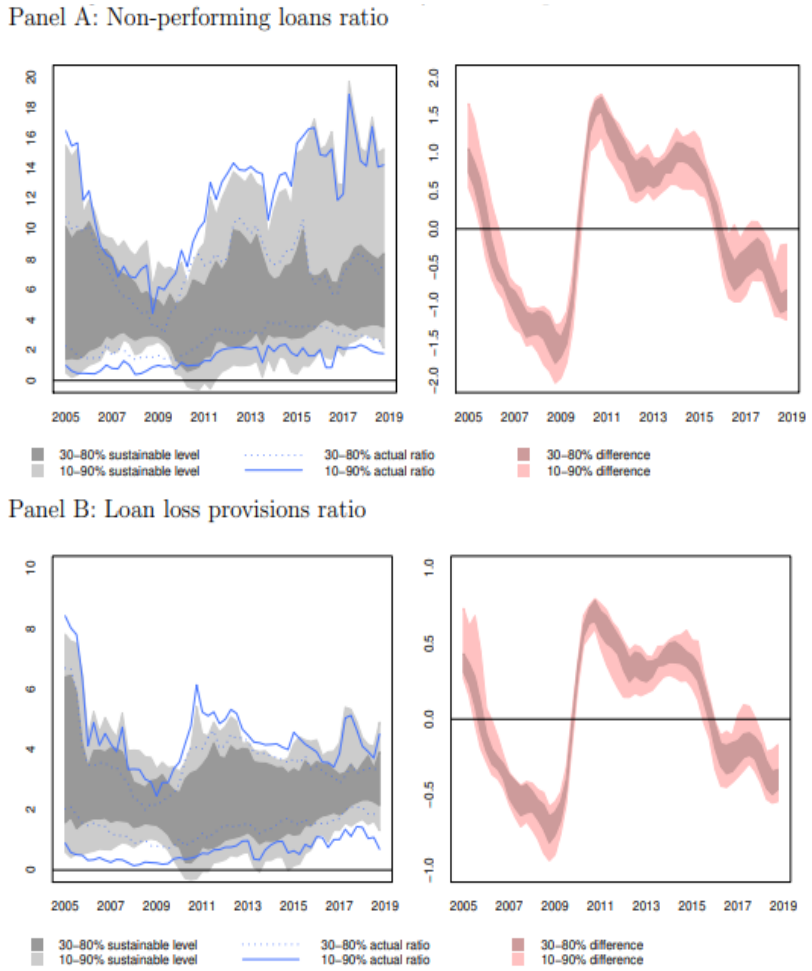
Note: Aggregate regression results; the output gap and trend are estimated using a small structural model. The decomposition with the output gap and trend estimated using the Hodrick-Prescott filter is given in Appendix B, Figure B1.

According to the decomposition, the pre-crisis period of 2006–2008 was characterized by the 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 B1 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 the end-point bias as discussed above.

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



Note: The output gap and output 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 B2.

Table 2 reports the estimation results with bank-specific control variables. 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 fewer 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 to 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 2).

Table 2. Panel Data Regression Results with Additional Controls

	(1)	(2)
Dependent variable	LLPL	NPLL
Output gap (t-4)	**-0.160*** **	**-0.391*** **
	(0.017)	**(0.035)**
Output trend, growth (t-4)	**-0.120*** **	-0.040
	(0.026)	(0.053)
ROA (t-1)	**0.076*** **	**0.235*** **
	(0.024)	**(0.048)**
Equity to assets (t-1)	**0.044*** **	0.040
	(0.014)	(0.028)
Bank size (t-1)	**-0.179***	0.320
	(0.100)	(0.203)
FE included	Yes	Yes
Observations	1,360	1,360
Within R^2	0.0155	0.105
Overall R^2	0.914	0.841

*Note: The output gap and output trend are estimated using a small structural model. The decomposition 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. Specification includes fixed effects. Standard errors reported in parentheses; ***, ** and * denote 1%, 5% and 10% significance levels.*

Conclusion

In this article, 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. 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.

