The Countercyclical Component of Capital Regulation

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Abstract

In this paper, I propose a measure that decomposes the contribution of the probabilities of default (PD) distribution to capital requirements into an average component and a component of the remaining moments of the distribution, for portfolios under the internal ratings-based (IRB) approach. The average component corresponds to a counterfactual scenario such that the capital requirements for the entire portfolio are calculated using the portfolio's average PD. The component of the remaining moments is obtained as the difference between the average component and the actual amount of capital requirements. I label this second component *Capital savings* because an increase in this component reduces total capital requirements. Using a hand-collected dataset, I show that *Capital savings* explains a substantial variation of average risk-weights across time and banks. Moreover, I find evidence that the variation of *Capital savings* during the business cycle reduces the procyclicality of capital ratios, especially for corporate portfolios.

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1 Introduction

The regulation on bank capital requirements has evolved substantially since the first international standard, the 1988 Basel Accord. At the heart of these changes is the link of capital charges to asset risk (BCBS, 2006, 2017; EBA, 2019a). Risk sensitivity of capital requirements was present in the first accord and it was greatly enhanced in the Basel II framework by giving banks the option to calculate capital requirements using risk estimates obtained from their own models, known as the internal ratings-based (IRB) approach. The rationale for risk-linked capital charges is that regulating capital via a simple capital to asset ratio can incentivize banks to take on excessive risk (Gordy and Heitfield, 2010; Kim and Santomero, 1988; Koehn and Santomero, 1980). The rationale for allowing internal models is the better alignment of risk estimates to actual portfolio risk (Barakova and Palvia, 2014) and the promotion of better risk management practices (Cucinelli et al., 2018).

However, both risk sensitivity and the use of internal models may have adverse consequences. First, linking capital charges to asset risk exacerbates the procyclicality of lending (Danielsson et al., 2001; Kashyap and Stein, 2004). As the overall credit quality deteriorates during economic downturns, capital requirements tighten, forcing banks to either raise equity or cut down lending. Theory and empirical evidence suggest that banks opt for the latter as raising equity is costly, even more so during recessions (Adrian and Shin, 2014; Behn et al., 2016; Repullo and Suarez, 2012). Second, the inherent flexibility of the IRB approach may allow for differences in capital requirements across banks that do not reflect portfolio risk but rather modeling choices (Behn et al., 2021; Berg and Koziol, 2017; Ferri and Pesic, 2017; Le Leslé and Avramova, 2012; Mariathasan and Merrouche, 2014).

This chapter contributes new knowledge about the cyclicality and variability of capital requirements, by identifying the effects of an unexplored feature of the IRB framework on capital requirements. Under the IRB approach, banks insert their own risk estimates, such as the probability of default (PD), into formulas set by the IRB framework which determine the amount of capital banks have to hold. Two characteristics of the framework are important for this analysis. First, the mapping from PD estimates to capital requirements is a concave function. Second, capital requirements are calculated for each asset separately and then added up to obtain the total capital charge. Because of these characteristics, actual capital requirements for a portfolio are lower than implied by the average PD of this portfolio. To illustrate, consider two portfolios. The first portfolio contains a low PD asset and a high PD asset in equal proportions. The second portfolio has the same total amount as the first but contains only an asset with a PD equal to the mean of the low and high PD. Because of the concavity of the IRB formula, capital requirements for the second portfolio are greater than capital requirements for the first. More generally, total capital requirements depend not only on banks' portfolio average PD—the location parameter of the PD distribution—, but also on the other moments of the PD distribution.

I propose a measure that decomposes the contribution of the PD distribution to capital requirements into an average component and a component of the remaining moments of the distribution. The average component corresponds to a counterfactual scenario such that the capital requirements for the entire portfolio are calculated using the portfolio's average PD. The component of the remaining moments is obtained as the difference between the average component and the actual amount of capital requirements. I label this second component *Capital savings* because an increase in this component reduces total capital requirements.

To calculate *Capital savings*, I hand-collected information on the distribution of credit risk parameters from banks' Pillar-3 reports. The sample consists of 59 large banking groups that have adopted the IRB approach. The dataset covers 15 countries and the years from 2007 to 2018.

With this novel dataset, I investigate the relationship between *Capital savings* and the business cycle. In theory, of the two capital requirements components, the average component is a source of the procyclicality as long the relationship between the business cycle and PD estimates is negative and monotonic. Conversely, the relationship between *Capital savings* and the business cycle is not trivial, even if we assume a monotonic relationship between

PD estimates and the business cycle. The ambiguity arises because *Capital savings* can only increase during a recession and decrease during an expansion, and therefore be countercyclical, if, not only the average but also other moments of the PD distribution are affected during the business cycle. If the PD estimates of the assets in a portfolio are equally affected during the business cycle, then there is only a shift of the location parameter of the PD distribution. Because the PD elasticity of capital requirements is lower for higher PD estimates, in this scenario *Capital savings* are procyclical. However, if riskier assets are sufficiently more sensitive to credit shocks than safer assets, then *Capital savings* are countercyclical.

I find *Capital savings* to be countercyclical. I estimate that a 1.7% GDP growth rate (one standard deviation) decreases the growth rate of *Capital savings* by 0.5 percentage points on average. In other words, a bank with the average risk-weight in the sample (35%) has to increase capital by 1.4% to keep its capital ratio constant during a standard expansion of the economy. The effect is also economically significant. The variation of *Capital savings* during the business cycle reduces the procyclicality of capital ratios by 13.7% on average. The results also suggest that the countercyclical relationship between GDP and *Capital savings* is mostly driven by wholesale portfolios, especially corporate portfolios. The results are robust to different model specifications, different measures of *Capital savings*, different measures of the business cycle, alternative sample selections, and the inclusion of several control variables. I also show that selection into the IRB approach does not explain the cyclicality of *Capital savings*.

I further analyze the relationship of the PD distribution moments with GDP growth and find that during economic recessions the average and the variance of PD distributions increase while the skewness decreases. Although the effect of the average PD is stronger, which makes capital requirements procyclical, both the higher variance and the lower skewness of the PD distribution mitigate the increase of capital requirements during recessions. Moreover, I argue that the change of skewness during the business cycle is consistent with a portfolio reallocation effect on *Capital savings*.

This chapter contributes to two strands of the banking literature. First, several studies document significant variability of capital requirements across otherwise similar banks. Some take this evidence as indicative of either excessive subjectivity in the current capital requirement rules or risk measurement manipulation by banks to decrease capital charges (Ferri and Pesic, 2017; Mariathasan and Merrouche, 2014). Others are more cautious and emphasize that part of the capital requirements variability is desirable, since it reflects differences in risk among banks (BCBS, 2016; Berg and Koziol, 2017; Cannata et al., 2012; EBA, 2019b). I contribute to this literature by showing that *Capital savings* are an important source of capital requirements variation across banks.

Second, this chapter contributes to the literature on the procyclical nature of the banking activity, particularly a strand that addresses banking regulations that enhance this procyclicality (Berger and Udell, 2004; Bertay et al., 2015; Huizinga and Laeven, 2019; Laeven and Majnoni, 2003; Rajan, 1994). While the literature shows that capital requirements, especially for portfolios under the IRB approach, are on average procyclical (Behn et al., 2016; Danielsson et al., 2001; Kashyap and Stein, 2004; Repullo and Suarez, 2012), I identify a countercyclical component of the current IRB framework. A better understanding of this countercyclical component can help policy makers design a less procyclical regulation on capital requirements in the future.

The remainder of this chapter is organized as follows. Section 2 describes the capital requirements formula under the IRB approach, why it creates *Capital savings*, and the hypothesis concerning the cyclicality of *Capital savings*. Section 3 describes the collected data and the measures of *Capital savings*. Section 4 presents correlations of *Capital savings* and bank characteristics. Section 5 presents evidence on the countercyclical feature of *Capital savings*. Section 6 explores the relationship between the moments of the PD distribution and *Capital savings* during the business cycle. Finally, Section 7 concludes.

