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

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Abstract: This article examines the procyclicality of banks' credit losses and provisions in the Czech Republic using pre-2018 data and then discusses the implications of the findings for provisioning in stage 3 under IFRS 9. This analysis is possible because the majority of banks seem to have aligned their accounting definitions of default with the regulatory definition before the implementation of IFRS 9. Based on our results, we find significant asymmetries in the Czech banks' behaviour over the cycle. Firstly, provisioning procyclicality is the strongest in the later contractionary phase and the 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 with lower credit risk. If this behaviour persists under IFRS 9 and banks do not change their provisioning behaviour from backward to forward-looking, it may lead to a delayed transfer of exposures between stages and aggravate cyclical fluctuations.

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

JEL Classification: C22, E32, G21

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Introduction

The global financial crisis (GFC) has increased the interest of many regulators in the mechanisms reinforcing the inherent procyclicality of banks' behaviour. 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.[3] Consequently, the question has arisen of how much the regulatory and accounting framework itself contributes to the procyclicality. Numerous studies have found that the accounting framework effective before 2018 (i.e.,

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

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 to respond to this criticism. However, some studies indicate that under certain assumptions, provisioning under IFRS 9 may remain procyclical or even aggravate the procyclicality relative to provisioning under IAS 39 (ESRB 2019).

This paper examines the procyclicality of banks' credit losses and provisioning in the Czech Republic using pre-2018 data and then discusses the implications of banks' behaviour for provisioning in stage 3 under IFRS 9. We consider procyclical such credit losses and provisions that negatively correlate with the business cycle, i.e., 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 (see, for example, FSF 2008). This paper aims to 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. Our results show that provisioning procyclicality in the Czech banking system is the strongest in the later contractionary phase and the early recovery phase, while it is non-existent in the early contractionary phase. Further, banks with higher credit risk are more sensitive and behave more procyclically.

Finally, we discuss the potential implications of our empirical findings for the new provisioning mechanism under IFRS 9. We argue that if the identified effects persist under IFRS 9, they may aggravate 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. Our results should raise the question of whether the IFRS 9 regime itself can overcome the 'too little, too late' problem or it is necessary to consider other boundaries to decrease the discretion among banks and increase the level of forward-looking aspect in banks' credit risk models by stricter model validation assessment by the supervisor.

The remainder of this paper is organised 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.

Provisioning Procyclicality under IAS 39 and IFRS 9

High procyclicality of provisioning is undesirable from the financial stability[4] perspective because it may negatively affect banks' capitalisation during economic downturns when capital is usually most needed. Consequently, it may lead to, or exacerbate, the procyclicality of bank credit supply when increasing provisioning during economic depression worsens banks' capital positions and banks have to decrease their credit supply. Lowered credit supply affects the real economy, and the macroeconomic fluctuations are thus

[4] As defined by the European Central Bank, financial stability is “a condition in which the financial system – which comprises financial intermediaries, markets and market infrastructures – is capable of withstanding shocks and the unravelling of financial imbalances”. Source: https://www.ecb.europa.eu/pub/financial-stability/html/index.en.html

amplified. Although procyclicality is inevitable and inherent in economic activity, we need to restrain it since it can lead to significant financial fluctuations and endogenous financial cycles. If the processes are not set to prevent the procyclicality, then monetary and macroprudential policy action is needed to mitigate and smooth out the fluctuations.

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.[5] The regulatory definition of default has implications for calculating 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 recognised and provisions created differently under different accounting approaches (IAS 39, the dynamic provisioning mechanism, IFRS 9[6]). 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.[7]

The inability of banks to create provisions before the occurrence of a loss event under IAS 39 was criticised for being 'too little, too late' (see, for example, Restroy et al. 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 et al. 2005, Huizinga et al. 2019). Additionally, some studies indicate there may be possible non-linearity over the cycle, which proves that banks provision more the deeper they are into an economic downturn (Laeven et al. 2003, Bouvatier et al. 2012).

