Loan Loss Accounting Rules and Bank Lending over the Cycle: Evidence from a Global Sample*

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Abstract

This study empirically analyzes how the cross-country differences in loan loss accounting rules affect banks' lending behavior over the business cycle. Our findings deliver new insights for the ongoing debate on the procyclicality of loan loss provisions and the potential impact on bank lending. Based on a novel dataset comprising detailed information on local GAAP provisioning rules in a large number of countries across the globe, we develop several indices that reflect banks' ability to take a forward-looking approach in the assessment of their credit risk reserves. These indices are used to explain the individual lending behavior of up to 4,575 banks in 52 countries. Consistent with the capital crunch hypothesis, we find that bank lending is more procyclical if banks are subject to more backward-looking loan loss accounting rules.

Key Words: Bank lending, loan loss provisioning, nonperforming loans, procyclicality.

JEL Classification: G21, M41.

1 Introduction

Bank lending often increases significantly during expansionary periods and then declines considerably during a subsequent downturn. These fluctuations are generally more than proportional to changes in economic activity, which indicates that at least part of the fluctuation is due to changes in loan supply (Berger and Udell (2004)).

The assumption that banks change their lending behaviour over the business cycle has long been studied from different perspectives. Asea and Blomberg (1998) demonstrate empirically that banks change their lending standards over the cycle, with laxer standards in expansionary periods and tighter standards in recessions. Among others, Rajan (1994) (short-term concerns), Berger and Udell (2004) (institutional memory hypothesis), Ruckes (2004) (screening profitability), and Ogura (2006) (bank rivalry) offer a variety of explanations for this observation.

Having short-term concerns means that bank management tries to improve its reputation by manipulating current earnings, which can be done by altering the bank's credit policy. In expansionary periods, Rajan (1994) argues that banks try to increase their reported earnings and thus their reputation through a more liberal credit policy. In recessionary periods, a bank's reputation does not significantly suffer if the entire borrowing sector is hit by a systematic adverse shock and other banks have to admit to poor earnings as well (cf. Bornemann *et al.* (2012) for empirical evidence). In this situation, banks' true earnings are low and they react by tightening their credit policy. According to the institutional memory hypothesis, an easing of credit standards in an expansion results from the deterioration in the ability of loan officers to detect potential loan problems as time passes since the bank's last significant experience with nonperforming loans (NPL). The screening profitability hypothesis posits that the average default probability of a borrower declines in an economic upswing which affects the profitability of screening and causes low screening activity in such times. This in turn leads to more intense price competition among banks and thus lower borrowing standards. The price competition disappears in a downswing, which leads to a tightening of credit standards. This is complemented by the bank rivalry hypothesis, which argues that banks loosen their credit standards in the second lending competition for a firm if they lose the first interbank competition.

All the theories outlined above presume that the credit quality in banks' loan portfolios, on average, declines in expansionary periods, although the low-quality borrowers might not systematically default on their payments until they are hit by a common adverse shock. In this context, the capital crunch hypothesis (Peek and Rosengren (1995)) argues that, in the presence of minimum capital requirements, large loan losses in recessionary periods potentially cause banks to restrict their lending activities (i. e. to "shrink") in order to meet those capital requirements.[1] In theory, this is particularly likely if banks are not allowed to generate provisions for latent credit risk as an additional buffer in an expansion, and vice versa (Wall and Koch (2000)). It is thus argued that the underlying loan loss accounting regime has the potential to amplify (mitigate) the capital crunch in a recession, in which case we speak of a procyclical (countercyclical) effect of loan loss provisioning rules (Dugan (2009)).

Our study contributes to the debate on the procyclicality of loan loss provisions and the associated impact on bank lending over the business cycle by explicitly analyzing the effect of the *underlying loan loss accounting rules* on the procyclicality of bank lending. In more detail, we exploit the heterogeneity in loan loss accounting rules across the globe to investigate whether the exclusive focus on *incurred losses* in the rules on the recognition of nonperforming loans and the related build-up of loan loss provisions leads to a higher fluctuation of bank lending with the business cycle than provisioning rules that allow or even require banks to take a forward-looking approach in the assessment of the credit risk reserve.

Following the theory, we hypothesize that banks' lending fluctuates more with the business cycle if the underlying loan loss accounting regime is backward-looking by international standards, i. e. if it does not allow latent risks to be taken into account through forward-looking specific loan loss provisions or different types of general loan loss provisions.

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[1] In a very similar context, Puri *et al.* (2011) confirm this relationship for German savings banks in the financial crisis.

For this purpose, we compile a comprehensive dataset that combines and processes information from various sources. Apart from accounting data at the bank level (BankScope) and macroeconomic data (IMF), we use data on loan loss accounting rules from the World Bank's Bank Regulation and Supervision Survey (e. g. Barth *et al.* (2012)), which are complemented by our own survey on loan loss accounting regimes among the central banks of eleven countries that are part of the Research Task Force on Regulation and Accounting of the Basel Committee on Banking Supervision (henceforth RTF-RA or Research Task Force). This information is aggregated in a number of provisioning indices that are supposed to reflect how "backward-looking" (or "forward-looking") a country's provisioning rules are. The empirical analyses based on these data cover up to 52 countries. In a large subsample, we are able to control for potential loan demand effects at the country level by incorporating information on quarterly changes in credit demand from various Bank Lending Surveys/Senior Loan Officer Surveys across the globe. Moreover, we account for the fact that international samples of banks are usually dominated in terms of observations by a few countries and in particular by Germany, the United States, and Japan. In one part of the paper, we thus apply a weighting scheme that assigns the same weight to all possible index values. This both increases heterogeneity in the indices and reduces the impact of a few large countries on the results.

Overall, we find that banks' lending fluctuates more with the business cycle (i. e. it is more procyclical) if they are subject to more backward-looking provisioning rules, which is in line with the theory and affirms the replacement of the *incurred loss model* in IAS 39 by the *expected loss model* in IFRS 9 from the perspective of economic and financial stability. In that sense, our paper has important policy implications. Furthermore, we do not find that a particular design of provisioning rules *per se* leads to stronger or weaker lending activities, which brings us to the tentative conclusion that the design of the loan loss accounting regime impacts on the "intertemporal allocation of lending activities". Our findings are robust to different macroeconomic variables, sample sizes, index weighting schemes (OLS vs. weighted least squares) as well as the choice of the provisioning index and the exclusion of the three largest countries in terms of bank-year observations.

Our paper complements a number of previous studies on the procyclicality of loan loss provisions and their impact on bank lending. Among existing cross-country studies, Laeven and Majnoni (2003) identify loan loss provisions to be procyclical in an international sample of banks, though the degree of procyclicality varies across countries, possibly due to differences in provisioning standards that are not considered in their study. Their finding is confirmed by Bikker and Metzemakers (2005) in a similar study with a focus on OECD countries and Pérez *et al.* (2008), Gebhardt and Novotny-Farkas (2011), and Domikowsky *et al.* (2014), who find different provisioning behavior in different loan loss accounting regimes or after changes in those regimes. Moreover, Fonseca and González (2008) and Vyas (2011) find that the institutional environment plays a role in banks' provisioning behavior. However, they do not consider the underlying structure of the provisioning regime either.[2] Closely related to our paper, Bouvatier and Lepetit (2008) and Soedarmono *et al.* (2012) investigate the effect of discretionary vs. non-discretionary loan loss provisions on bank lending. Both find that non-discretionary provisions amplify credit fluctuations, whereas discretionary provisions do not affect lending.[3] Finally, Beatty and Liao (2011) exploit the variation in the delay of expected loss recognition under the current *incurred loss model* in the U.S. and find that banks with more timely loss recognition keep lending activities in recessions more stable compared to banks with less timely loss recognition. Overall, however, none of these studies has yet been able to identify how the *underlying rules* affect banks' lending behavior over the business cycle. Our paper aims to close this gap.

The remainder of the paper is organized as follows: Section 2 introduces the data sources this study is based on. Section 3 explains our methodology and describes the baseline results. Section 4 presents various robustness tests. Section 5 concludes.

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2 Interestingly, Fonseca and González (2008) implicitly use data from the Bank Regulation and Supervision Survey by employing regulatory indices that were developed by Barth *et al.* (2004).

3 Their measure of non-discretionary loan loss provisions is based on loans that are reported as nonperforming. Our own data on provisioning rules from the Bank Regulation and Supervision Survey, however, indicate that many countries allow banks to classify a loan as nonperforming based on a forward-looking estimate of the PD. In that case, the decision to classify a loan as nonperforming is already discretionary.

2 Data

2.1 Bank-level data

Relevant accounting data on a large international sample of 4,575 banks from 52 countries between 1997 to 2012 are obtained from Bureau van Dijk's BankScope database. We conduct some standard adjustments to the raw data: First, we drop banks that are classified as "dissolved" or "dissolved (merger)" to avoid double-counting of bank-year observations.[4] Second, we keep only banks with business models that are subject to the Basel guidelines and thus relevant for this study. These bank types are commercial banks, savings banks, cooperative banks, bank holding companies and real estate and mortgage banks. Third, we drop countries with questionable data quality or very few observations from the original dataset which contained additional countries (e. g. Papua New Guinea, Yemen, Zimbabwe). Conventional regression diagnostics, e. g. an analysis of studentized residuals, indicate that including these countries in our regressions yield outliers with high leverage regarding coefficient estimates, which is likely to bias our results. Fourth, we exclude banks with fewer than six observations over the sample period. This is because both the quantity and the quality of the data in BankScope have evidentially improved over time and banks with very short histories are usually at the upper bound of the sample, which would put too much weight on the most recent periods. Additionally, a minimum number of observations per bank can generally be useful in a study on procyclicality. Fifth, we winsorize all non-binary bank-specific variables at the 1% and 99% levels.

[4] BankScope treats merging banks as a new bank with a new ID and consolidates the annual reports of the pre-merger banks backwards. By dropping the pre-merger observations of those banks, we avoid double-counting of bank-year observations.

2.2 Macroeconomic variables

Macroeconomic variables are provided by the IMF's International Financial Statistics (IFS) database and available for most of the countries of the initial BankScope sample. The macroeconomic regressor in our baseline specification is the growth rate of nominal GDP since loans are reported in nominal terms as well. To test the sensitivity of the results to the choice of macroeconomic regressor, we use the growth rate of real GDP and the unemployment rate for alternative specifications. Real GDP does not move through changes in inflation, which may otherwise cloud the true GDP dynamics if inflation is high and volatile. Since the retail part of banks' lending business has frequently turned out to be more responsive to the unemployment rate than to GDP, we decided to include the former in a robustness test, too.

Our provisioning indices are not binary variables but assume a range of different values (cf. Table 2), which is also reflected in the interaction terms of the provisioning indices with the relevant macroeconomic regressor. Because the interaction term is at the core of the paper's main hypothesis, the structure chosen for the two main provisioning indices will play a crucial role in testing the research hypothesis. In order to confirm that the empirical results are robust to both the construction of the provisioning indices and the resulting interaction terms, we not only replace the indices through sets of binary variables in one set of regressions (cf. Section 4.1), but also use a binary indicator published by the Economic Cycle Research Institute (ECRI) representing the peaks and troughs in the business cycle as a separate robustness test. The ECRI indicators are available for 15 industrialized and emerging-market countries in our initial dataset. We extend the indicators by defining all periods following a trough up to and including the subsequent peak as economic expansions, while all other periods represent recessions. These robustness tests are presented in Section 4.2.