The estimation results show that the sustainable levels of the non-performing loans ratio and the loan loss provisions ratio in the Czech banking sector oscillate around 5% and 3%, respectively. The difference between the two indicates that the sustainable amount of impaired loans that can be expected to be recovered in the future is about 2% of total loans. Besides, the results show that credit losses and provisions behave procyclically (i.e. decrease with a rising output gap and increase with a falling output gap) while banks recognize impaired credit losses and create provisions with a delay of three to four quarters after the output gap starts to decrease.

The delayed transfer of exposures between stages may result in a sharp increase in lifetime expected credit losses and provisions in response to a deterioration in economic conditions. Expected credit loss models under IFRS 9 rely heavily on forward-looking information about future macroeconomic developments produced by models which tend to underestimate the probability and severity of recessions. 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 IFRS 9 standard, especially their definition of a significant increase in credit risk. 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 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.

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.

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Appendix A

Table A1. Summary Statistics and Data Sources

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

Data Sources

Variable	Source	Comment
Dependent		
Loan loss provisions	CNB internal database (available at ARAD)	used as a ratio of loan loss provisions to total loans
Non-performing loans	CNB internal database (available at ARAD)	used as a ratio of non-performing loans to total loans
Explanatory		
HDP	Czech statistical office (CZSO)	The gap and trend part decomposed by 2 ways: a small structural model (SSM), HP filter. The output gap is expressed in percentages of the output trend (potential output) and the output trend is expressed in annual percentage changes.
Total loans	CNB internal database (available at ARAD)	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 percentages of potential output.
Property prices	Czech statistical office (CZSO)	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 percentages 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.
Bank specific explanatory		
ROA	CNB internal database (available at ARAD)	defined as: banks' profits before tax and loan loss provisions over total assets
Equity	CNB internal database (available at ARAD)	used as: equity over total assets
Assets (bank size)	CNB internal database (available at ARAD)	used as: the logarithm of total assets

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

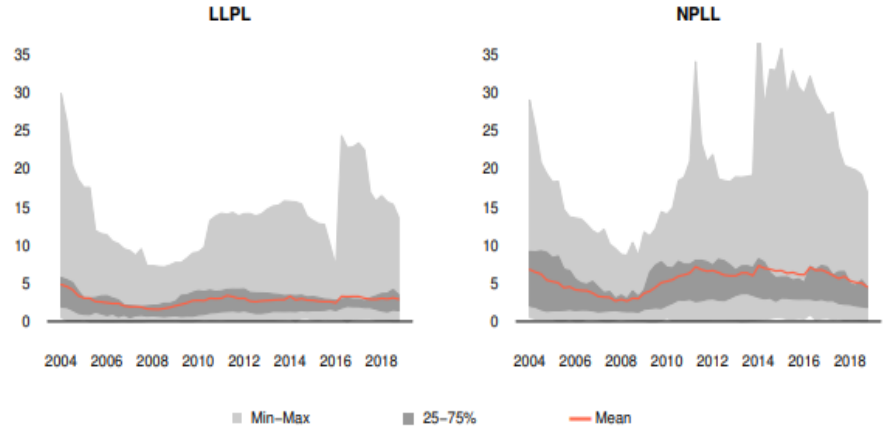


Figure A2. Impaired Credit Losses and Change in Non-Performing Loans (CZK billions)