2 Institutional background and hypotheses

2.1 Capital requirements under the IRB approach

In June 2004, the BCBS issued a revised framework on international convergence of capital measurements and capital standards (BCBS, 2006), known as Basel II, which serves as the basis for national rulemaking and implementation processes. The link of capital charges to asset risk was at the heart of the revision. Since the first accord from 1988 (Basel I), minimum capital requirements are calculated as a percentage of risk-weighted assets (RWA). Hence, choosing the approach that defines risk-weights is crucial. In Basel I, risk-weights were constant within portfolio categories. For instance, all sovereign exposures were weighted by 0% and all corporate exposures by 100%. However, regulating capital via a simple capital to asset ratio can incentivize banks to take on excessive risk as the cost in terms of capital requirements is the same within a portfolio category (Gordy and Heitfield, 2010; Kim and Santomero, 1988; Koehn and Santomero, 1980). Therefore, since Basel II, financial institutions may choose between two approaches to calculate capital requirements for credit risk: the standardized approach (essentially a slightly modified version of the first accord) or the IRB approach.

Under the IRB approach, banks are required to estimate their credit risk parameters using internal risk models. The risk parameters are the probability of default (PD), the loss given default (LGD), and the exposure at default (EAD). The main rationale for allowing internal models is the better alignment of regulatory risk estimates to actual portfolio risk (Barakova and Palvia, 2014) as banks are expected to have better knowledge of and more resources to monitor their portfolio than supervisors have. Because the internal models have to be approved by the supervisors before they can be implemented for regulatory purposes, regulators also expected the IRB approach to promote better risk management practices in the banking industry (BCBS, 2006; Cucinelli et al., 2018).

The estimated risk parameters are then used in regulatory formulas to calculate risk-weights. The regulatory formulas come from a model characterized by the property that the risk-weight of each asset depends only on the estimated credit risk parameters for this asset and not on the composition of the portfolio, i.e., the model is portfolio invariant. This feature leads to a bottom-up approach, where capital requirements are determined on the asset level and the total requirement is simply the sum of assets' individual requirements. Equation 1 is the risk-weight formula in its most simple form:

$$\begin{aligned}&\mathrm{RW}(\mathrm{LGD}_i, \mathrm{PD}_i) = \\ &\quad 12.5 \cdot \mathrm{LGD}_i \cdot \left[N\left(\sqrt{\frac{1}{1-R}} \cdot N^{-1}(\mathrm{PD}_i) + \sqrt{\frac{R}{1-R}} \cdot N^{-1}(0.999) \right) - \mathrm{PD}_i \right],\end{aligned} \tag{1}$$

where the subscript i indexes an asset in the portfolio, N is the standard normal cumulative distribution, and R is a correlation coefficient, which for certain portfolios is also a function of the PD.[1] The Basel accords segment credit portfolios into several categories, each having different additional features while keeping the basic structure of equation 1. For instance, the formula for wholesale exposures has an adjustment that is dependent on the maturity of the exposure, and the correlation coefficient for exposures to SMEs is adjusted by the firm's annual sales turnover. Although the regulatory formulas are common for all banks, the extent to which banks are allowed to use their internal models varies. Under the foundation IRB (F-IRB) approach, banks can use internal PD estimates but are required to use values defined by the regulator for the other parameters. Only banks approved to use the advanced IRB (A-IRB) approach can use internal estimates for all the risk parameters.

Because of the portfolio invariant feature of the model, the average risk-weight, RW^f, is the exposure weighted average of the risk-weights of all individual assets, as shown in equation 2:[2]

$$\mathrm{RW}^f = \sum_i q_i \cdot \mathrm{RW}(\mathrm{LGD}_i, \mathrm{PD}_i). \tag{2}$$

[1]For residential mortgage and qualifying revolving exposures the correlation coefficient is fixed at 0.15 and 0.04, respectively. For exposures to corporations, banks, sovereigns, and other retail the coefficient is calculated as $R = a \cdot [b \cdot \{(1 - e^{-c \cdot PD})/(1 - e^{-c})\} + d \cdot \{1 - (1 - e^{-c \cdot PD})/(1 - e^{-c})\}]$, with specific fixed parameters a, b, c, d for each type of exposure.

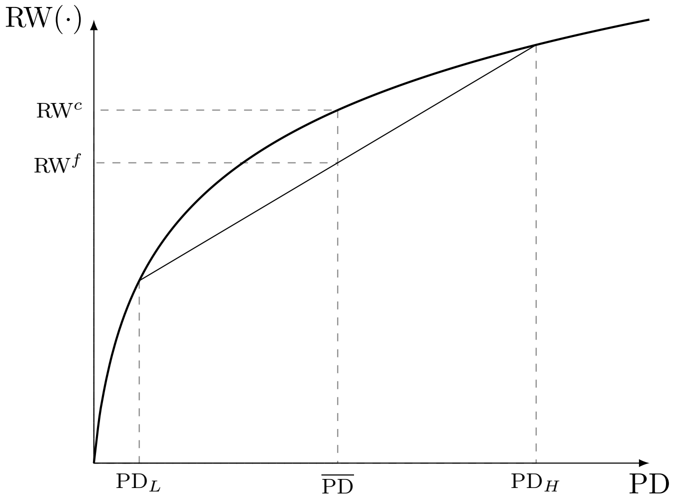
[2]The superscript f (for factual) is used to differentiate the average value from the RW function.

where $q_i = \mathrm{EAD}_i / \sum_j \mathrm{EAD}_j$. The total amount of RWA for this portfolio is $\mathrm{RW}^f \cdot \sum_i \mathrm{EAD}_i$ and the total amount of capital requirements is a percentage of RWA.

2.2 Probability of default distribution and capital savings

Figure 1 plots the mapping from PD to risk-weights according to equation 1. For this chapter, the important characteristic of this mapping is that it is a concave function. The concavity of the regulatory formula, together with the bottom-up method to aggregate capital requirements, result in that total capital requirements for a portfolio do not depend only on the portfolio average PD but also on other moments of the PD distribution. To illustrate, consider two portfolios. The first portfolio contains an asset with low PD (PD_L) and an asset with high PD (PD_H) in proportions q and $1-q$. The second portfolio has the same amount of exposure as the first but contains only an asset with a PD that is the mean of low PD and high PD weighted by their respective shares. Because of the concavity of the IRB formula and Jensen's inequality, the capital requirement for the second portfolio is greater than the first. Figure 1 illustrates the comparison. RW^f and RW^c are the average risk-weight for the first portfolio and the second portfolio, respectively. More generally, any PD distribution with positive variance is charged with a capital requirement lower than implied by the average of the distribution.

Figure 1: Mapping from PD to risk-weights



Notes: The figure plots the mapping from PD to risk-weights according to equation 1.

I propose a method that decomposes the contribution of the PD distribution to capital requirements into an average component and a residual component. The method is a generalization of the example in Figure 1. The average component is the amount of capital requirements if the portfolio's average PD is used for the entire portfolio. Similar to RW^c in Figure 1, the average component is defined as the following:

$$\mathrm{RW}^c = \sum_i q_i \cdot \mathrm{RW}(\mathrm{LGD}_i, \overline{\mathrm{PD}}), \tag{3}$$

where the PD parameter for all assets is replaced by the portfolio weighted average. The latter is defined as the following:

$$\overline{\mathrm{PD}} = \frac{\sum_i \mathrm{EAD}_i \cdot \mathrm{LGD}_i \cdot \mathrm{PD}_i}{\sum_i \mathrm{EAD}_i \cdot \mathrm{LGD}_i}.$$

The residual component is the difference between RW^c and RW^f. This component measures any contribution to capital requirements from the PD distribution that is not related to the location of this distribution. It can also be interpreted as the amount of *Capital savings* per unit of EAD, due to the concavity of the IRB formula and all the moments of the PD distribution but the average. I define this intensity measure of *Capital savings* as the following:

$$\mathrm{RW}^s = \mathrm{RW}^c - \mathrm{RW}^f. \tag{4}$$

The total amount of *Capital savings* is simply RW^s multiplied by total EAD in the portfolio as follows:

$$\mathrm{RWA}^S = \mathrm{RWA}^c - \mathrm{RWA}^f = \mathrm{RW}^s \cdot \sum_i \mathrm{EAD}_i. \tag{5}$$

Because this is a measure in monetary units, RWA^S is mechanically larger for bigger banks and they increase as the portfolio rolls out to the IRB approach.