2.3 Provisioning indices

In order to investigate the impact of provisioning models on the procyclicality of bank lending, it is crucial to compile a dataset that contains information on the most relevant characteristics of loan loss accounting regimes that might either amplify or mitigate the timeliness of loan loss provisions and, in a second step, the procyclicality of bank lending. Moreover, the attempt to establish a relationship between provisioning rules and bank lending requires sufficient heterogeneity in the underlying loan loss accounting regimes.

For this purpose, we use a comprehensive dataset on provisioning rules in more than 150 countries and aggregate the information in this dataset by creating indices that are supposed to reflect how "backward-looking" (or "forward-looking") a country's provisioning rules are. The term "backward-looking" is used to specify how far a country's provisioning rules follow an *incurred loss model*, whereas the term "forward-looking" is used to describe to what extent the recognition of *expected losses* and/or *latent risks* is allowed. In a companion paper, Domikowsky (2014) provides a detailed description of the data collection process, the process of generating different indices and the distributions of these indices across the globe. In this paper, we limit ourselves to a short description of the data and the indices that are relevant for this study.[5]

Data on provisioning rules are available from the World Bank's Bank Regulation and Supervision Survey (BRSS). The survey has so far been conducted four times with releases in the years 2000, 2003, 2007 and 2012.[6] The BRSS comprises a total of twelve sections that provide in-depth information on bank accounting as well as bank regulation and supervision across the globe. Section 9 of the BRSS explicitly covers provisioning requirements. Unfortunately, both the number of participating countries as well as the questions on provisioning requirements have changed over time. For example, information on the requirement to build general provisions was

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[5] Nonetheless, we emphasize that the description of the indices as well as the associated tables are almost identical to those in Domikowsky (2014).

[6] This section draws heavily on Barth *et al.* (2001), Barth *et al.* (2004), Barth *et al.* (2008) and Barth *et al.* (2012).

only introduced in 2012. Thus the indices that we establish partly rely on the assumption that loan loss accounting rules do not significantly change over time, which is a common drawback shared by other studies (e. g. Bouvatier and Lepetit (2008) or Bushman and Williams (2012)). To address this issue, however, we ask the same questions as the BRSS as part of our own survey on loan loss accounting rules among the central banks of eleven (rather highly developed) countries in which structural changes in loan loss accounting rules over time are explicitly covered.[7] Thus for the largest countries, we have very reliable information on loan loss accounting rules. This subsample is examined in a robustness test in Section 4.4. The BRSS information that is relevant for this study can be collected from the 2007 and 2012 survey rounds. Overall, we obtain the following information[8]:

1. *Is there a formal definition of a nonperforming loan? (Yes/No = 1/0)*
2. *Is the primary classification as a nonperforming loan based on days in arrears? (Yes/No = 1/0)*
3. *Is the primary classification as a nonperforming loan based on a forward-looking estimate of the PD? (Yes/No = 1/0)*
4. *Is there a minimum provision required if a loan is classified as nonperforming? (Yes/No = 1/0)*
5. *Are banks required to build general provisions for the loan portfolio? (Yes/No = 1/0)*

We generally adopt the (Yes/No = 1/0) classification from the BRSS, which makes the information suitable for an application in empirical analyses. We interpret the information in the following way: Question (Q) 1 is a first indicator of the stringency of a loan classification scheme. We associate the existence of formal rules with less discretion, but their existence does not necessarily imply that those rules are

[7] This survey was conducted among the members of the Research Task Force on Regulation and Accounting (RTF-RA) of the Basel Committee on Banking Supervision.

[8] For a better presentation, the wording of the questions is slightly different from the wording of the BRSS, but it should not alter their meaning.

backward-looking. Q2 and Q3 are very important questions about how backward-looking (or forward-looking) a loan classification scheme is. Obviously, we do not learn about the precise design of such a scheme (it certainly makes a difference if a loan is classified as in arrears after 30 or 180 days), but the questions allow us to gain some insight about the underlying structure of a loan classification scheme. Despite the word "primary", a comparatively large number of countries affirmed both Q2 and Q3. Q4 attempts to connect the loan classification scheme to explicit provisioning rules. If it is affirmed, banks are required to build a minimum provision once a loan is classified as nonperforming. Minimum provisions are effectively a lower bound and thus an indicator of limited discretion. In this setting, we acknowledge that we do not distinguish between minimum provisions of 20% or 90% or the consideration of collateral, which clearly makes a difference. However, it helps to learn about the underlying structure of a country's loan classification and provisioning scheme. Q5 is designed to collect information on the requirement to explicitly build a buffer for latent risks with the help of general loan loss provisions, which is another indicator of a forward-looking provisioning scheme. Unfortunately, this question only helps to learn about the *requirement* to build general provisions, but it might still be possible that banks are *allowed* to do so in the absence of such requirement.

We then aggregate this information in different indices that are meant to reflect how backward-looking a provisioning regime is. The process of establishing these indices is obviously to some degree discretionary. Thus we will describe the rationale behind the indices in detail and offer three alternative grouping options.[9]

The indices are generated in a two-stage process. In the first stage, we assign different values to different combinations of loan classification and provisioning characteristics that we directly associate with a more backward-looking (or more forward-looking) provisioning regime. A higher index value implies a more backward-looking provi-

[9] We take a different approach to that of Barth *et al.* (2001) in their indices on loan classification and provisioning stringency, primarily because they do not distinguish between forward-looking and backward-looking systems and because of a limited applicability in multivariate analyses. A detailed explanation can be found in Domikowsky (2014).

sioning regime.[10] The calculation of three alternative first-stage indices is displayed in Table 1.

Table 1: Possible index values of the first stage of three indices for backward-looking provisioning.

First-stage indices						
Indices			Question no.			
(1)	(2)	(3)	Q2	Q3	Q4	Description
1	1	1	No	Yes	No	NPL classification is based exclusively on a forward-looking estimate of the PD and there is no minimum provision for NPL.
2			No	Yes	Yes	NPL classification is based exclusively on a forward-looking estimate of the PD and there is a minimum provision for NPL.
3	2		Yes	Yes	No	NPL classification is based both on days in arrears and on a forward-looking estimate of the PD and there is no minimum provision.
4			Yes	Yes	Yes	NPL classification is based both on days in arrears and on a forward-looking estimate of the PD and there is a minimum provision.
5	3	2	Yes	No	No	NPL classification is based on days in arrears only and there is no minimum provision.
6			Yes	No	Yes	NPL classification is based on days in arrears only and there is a minimum provision.

NB: The table shows the construction of the first stage of three different impairment indices before increasing the index value if there is a formal definition of NPL (+1) and before accounting for general provisions (–1). Columns 1-3 present the index values. The solid lines under the values in columns 1-3 separate the index categories. Columns 4-6 provide the combination of responses to the different questions. Column 7 provides a written summary of the information in columns 4-6. The combinations *No—No—No* and *No—No—Yes* for Q2-Q4 are not part of any first-stage index because we presume that days in arrears and a forward-looking estimate of the PD are the two core drivers of NPL classification.

Index (1) is the most detailed first-stage index and can adopt six values. In our classification, a provisioning regime belongs to the most forward-looking category if the classification of a loan as nonperforming is exclusively based on a forward-looking estimate of the PD and, if a loan is nonperforming, banks can decide about the size of the provision without being restricted by a minimum provision. This is both forward-looking and gives additional flexibility due to the lack of a minimum provision. The second category is almost identical to the first one, with the exception that banks in such provisioning regimes have to build a minimum provision for

[10] This is essentially a matter of taste and could be designed the other way round.

nonperforming loans. In categories 3 and 4, the loan classification is based both on days in arrears and a forward-looking estimate of the PD and they differ only in the requirement of minimum provisions. One could argue that these systems are more comprehensive than the ones in categories 1 and 2. We argue, however, that the forward-looking component enables banks to build provisions for expected losses in times of economic well-being, but the backward-looking component (days in arrears) prohibits any flexibility in economic downswings. Categories 5 and 6 are closest to what is generally described as an incurred loss model: NPL are exclusively based on days in arrears and there is no forward-looking component. Category 6 even demands a minimum provision for NPL. It becomes clear that we put more emphasis on the loan classification than on minimum provisions because we assume that banks generally have to build some sort of provision once they classify a loan as nonperforming and minimum provisions just restrict banks' discretion as regards the size of the provision.

Index (1) is the most comprehensive index definition. By specifying equidistant index values, we implicitly assume equal incremental effects by moving from one index category to an adjacent category. To test if this is indeed the case and to allow for heterogeneous effects of different index values, we also estimate the incremental effect of each index value separately in a robustness test using binary variables instead of an index. Moreover, we offer two alternative index definitions that are less granular than Index (1). Index (2), which is displayed in column 2 of Table 1, can adopt one of three different values that reflect systematic differences in the underlying loan classification scheme (forward-looking only, forward- and backward-looking, and backward-looking only). It thus neglects the information on minimum provisions. Index (3) can only adopt one of two different values and distinguishes whether or not a provisioning regime has a forward-looking component at all. Index (3) also reflects our expectation that the most fundamental aspect of a loan loss accounting regime should be captured by the difference between regimes with a forward-looking component and those without a forward-looking component.

At the second stage of each index, we add +1 if there is a formal definition of a nonperforming loan in a provision regime (yes to Q1). For a subsample of countries that participated in the 2012 BRSS, we can extend the indices and reduce them by one (-1) if a provisioning regime allows or requires banks to build general provisions (yes to Q5). Finally, it is clear that a formal NPL definition and the requirement to build general provisions, if applicable, have different weights depending on which of the first-stage indices they are added to. The values that the different second-stage indices can take are reported in Table 2.

Table 2: Possible index values of the second stage of the indices for backward-looking provisioning.

Second-stage indices					
+1 for a formal definition of NPL (Q1)			+1 for a formal definition of NPL (Q1) – 1 if general provisions are required (Q5)		
(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
			0	0	0
1	1	1	1	1	1
2	2	2	2	2	2
3	3	3	3	3	3
4	4		4	4	
5			5		
6			6		
7			7		

NB: The table shows the construction of the second stage of three different impairment indices, i. e. after increasing the index value if there is a formal definition of NPL (+1) and before accounting for general provisions (–1). Columns 1-3 present the possible index values when general provisions are not considered at all. Columns 4-6 present the possible index values including general provisions.

2.4 Loan demand

The observation of a decline in lending volume can stem from an adverse shock to loan supply or loan demand. Separating loan supply effects from loan demand effects is generally difficult, especially when borrower-level information is lacking (Kashyap and Stein (2000), Puri *et al.* (2011)). In our setting, controlling for loan demand should be less important than in other studies because we analyze changes in lending due to differences in provisioning standards. From an economic perspective, provisioning standards should only affect the *supply* side of changes in bank lending. Shocks to loan *demand* in a recession, on the contrary, should not be systematically related to provisioning standards, but rather be similar in all countries. Nonetheless, we control for loan demand in two different ways, one of which involves data from different *Bank Lending Surveys (BLS)* and *Senior Loan Officer Surveys (SLOS)*.

BLS/SLOS are quarterly surveys that were introduced to expand knowledge about the role of lending in the monetary transmission process. These surveys are available for 27 countries, with a clear focus on Europe and North America.[11] Since most bank-year observations are from these regions as well, the BLS/SLOS subsample contains a large share of the full sample. On the positive side, the surveys are very similar in terms of structure and frequency. On the negative side, the different surveys are not available for the full sample period, but did not start until 1999 (United States, Canada), 2000 (Japan), 2003 (most of the euro area) or 2007 (Norway, United Kingdom).