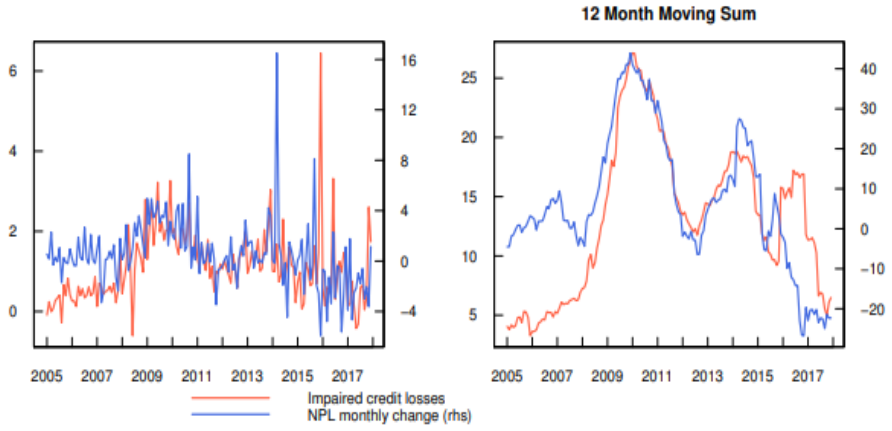


Figure A3: Proxy Variables for Business Cycle and Trend

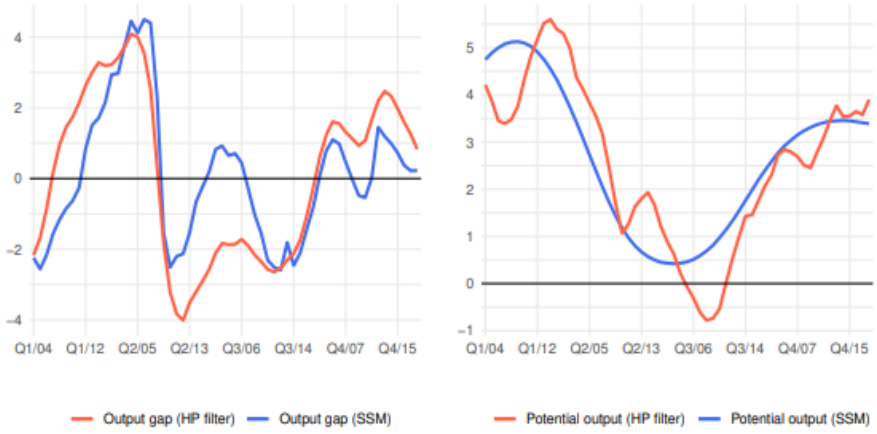
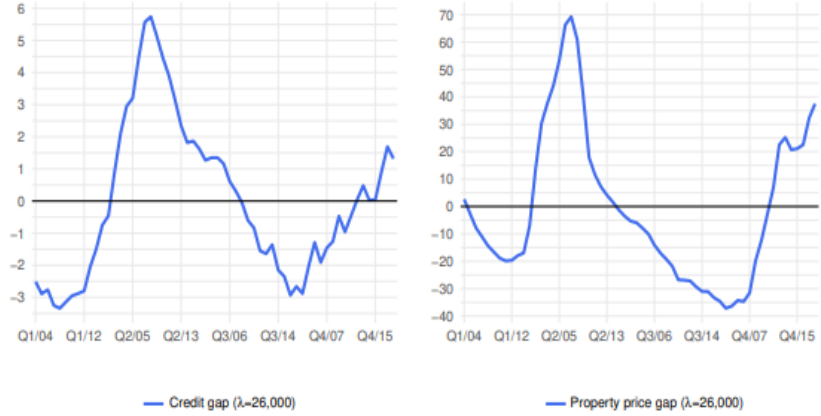


Figure A4: Proxy Variables for Credit and Property Price Cycle



Appendix B

Table B1. Regression results – Specifications with Different Lags and Leads

Panel A: Goodness of Fit

Dependent var.:	LLPL					
Independent var.:	Output gap and trend (HP)			Output gap and trend (SSM)		
R^2:	Overall	Within	Aggr.	Overall	Within	Aggr.
4 lags	0.911	0.061	0.831	0.91	0.077	0.834
3 lags	0.909	0.053	0.814	0.911	0.069	0.878
2 lags	0.900	0.043	0.745	0.905	0.059	0.862
1 lag	0.886	0.037	0.65	0.894	0.049	0.784
No lag	0.868	0.033	0.542	0.876	0.036	0.65
1 lead	0.87	0.024	0.444	0.873	0.017	0.48
2 leads	0.87	0.015	0.331	0.871	0.005	0.325
3 leads	0.871	0.011	0.247	0.871	0.001	0.229
4 leads	0.872	0.012	0.199	0.872	0.001	0.181