An alternative way to measure the intensity of *Capital savings* is the ratio of equation 3 to equation 2 as follows:

$$\mathrm{RWA}^s = \frac{\mathrm{RWA}^c}{\mathrm{RWA}^f}. \tag{6}$$

RWA^s is the rate at which a bank saves capital. For instance, a value of 1.5 means this portfolio would require 50% more capital in the absence of *Capital savings* to keep the same capital ratio. A value of 1 means that there are no *Capital savings* and implies a portfolio with a degenerate PD distribution. Any PD distribution with positive variance results in positive *Capital savings*.

RWA^s is also a useful measure of *Capital savings* because it is the most straightforward measure to evaluate the impact of *Capital savings* on the capital ratio during the business cycle. In the empirical analysis, I study the behavior of variables during the business cycle by relating their growth rates to GDP growth rate. Hence, I regress the change in the logarithm of my variables of interest on the GDP growth rate. Taking my empirical approach into account, RWA^s becomes the natural measure of *Capital savings* as the following decomposition of the log of capital ratio shows:

$$\begin{aligned}
\text{Log}\left(\frac{\text{Capital}}{\text{RWA}^f}\right) &= \text{Log Capital} - \text{Log RWA}^f \\
&= \text{Log Capital} - \text{Log}\left(\frac{\text{RWA}^c}{\text{RWA}^s}\right) \\
&= \text{Log Capital} - \text{Log RWA}^c + \text{Log RWA}^s
\end{aligned} \tag{7}$$

If I regress the change of these four variables—$\frac{\text{Capital}}{\text{RWA}^f}$, Capital, Log RWA^c, and Log RWA^s—on GDP growth rate, I obtain four estimates $\hat{\beta}_{\text{Cap. ratio}}$, $\hat{\beta}_{\text{Capital}}$, $\hat{\beta}_{\text{RWA}^c}$, and $\hat{\beta}_{\text{RWA}^s}$, respectively. Using the predicted values implied by these estimated in Equation 7 we get the following equality: $\hat{\beta}_{\text{Cap. ratio}} = \hat{\beta}_{\text{Capital}} - \hat{\beta}_{\text{RWA}^c} + \hat{\beta}_{\text{RWA}^s}$, which can be used to obtain the relative importance of changes of each of these three variables to changes of the capital ratio during the business cycle.

Note that I defined *Capital savings* such that positive values translate to lower actual capital requirements and consequently RW$^s \geq 0$, RWA$^S \geq 0$, and RWA$^s \geq 1$.

Lastly, for robustness of the empirical analysis, I also calculate the Gini coefficient of the PD distribution as an alternative measure of *Capital savings*.

2.3 Hypotheses on capital savings during the business cycle

Overall, capital requirements under the IRB approach are procyclical. During economic downturns, credit risk increases which raises capital requirements forcing banks to either raise equity or cut down lending. Theory and empirical evidence suggest that banks opt for the latter as raising equity is costly, even more so during recessions (Behn et al., 2016; Danielsson et al., 2001; Kashyap and Stein, 2004; Repullo and Suarez, 2012).

Of the two capital requirement components, the average component is a source of the procyclicality as long the relationship between the business cycle and PD is negative and monotonic. Consider again the example shown in Figure 1 with a portfolio containing a share q of a safe asset with PD equal to PD$_L$ and a share $1 - q$ of a risky asset with PD equal to PD$_H$ such that PD$_H >$ PD$_L$. For practical reasons, I restrict the analysis to PD $\in [0, 0.25)$.

Figure 10 in Appendix A shows that the percentage of PD within the $[0, 0.25)$ interval is between 99.35% and 99.98%. Figure 11 in Appendix A shows that for $\text{PD} \in [0, 0.25)$, $\frac{\partial \text{RW}}{\partial \text{PD}} > 0$, $\frac{\partial^2 \text{RW}}{\partial \text{PD}^2} < 0$, and $\frac{\partial^3 \text{RW}}{\partial \text{PD}^3} > 0$. I assume a constant $\text{LGD}_i = \text{LGD}$ and constant q. Using the weighted average of this portfolio in equation 3, the average component for this portfolio is equal to the following:

$$\text{RW}^c(\text{PD}_L, \text{PD}_H) = \text{RW}\Big(q \cdot \text{PD}_L + (1-q) \cdot \text{PD}_H\Big). \tag{8}$$

Because $\frac{\partial \text{RW}}{\partial \text{PD}} > 0$ and as long PD estimates are affected monotonically and negatively by GDP growth, the average component of capital requirements increases during economic downturns.

Conversely, the direction of *Capital savings* during the business cycle is not trivial, even when assuming a monotonic relationship between PD estimates and the business cycle. The ambiguity arises because *Capital savings* can only increase during a recession and decrease during an expansion, and therefore be countercyclical, if, not only the average but also other moments of the PD distribution are affected during the business cycle. If the PD estimates are equally affected during the business cycle, then there is only a shift of the location parameter of the PD distribution. Because the PD elasticity of capital requirements is lower for higher PD estimates, in this scenario *Capital savings* are procyclical. However, if riskier assets are sufficiently more sensitive to credit shocks than safer assets, then *Capital savings* are countercyclical. To illustrate the ambiguity, I consider three cases.

First, note that using the example in Figure 1, *Capital savings* can be written as the following:

$$\begin{aligned} \text{RW}^s(\text{PD}_L, \text{PD}_H) =& \text{RW}\Big(q \cdot \text{PD}_L + (1-q) \cdot \text{PD}_H\Big) \\ &- \Big[q \cdot \text{RW}(\text{PD}_L) + (1-q) \cdot \text{RW}(\text{PD}_H)\Big]. \end{aligned} \tag{9}$$

We can find the effect of changes in the PD distribution on *Capital savings* by taking the total derivative of 9:

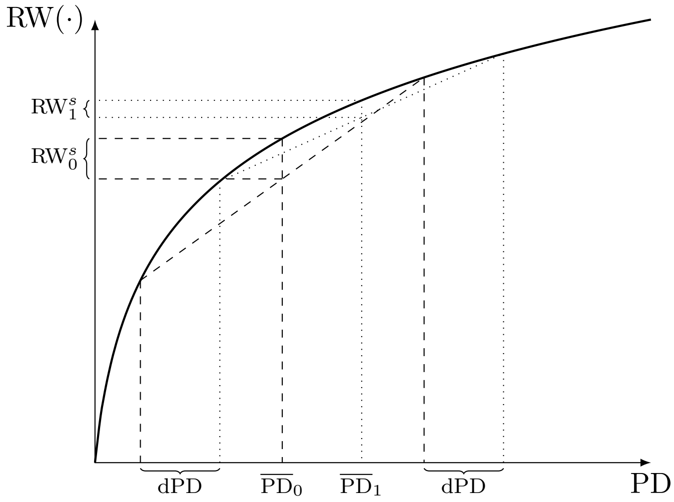
$$\begin{aligned} \mathrm{dRW}^s(\mathrm{PD}_L, \mathrm{PD}_H) = & \Big[q \cdot \mathrm{RW}'\Big(q \cdot \mathrm{PD}_L + (1-q) \cdot \mathrm{PD}_H\Big) \\ & - q \cdot \mathrm{RW}'(\mathrm{PD}_L)\Big] \cdot d\mathrm{PD}_L \\ & + \Big[(1-q) \cdot \mathrm{RW}'\Big(q \cdot \mathrm{PD}_L + (1-q) \cdot \mathrm{PD}_H\Big) \\ & - (1-q) \cdot \mathrm{RW}'(\mathrm{PD}_H)\Big] \cdot \mathrm{dPD}_H \end{aligned} \tag{10}$$