The provisioning procyclicality under IAS 39 led some countries to adopt a dynamic provisioning mechanism[8] and eventually motivated the implementation of IFRS 9. IFRS 9 builds on an expected credit loss (ECL) model, which requires banks to set aside 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 recognise a significant proportion of credit losses well in advance and determine the amount of provisions set aside. This approach 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 loan's inception, the exposure is immediately categorised as stage 1, and an

[5] An exposure is non-performing (in default) when the obligor is unlikely to repay their credit obligations or is past due more than 90 days on any material credit obligation, or both (see Article 178, CRR (EU) 575/2013).

[6] In the Czech Republic, banks were allowed to 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).

[7] 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 their credit obligation in full.

[8] 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 provided by, for example, Wezel et al. 2012.

impairment allowance is set aside to cover losses at the 12-month horizon. Once a significant increase in credit risk occurs,[9] the exposure is transferred to stage 2, and a credit impairment allowance is set aside to cover the credit losses expected to materialise over the asset's lifetime. 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 11). Credit impairment allowances should still cover lifetime expected credit losses at this stage. Stage 3 under IFRS 9 is conceptually most similar to the incurred loss approach under IAS 39, which already required estimation of lifetime expected credit losses for impaired loans.[10]

Despite the original intention of the new accounting standard, the amount of discretion under IFRS 9 may lead to higher procyclicality of banks' behaviour relative to IAS 39, as suggested by some studies (ESRB 2017, 2019).[11] There are a few core limitations that may prevent ECL models from correctly determining the amount of provisions that 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 modelling techniques must be adequate. However, standard macroeconomic models' difficulty 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 stylised and

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[9] 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 should be guided by the definition used for regulatory purposes, i.e., Article 178, CRR (EU) 575/2013.

[10] 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.

[11] 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).

necessarily abstract from many important economic linkages and transmission mechanisms. Therefore, they cannot be expected to forecast an abrupt change in economic conditions accurately. 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 modelling, a delay in the transfer of exposures from stage 1 to stage 2 and 3, and reinforced procyclicality (ESRB 2019).

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 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 be a 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 recognise credit losses well in advance may mitigate the cliff effect. However, it would lead to a significant deterioration in banks' profits, potentially affecting their capitalisation and creating excessive restrictions on lending (Abad et al. 2017, Krüger et al. 2018, Plata et al. 2017).[12]

Empirical Framework

Model specification

The baseline model specification is as follows:

$$Y_{i,t} = \beta_1 OutputGap_{t-4} + \gamma_1 OutputTrend_{t-4} + \omega_1 X_{i,t-1} + \alpha_{1,i} + \epsilon_{1,t} \qquad (1)$$

where $Y_{i,t}$ is either $LLPL_{i,t}$ or $NPLL_{i,t}$, $X_{i,t-1}$ is a vector of control variables, $\alpha_{1,i}$ is a time-invariant individual effect of bank i and $\epsilon_{1,t}$ is an error term. $LLPL_{i,t}$ is the ratio of loan loss provisions to total loans and $NPLL_{i,t}$ is the ratio of non-performing loans to total loans. $OutputGap_{t-4}$ and $OutputTrend_{t-4}$ are, respectively, the output gap expressed in percentages of the output trend (potential output) and the output trend expressed in annual percentage changes.

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

We estimate the relationship containing output gap $OutputGap_{t-4}$ and potential output $OutputTrend_{t-4}$ as these are generally used to characterise the position within the business cycle and trend development of the economy. 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. 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 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. 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 – 2018 Q4 (both gaps and trends are depicted in Figure A3 in Appendix A).