The BLS/SLOS provide important information for this study because they assess *past changes in credit demand* based on interviews with senior loan officers at a number of banks in each participating country. More precisely, the senior loan officers are asked to give an estimate of how credit demand has changed quarter-over-quarter. In the BLS of the ECB (European Central Bank (2014)), the precise question is

"Over the past three months, how has the demand for loans or credit lines to enterprises changed at your bank, apart from normal seasonal fluctuations?".

The aggregate responses to questions related to credit demand are generally reported as the difference ("net percentage") between the share of banks that report an increase in loan demand and the share of banks reporting a decline. A positive net percentage indicates that a larger proportion of banks have reported an increase in loan demand, whereas a negative net percentage indicates that a larger proportion of banks have reported a decline in loan demand. An alternative measure of the responses to questions related to changes in credit demand is the "diffusion index". This measure is defined by the ECB as the *weighted* difference between the share of banks reporting an increase in loan demand and the share of banks reporting a decline (European Central Bank (2014)). The diffusion index is constructed in the

[11] The actual number of countries that are covered in the analyses will be lower due to data restrictions regarding other relevant variables, e. g. data on loan loss accounting rules.

following way: Loan officers responding that loan demand has increased/decreased "considerably" are given a weight twice as high (score of 1) as loan officers responding that loan demand has increased/decreased "somewhat" (score of 0.5). The interpretations of the diffusion indices and net percentages are identical (European Central Bank (2014)).

Our variable to control for loan demand is a country's average reported net percentage change in loan demand over one year. It can take values from –100 to +100. For seven countries, we take the diffusion index instead of the net percentage because the latter is not available.

3 Empirical results

3.1 Methodology

In order to test the hypothesis that banks in jurisdictions with more backward-looking provisioning regimes will contract lending more strongly during economic downturns than banks operating under more forward-looking loan loss accounting rules, we regress the growth rate of total loans on a number of standard bank-specific control variables, a macroeconomic regressor capturing the business cycle, the accounting index, and an interaction term pairing the macroeconomic regressor with the accounting index. Equation (1) is our baseline model:

$$\begin{aligned}\Delta\text{Loans}_{i,t} = \beta_0 &+ \beta_1 \cdot \text{NDI}_{i,t-1} + \beta_2 \cdot \text{Equity}_{i,t-1} + \beta_3 \cdot \text{Loans}_{i,t-1} \\ &+ \beta_4 \cdot \text{Deposits}_{i,t-1} + \beta_5 \cdot \log(\text{TA})_{i,t-1} \\ &+ \beta_6 \cdot \Delta\text{NGDP}_{c,t} + \beta_7 \cdot \text{ProvIndex(1/2/3)b}_{c,t} \\ &+ \beta_8 \cdot \Delta\text{NGDP}_{c,t} \cdot \text{ProvIndex(1/2/3)b}_{c,t} + \epsilon_{i,t}.\end{aligned} \tag{1}$$

Our main measure of banks' lending behavior is the loan growth rate $\Delta\text{Loans}_{i,t}$, which is defined as the relative change in total lending of bank i from year $t-1$ to year t. In terms of the dependent variable as well as bank-specific control variables, we largely follow Beatty and Liao (2011). The bank-specific control variables comprise a bank's non-discretionary income ($\text{NDI}_{i,t-1}$), its equity ($\text{Equity}_{i,t-1}$), its share of loans to total assets ($\text{Loans}_{i,t-1}$), its deposit volume ($\text{Deposits}_{i,t-1}$) and the natural logarithm of its total assets ($\log(\text{TA})_{i,t-1}$). All bank-specific control variables are specified with a one-period lag and, with the exception of the log of total assets, are divided by total assets. We expect a bank with a comparatively high non-discretionary income to increase its loan supply in the next period. The same applies to banks with a high equity ratio because those banks are less likely to be exposed to a capital crunch. We use a bank's equity ratio as a proxy for its regulatory capital ratio because the latter is only weakly covered in BankScope. Additionally, we expect banks to increase their lending relatively less in the next period if their share of loans to total assets is already high. Based on Ivashina and Scharfstein (2010), we expect to see a positive relationship between a bank's share of deposits to total assets and its loan supply in the following year. The lagged log of total assets is included to control for potential size effects (e. g. Kashyap and Stein (2000)).

$\Delta\text{NGDP}_{c,t}$ is a country's nominal GDP growth rate, and $\text{ProvIndex}(1/2/3)\text{b}_{c,t}$ are our baseline accounting indices based on the right half of Table 2 ($\text{ProvIndex1b}_{c,t}$ vs. $\text{ProvIndex2b}_{c,t}$ vs. $\text{ProvIndex3b}_{c,t}$). We are primarily interested in $\Delta\text{NGDP}_{c,t} \cdot \text{ProvIndex}(1/2/3)\text{b}_{c,t}$, which is the interaction of these variables. While the control variables are all bank-specific, nominal GDP, the accounting index, and the interaction term that pairs the growth rate of nominal GDP with one of the accounting indices are country-specific. They take on identical values for all banks domiciled in the same jurisdiction.

The coefficient β_7 shows whether banks in countries with a more backward-looking provisioning regime display a higher or lower average loan growth rate than banks governed by a more forward-looking accounting regime. Since the accounting index is the only group-level intercept variable in the regression, part of the difference in loan growth in each group of countries sharing the same index value may be unrelated to the accounting regime, so we interpret that coefficient with caution. While the coefficient β_6 captures the responsiveness of loan growth to nominal GDP growth that is shared by all banks in the sample, β_8 addresses our main hypothesis by showing the incremental response by bank i depending on the accounting regime under which it operates.

The baseline regression, as well as most of the robustness tests, are estimated under pooled OLS to allow for the identification of β_7. If we were to allow for fixed effects (i.e. bank-specific intercepts) or country-specific intercepts, those regressors would completely pre-empt the information required to identify the impact of the accounting regime on average loan growth. Because the macroeconomic regressor is country-specific, we need to cluster the standard errors by country to account for the residual correlation across banks domiciled in the same country that arises by construction.[12]

[12] Clustering by index value would result in too few clusters, each of a very large size; hence we deliberately chose to cluster by country.

3.2 Descriptive statistics

Table 3 reports descriptive statistics for the dependent variable as well as our bank-level control variables and different macroeconomic variables. The numbers are based on the full sample.

Table 3: Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	p25	p50	p75
$\Delta\text{Loans}_{i,t}$	57,565	0.085	0.255	-0.006	0.037	0.101
$\text{NDI}_{i,t-1}$	65,070	0.007	0.013	0.003	0.006	0.011
$\text{Equity}_{i,t-1}$	65,256	0.096	0.104	0.050	0.071	0.103
$\text{Loans}_{i,t-1}$	64,667	0.602	0.198	0.504	0.628	0.735
$\text{Deposits}_{i,t-1}$	63,497	0.681	0.211	0.596	0.728	0.824
$\Delta\text{NGDP}_{c,t}$	57,968	0.031	0.047	0.013	0.026	0.049
$\Delta\text{RGDP}_{c,t}$	57,811	0.015	0.027	0.004	0.018	0.032
$\Delta\text{UR}_{c,t}$	57,613	0.011	0.174	-0.081	-0.030	0.075
$\text{ECRI\_PT}_{c,t}$	56,008	0.743	0.437	0.000	1.000	1.000
$\text{BLS\_Demand}_{c,t}$	43,891	-1.516	21.910	-14.062	2.500	14.275

$\Delta\text{Loans}_{i,t}$ exhibits a mean value of 8.5% and a median of 3.7%, which indicates that banks substantially expanded their their lending during our sample period. The distribution of $\Delta\text{Loans}_{i,t}$ is right-skewed, and 25% of all observations report a loan growth rate of more than 10.1%. It is important to note that these are *nominal* growth rates, and that some countries exhibited an expansionary monetary policy during our sample period. *Real* loan growth rates could be significantly lower.

The distribution of our bank-specific control variables is generally in line with our expectations. ($\text{NDI}_{i,t}$) has a mean value of 0.7%, and ($\text{Equity}_{i,t}$) has a mean value of 9.6%, indicating that the banks in our sample are *on average* sufficiently capitalized. The median and p25 equity ratios, however, are far below that value, which supports the expectation that capital crunches may exist in our data. Further, the banks in our sample have an average ratio of loans to total assets ($\text{Loans}_{i,t}$) of 60.2%, and a ratio of deposits to total liabilities ($\text{Deposits}_{i,t}$) of 68.1%. Those values emphasize the considerable importance of lending and deposit business for the banks in our sample. The distribution of the bank size is heavily right-skewed, so we consider the natural logarithm of total assets ($\log(\text{TA})_{i,t}$) as our measure of bank size.

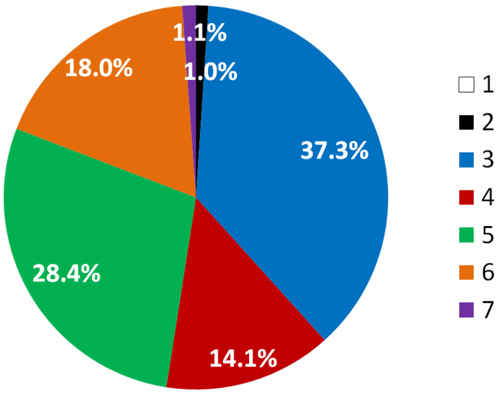
Beside the dependent variable and the bank-specific control variables, Table 3 reports the summary statistics for different macroeconomic variables. ($\Delta \text{NGDP}_{c,t}$), which is used to measure the cyclicality of banks' loan growth relative to macroeconomic indicators in the baseline model, exhibits a mean value of 3.1% and a slightly lower median of 2.6%. Given that $\Delta \text{Loans}_{i,t}$ is measured in nominal terms, we prefer this measure to the growth rate of real GDP ($\Delta \text{RGDP}_{c,t}$), which we consider in a robustness test in Section 4.2. Moreover, we use alternative macroeconomic variables, including the change in the unemployment rate ($\Delta \text{UR}_{c,t}$) and the business cycle peak and trough dates provided by the Economic Cycle Research Institute ($\text{ECRI\_PT}_{c,t}$), in a robustness test in the same section. Table 3 provides the summary statistics for those variables as well.

In Section 4.3, we also consider bank lending survey data to check our results for robustness regarding loan demand effects. The variable $\text{BLS\_Demand}_{c,t}$, as explained in Section 2.4, reflects the net percentage change of loan demand (alternatively, the change in the diffusion index). The mean change of this variable is close to zero.

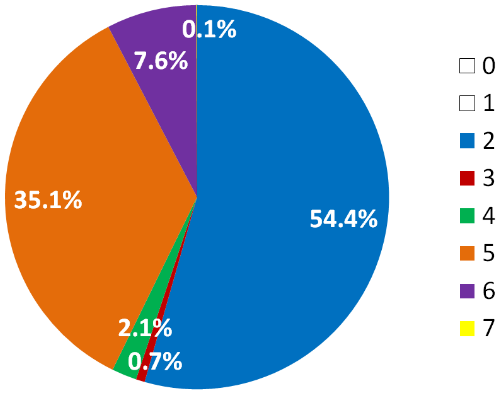
For an empirical description of the six provisioning indices defined in Table 2, we depict the distribution of observations across index values in Figure 1. These distributions are not only interesting in their own right, but will also have a considerable influence on the statistical identification of our empirical hypothesis. For the two versions of the most granular index definition, ProvIndex1a and ProvIndex1b, we find that index value 1 for ProvIndex1a and index values 0 and 1 for ProvIndex1b are not represented at all in the two different samples. While the resulting range of sample values is identical for the two index definitions, ProvIndex1b incorporates more information than ProvIndex1a. In both indices there are two values which are supported by only around 1% (ProvIndex1a), or even less than 1% (ProvIndex1b), of sample observations. The absence or weak representation of several index values is a drawback of the sample under both index definitions, but the fact that the more strongly represented index values span a major part of the spectrum of admissible values in each case will help to strengthen identification.