Dependent var.:	NPLL					
Independent var.:	Output gap and trend (HP)			Output gap and trend (SSM)		
R^2:	Overall	Within	Aggr.	Overall	Within	Aggr.
4 lags	0.831	0.127	0.818	0.835	0.13	0.81
3 lags	0.827	0.116	0.827	0.834	0.121	0.869
2 lags	0.817	0.100	0.804	0.827	0.106	0.878
1 lag	0.802	0.087	0.741	0.812	0.09	0.83
No lag	0.781	0.069	0.635	0.791	0.067	0.73
1 lead	0.784	0.051	0.516	0.790	0.047	0.597
2 leads	0.786	0.032	0.389	0.791	0.031	0.472
3 leads	0.788	0.022	0.277	0.794	0.028	0.393
4 leads	0.789	0.017	0.191	0.797	0.029	0.361

Panel B: Estimated Elasticities on Output Gap Variable

Dependent var.:	LLPL			
Independent var.:	Output gap and trend (HP)		Output gap and trend (SSM)	
R^2:	Panel	Aggr.	Overall	Aggr.
4 lags	-0.105***	-0.109***	-0.177***	-0.17***
3 lags	-0.137***	-0.138***	-0.207***	-0.197***
2 lags	-0.171***	-0.17***	-0.241***	-0.227***
1 lag	-0.198***	-0.196***	-0.263***	-0.244***
No lag	-0.218***	-0.215***	-0.268***	-0.245***
1 lead	-0.208***	-0.203***	-0.205***	-0.182***
2 leads	-0.19***	-0.184***	-0.11***	-0.09
3 leads	-0.174***	-0.169***	-0.013	0.003
4 leads	-0.164***	-0.159***	0.064***	0.074

Dependent var.:	NPLL			
Independent var.:	Output gap and trend (HP)		Output gap and trend (SSM)	
R^2:	Panel	Aggr.	Overall	Aggr.
4 lags	-0.214***	-0.2***	-0.401***	-0.353***
3 lags	-0.266***	-0.25***	-0.439***	-0.387***
2 lags	-0.305***	-0.29***	-0.451***	-0.397***
1 lag	-0.328***	-0.315***	-0.439***	-0.383***
No lag	-0.339***	-0.327***	-0.414***	-0.355***
1 lead	-0.311***	-0.302***	-0.318***	-0.26***
2 leads	-0.274***	-0.27***	-0.173***	-0.118
3 leads	-0.242***	-0.241***	-0.008	0.041
4 leads	-0.215***	-0.221***	0.144***	0.182*

Panel C: Estimated Elasticities on Output Trend Variable

Dependent var.:	LLPL			
Independent var.:	Output gap and trend (HP)		Output gap and trend (SSM)	
R^2:	Panel	Aggr.	Overall	Aggr.
4 lags	-0.317***	-0.3***	-0.103***	-0.104***
3 lags	-0.293***	-0.274***	-0.07***	-0.072**
2 lags	-0.251***	-0.232***	-0.021	-0.027
1 lag	-0.199***	-0.181***	0.023	0.012
No lag	-0.14***	-0.125***	0.053**	0.037
1 lead	-0.102***	-0.085*	-0.001	-0.015
2 leads	-0.06***	-0.042	-0.09***	-0.099
3 leads	-0.015	0.003	-0.179***	-0.181**
4 leads	0.034*	0.051	-0.24***	-0.235**

Dependent var.:	NPLL			
Independent var.:	Output gap and trend (HP)		Output gap and trend (SSM)	
R^2:	Panel	Aggr.	Overall	Aggr.
4 lags	-0.52***	-0.589***	-0.056	-0.163**
3 lags	-0.486***	-0.556***	-0.02	-0.132**
2 lags	-0.435***	-0.506***	0.002	-0.116**
1 lag	-0.376***	-0.447***	0.009	-0.112*
No lag	-0.305***	-0.376***	0.013	-0.112
1 lead	-0.25***	-0.318***	-0.062	-0.185*
2 leads	-0.188***	-0.253***	-0.193***	-0.313**
3 leads	-0.125***	-0.184*	-0.35***	-0.461***
4 leads	-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 1%, 5% and 10% significance levels.*