Next, consider the case that all assets are affected equally during the business cycles in term of PD, i.e., $d\mathrm{PD}_H = d\mathrm{PD}_L = d\mathrm{PD}$. In this scenario equation 10 becomes:

$$\begin{aligned} \mathrm{dRW}^s = & \Big[\mathrm{RW}'\Big(q \cdot \mathrm{PD}_L + (1-q) \cdot \mathrm{PD}_H\Big) \\ & - \Big(q \cdot \mathrm{RW}'(\mathrm{PD}_L) + (1-q) \cdot \mathrm{RW}'(\mathrm{PD}_H)\Big)\Big] \cdot \mathrm{dPD}. \end{aligned} \tag{11}$$

Note that $\frac{\partial \mathrm{RW}}{\partial \mathrm{PD}}$ is a convex function of PD (see Figure 11). Hence, from Jensen's inequality, equation 11 shows that if $d\mathrm{PD}_H = d\mathrm{PD}_H = d\mathrm{PD}$ then $d\mathrm{RW}^s/d\mathrm{PD} < 0$. In this case, *Capital savings* are procyclical, decreasing during economic downturns. Figure 2 diagrams this first case.

Figure 2: The procyclical *Capital savings* case



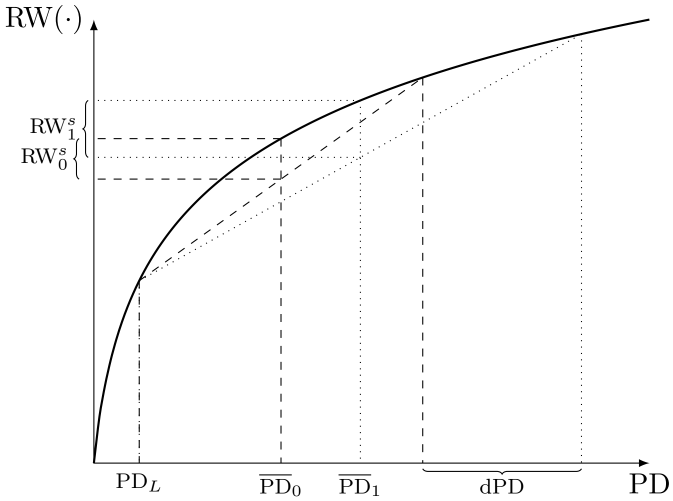
Notes: The figure shows how changes in PD can lead to procyclical *Capital savings*. The dashed lines correspond to the portfolio before a negative credit risk shock (with average PD equal to $\overline{\mathrm{PD}}_0$) and the dotted lines to the portfolio after the shock (with average PD equal to $\overline{\mathrm{PD}}_1 > \overline{\mathrm{PD}}_0$). In this case, where safer and riskier assets are affected equally, $\mathrm{RW}_0^s > \mathrm{RW}_1^s$.

Next, consider the case that riskier assets are more affected during the business cycles in term of PD, i.e., $\mathrm{dPD}_H > \mathrm{dPD}_L$. For simplicity, consider the extreme case of $\mathrm{dPD}_H = \mathrm{dPD}$ and $\mathrm{dPD}_L = 0$. In this scenario, equation 10 becomes:

$$\begin{aligned}\mathrm{dRW}^s = &\Bigg[\mathrm{RW}'\Big(q \cdot \mathrm{PD}_L + (1-q) \cdot \mathrm{PD}_H\Big) \\ &- \mathrm{RW}'(\mathrm{PD}_H)\Bigg] \cdot (1-q) \cdot \mathrm{dPD}\end{aligned} \tag{12}$$

Because $\frac{\partial^2 \mathrm{RW}}{\partial \mathrm{PD}^2} < 0$ and $\mathrm{PD}_H > q\mathrm{PD}_L + (1-q)\mathrm{PD}_H$, $\mathrm{dRW}^s/\mathrm{dPD} > 0$. In this case, *Capital savings* are countercyclical, increasing when PD estimates increase. In other words, the marginal capital requirement decreases during economic downturns. Figure 3 diagrams the second case.

Figure 3: The countercyclical *Capital savings* case



Notes: The figure shows how changes in PD can lead to countercyclical *Capital savings*. The dashed lines correspond to the portfolio before a negative credit risk shock (with average PD equal to $\overline{\text{PD}}_0$) and the dotted lines to the portfolio after the shock (with average PD equal to $\overline{\text{PD}}_1 > \overline{\text{PD}}_0$). In this case, where riskier are more affected, $\text{RW}_0^s < \text{RW}_1^s$.

Finally, consider the case where $\text{dPD}_H = \text{dPD}$ and $\text{dRW}^s = 0$. Using equation 10, we can find dPD_L satisfying these conditions:

$$d\text{PD}_L = \frac{(1-q)}{q} \cdot \frac{\left[\text{RW}'(\text{PD}_H) - \text{RW}'\Big(q \cdot \text{PD}_L + (1-q) \cdot \text{PD}_H\Big)\right]}{\left[\text{RW}'\Big(q \cdot \text{PD}_L + (1-q) \cdot \text{PD}_H\Big) - \text{RW}'(\text{PD}_L)\right]} \cdot d\text{PD} \tag{13}$$

Because $\frac{\partial \text{RW}}{\partial \text{PD}} < 0$ and $\text{PD}_H > q\text{PD}_L + (1-q)\text{PD}_H > \text{PD}_L$, both the denominator and the numerator of equation 13 are negative and consequently, $\text{dPD}_L > 0$. We also know from the first case that $\text{dPD}_L < \text{dPD}$, otherwise dRW^s would be negative. Hence, the difference between the impact of the business cycle on riskier and safer assets has to be sufficiently large such that *Capital savings* are countercyclical. If that is not the case, then the procyclical effect on *Capital savings* shown in equation 11 dominates.

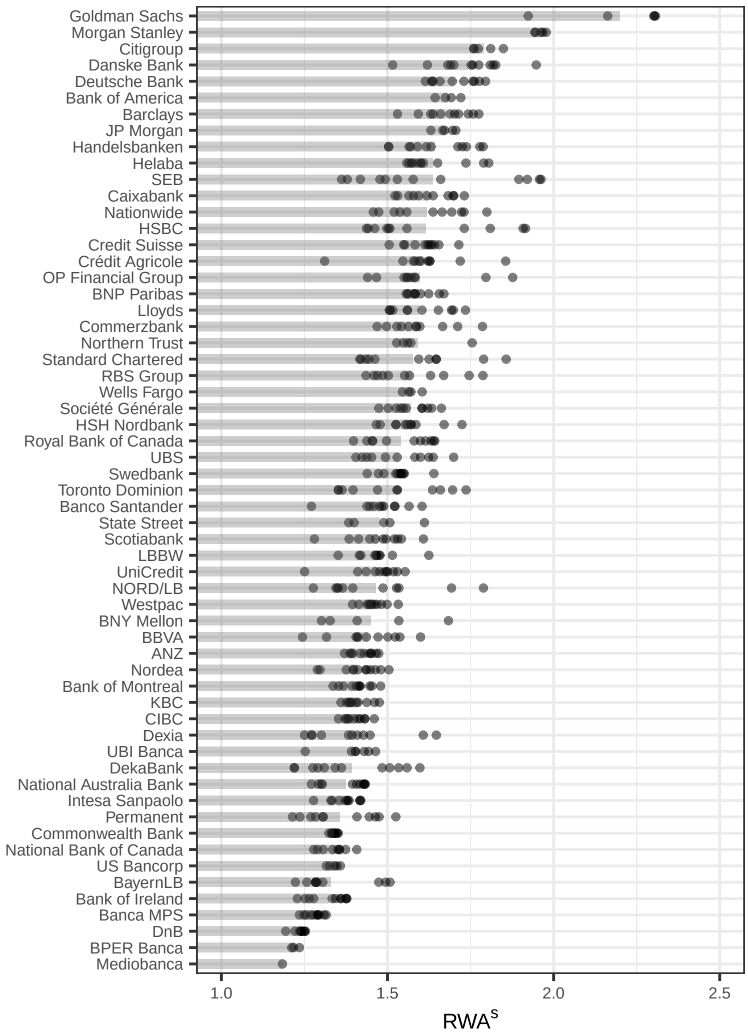
Whether *Capital savings* are pro or countercyclical is an empirical question, as the direction of the cyclicality depends on how higher-order moments of the PD distribution change during the business cycle.