Moving to the less granular index definitions ProvIndex2a and ProvIndex2b, we again find that index value 1 for ProvIndex2a and index value 0 for ProvIndex2b are not at all supported by sample observations. The distributions of observations across index values found for ProvIndex2a and ProvIndex2b are almost identically reflected in the corresponding distributions for ProvIndex3a and ProvIndex3b, with all index values shifted by one category. The more balanced distribution of observations across index values relative to ProvIndex1a and ProvIndex1b makes all of the less granular indices particularly useful for robustness tests as regards econometric alternatives to our baseline setup. Viewing the distributions of observations across index values together, we can expect all six index definitions to be properly identified in our regression setup. However, when we want to confirm the validity of the chosen structure for each of the indices by using binary indicators for each index value separately, we need to bear in mind that some index values will be more robustly identified than others.

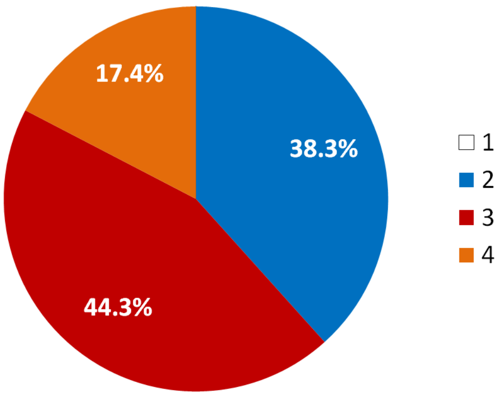
Figure 1: Distribution of observations across index values for the indices ProvIndex(1/2/3)a and ProvIndex(1/2/3)b.



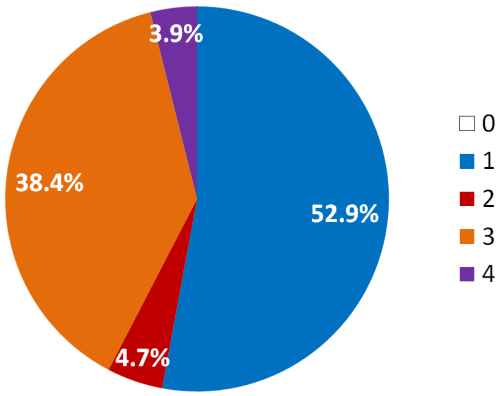
(a) ProvIndex1a



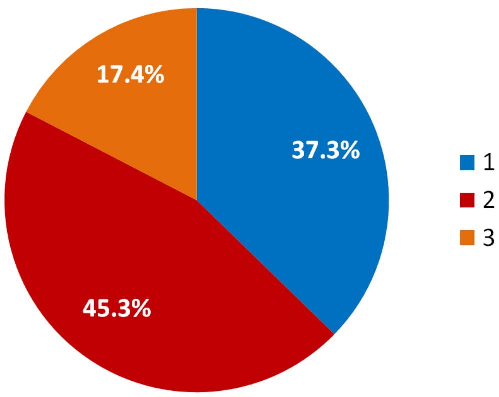
(b) ProvIndex1b



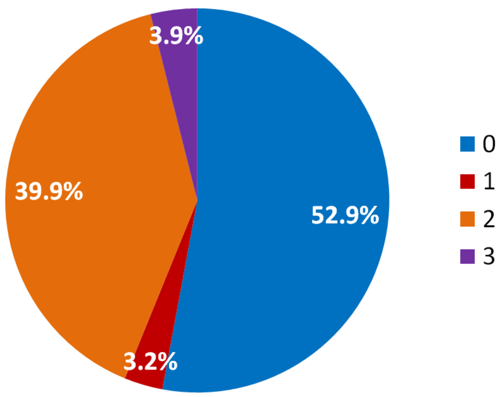
(c) ProvIndex2a



(d) ProvIndex2b



(e) ProvIndex3a



(f) ProvIndex3b

3.3 Baseline results

Table 4 presents our baseline results. It is evident that the coefficients for $\Delta \mathrm{NGDP}_{c,t}$ as stand-alone variables are statistically insignificant, as are coefficient estimates for all specifications of ProvIndex(1/2/3)$\mathrm{b}_{c,t}$. However, the interaction terms for $\Delta \mathrm{NGDP}_{c,t} \cdot$ ProvIndex(1/2/3)$\mathrm{b}_{c,t}$ in models (1)–(3) exhibit positive and significant coefficients. This implies that a more backward-looking provisioning regime amplifies the effect of GDP growth on bank lending, which is a sign of higher cyclicality of bank lending.

These results can be illustrated in a numerical example. The overall effect of nominal GDP growth on bank lending for a bank with $\mathrm{ProvIndex3b}_{c,t} = 0$ would be $\beta_6 + 0 \cdot \beta_8 = 0.236$, indicating that the estimated effect of a 1% increase in GDP growth would be a 0.236% increase in loan growth. In a more backward-looking provisioning regime, where $\mathrm{ProvIndex3b}_{c,t} = 3$, the effect would be higher ($\beta_6 + 3 \cdot \beta_8 = 1.352$), meaning that a 1% increase in GDP growth would translate into a 1.352% increase in loan growth. This finding suggests that banks' lending fluctuates more with the business cycle if the underlying loan loss accounting regime is comparatively backward-looking by international standards, which was our initial hypothesis.

This result is evident for all specifications of ProvIndex(1/2/3)$\mathrm{b}_{c,t}$, which are tested in models (1)–(3) of Table 4. Moreover, the coefficients of our control variables largely exhibit their expected signs. A higher non-discretionary income ($\mathrm{NDI}_{i,t-1}$) translates into stronger loan growth because more profitable banks are able to finance higher growth rates. The same rationale holds for banks with higher equity ratios ($\mathrm{Equity}_{i,t-1}$), as well-capitalized banks are strong enough to grow at higher rates than relatively weak banks. Further, our baseline regressions show that smaller banks in terms of $\log(\mathrm{TA})_{i,t-1}$ as well as banks that have a low fraction of assets invested in $\mathrm{Loans}_{i,t-1}$ exhibit lower loan growth rates. Our definition of $\Delta \mathrm{Loans}_{i,t}$ is the *relative* growth rate from $t-1$ to the year t, where the reference level in $t-1$ is lower for banks with fewer loans among their assets. Hence, a similar absolute lending increase

Table 4: Baseline results for ProvIndex(1/2/3)$b_{c,t}$ and $\Delta NGDP_{c,t}$.

Dep. Variable	(1) $\Delta Loans_{i,t}$	(2) $\Delta Loans_{i,t}$	(3) $\Delta Loans_{i,t}$
$NDI_{i,t-1}$	1.008*	0.973*	0.973*
	(0.504)	(0.497)	(0.497)
$Equity_{i,t-1}$	0.153**	0.165**	0.173***
	(0.065)	(0.063)	(0.062)
$Loans_{i,t-1}$	-0.151***	-0.145***	-0.140***
	(0.031)	(0.029)	(0.027)
$Deposits_{i,t-1}$	-0.033	-0.029	-0.027
	(0.022)	(0.024)	(0.024)
$\log(TA)_{i,t-1}$	-0.005***	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)
$\Delta NGDP_{c,t}$	-0.071	-0.144	0.236
	(0.322)	(0.298)	(0.211)
$ProvIndex1b_{c,t}$	0.006		
	(0.004)		
$\Delta NGDP_{c,t} \cdot ProvIndex1b_{c,t}$	0.184***		
	(0.060)		
$ProvIndex2b_{c,t}$		0.005	
		(0.006)	
$\Delta NGDP_{c,t} \cdot ProvIndex2b_{c,t}$		0.382***	
		(0.108)	
$ProvIndex3b_{c,t}$			0.005
			(0.006)
$\Delta NGDP_{c,t} \cdot ProvIndex3b_{c,t}$			0.372***
			(0.114)
Constant	0.203***	0.198***	0.196***
	(0.023)	(0.025)	(0.024)
Observations	35,780	35,780	35,780
R^2	0.062	0.062	0.062
$ProvIndex_{c,t}$: Min. value	2	1	0
$ProvIndex_{c,t}$: Max. value	7	4	3

NB: This table reports the baseline regressions of nominal loan growth ($\Delta Loans_{i,t}$) on the first lag of bank-specific control variables ($NDI_{i,t-1}$, $Equity_{i,t-1}$, $Loans_{i,t-1}$, $Deposits_{i,t-1}$ and $\log(TA)_{i,t-1}$) and the key explanatory variables. Those are the growth rate of nominal GDP ($\Delta NGDP_{c,t}$) in country c and its interaction terms with three loan loss provisioning indices ProvIndex(1/2/3)$b_{c,t}$. The mean values (standard deviations) of the accounting indices in models (1), (2), and (3) are 3.4 (1.6), 1.9 (1.0), and 0.9 (1.0), respectively. The sample covers 31 countries. Coefficients are estimated using OLS. Country-clustered standard errors are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

by those banks leads to a higher value of $\Delta\text{Loans}_{i,t}$, which is empirically represented by the significant coefficient β_3.

The baseline models in Table 4 employ the accounting indices $\text{ProvIndex(1/2/3)b}_{c,t}$, which we prefer because they contain more information on provisioning rules than $\text{ProvIndex(1/2/3)a}_{c,t}$. Unfortunately, those indices are not available for countries for which the response to Q5, i. e. the information on general provisions, is missing (cf. Section 2.3). As this data gap reduces the sample size and the number of countries in our baseline specification somewhat, we rerun the same regressions in Table 5 using the accounting indices ProvIndex(1/2/3)a instead to benefit from a larger sample. The gain in data coverage is quite sizeable, with the number of countries increasing from 31 to 52 and the number of observations from 35,780 to 50,783. The results for the larger sample are very similar to those in Table 4, with occasionally even higher statistical significance. $\text{Deposits}_{i,t-1}$, which is not significant in any of the models of the baseline specification, is highly significant with a negative coefficient in all three models of Table 5, which does not support the assumption that a higher deposit share in funding tends to support bank lending. Similarly, the positive coefficient on $\text{NDI}_{i,t-1}$ across all three models visibly increases in statistical significance and also slightly in magnitude in the larger sample. Most importantly, the coefficient on the interaction term remains statistically significant (despite a marginal drop in the significance level) in all three models and even rises a little further in magnitude. This finding confirms that the significant impact of the loan loss provisioning regime on lending dynamics is not an artefact from an inadvertent sample selection in our baseline model but is, in fact, robust across the different index definitions, even in a larger sample.

Altogether, our baseline results reveal that loan growth by banks in our global sample is cyclical, and that this cyclicality is significantly stronger if the accounting regime prescribes more backward-looking loan loss provisioning rules. This finding holds true for several accounting indices and for different macroeconomic variables. In the following section, we test the robustness of these findings for a number of other settings.

Table 5: Larger sample and ProvIndex(1/2/3)$a_{c,t}$.