Table B2. Regression Results – Mean Effect

(A) Dependent variable: LLPL

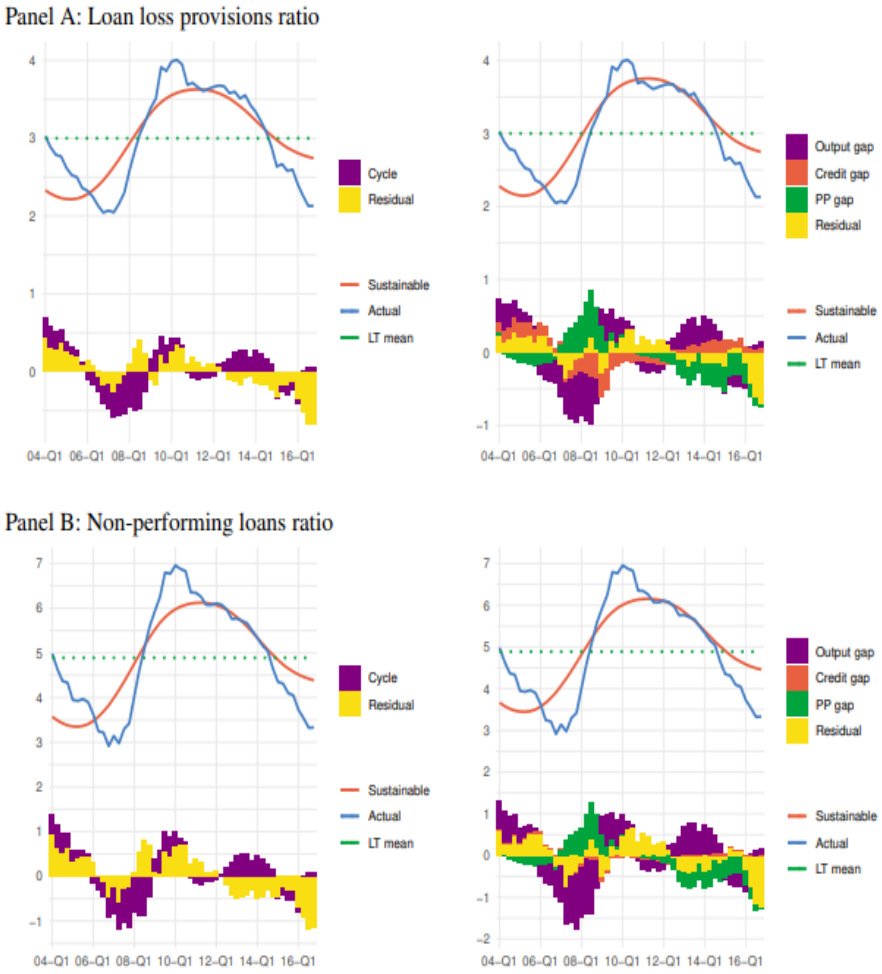
Data:	Aggr.	Panel	Aggr.	Panel
Constant	**3.755*** **	**2.633*** **	**3.897*** **	3.167
	(0.067)	**(0.089)**	**(0.125)**	(0.171)
Output gap (t-4)	**-0.109*** **	**-0.218*** **	**-0.145*** **	**-0.154*** **
	(0.018)	**(0.014)**	**(0.021)**	**(0.017)**
Output trend, growth (t-4)	**-0.3*** **	**-0.14*** **	**-0.341*** **	**-0.341*** **
	(0.022)	**(0.017)**	**(0.044)**	**(0.035)**
Credit gap (t-4)			-0.064	**-0.224*** **
			(0.047)	**(0.337**
Property price gap (t-4)			**0.009** **	**0.009*** **
			(0.004)	**(0.003)**
Within R^2		0.033		0.044
Overall R^2		0.868		0.874
Adjusted R^2	0.824		0.853	