3 Data and capital savings measures

To calculate the proposed measures of capital savings, information must be gathered on the distribution of banks' regulatory risk parameters. However, data at such granularity is not available in the most commonly used balance sheet datasets. Also, although very detailed, datasets from credit registers are restricted to one country, and may still lack the relevant information. Therefore, to overcome data limitations, I collected information on the distribution of credit risk parameters (PD, EAD, and LGD) from banks' Pillar-3 reports. The sample consists of 59 large banking groups, from 15 countries, that have adopted the IRB approach. For each bank, I collected consolidated information from the year the IRB approach was approved until 2018. The dataset distinguishes between wholesale, retail, and equity portfolios and, in most cases, between their sub-categories (for instance, corporate, sovereign, and banks for wholesale, and real estate, qualifying revolving credit, and others for retail). This level of portfolio breakdown is important because regulatory formulas vary across categories, and consequently, more precise knowledge of portfolio composition reduces measurements errors.

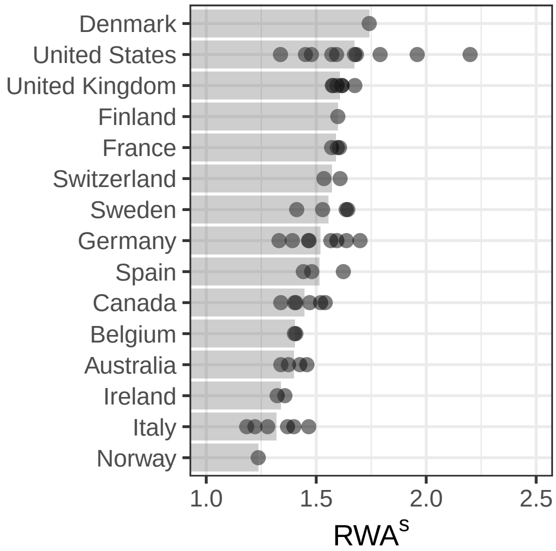
Figure 4 shows *Capital savings* calculated according to equation 6 i.e., the ratio of the average component of RWA to actual RWA. Each point is a bank-year observation and the bars indicate the average value across time for each bank. There is substantial variation across banks with Goldman Sachs saving the highest at an average rate of 220% and Mediobanca the lowest at an average rate of 118%. Variation within a bank across time can be considerable with, for instance, *Capital savings* for SEB decreasing from 196% in 2011 to 136% in 2016. *Capital savings* also vary between and within countries. Figure 5 aggregates the dataset by country. In the figure, each point is the average *Capital savings* for a bank and the bars are the average across banks within a country. The difference between countries reaches its maximum at 50% (Denmark versus Norway) and within a country at 75% (between BNY Mellon and Goldman Sachs in the United States).

Figure 4: *Capital savings* by bank



Notes: The figure plots *Capital savings* using equation 6, the ratio of the average component of RWA to actual RWA, as the measure. Each point in the plot is a bank-year observation and bars are the averages across time for each bank.

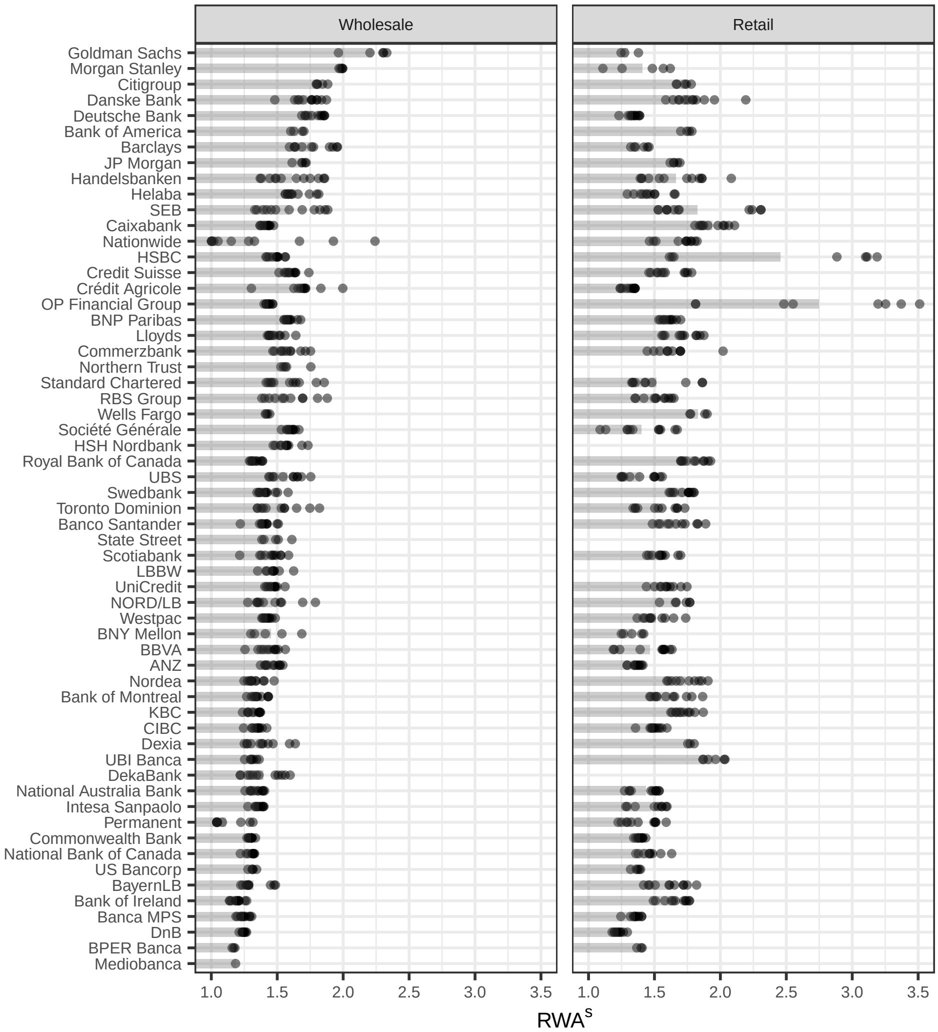
Figure 5: *Capital savings* by country



Notes:The figure plots *Capital savings* using equation 6, the ratio of the average component of RWAs to actual RWAs, as the measure. Each point is the across-time average *Capital savings* for a bank and the bars are the average across banks within a country.