Dep. Variable	(1) $\Delta\text{Loans}_{i,t}$	(2) $\Delta\text{Loans}_{i,t}$	(3) $\Delta\text{Loans}_{i,t}$
$\text{NDI}_{i,t-1}$	1.191***	1.196***	1.195***
	(0.316)	(0.305)	(0.305)
$\text{Equity}_{i,t-1}$	0.191***	0.210***	0.213***
	(0.050)	(0.052)	(0.051)
$\text{Loans}_{i,t-1}$	-0.146***	-0.137***	-0.134***
	(0.027)	(0.025)	(0.024)
$\text{Deposits}_{i,t-1}$	-0.048***	-0.050***	-0.048***
	(0.012)	(0.011)	(0.011)
$\log(\text{TA})_{i,t-1}$	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
$\Delta\text{NGDP}_{c,t}$	-0.087	-0.368	0.017
	(0.553)	(0.639)	(0.489)
$\text{ProvIndex1a}_{c,t}$	0.005		
	(0.006)		
$\Delta\text{NGDP}_{c,t} \cdot \text{ProvIndex1a}_{c,t}$	0.194*		
	(0.103)		
$\text{ProvIndex2a}_{c,t}$		0.000	
		(0.010)	
$\Delta\text{NGDP}_{c,t} \cdot \text{ProvIndex2a}_{c,t}$		0.431**	
		(0.202)	
$\text{ProvIndex3a}_{c,t}$			0.000
			(0.010)
$\Delta\text{NGDP}_{c,t} \cdot \text{ProvIndex3a}_{c,t}$			0.449**
			(0.224)
Constant	0.192***	0.197***	0.195***
	(0.019)	(0.022)	(0.022)
Observations	50,783	50,783	50,783
R^2	0.094	0.092	0.092
$\text{ProvIndex}_{c,t}$: Min. value	2	2	1
$\text{ProvIndex}_{c,t}$: Max. value	7	4	3

NB: This table reports the baseline results for the larger sample using the accounting indices ProvIndex/1/2/3)$a_{c,t}$ as shown on the left-hand side of Table 2. The mean values (standard deviations) of the accounting indices in models (1), (2), and (3) are 4.3 (1.2), 2.8 (0.7), and 1.8 (0.7), respectively. The sample covers 52 countries. Coefficients are estimated using OLS. Country-clustered standard errors are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

4 Robustness

4.1 Empirical methodology

Weighted least squares Identifying differences in provisioning regimes across jurisdictions by applying an accounting index hinges on the distribution of index values across the regression sample. If the vast majority of observations are concentrated in a very few index values while part of the spectrum of admissible values is not sufficiently supported by data points, identification may be severely affected. While in our baseline sample (ProvIndex(1/2/3)b$_{c,t}$) the distribution of index values across *countries* is rather skewed, it turns out that the distribution of index values across *observations* is somewhat more even. In order to further sharpen the identification through differences in loan loss accounting regimes, we apply a weighted least squares (WLS) estimator to the sample in order to attain a uniform distribution of index values across *effective observations* in the weighted sample.

Sample adjustments through weighted estimation were originally applied in the empirical literature to compensate for undersampling of individual groups. In our case, however, we do not seek to align the effective sample distribution with the corresponding population distribution but instead to achieve a uniform effective sample distribution of index values. If a bank is domiciled in a jurisdiction with an index value that is relatively underrepresented in our baseline sample, the observations of that bank will obtain a higher weight than in an unweighted sample, while banks from relatively overrepresented jurisdictions will obtain a lower weight than under unweighted estimation. If we were to repeat the depiction of observations across index values in Figure 1 for weighted observations, all sections in each of the pie charts would turn out equally large. The interpretation of the results from weighted estimation will be the same as under standard estimation. However, when the weighted estimates turn out qualitatively and even quantitatively similar to our baseline estimates, they will confirm that the identification of index categories under standard estimation is sufficiently strong and robust.

As the influence of observations on underrepresented accounting regime values on coefficient estimates may rise significantly under weighted estimation, WLS requires an at least moderately balanced distribution of (unweighted) observations at the outset in order to obtain meaningful results. It turns out that the distribution of observations across index values is highly uneven for the index series ProvIndex(1/2/3)$b_{c,t}$ used in the baseline specification, but more balanced for the larger sample that we obtain when we apply ProvIndex(1/2/3)$a_{c,t}$ as in Table 5. For this reason, we apply WLS estimation to the larger sample rather than the baseline sample. For evaluating the impact of using WLS, we therefore compare the coefficient estimates of the weighted estimation in Table 6 with the standard OLS results for the larger sample reported in Table 5.

Comparing weighted coefficient estimates with unweighted coefficient estimates for model (1) shows that under ProvIndex1$a_{c,t}$, weighted estimation leads to a complete loss of significance for all of the control variables but $\text{Loans}_{i,t-1}$. The interaction term moderately decreases in magnitude but gains in statistical significance. When we compare weighted coefficient estimates with unweighted coefficients for models (2) and (3), however, we find that the WLS estimates are all very close in magnitude and statistical significance to the corresponding unweighted estimates. Given that sample observations are relatively more unbalanced across ProvIndex1$a_{c,t}$ (with two out of six index values supported by only about 1% of observations) than for ProvIndex2$a_{c,t}$ and ProvIndex3$a_{c,t}$, the stronger distortion from applying WLS to model (1) than for the other two models attests to the caveat stated before. The highly robust results for models (2) and (3), however, confirm that, specifically for index series ProvIndex2$a_{c,t}$ and ProvIndex3$a_{c,t}$, even the unweighted sample distribution displays sufficient variation such that applying WLS appears unnecessary. This can also be seen by comparing the dispersion of index values in models (2) and (3) in Table 5 with the corresponding figures in Table 6: We find a mean index value of 2.79 (Table 6: 3) with a standard deviation of 0.72 (1) for model (2), and a mean value of 1.80 (2) with a standard deviation of 0.71 (1) for model (3).

Static and dynamic fixed effects OLS Applying pooled OLS to our data panel to allow for the statistical identification of the accounting index as a stand-alone re-

Table 6: Robustness – Weighted least squares.

Dep. Variable	(1) ΔLoans$_{i,t}$	(2) ΔLoans$_{i,t}$	(3) ΔLoans$_{i,t}$
NDI$_{i,t-1}$	0.787	1.282***	1.285***
	(1.099)	(0.416)	(0.418)
Equity$_{i,t-1}$	0.242	0.214***	0.217***
	(0.169)	(0.057)	(0.057)
Loans$_{i,t-1}$	-0.216***	-0.139***	-0.137***
	(0.058)	(0.022)	(0.022)
Deposits$_{i,t-1}$	-0.022	-0.045***	-0.044***
	(0.022)	(0.010)	(0.010)
log(TA)$_{i,t-1}$	-0.002	-0.003***	-0.003***
	(0.003)	(0.001)	(0.001)
ΔNGDP$_{c,t}$	0.292	-0.296	0.056
	(0.235)	(0.568)	(0.436)
ProvIndex1a$_{c,t}$	0.003		
	(0.007)		
ΔNGDP$_{c,t}$ · ProvIndex1a$_{c,t}$	0.122**		
	(0.053)		
ProvIndex2a$_{c,t}$		-0.005	
		(0.008)	
ΔNGDP$_{c,t}$ · ProvIndex2a$_{c,t}$		0.403**	
		(0.172)	
ProvIndex3a$_{c,t}$			-0.005
			(0.008)
ΔNGDP$_{c,t}$ · ProvIndex3a$_{c,t}$			0.423**
			(0.188)
Constant	0.191***	0.195***	0.188***
	(0.046)	(0.022)	(0.020)
Observations	50,783	50,783	50,783
R^2	0.086	0.084	0.083
ProvIndex$_{c,t}$: Min. value	2	2	1
ProvIndex$_{c,t}$: Max. value	7	4	3

NB: This table reports results for the larger sample using the accounting indices ProvIndex1a$_{c,t}$, ProvIndex2a$_{c,t}$, and ProvIndex3a$_{c,t}$, and applying a weighting by accounting indices. The mean values (standard deviations) of the accounting indices in models (1), (2), and (3) are *by construction* 4.5 (1.9), 3 (1), and 2 (1), respectively. The sample covers 52 countries. Coefficients are estimated using WLS. Country-clustered standard errors are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

gressor prevents us from explicitly capturing any unobserved heterogeneity across banks in the sample. To test whether our regression approach thereby leads to distortions in any of the coefficient estimates, we re-estimate the baseline specification by applying a fixed effects estimator in Table 7. Fixed effects (bank-specific intercepts) by construction remove the accounting index from the regression specification ($\beta_7 = 0$), so we can only include the interaction term (with coefficient β_8) from our baseline regression in the fixed effects setup. Models (1) and (2) in Table 7 repeat the baseline specification based on the baseline sample and the large sample, respectively, using static fixed effects. A comparison of models (1) and (2) with model (1) in Tables 5 and 4, respectively, shows a similar pattern of coefficient estimates, only $\text{Equity}_{i,t-1}$ turns statistically insignificant under fixed effects while the coefficient values for $\text{Loans}_{i,t-1}$ and $\log(\text{TA})_{i,t-1}$ increase in absolute value. For model (1) in Table 7, $\Delta\text{NGDP}_{c,t}$ becomes statistically significant with a negative coefficient, and the significance level of the interaction term also rises visibly. For banks in the most forward-looking loan loss provisioning regime in the sample ($\text{ProvIndex1a}_{c,t} = 2$), this implies a response of lending growth to the business cycle of virtually zero, while for all other index values lending growth fluctuates positively and significantly with macroeconomic conditions. The constant term here reports the mean of all bank-specific intercepts, and the greater flexibility of the fixed effects specification leads to a visible increase in R^2 relative to pooled OLS.[13]

Like unobserved heterogeneity, another important consideration to avoid distortions in panel data estimation is the choice between static and dynamic models. When applying a static panel model, particularly if, as in our specification, some of the regressors enter with a time lag, there is an increased chance that coefficient estimates may partly pick up the impact of variables not included in the regression equation. If variables missing from the specification happen to be both relevant for explaining the dependent variable and correlated with included regressors, reported coefficient estimates may suffer from omitted variable bias. One way of testing whether such an effect may be present in a static specification is to apply a dynamic panel model by including the first lag of the dependent variable on the right-hand side of the regression equation. The lagged dependent variable will partly account for the effect

[13] In the fixed effects specification, we consider the R^2_{within}.

of any missing variables, thereby reducing the potential bias in the other coefficient estimates. If the lagged dependent variable turns out highly significant while coefficient estimates that were statistically significant in a static specification become insignificant under the dynamic model, then omitted variable bias is a major concern; otherwise the static model can be regarded as robust.

The results in models (3) and (4) of Table 7 show that the static specification in models (1) and (2) is remarkably robust. There are almost no changes in statistical significance, and even the magnitude of all significant coefficients changes relatively little. The lagged dependent variable is only marginally significant with a very small coefficient in model (3) and completely insignificant in model (4). The coefficients on $\mathrm{NDI}_{i,t-1}$ gain a little in size relative to the static setup, while the responses to $\Delta\mathrm{NGDP}_{c,t}$ in model (3) and to the interaction term in models (3) and (4) become smaller. Taken together, these results confirm that a static model is the appropriate specification for the question at hand and that we do not incur any relevant distortions by choosing pooled OLS as our baseline specification.

Accounting indices replicated through binary variables In order to verify that our accounting indices do indeed represent increasingly backward-looking loan loss provisioning regimes over increasing index values and to test the implicit assumption of roughly equal incremental effects by moving from one index value to an adjacent value, we replicate the baseline indices $\mathrm{ProvIndex}(1/2/3)\mathrm{b}_{c,t}$ through sets of binary variables in Table 8. Under this setup, each index value represented in the sample is replaced by a separate indicator variable except for the lowest value, which is chosen as the default category in each case. If the provisioning indices in Table 2 have been appropriately defined, we would expect to see positive coefficient values on the binary interaction terms that are expected to increase in index values. We do not have specific expectations for the stand-alone coefficients on the binary variables, except that those should rarely be significant and of a relatively small order of magnitude.