(B) Dependent variable: NPLL

Data:	Aggr.	Panel	Aggr.	Panel
Constant	**6.37*** **	**6.03*** **	**6.397*** **	7.053
	(0.136)	**(0.155)**	**(0.246)**	(0.291)
Output gap (t-4)	**-0.2*** **	**-0.339*** **	**-0.295*** **	**-0.197*** **
	(0.037)	**(0.026)**	**(0.041)**	**(0.033)**
Output trend, growth (t-4)	**-0.589*** **	**-0.305*** **	**-0.576*** **	**-0.5549*** **
	(0.046)	**(0.032)**	**(0.086)**	**(0.067)**
Credit gap (t-4)			-0.017	**-0.254*** **
			(0.093)	**(0.07)**
Property price gap (t-4)			**0.013***	0.002
			(0.007)	(0.005)
Within R^2		0.069		0.106
Overall R^2		0.781		0.79
Adjusted R^2	0.81		0.851	

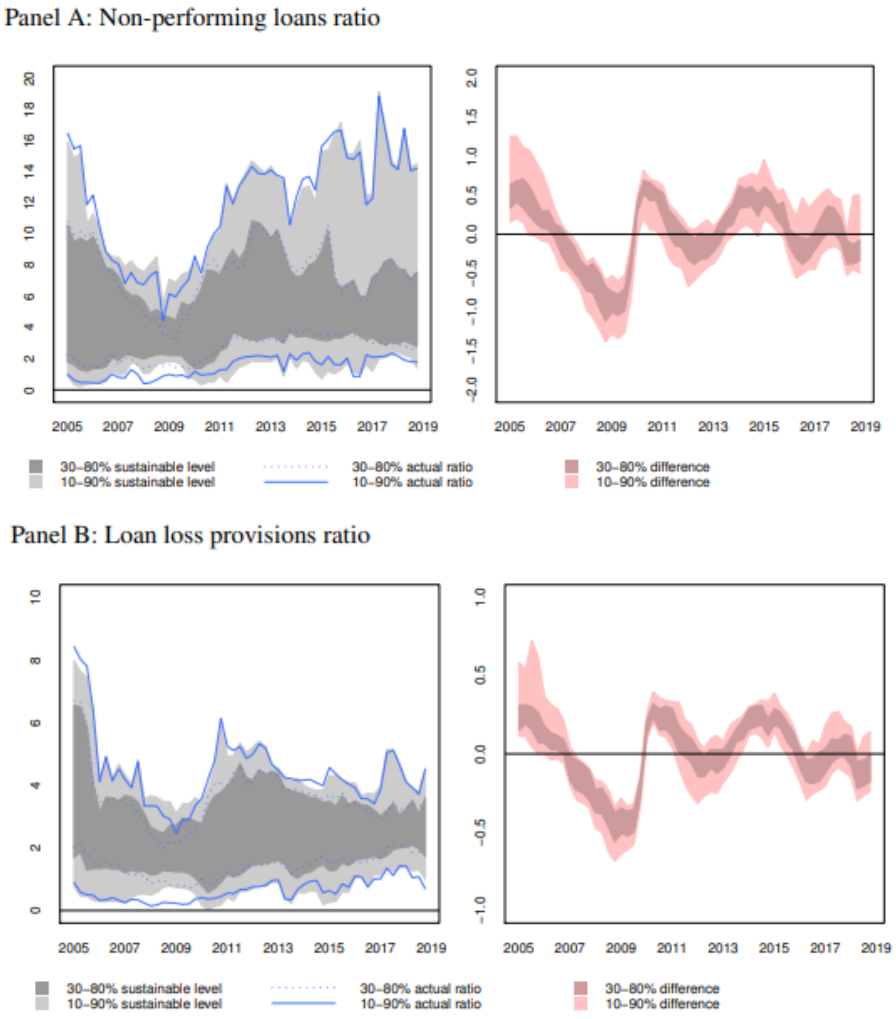
Note: The output gap and trends are estimated using the Hodrick-Prescott filter.

Figure B1. Sustainable Level and Cyclical Components – Aggregate-Level Estimates



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

Figure B2. Sustainable Level and Cyclical Components- Panel Data Estimates



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