We use the fourth lag of the output gap and trend as this specification best explains the variability of both dependent variables. The explained variance decreases significantly with fewer lags and more leads.[13] Simple correlation analysis confirms the results: the correlation is the highest at the fourth lag (about 90%) and decreases with fewer lags. 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 may eventually result in debt-servicing difficulties. Additionally, the usual trigger for categorising 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.[14] Therefore, such a delay is not surprising, but it may potentially reinforce banks' inherent procyclicality.

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' capitalisation (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 capitalisation 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 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,

[13] Estimation results with different lags and leads are not reported but available upon request. The variants of estimations were made by changing the number of lags or leads and the final choice was based on the final degree of explained variability.

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

for example, Greenwalt 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, Bouvatir 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.

Changes in non-performing loans may be understood as a proxy for changes in lifetime expected credit losses in stage 3. This assumption 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 recognising 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 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 indicate provisioning procyclicality in stage 3 and potential triggers for a cliff effect under IFRS 9.

To explore potential asymmetries in the relationship, we introduce interaction dummies for a positive output gap (*dPositive*) and a rising output gap (*dRising*). As such, we can analyse 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).

$$Y_{i,t} = [\beta_2^1 dRising + \beta_2^2 d(1 - Rising)]OutputGap_{t-4} + \gamma_2 OutputTrend_{t-4} + \omega_2 X_{i,t-1} + \alpha_{2,i} + \epsilon_{2,t} \tag{2}$$

$$Y_{i,t} = [\beta_3^1 dPositiveRising + \beta_3^2 dPositive(1 - Rising) + \beta_3^3 (1 - dPositive)Rising + \beta_3^4 (1 - dPositive)(1 - Rising)]OutputGap_{t-4} + \gamma_3 OutputTrend_{t-4} + \omega_3 X_{i,t-1} + \alpha_{3,i} + \epsilon_{3,t} \tag{3}$$

Estimation Techniques

We use two estimation techniques. First, we employ a weighted fixed-effects model to estimate mean effects. 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] Second, we employ a quantile regression to examine how the response differs along with the distribution of the dependent variable. We implement the penalised quantile regression as proposed by Koenker (2004) 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 reduces variability. The degree of this shrinkage is controlled by a penalty parameter λ (for more details, see Koenker 2004).[16]

Data

We examine the proposed relationships using a sample period running from 2004 Q1 to 2017 Q4. We exclude data from January 2018 onward to estimate the effects consistently and 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] Due to data availability, the final sample covers 34 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 (foreign owners managed 92.1% of its total assets as of 2017 Q4). Most of the banks operate under a universal business model; only two banks can be categorised 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 characterised by high liquidity stemming from its strong client deposit base and growth in exposures to

[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.
[16] The estimation methods are implemented using the R package *plm* for the fixed effects model and *rqpd* for the quantile regression model.
[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 https://www.cnb.cz/en/financial-stability/macroprudential-policy/list-of-other-systemically-important-institutions/.

the central bank.[21] This fact provides banks with sufficient resources to ensure a stable and/or increasing credit supply.

Empirical Results

This subsection examines potential asymmetries in the relationship by employing panel data quantile regression and interaction dummy variables as described in section 3.[22] The mean regression results of equations (2) and (3) are reported in Table 1. 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 1). Complete estimation results are presented in Appendix B.[23]

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 the 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 et al. 2003, Bouvatier et al. 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 the strongest when loan loss provisions and non-performing loans are the highest. This finding indicates that banks with the highest credit risk are the most sensitive to changes in the business cycle, which is in line with similar studies (e.g., Quagliariello et al. 2009). 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 business cycle phase (Figure 1). This finding 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 capitalisation on loan loss provisions is positive and statistically significant, while the effect of banks' size is negative and statistically

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[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).

[22] 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.

[23] 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.

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 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).