For the sake of a better overview of the key results, the coefficients on the bank control variables are not displayed in Table 8. We note, however, that they are vir-

Table 7: Robustness – Static and dynamic fixed effects OLS.

Dep. Variable	(1) $\Delta \text{Loans}_{i,t}$	(2) $\Delta \text{Loans}_{i,t}$	(3) $\Delta \text{Loans}_{i,t}$	(4) $\Delta \text{Loans}_{i,t}$
$\Delta \text{Loans}_{i,t-1}$			0.052*	0.030
			(0.029)	(0.032)
$\text{NDI}_{i,t-1}$	1.434***	1.336**	1.782***	1.747***
	(0.366)	(0.521)	(0.368)	(0.525)
$\text{Equity}_{i,t-1}$	0.078	0.097	-0.004	0.024
	(0.071)	(0.087)	(0.086)	(0.110)
$\text{Loans}_{i,t-1}$	-0.584***	-0.555***	-0.587***	-0.563***
	(0.066)	(0.071)	(0.068)	(0.072)
$\text{Deposits}_{i,t-1}$	-0.055	-0.073*	-0.015	-0.037
	(0.036)	(0.036)	(0.047)	(0.049)
$\log(\text{TA})_{i,t-1}$	-0.135***	-0.139***	-0.128***	-0.132***
	(0.015)	(0.017)	(0.018)	(0.020)
$\Delta \text{NGDP}_{c,t}$	-0.372**	-0.101	-0.246***	-0.056
	(0.148)	(0.096)	(0.087)	(0.061)
$\Delta \text{NGDP}_{c,t} \cdot \text{ProvIndex1a}_{c,t}$	0.146***		0.103***	
	(0.033)		(0.024)	
$\Delta \text{NGDP}_{c,t} \cdot \text{ProvIndex1b}_{c,t}$		0.108***		0.071***
		(0.029)		(0.020)
Constant	2.422***	2.350***	2.299***	2.240***
	(0.217)	(0.240)	(0.272)	(0.290)
Observations	50,783	35,780	43,943	31,602
R^2	0.120	0.103	0.108	0.091
Number of banks	4,575	2,999	4,288	2,886
$\text{ProvIndex}_{c,t}$: Min. value	2	2	2	2
$\text{ProvIndex}_{c,t}$: Max. value	7	7	7	7

NB: This table applies static and dynamic fixed effects estimation (bank-level fixed effects). Models (1) and (2) estimate a static fixed effects model using indices $\text{ProvIndex1a}_{c,t}$ and $\text{ProvIndex1b}_{c,t}$, respectively, whereas models (3) and (4) employ dynamic fixed effects estimation for the same two indices. The samples for models (1)–(4) cover 52, 31, 51, and 29 countries, respectively. The constant term reports the mean of all bank-specific intercepts in the sample, and R^2 captures the within variation of the model. Country-clustered standard errors are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Robustness – Accounting indices replicated through binary variables.

Dep. Variable	(1) $\Delta\text{Loans}_{i,t}$	(2) $\Delta\text{Loans}_{i,t}$	(3) $\Delta\text{Loans}_{i,t}$
$\text{CONTROLS}_{i,t-1}$	YES	YES	YES
$\Delta\text{NGDP}_{c,t}$	0.406***	0.018	0.017
	(0.007)	(0.014)	(0.014)
$\text{ProvIndex(1/2/3)b}_{c,t} = 1$			0.031**
			(0.012)
$\text{ProvIndex(1/2/3)b}_{c,t} = 2$		0.030***	0.009
		(0.010)	(0.012)
$\text{ProvIndex(1/2/3)b}_{c,t} = 3$	-0.032***	0.008	0.010
	(0.010)	(0.012)	(0.010)
$\text{ProvIndex(1/2/3)b}_{c,t} = 4$	0.003	0.009	
	(0.019)	(0.010)	
$\text{ProvIndex(1/2/3)b}_{c,t} = 5$	-0.010		
	(0.015)		
$\text{ProvIndex(1/2/3)b}_{c,t} = 6$	-0.033**		
	(0.015)		
$\text{ProvIndex(1/2/3)b}_{c,t} = 7$	-0.020		
	(0.072)		
$\Delta\text{NGDP}_{c,t} \cdot [\text{ProvIndex(1/2/3)b}_{c,t} = 1]$			0.899***
			(0.109)
$\Delta\text{NGDP}_{c,t} \cdot [\text{ProvIndex(1/2/3)b}_{c,t} = 2]$		0.779***	0.937***
		(0.145)	(0.094)
$\Delta\text{NGDP}_{c,t} \cdot [\text{ProvIndex(1/2/3)b}_{c,t} = 3]$	-0.390***	0.960***	1.172***
	(0.020)	(0.092)	(0.401)
$\Delta\text{NGDP}_{c,t} \cdot [\text{ProvIndex(1/2/3)b}_{c,t} = 4]$	0.245	1.171***	
	(0.489)	(0.399)	
$\Delta\text{NGDP}_{c,t} \cdot [\text{ProvIndex(1/2/3)b}_{c,t} = 5]$	0.462***		
	(0.161)		
$\Delta\text{NGDP}_{c,t} \cdot [\text{ProvIndex(1/2/3)b}_{c,t} = 6]$	0.622***		
	(0.072)		
$\Delta\text{NGDP}_{c,t} \cdot [\text{ProvIndex(1/2/3)b}_{c,t} = 7]$	0.761**		
	(0.329)		
Constant	0.246***	0.215***	0.219***
	(0.024)	(0.022)	(0.024)
Observations	35,780	35,780	35,780
R^2	0.065	0.064	0.064

NB: This table reports results for the baseline sample by replacing the accounting indices $\text{ProvIndex(1/2/3)b}_{c,t}$ with sets of binary variables, specifying one indicator for each index value represented in the sample (except for the lowest, which has been defined to be the default category in each model). The sample covers 31 countries. Coefficients are estimated using OLS. Country-clustered standard errors are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

tually identical to those in Table 4 across all three models, as we would expect. The coefficients on the intercept dummy variables for each index value are statistically significant in roughly one-third of the cases, but each time with an absolute coefficient value of only about 0.03, so we can safely disregard them. In model (1), we find a highly significant value of about 0.41 for the coefficient on $\Delta\text{NGDP}_{c,t}$, which represents the response of lending growth to the business cycle for banks with $\text{ProvIndex1b}_{c,t} = 2$. The interaction term for $\text{ProvIndex1b}_{c,t} = 3$ carries a *negative* and significant coefficient of -0.39, which implies that banks operating under that loan loss provisioning regime respond with a coefficient value of only 0.02 to the business cycle. This finding appears to contradict the ordering of accounting regimes in $\text{ProvIndex1b}_{c,t}$, but when we look at the country contributions to the index values 2 and 3 of that index, it turns out that they are each at more than 97%, dominated by observations on banks in Germany and Belgium, respectively. Hence the coefficient on $\Delta\text{NGDP}_{c,t} \cdot [\text{ProvIndex1b}_{c,t} = 3]$ clearly shows that lending growth for banks in Belgium reacts much less to the domestic business cycle than for banks in Germany, yet may carry relatively little information on differences between those two values of the loan loss provisioning index in general. The coefficients on the other four interaction terms show precisely the pattern of positive, increasing, and in three cases statistically significant values as hypothesized.[14] The lack of statistical significance for the coefficient on $\Delta\text{NGDP}_{c,t} \cdot [\text{ProvIndex1b}_{c,t} = 4]$ may be due to the relatively small number of observations for that index value, but could also be country-specific as those observations are dominated by banks from Mexico (54%) and Uruguay (20%).

Model (2) reports an insignificant coefficient on $\Delta\text{NGDP}_{c,t}$, implying that lending growth for banks for which $\text{ProvIndex2b}_{c,t} = 1$ applies does not respond to the business cycle at all. However, the coefficients on the three interaction terms show large, positive, highly significant, and monotonically increasing values. This pattern strongly confirms that $\text{ProvIndex2b}_{c,t}$ characterizes the differences in loan loss provisioning regimes very well. Moreover, it supports the assumption that the existence

[14] As a statistically insignificant coefficient is interpreted as zero, loan growth for banks falling under that value of the accounting index respond to the business cycle with a coefficient identical to the default category, i. e. 0.41. By that reasoning, for index values 2–7 we obtain coefficients on $\Delta\text{NGDP}_{c,t}$ of about 0.41, 0.02, 0.41, 0.87, 1.03, and 1.17., respectively.

of minimum provisions is less important for the cyclicality of bank lending than the underlying orientation (backward- vs. forward-looking) of a loan loss accounting regime. We acknowledge that, under this definition of the index, the default category ($\text{ProvIndex2b}_{c,t} = 1$) is exclusively supported by observations on German banks, while the contribution of Belgium to the category $\text{ProvIndex2b}_{c,t} = 2$ is only around 15%. Therefore, the results for model (2) suggest that the negative coefficient on $\Delta\text{NGDP}_{c,t} \cdot [\text{ProvIndex1b}_{c,t} = 3]$ in model (1) is more driven by the observations on Belgian banks than the observations on German banks in the default category.

An identical coefficient pattern to that under model (2) arises for model (3). Lending growth for banks in the default category ($\text{ProvIndex3b}_{c,t} = 0$) does not react to the business cycle at all, while the coefficients on the three interaction terms are almost identical to those under model (2), only with an even higher coefficient on the very first interaction term. Here too, the default category is completely based on observations on German banks, while banks in Belgium contribute almost 23% to the observations for $\text{ProvIndex3b}_{c,t} = 1$. Taken together, these results provide very strong support for the appropriateness of the definitions of all three versions of the accounting index. Given the consistency of the results reported for the three models in Table 8, we can expect our estimation results to be robust regardless of which definition of the accounting index is applied.

4.2 Alternative macroeconomic variables

The cyclicality of bank lending is defined against a certain reference point. Our baseline results in Table 4 use the growth rate of nominal GDP as a macroeconomic determinant of banks' loan growth. This is why we also test the importance of the loan loss provisioning regime on the cyclicality of bank lending relative to several other regressors: the growth rate of real GDP ($\Delta\text{RGDP}_{c,t}$), the change in the unemployment rate ($\Delta\text{UR}_{c,t}$), and a binary business cycle indicator reflecting expansionary and recessionary periods ($\text{ECRI\_PT}_{c,t}$). Table 9 reports the corresponding regression results.

Table 9: Robustness – Alternative macroeconomic variables.