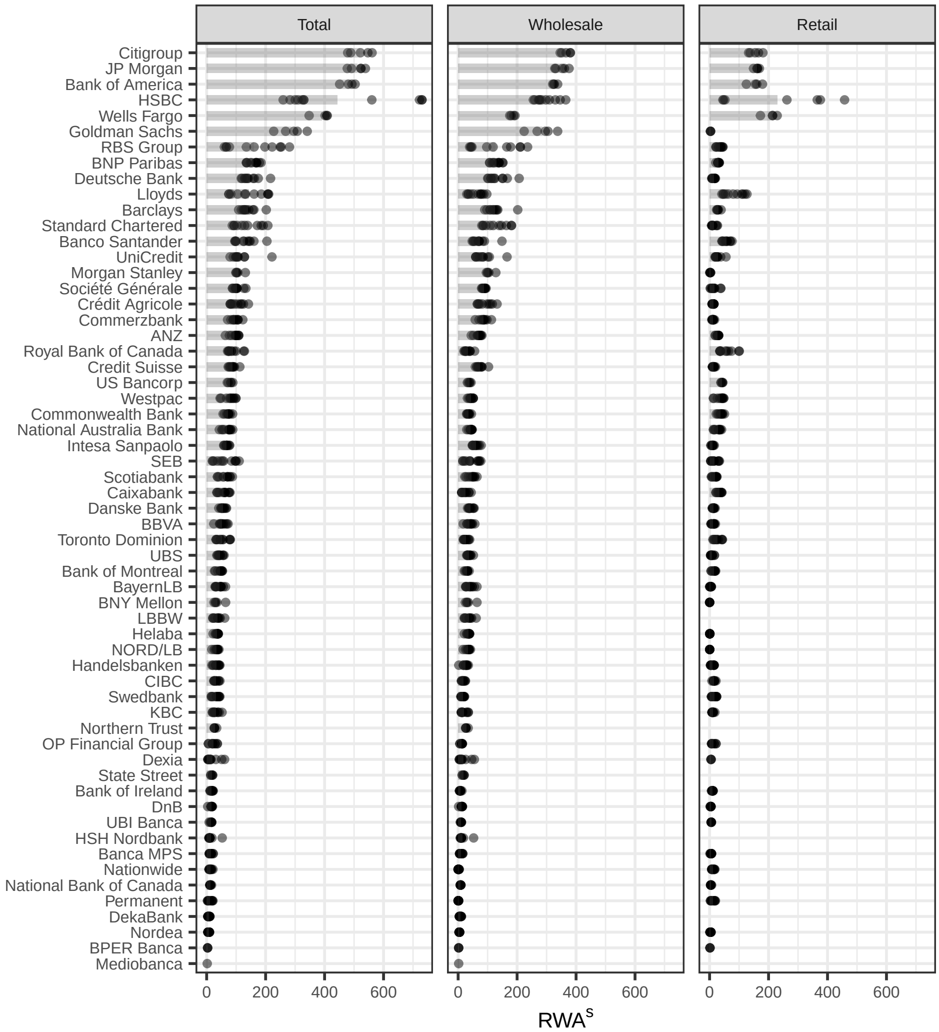
Figure 6 shows *Capital savings* for wholesale and retail portfolios using the ranking of Figure 4. The extent to which each bank benefits from *Capital savings* from a particular portfolio varies. For instance, while Goldman Sachs has an average rate of 222% for its wholesale portfolio, the average rate for its retail portfolio is 130%. On the contrary, the average rate for the OP financial group's retail portfolio is 275% and 143% for its wholesale portfolio. Moreover, the correlation coefficient between total *Capital savings* and *Capital savings* from wholesale portfolios is 0.85 and *Capital savings* from retail portfolios is 0.37. These coefficients suggest that wholesale portfolios are the main source of variation in *Capital savings* across banks.

Figure 6: *Capital savings* for wholesale and retail portfolios



Notes: The figure plots *Capital savings* using equation 6, the ratio of the average component of RWAs to actual RWAs, as the measure. The left-hand side plot shows *Capital savings* for wholesale portfolios and the right-hand side for retail portfolios. Each point in the plot is a bank-year observation and bars are the averages across time for each bank.

Figure 7: *Capital savings* in USD billions



Notes: The figure plots *Capital savings* using equation 5, the amount of the average component of RWAs minus the actual RWAs, as the measure. The left-hand side plot shows, for each bank, *Capital savings* for their entire portfolio, the middle plot for their wholesale portfolio, and the right-hand side for their retail portfolio. Each point in the plot is a bank-year observation and bars are the averages across time for each bank.

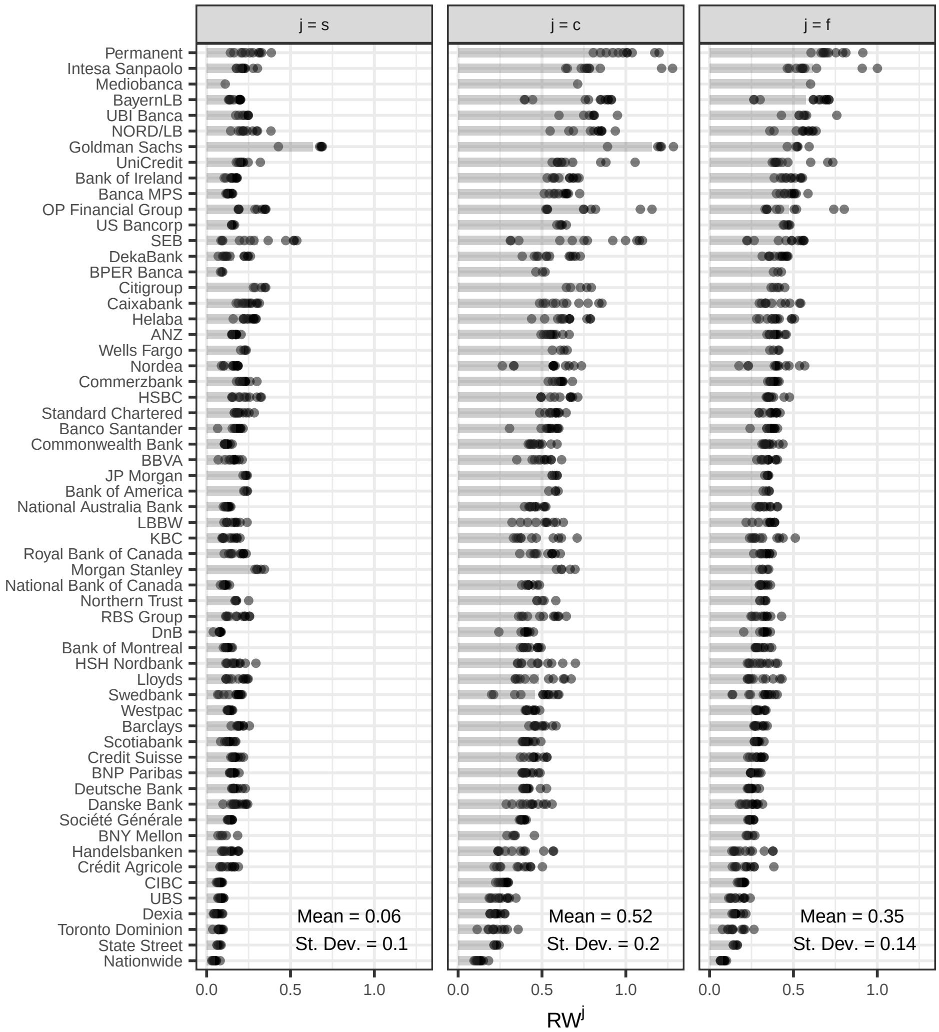
The differences across banks are even bigger when we consider *Capital savings* in monetary terms. Figure 7 shows *Capital savings* calculated in USD according to equation 5. Besides the intensity of *Capital savings* (as shown in Figure 4), the values in Figure 7 are also impacted by the size of the banks and the proportion of their portfolio under the IRB approach. For this reason, American banks stick out from the rest as they are both large and use the IRB approach for their entire portfolio.