Table 1: Panel Data Regression Results with Additional Controls and Interaction Variables

(A) Dependent variable: LLPL

Data:	(1)	(2)	(3)
Output gap (t-4)	**-0.160*** **		
	(0.017)		
Output gap (t-4)*dRising		**-0.191*** **	
		(0.021)	
Output gap (t-4)*(1-dRising)		**-0.132*** **	
		(0.022)	
Output gap (t-4)*dPositive*dRising			-0.031
			(0.036)
Output gap (t-4)*(1-dPositive)*dRising			**-0.357*** **
			(0.033)
Output gap (t-4)*dPositive*(1-dRising)			0.057
			(0.035)
Output gap (t-4)*(1-dPositive)*(1-dRising)			**-0.286*** **
			(0.033)
Output trend, growth (t-4)	**-0.120*** **	**-0.116*** **	**-0.128*** **
	(0.026)	**(0.028)**	**(0.029)**
ROA (t-1)	**0.076*** **	**0.075*** **	**0.060** **
	(0.024)	**(0.024)**	**(0.023)**
Equity to Assets (t-1)	**0.044*** **	**0.037*** **	**0.049*** **
	(0.014)	**(0.014)**	**(0.014)**
Bank size (t-1)	**-0.179* **	**-0.226** **	**-0.176* **
	(0.100)	**(0.103)**	**(0.102)**
FE included	Y	Y	Y
Observations	1,360	1,324	1,324
Within R2	0.155	0.148	0.145
Overall R2	0.914	0.916	0.919

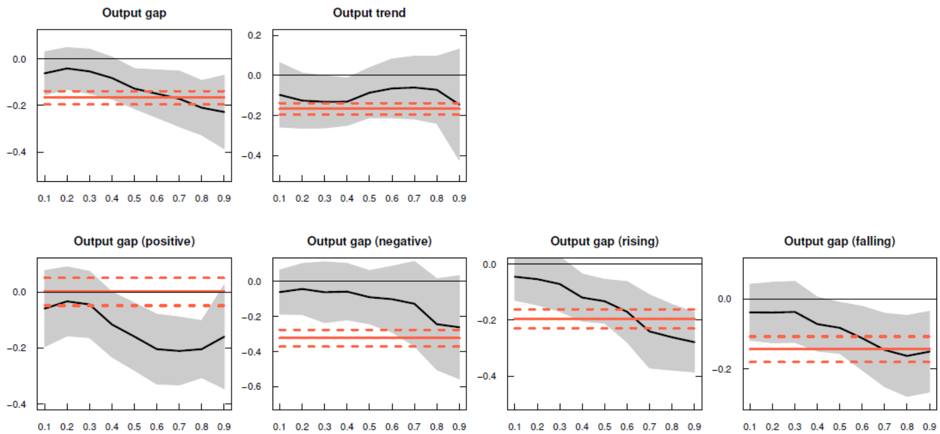
(B) Dependent variable: NPLL

Data:	(4)	(5)	(6)
Output gap (t-4)	**-0.391*** **		
	(0.035)		
Output gap (t-4)*dRising		**-0.433*** **	
		(0.041)	
Output gap (t-4)*(1-dRising)		**-0.343*** **	
		(0.044)	
Output gap (t-4)*dPositive*dRising			**-0.217*** **
			(0.072)
Output gap (t-4)*(1-dPositive)*dRising			**-0.667*** **
			(0.066)
Output gap (t-4)*dPositive*(1-dRising)			-0.057
			(0.071)
Output gap (t-4)*(1-dPositive)*(1-dRising)			**-0.586*** **
			(0.066)
Output trend, growth (t-4)	-0.040	-0.042	-0.048
	(0.053)	(0.055)	(0.058)
ROA (t-1)	**0.235*** **	**0.228*** **	**0.0205*** **
	(0.048)	**(0.047)**	**(0.047)**
Equity to Assets (t-1)	0.040	0.020	0.038
	(0.028)	(0.028)	(0.028)
Bank size (t-1)	0.320	0.229	0.304
	(0.203)	(0.206)	(0.0204)
FE included	Y	Y	Y
Observations	1,360	1,324	1,324
Within R2	0.105	0.098	0.093
Overall R2	0.841	0.849	0.852