Dep. Variable	(1) $\Delta \text{Loans}_{i,t}$	(2) $\Delta \text{Loans}_{i,t}$	(3) $\Delta \text{Loans}_{i,t}$
$\text{NDI}_{i,t-1}$	1.208**	1.277**	1.430**
	(0.499)	(0.529)	(0.576)
$\text{Equity}_{i,t-1}$	0.177***	0.206***	0.150*
	(0.063)	(0.065)	(0.071)
$\text{Loans}_{i,t-1}$	-0.159***	-0.161***	-0.111***
	(0.037)	(0.038)	(0.022)
$\text{Deposits}_{i,t-1}$	-0.025	-0.014	-0.036
	(0.027)	(0.031)	(0.021)
$\log(\text{TA})_{i,t-1}$	-0.004**	-0.003*	-0.004*
	(0.002)	(0.002)	(0.002)
$\text{ProvIndex1b}_{c,t}$	0.008**	0.017***	0.003
	(0.004)	(0.003)	(0.003)
$\Delta \text{RGDP}_{c,t}$	-0.564**		
	(0.210)		
$\Delta \text{RGDP}_{c,t} \cdot \text{ProvIndex1b}_{c,t}$	0.393***		
	(0.064)		
$\Delta \text{UR}_{c,t}$		0.024	
		(0.021)	
$\Delta \text{UR}_{c,t} \cdot \text{ProvIndex1b}_{c,t}$		-0.025***	
		(0.008)	
$\text{ECRI\_PT}_{c,t}$			-0.025**
			(0.008)
$\text{ECRI\_PT}_{c,t} \cdot \text{ProvIndex1b}_{c,t}$			0.011**
			(0.003)
Constant	0.183***	0.150***	0.180***
	(0.027)	(0.031)	(0.026)
Observations	35,779	35,645	32,492
R^2	0.054	0.047	0.031
$\text{ProvIndex}_{c,t}$: Min. value	2	2	2
$\text{ProvIndex}_{c,t}$: Max. value	7	7	6

NB: This table reports the results for alternative key explanatory variables. Those are three alternative macroeconomic variables (the real GDP growth rate $\Delta \text{RGDP}_{c,t}$, the change in the unemployment rate $\Delta \text{UR}_{c,t}$, or the business cycle peak and trough indicator $\text{ECRI\_PT}_{c,t}$), and their interaction terms with $\text{ProvIndex1b}_{c,t}$. The mean values (standard deviations) of the accounting indices in models (1), (2), and (3) are 3.4 (1.6), 3.4 (1.6), and 3.3 (1.5), respectively. The sample for model (1) covers 31 countries, model (2) is estimated for 30 countries, and model (3) for 9 countries. Coefficients are estimated using OLS. Country-clustered standard errors are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Most importantly, the coefficients for the interactions of the macroeconomic variables with the accounting index show the expected signs. In model (1), real GDP growth combined with backward-looking provisioning ($\Delta\text{RGDP}_{c,t} \cdot \text{ProvIndex1b}_{c,t}$) leads to higher cyclicality of bank lending.[15] In model (2), an increase in the unemployment rate ($\Delta\text{UR}_{c,t}$) leads to significantly lower loan growth, in particular if the loan loss provisioning regime is backward-looking. In model (3), loan growth is significantly higher in expansionary periods ($\text{ECRI\_PT}_{c,t} = 1$) than in the downturn under a more backward-looking provisioning regime. Note, however, that this model is limited to observations from those countries for which this business cycle indicator is available.

4.3 Credit demand and supply

BLS/SLOS demand and supply effects One of the key concerns in identifying the determinants of loan growth is the distinction between loan demand and loan supply. The effects on the lending business and the consequences for the real sector may vary considerably depending on whether a driver of loan growth predominantly affects the supply or demand side. Loan demand is typically determined by the real sector and real interest rates and will hardly react to developments in the banking business or changes in bank regulation. Loan supply is instead known to respond to financial conditions, prudential regulation, and possibly also the accounting framework. For regulatory policy purposes in general and in order to address the question of how the loan loss provisioning regime may affect lending in particular, it is necessary to look at the supply side of lending. Since e. g. the macroeconomic regressor(s) in our regression could reflect either demand- or supply-side effects, we attempt to account for loan demand separately in the regression, which means that the remaining regressors will more likely reflect loan supply. In Table 10, we include data series constructed from the BLS/SLOS to reflect changes in loan demand by country and over time (cf. Section 2.4 for details).

[15] Note that the significantly negative coefficient for $\Delta\text{RGDP}_{c,t}$ does *not* imply that higher real GDP growth leads to lower loan growth, as we have to consider the positive coefficient for $\Delta\text{RGDP}_{c,t} \cdot \text{ProvIndex1b}_{c,t}$ as well. As $\text{ProvIndex1b}_{c,t} \geq 2$, the overall effect is always positive.

Table 10: Robustness – BLS/SLOS demand and supply effects.

Dep. Variable	(1) ΔLoans$_{i,t}$	(2) ΔLoans$_{i,t}$	(3) ΔLoans$_{i,t}$
NDI$_{i,t-1}$	1.168**	1.170**	1.193**
	(0.528)	(0.527)	(0.525)
Equity$_{i,t-1}$	0.217**	0.216**	0.221***
	(0.074)	(0.073)	(0.072)
Loans$_{i,t-1}$	-0.142***	-0.139***	-0.133***
	(0.030)	(0.027)	(0.024)
Deposits$_{i,t-1}$	-0.025	-0.024	-0.022
	(0.018)	(0.019)	(0.019)
log(TA)$_{i,t-1}$	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)
ΔNGDP$_{c,t}$	-0.566**	-0.492***	0.144
	(0.222)	(0.109)	(0.082)
ProvIndex1b$_{c,t}$	-0.005		
	(0.004)		
ΔNGDP$_{c,t}$ · ProvIndex1b$_{c,t}$	0.400***		
	(0.055)		
BLS_Demand$_{c,t}$	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
ProvIndex2b$_{c,t}$		-0.007	
		(0.006)	
ΔNGDP$_{c,t}$ · ProvIndex2b$_{c,t}$		0.645***	
		(0.074)	
ProvIndex3b$_{c,t}$			-0.005
			(0.007)
ΔNGDP$_{c,t}$ · ProvIndex3b$_{c,t}$			0.589***
			(0.092)
Constant	0.150***	0.147***	0.135***
	(0.024)	(0.025)	(0.019)
Observations	23,606	23,606	23,606
R^2	0.054	0.055	0.054
ProvIndex$_{c,t}$: Min. value	2	1	0
ProvIndex$_{c,t}$: Max. value	6	4	3

NB: This table reports the results using the accounting indices ProvIndex(1/2/3)b$_{c,t}$ and including the BLS/SLOS control variable BLS_Demand$_{c,t}$. The mean values (standard deviations) of the accounting indices in models (1), (2), and (3) are 3.3 (1.5), 0.9 (1.0), and 1.9 (1.0), respectively. The sample covers 14 countries. Coefficients are estimated using OLS. Country-clustered standard errors are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The results show that the coefficient estimates for the loan demand series are virtually zero throughout and statistically insignificant. All coefficients on bank control variables stay almost the same in terms of sign, magnitude, and statistical significance. Only $\log(\text{TA})_{i,t-1}$ becomes insignificant while the coefficient on $\Delta\text{NGDP}_{c,t}$ in models (1) and (2) gains statistical significance and becomes larger in absolute size. As before, while the negative and significant coefficient on $\Delta\text{NGDP}_{c,t}$ in models (1) and (2) appears to suggest countercyclical lending dynamics, combining those estimates with the relevant multiple of the coefficient on the accounting index interaction term always results in a positive coefficient for $\Delta\text{NGDP}_{c,t}$. In all three models, the coefficient on the interaction term becomes visibly larger, more than doubling in size for model (1) and rising by more than half in models (2) and (3), which is partly in reaction to the change in magnitude of the $\Delta\text{NGDP}_{c,t}$ coefficient. Note that since sufficiently long loan demand series are available for only a limited number of countries, models (1)–(3) are based on data for 14 countries only, whereas the baseline regressions in Table 4 cover 31 countries. Given that the loan demand series have virtually no impact at all on our estimation results, we omit them in all other specifications, which can therefore be based on larger samples.

Small vs. large banks Based on Kashyap and Stein (2000), we try to disentangle loan supply from demand effects by re-estimating Equation (1) for small and large banks separately. This is based on the rationale that bank size is a variable that is related to loan supply, but unrelated to loan demand (Beatty and Liao (2011)). We split small vs. large banks by country to address the concern that the results are driven by country-specific differences in the structure of the banking system. To investigate whether there is significant heterogeneity among the banks in our sample that is not visible from a pooled specification, we split the sample according to bank size (measured by $\log(\text{TA})_{i,t}$) at the country-specific median value. The results are displayed in Table 11. Small banks (those strictly below the median) are shown in models (1) and (3), large banks in models (2) and (4). While models (1) and (2) employ the accounting index $\text{ProvIndex1a}_{c,t}$, resulting in relatively larger data coverage as in Table 5, models (3) and (4) use the baseline index $\text{ProvIndex1b}_{c,t}$ as in Table 4.

When we compare models (1) and (2) with model (1) of Table 5, we find that the coefficients on all bank control variables are similar across the two split-sample specifications and the pooled specification, with largely identical significance levels. The coefficient values in the pooled specification are often somewhere in the middle of the two split-sample models. It turns out, however, that the pooled results are more strongly driven by larger banks than by smaller banks when judging by statistical significance. Unlike for large banks, $\text{NDI}_{i,t-1}$ and $\text{Deposits}_{i,t-1}$ are not significant determinants of loan growth for small banks and, most importantly, the coefficient on the interaction term $\Delta\text{NGDP}_{c,t} \cdot \text{ProvIndex1a}_{c,t}$ is not statistically significant for the smaller banks in the sample. This would imply that based on the larger sample of Table 5, the increased cyclicality in the lending business observed for banks operating under more backward-looking loan loss provisioning regimes is predominantly driven by larger banks.

Comparing the coefficient estimates for models (3) and (4) with those for model (1) in Table 4, we observe a similar pattern for the relationship between the split-sample coefficient estimates and the pooled estimates for the bank regressors. The value of the pooled estimates is often between the corresponding values of the two split-sample estimates, and $\text{NDI}_{i,t-1}$ and $\log(\text{TA})_{i,t-1}$ are insignificant for smaller banks. $\text{Deposits}_{i,t-1}$ is a significant determinant of loan growth for large banks, whereas it is statistically insignificant both for smaller banks and for the pooled sample. For the coefficient on $\text{Equity}_{i,t-1}$, we find that the statistical significance obtained under the pooled regression is predominantly driven by the smaller banks. For large banks, that coefficient turns out insignificant. Most importantly, and in contrast to the results for the larger sample in models (1) and (2), we now find that the positive and significant coefficient on the interaction term $\Delta\text{NGDP}_{c,t} \cdot \text{ProvIndex1b}_{c,t}$ is shared by small and large banks alike, with very similar coefficient values. For this index, the higher cyclicality of lending resulting from a more backward-looking loan loss provisioning regime is to be found across all banks in the sample, and we do not lose important information by pooling all banks in one sample regardless of their size.

Table 11: Robustness – Small vs. large banks.