The total amount of *Capital savings* in the sample is USD 47.9 trillion, a substantial amount considering the total amount of RWA in the sample, USD 86.3 trillion. Figure 7 also shows the amount of *Capital savings* split between wholesale and retail portfolios. The total amount of *Capital savings* for the former is USD 34.5 trillion and for the latter USD 13.4 trillion. Hence, 72% of *Capital savings* comes from wholesale portfolios. Among wholesale portfolios, USD 20.9 trillion come from exposures to corporate, USD 2.2 trillion from exposures to sovereigns, and USD 2.8 trillion from exposures to banks.[3]

Lastly, in terms of risk-weights, Figure 8 plots *Capital savings*, the average component, and total risk-weights, following equations 4, 3, and 2, respectively. Banks are ranked by total risk-weight. From equation 4, the third column is obtained by subtracting the first column from the second, i.e., total risk-weights are equal to the average component minus *Capital savings*. As expected, the average component is larger than *Capital savings*. Still, because of *Capital savings*, the variation and level of total risk-weights are substantially lower than implied by the average component. Total risk-weights are, on average, 17 percentage points lower than the average component, and the standard deviation is 6 percentage points lower.

[3]The sum of *Capital savings* from exposures to corporate, sovereign, and banks do not add up to the total for wholesale because some banks only report values aggregated at the wholesale level.

Figure 8: *Capital savings*, the average component, and risk-weights



Notes: The figure plots, in terms of risk-weights, *Capital savings* (RW^s), the average component (RW^c), and total risk-weights (RW^f), following equations 4, 3, and 2, respectively. Each point in the plot is a bank-year observation and bars are the averages across time for each bank.

4 Capital savings and bank characteristics

In this section, I study the correlation between *Capital savings* and some bank characteristics. In each column of Table 1, I regress the measure of *Capital savings* of a portfolio on the following variables. As a measure of size, I use the log of total assets. The evidence that size is an important determinant of *Capital savings* is weak. For all portfolios, except sovereign exposures, the association between size and *Capital savings* is positive but only for corporate portfolios the coefficient is statistically significant at the 10% level.

Table 1: Capital savings and bank characteristics

The table shows estimates for the following model:

$$\mathrm{RW}_{i,t}^{s,j} = \beta X_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}.$$

The dependent variable is the change in *Capital savings* from portfolio j. In all regressions, the measure of *Capital savings* is in terms of risk-weights following equation 4. $X_{i,t}$ is a vector of bank variables. All regressions include bank and year fixed effects. Robust standard errors adjusted for clustering at the country and year level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

	j = Total	j = Retail	j = Wholesale	j = Corporate	j = Sovereign	j = Banks
	(1)	(2)	(3)	(4)	(5)	(6)
Log assets$_{i,t}$	0.015	0.006	0.012	0.041*	−0.004	0.007
	(0.012)	(0.017)	(0.015)	(0.020)	(0.015)	(0.020)
ROA$_{i,t}$	−1.004	0.023	−2.508**	−3.572**	−0.155	−3.351**
	(0.831)	(0.954)	(0.983)	(1.393)	(0.974)	(1.221)
LLR / loans$_{i,t}$	0.941*	1.832**	1.202*	1.561*	−0.036	0.440
	(0.432)	(0.684)	(0.587)	(0.782)	(0.298)	(0.498)
NPL / loans$_{i,t}$	−0.070	−0.536	−0.046	−0.191	−0.433	−0.128
	(0.232)	(0.420)	(0.400)	(0.565)	(0.340)	(0.492)
NII / oper. rev.$_{i,t}$	−0.004	−0.046*	−0.010	0.022	−0.005	0.002
	(0.011)	(0.023)	(0.020)	(0.034)	(0.028)	(0.047)
Loans / assets$_{i,t}$	−0.070	−0.096	−0.037	−0.153	−0.115	0.137
	(0.052)	(0.090)	(0.091)	(0.102)	(0.084)	(0.083)
Equity / assets$_{i,t}$	0.521*	0.341	0.987**	0.632	0.818**	0.956*
	(0.283)	(0.349)	(0.338)	(0.490)	(0.333)	(0.495)
Deposit / assets$_{i,t}$	−0.046	0.024	−0.031	0.090	−0.194**	0.016
	(0.049)	(0.066)	(0.086)	(0.100)	(0.070)	(0.083)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	71	64	71	62	52	55
N	529	452	529	469	337	416
R^2	0.790	0.758	0.777	0.696	0.608	0.614

Next, I include three measures of performance. First, *Capital savings* from wholesale portfolios is negatively associated with the return on assets (ROA), in particular from exposures to corporate and banks. According to column 3 of Table 1, one standard deviation higher ROA (0.5 percentage points) is associated with *Capital savings* from wholesale portfolio being 1.2 percentage points higher, explaining 16.7% of its variation. The second measure of performance, the loan loss reserve to total assets ratio (LLR ratio) is positively associated with *Capital savings* for all portfolios except for exposures to sovereigns. The other measure of performance is the ratio of non-performing loans to gross loans. I find no association between this variable and *Capital savings*. Taken together, these correlations suggest that current bad performance (lower ROA) and expected bad performance (higher LLR ratio) result in higher dispersion of PD estimates and, consequently, higher *Capital savings*.

Finally, I include two measures of the source of income, the gross loans to total asset ratio and the ratio of net interest revenue to total operating revenue, and two measures of funding composition, the total deposit to total assets ratio and the equity to total asset ratio (leverage ratio). From these, only the association between the leverage ratio and *Capital savings* is robust, with all coefficients having the same positive sign and four out of six being statistically significant. The positive coefficient for the leverage ratio suggests that worse capitalized banks do not explore *Capital savings* as a means to increase their risk-weighted capital ratios. Conversely, better capitalized banks might have the condition to choose a more diversified portfolio, in terms of PD, and benefit from lower capital requirements due to *Capital savings*. Reverse causality could also explain the positive association. Conditional on other characteristics, banks with higher *Capital savings* have higher risk-weighted capital ratios. Because higher capital ratios are perceived by markets as resulting in a lower probability of failure, banks with higher *Capital savings* might benefit from a lower cost of capital to issue equity. To sum up, Table 1 suggests that asset performance and capital position are potential determinants of *Capital savings*.

5 Capital savings and the business cycle

In this section, I investigate the relationship between *Capital savings* and the business cycle. I show that *Capital savings* are countercyclical, i.e., for a given average PD, capital requirements are lower during economic recessions.

Throughout this section, I report the results from estimating the following specification:

$$\Delta \mathrm{Y}_{i,t}^{j} = \beta \Delta \mathrm{Log\ GDP}_{i,t} + \alpha_i + \varepsilon_{i,t}.$$

The dependent variable is the yearly change in a variable associated with portfolio j for bank i at year t. The change in the logarithm of real GDP per capita comes from the country where the bank has its headquarter. All regressions include bank fixed effects and standard errors are clustered at the country-year level.

Table 2 shows the results using equation 4, the amount of *Capital savings* per unit of EAD, as the measure of *Capital savings.* According to regression 1, an increase of 1.7 percentage points in GDP growth rate (one standard deviation) decreases total *Capital savings* growth rate by 0.5 percentage points on average. The effect is economically sizable, representing 22% of total *Capital savings* standard deviation in the sample. In other words, a bank with the average risk-weight in the sample (35%) has to increase capital by 1.4% to keep its capital ratio constant during a standard expansion of the economy.[4]

The remaining columns of Table 2 suggest that the countercyclical relationship between GDP and *Capital savings* is mostly driven by wholesale portfolios, especially corporate portfolios. The negative estimated coefficient in Column 2 suggests that *Capital savings* generated by retail portfolios are also countercyclical. However, this coefficient is not statistically significant. On the other hand, the coefficient of GDP growth rate on *Capital savings* from wholesale portfolios is statistically and economically significant. According to regression 3, one standard deviation increase in GDP growth rate decreases

[4] A α percentage point decrease in *Capital savings* in terms of risk-weights means that total risk-weight (RW) increases by α percentage points. Hence, capital must increase by $(\alpha/\mathrm{RW})\%$ to keep the capital ratio constant.

the growth rate of *Capital savings* from wholesale portfolios by 0.8 percentage points, on average. The effect is 25% of the dependent variable's standard deviation. Columns 3 to 6 indicate that within the wholesale portfolio most of the countercyclical variation appears to come from corporate portfolios. It is only in regression 4 that the coefficient of GDP growth rate is statistically significant.