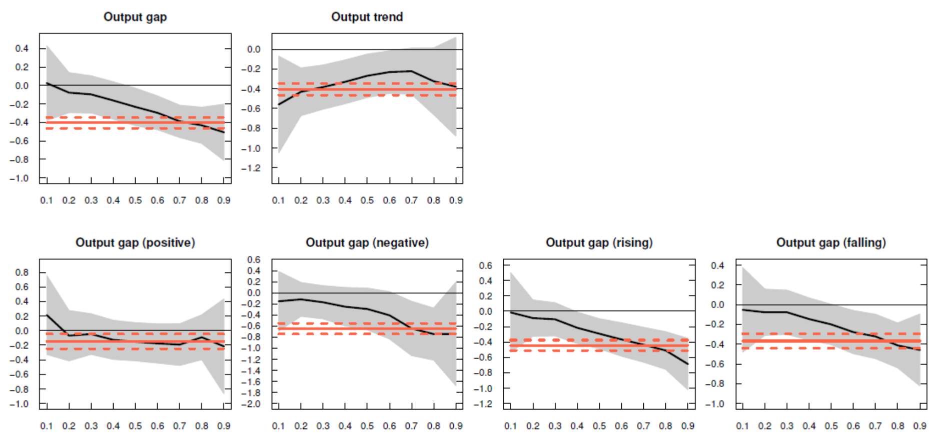
*Note: Specifications are estimated using the weighted fixed-effects model with time-invariant individual effects. Standard errors reported in parentheses; ***, **, and * denote the 1%, 5%, and 10% significance levels. The output gap and trend are estimated using a small structural model. The regression 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.*

Figure 1: 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.

Implications for Provisioning Procyclicality under IFRS 9

In what follows, we are going to discuss the potential implications of our empirical findings for provisioning procyclicality under IFRS 9. Firstly, it is essential to note that banks have only been applying IFRS 9 since the beginning of 2018, which limits the assessment of its potential effects. A complete 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 before the implementation of IFRS 9; therefore, our results indicate the provisioning procyclicality of exposures in stage 3, as explained in section 3, and potential delays in 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 summarised in Table 2. In particular, banks seem to recognise credit losses and create provisions with a delay with respect to worsening economic conditions: the increase in credit losses and loan loss provisions is concentrated mainly 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.[24] 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 aggravating 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 business cycle upturn and downturn 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 can usually 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 develop an adequate modelling 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

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

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 2: 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 1, columns 3 and 6.

Conclusions

In this paper, we examined banks' procyclicality using pre-2018 data, with an emphasis on potential asymmetries. Afterwards, we discussed the implications of this behaviour for provisioning in stage 3 under IFRS 9.

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

Further research can be done on the actual impacts and effectiveness of implementing the IFRS 9 standard. However, this can be possible when long enough time series are available. Based on this, macroprudential policymakers would have to analyse and, if necessary, react by calibrating the macroprudential policy tools that would smooth out the fluctuations. Another possible result is the successful implementation that would mean that banks create the provisions well in advance and can assess the creditworthiness of their borrowers in a forward-looking manner. Then the new provisioning regime would fulfil its intended effect. Successful implementation of the IFRS 9 regime is conditional on the availability of sufficient credit risk models and gradually decreasing the level of discretion of banks. Model validation of bank supervisors can at least partly contribute to the aggregate decrease of procyclicality of provisioning. However, it will take time to prevent the discretion between banks and support them in developing adequate credit risk models on the individual bank level.