Dep. Variable	(1) Small banks $\Delta \text{Loans}_{i,t}$	(2) Large banks $\Delta \text{Loans}_{i,t}$	(3) Small banks $\Delta \text{Loans}_{i,t}$	(4) Large banks $\Delta \text{Loans}_{i,t}$
$\text{NDI}_{i,t-1}$	0.542	1.875***	0.443	1.791***
	(0.416)	(0.250)	(0.574)	(0.351)
$\text{Equity}_{i,t-1}$	0.233***	0.165***	0.200**	0.124
	(0.062)	(0.046)	(0.078)	(0.074)
$\text{Loans}_{i,t-1}$	-0.165***	-0.140***	-0.166***	-0.147***
	(0.039)	(0.019)	(0.047)	(0.019)
$\text{Deposits}_{i,t-1}$	-0.030	-0.030**	-0.004	-0.057***
	(0.022)	(0.013)	(0.033)	(0.019)
$\log(\text{TA})_{i,t-1}$	-0.007***	-0.007***	-0.010	-0.015***
	(0.002)	(0.002)	(0.007)	(0.002)
$\Delta \text{NGDP}_{c,t}$	0.041	-0.252	-0.002	-0.018
	(0.691)	(0.476)	(0.401)	(0.346)
$\text{ProvIndex1a}_{c,t}$	0.004	0.010		
	(0.007)	(0.006)		
$\Delta \text{NGDP}_{c,t} \cdot \text{ProvIndex1a}_{c,t}$	0.180	0.203**		
	(0.129)	(0.088)		
$\text{ProvIndex1b}_{c,t}$			0.006	0.012***
			(0.004)	(0.002)
$\Delta \text{NGDP}_{c,t} \cdot \text{ProvIndex1b}_{c,t}$			0.173**	0.167**
			(0.075)	(0.065)
Constant	0.220***	0.215***	0.240**	0.344***
	(0.034)	(0.030)	(0.089)	(0.037)
Observations	24,958	25,825	18,228	17,552
R^2	0.095	0.101	0.064	0.071
$\text{ProvIndex}_{c,t}$: Min. value	2	2	2	2
$\text{ProvIndex}_{c,t}$: Max. value	7	7	7	7

NB: This table breaks down results by bank size. The mean values (standard deviations) of the accounting indices in models (1)–(4) are 4.28 (1.23), 4.29 (1.18), 3.44 (1.60), and 3.38 (1.56), respectively. Models (1) and (3) are for small banks (those strictly below the median of $\log(\text{TA})_{i,t}$), models (2) and (4) for large banks. Models (1) and (2) employ $\text{ProvIndex1a}_{c,t}$, resulting in relatively larger data coverage based on 52 countries, while models (3) and (4) use the baseline accounting index $\text{ProvIndex1b}_{c,t}$ and include 31 countries. Coefficients are estimated using OLS. Country-clustered standard errors are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

4.4 Sample composition

Excluding the largest countries Since we use bank-level data from BankScope, some countries will inevitably dominate our sample in terms of bank-year observations, which raises the concern that the results are driven by those countries. We addressed this issue in Section 4.1 by re-estimating our baseline model using WLS instead of standard pooled OLS. We now take this one step further and re-estimate our baseline model using WLS *and* excluding the three largest countries of our sample (Germany, Japan, and the U.S.) both separately and together. We use $\text{ProvIndex1a}_{c,t}$ instead of $\text{ProvIndex1b}_{c,t}$ again to ensure a) that a large number of categories are occupied with more than one country, and b) that the weighting of the indices does not lead to some small countries getting too much weight, especially in the most "extreme" categories. By doing so, we obviously lose the information on general provisions, which is a trade-off that we accept in this robustness test. The results are displayed in Table 12.

We compare the results to those we obtained in model (1) of Table 6 and observe no changes that would lead to different conclusions than before. The results for the interaction term $\Delta\text{NGDP}_{c,t} \cdot \text{ProvIndex1a}_{c,t}$ are even highly significant in those cases when either all of the three countries are excluded *or* Japan is excluded. The exclusion of Germany (model (2)) or the U.S. (model (4)) slightly decreases the significance of the results in model (1) of Table 6. However, the results in models (2) and (4) are still significant, albeit not strongly. The signs of the control variables are similar to those of the WLS regressions earlier. The same applies for their significance, except that the coefficient for $\text{Equity}_{i,t-1}$ is significant when we exclude Japan or all three countries. Overall, we are confident to confirm the baseline results since they hold even in the absence of the largest countries.

RTF-RA countries Like previous studies, we cannot fully rule out the possibility of some noise in the BRSS data on loan loss accounting rules since these data do not allow us to identify structural breaks in the accounting rules. The large number of countries, together with the long time period of our sample and the ongoing

Table 12: Robustness – Excluding the three largest countries (Germany (DE), Japan (JP), and the U.S. (US)).

Dep. Variable	(1) w/o DE JP US ΔLoans$_{i,t}$	(2) w/o DE ΔLoans$_{i,t}$	(3) w/o JP ΔLoans$_{i,t}$	(4) w/o US ΔLoans$_{i,t}$
NDI$_{i,t-1}$	0.152	0.761	0.305	0.667
	(0.862)	(1.140)	(0.859)	(1.065)
Equity$_{i,t-1}$	0.258**	0.238	0.278**	0.213
	(0.113)	(0.180)	(0.113)	(0.158)
Loans$_{i,t-1}$	-0.257***	-0.222***	-0.250***	-0.230***
	(0.044)	(0.067)	(0.038)	(0.053)
Deposits$_{i,t-1}$	0.075*	-0.015	0.052	-0.012
	(0.039)	(0.024)	(0.040)	(0.022)
log(TA)$_{i,t-1}$	-0.001	-0.003	0.000	-0.003
	(0.005)	(0.003)	(0.004)	(0.003)
ΔNGDP$_{c,t}$	0.185	0.323	0.207	0.381
	(0.179)	(0.292)	(0.196)	(0.239)
ProvIndex1a$_{c,t}$	0.004	0.003	0.002	0.008
	(0.010)	(0.009)	(0.008)	(0.007)
ΔNGDP$_{c,t}$ · ProvIndex1a$_{c,t}$	0.116***	0.118*	0.126***	0.096*
	(0.040)	(0.061)	(0.047)	(0.048)
Constant	0.159***	0.201***	0.139***	0.191***
	(0.045)	(0.061)	(0.049)	(0.046)
Observations	17,995	31,692	43,923	43,946
R^2	0.071	0.086	0.070	0.094
ProvIndex$_{c,t}$: Min. value	2	2	2	2
ProvIndex$_{c,t}$: Max. value	7	7	7	7

NB: This table displays the results of the baseline model excluding the largest countries in terms of observations. Model (1) excludes the three largest countries, whereas models (2)–(4) each exclude one of the three largest countries. ProvIndex1a$_{c,t}$ is applied to ensure sufficient heterogeneity, i. e. that large number of categories are occupied with countries. The mean values (standard deviations) of the accounting indices in models (1)–(4) are 4.8 (1.92), 4.8 (1.92), 4.5 (1.87), and 4.5 (1.87), respectively. The sample covers 49 countries in model (1) and 51 countries in models (2)–(4). Coefficients are estimated using WLS. Country-clustered standard errors are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

international tendency to converge local accounting rules towards IFRS, makes it likely that some countries changed their loan loss accounting rules during our sample period. To address this potential issue, we re-estimate our baseline model for the RTF-RA countries that participated in our survey. The survey explicitly asked for structural breaks in loan loss accounting rules, which are considered in our data. Besides, we expect the bank-level data to be most accurate in those countries.[16] The results are displayed in Table 13.

For the interaction $\Delta \text{NGDP}_{c,t} \cdot \text{ProvIndex(1/2/3)b}_{c,t}$ that we focus on, we observe no noticeable difference between the baseline results in Table 4 and the results in Table 13. However, the coefficient of $\Delta \text{NGDP}_{c,t}$ is negative and significant in models (1) and (2) of the RTF-RA subsample. Taken together, the *total* effect for banks in the lowest index category would be close to zero, i. e. indicating that lending is not cyclical at all. This is different in the full sample for which our results imply that lending is still procyclical, even in the most forward-looking category. Given that our focus lies on the additional cyclical effects of more backward-looking loan loss accounting rules, the results are very much consistent with those for the full sample. The same applies for the control variables, which are mostly similar to the baseline results in both size and statistical significance. In sum, the results support our hypothesis that lending fluctuates more with the business cycle in countries with more backward-looking loan loss accounting rules.

16 The RTF-RA countries in this analysis are Belgium, Germany, the Netherlands, Norway, Saudi Arabia, Spain, the United Kingdom and the U.S. The data for the remaining three RTF-RA countries could not be used due to extreme outliers (Brazil, China) or the lack of a sufficient number of observations (Republic of Korea). Cf. Section 2.1 for details.

Table 13: Robustness – RTF-RA countries.

	(1)	(2)	(3)
Dep. Variable	$\Delta\text{Loans}_{i,t}$	$\Delta\text{Loans}_{i,t}$	$\Delta\text{Loans}_{i,t}$
$\text{NDI}_{i,t-1}$	1.791***	1.765***	1.765***
	(0.317)	(0.318)	(0.318)
$\text{Equity}_{i,t-1}$	0.179*	0.177*	0.177*
	(0.080)	(0.080)	(0.080)
$\text{Loans}_{i,t-1}$	-0.125***	-0.123***	-0.123***
	(0.028)	(0.027)	(0.027)
$\text{Deposits}_{i,t-1}$	-0.048*	-0.049*	-0.049*
	(0.024)	(0.023)	(0.023)
$\log(\text{TA})_{i,t-1}$	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)
$\Delta\text{NGDP}_{c,t}$	-0.447*	-0.445***	0.005
	(0.205)	(0.115)	(0.013)
$\text{ProvIndex1b}_{c,t}$	0.000		
	(0.004)		
$\Delta\text{NGDP}_{c,t} \cdot \text{ProvIndex1b}_{c,t}$	0.252**		
	(0.083)		
$\text{ProvIndex2b}_{c,t}$		-0.002	
		(0.006)	
$\Delta\text{NGDP}_{c,t} \cdot \text{ProvIndex2b}_{c,t}$		0.450***	
		(0.109)	
$\text{ProvIndex3b}_{c,t}$			-0.002
			(0.006)
$\Delta\text{NGDP}_{c,t} \cdot \text{ProvIndex3b}_{c,t}$			0.450***
			(0.109)
Constant	0.211***	0.215***	0.213***
	(0.016)	(0.014)	(0.016)
Observations	28,833	28,833	28,833
R^2	0.042	0.042	0.042
$\text{ProvIndex}_{c,t}$: Min. value	2	1	0
$\text{ProvIndex}_{c,t}$: Max. value	6	3	2

NB: This table displays the results of the baseline model for RTF-RA countries only. $\text{ProvIndex}(1/2/3)\text{b}_{c,t}$ are applied since the information on the existence of general provisions is available for all RTF-RA countries. The mean values (standard deviations) of the accounting indices in models (1)–(3) are 3.03 (1.44), 1.68 (0.94), and 0.68 (0.94), respectively. The sample covers 8 countries. Coefficients are estimated using OLS. Country-clustered standard errors are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5 Conclusions

The capital crunch hypothesis predicts that the existence of regulatory minimum capital requirements may lead to cutbacks in lending activities if banks fall short of regulatory capital, which is particularly likely in recessionary periods. Loan loss accounting rules that lead to a procyclical build-up of loan loss provisions over the business cycle may reinforce a lending boost in expansionary periods and a capital crunch during recessions. In this context, we study how loan loss accounting rules impact on bank lending over the business cycle based on an international sample of banks. Unlike previous studies, we collect detailed information on local GAAP loan loss accounting rules in a large number of countries and develop alternative indices that reflect how backward-looking (or forward-looking) a loan loss accounting regime is. The heterogeneity in those indices (i. e. in the loan loss accounting rules) is then exploited to identify how provisioning rules affect bank lending over the business cycle.

In line with the theory (Peek and Rosengren (1995)), we find banks' lending behavior to be more procyclical if they are subject to more backward-looking provisioning rules. This finding is robust to variations in the composition and subdivision of the baseline index as well as to variations in the macroeconomic variable and sample composition. Besides, taking account of potential loan demand effects and a different, index-based weighting scheme does not alter the results.

Our finding has important policy implications in the current reshaping of international loan loss accounting rules, i. e. in the transition from the *incurred loss model* in IAS 39 to the *expected loss model* in IFRS 9. Although we are unable to address every country-specific feature in terms of provisioning rules, we show that banks' lending behavior is more procyclical if their credit risk reserve is restricted to the recognition of incurred losses. Consequently, we conclude that a forward-looking approach in the assessment of the credit risk reserve can generally be beneficial from a macroeconomic perspective. We do not conceal that such an approach is at the same time more likely to introduce discretionary leeway that can be exploited by bank management, which needs to be considered when designing provisioning rules.

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