Insufficient provisioning may justify implementing 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., 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 was decomposed in 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 (%)

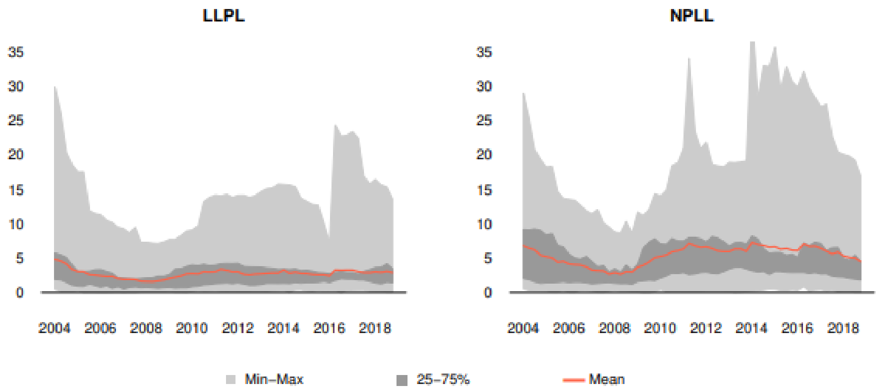


Figure A2: Impaired Credit Losses and Change in Non-Performing Loans (CZK billions)

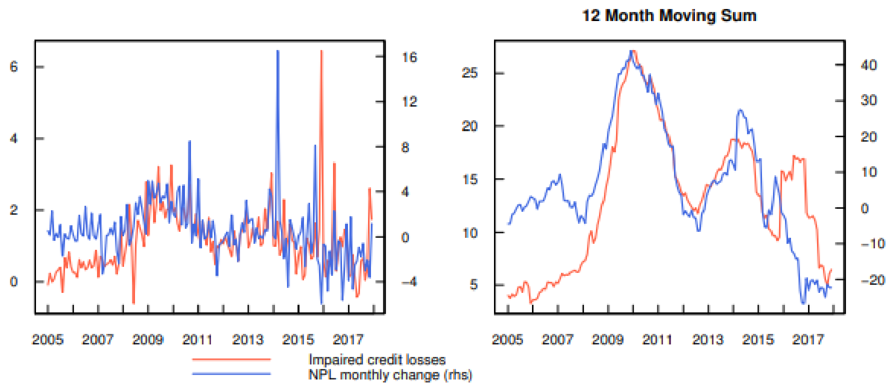
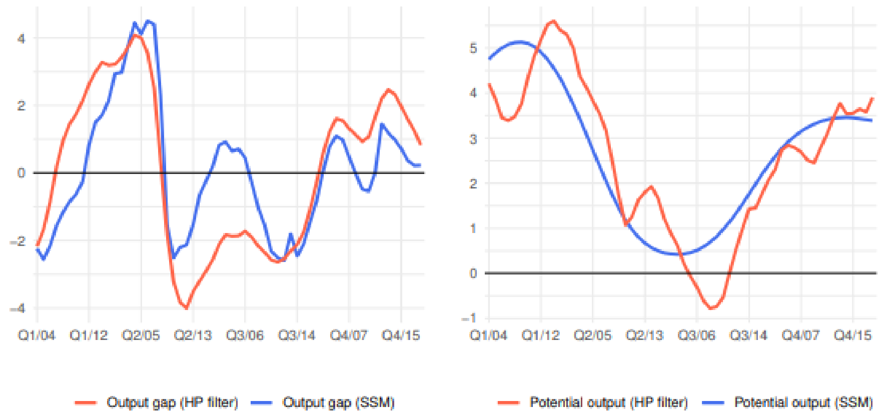


Figure A3: Proxy Variables for Business Cycle and Trend



Note: The output gap is expressed in percentages of the output trend (potential output), and the output trend is expressed in annual percentage changes.

Appendix B:

Table B1: Full Regression Results – Quantile Regression (2)

Panel A: Dependent variable: Loan loss provisions ratio

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
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

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
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 B2: Full Regression Results – Quantile Regression (3)

Panel A: Dependent variable: Loan loss provisions ratio

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
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

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
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.*