Table 2: Capital savings and the business cycle

The table shows estimates for the following model:

$$\Delta \text{RW}^{s,j}_{i,t} = \beta \Delta \text{Log GDP}_{i,t} + \alpha_i + \varepsilon_{i,t}.$$

The dependent variable is the change in *Capital savings* from portfolio j. In all regressions, the measure of *Capital savings* is in terms of risk-weights following equation 4. ΔLog GDP$_{i,t}$ is the real GDP per capita growth rate. All regressions include bank fixed effects. The table also includes the p-values of Chow-tests for the difference among coefficients. The first row shows the test for the difference between the coefficient for the total portfolio and the coefficients for its components, retail and wholesale portfolios. The second row shows the test for the difference between the coefficients for retail portfolio and wholesale portfolio. The third row shows the test for the difference between the coefficient for wholesale portfolio and the coefficients for its components, corporate, sovereign, and banks. Robust standard errors adjusted for clustering at the country-year level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

	j = Total	j = Retail	j = Wholesale	j = Corporate	j = Sovereign	j = Banks
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog GDP$_{i,t}$	−0.310***	−0.077	−0.466***	−0.690***	−0.213	−0.236
	(0.081)	(0.105)	(0.106)	(0.126)	(0.165)	(0.159)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	145	142	145	143	99	132
T-test (p-value)						
j = Total		0.054	0.004			
j = Retail			0.011			
j = Wholesale				0.016	0.151	0.146
N	509	435	509	456	318	409
R^2	0.082	0.114	0.081	0.127	0.039	0.027

In Table 3, I study if the effect of GDP growth rate on *Capital savings* is symmetrical. In this table, I regress *Capital savings* on the GDP growth rate interacted with two dummy variables, one that takes the value of 1 if the GDP growth rate is positive and zero otherwise, and another that takes the value of 1 if the GDP growth rate is negative and zero otherwise. Hence, the first interaction captures the effect in the upturn of the cycle and the second captures the effect in the downturn. The results suggest a stronger effect during downturns, albeit only the difference between the coefficients for corporate portfolios is statistically significant at 10%. Notwithstanding, all coefficients from downturns have a greater magnitude compared to their respective coefficients from upturns, and 4 out 6 coefficients from downturns are significantly different from zero while, for upturns, only 2 are statistically significant.

Table 3: Capital savings during recessions and expansions

The table shows estimates for the following model:

$$\Delta \text{RW}^{s,j}_{i,t} = \beta \Delta \text{Log GDP}_{i,t} \times \text{I}(\Delta \text{Log GDP}_{i,t} > 0) + \gamma \Delta \text{Log GDP}_{i,t} \times \text{I}(\Delta \text{Log GDP}_{i,t} < 0) + \alpha_i + \varepsilon_{i,t}.$$

The dependent variable is the change in *Capital savings* from portfolio j. In all regressions, the measure of *Capital savings* is in terms of risk-weights following equation 4. ΔLog GDP$_{i,t}$ is the real GDP per capita growth rate. I(ΔLog GDP$_{i,t} > 0$), I(ΔLog GDP$_{i,t} < 0$) are indicator functions that equal 1 if the growth rate of real GDP per capita is, respectively, above and below zero. All regressions include bank fixed effects. Robust standard errors adjusted for clustering at the country-year level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

	j = Total	j = Retail	j = Wholesale	j = Corporate	j = Sovereign	j = Banks
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog GDP$_{i,t} > 0$	−0.145	0.075	−0.313**	−0.420**	0.076	−0.180
	(0.115)	(0.138)	(0.152)	(0.177)	(0.238)	(0.278)
ΔLog GDP$_{i,t} < 0$	−0.542***	−0.282	−0.683***	−1.082***	−0.630**	−0.320
	(0.189)	(0.236)	(0.252)	(0.257)	(0.307)	(0.389)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
T-test (p-value)	0.129	0.255	0.287	0.072	0.116	0.810
N clusters	145	142	145	143	99	132
N	509	435	509	456	318	409
R^2	0.087	0.119	0.084	0.133	0.047	0.027

Next, I evaluate the impact of *Capital savings* on the capital ratio during the business cycle. I also regress the yearly change of each capital ratio component, as shown in equation 7, on the GDP growth rate. Hence, for each of the dependent variables—Log capital ratio, Log Capital, Log RWA^c, and Log RWA^s—I obtain one estimate of the effect of GDP growth rate, $\hat{\beta}_{\text{Cap. ratio}}$, $\hat{\beta}_{\text{Capital}}$, $\hat{\beta}_{\text{RWA}^c}$, and $\hat{\beta}_{\text{RWA}^s}$, respectively. Using the predicted values implied by these estimated in equation 7, we get the following equality: $\hat{\beta}_{\text{Cap. ratio}} = \hat{\beta}_{\text{Capital}} - \hat{\beta}_{\text{RWA}^c} + \hat{\beta}_{\text{RWA}^s}$, which can be used to obtain the relative importance of changes of each component to changes of the capital ratio during the business cycle. The contributions are the ratio of the estimated coefficient for each component to the coefficient for the capital ratio regression, i.e., $\hat{\beta}_{\text{Capital}}/\hat{\beta}_{\text{Cap. ratio}}$, $\hat{\beta}_{\text{RWA}^c}/\hat{\beta}_{\text{Cap. ratio}}$, and $\hat{\beta}_{\text{RWA}^s}/\hat{\beta}_{\text{Cap. ratio}}$.

Table 4 shows that the growth rate of *Capital savings* is the only countercyclical component of capital ratio growth rate. As expected, both the amount of capital and RWA are procyclical, and this translates to capital ratios also being procyclical. The results also confirm the expectation that the procyclical effect of the average component dominates over the countercyclical *Capital savings*. Nevertheless, the contribution of *Capital savings* is economically relevant, reducing the procyclicality of capital ratios by 13.7%, on average.[5]

Table 4: Capital savings effect on capital ratio procyclicality

The table shows estimates for the following model:

$$\Delta \mathrm{Y}^{s}_{i,t} = \beta \Delta \mathrm{Log\ GDP}_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}.$$

Where $\Delta \mathrm{Y}_{i,t}$ is one component of the capital ratio according to equation 7. The dependent variables are the change in the logarithm of the capital ratio in column 1, of total capital in column 2, of total RWAs in column 3, of the average component in column 4, and of *Capital savings* in column 5. The average component is the amount of capital requirements if the portfolio's average PD is used for the entire portfolio. *Capital savings* is the ratio of the average component of RWAs to actual RWAs (equation 6). $\Delta \mathrm{Log\ GDP}_{i,t}$ is the real GDP per capita growth rate. The table shows the contribution of each component to the cyclicality of capital ratios, which is the respective coefficient divided by the coefficient in column 1. All regressions include bank and year fixed effects. Robust standard errors adjusted for clustering at the country-year level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

	ΔLog capital ratio$_{i,t}$	ΔLog capital$_{i,t}$	ΔLog RWA$^{f}_{i,t}$	ΔLog RWA$^{c}_{i,t}$	ΔLog RWA$^{s}_{i,t}$
	(1)	(2)	(3)	(4)	(5)
ΔLog GDP$_{i,t}$	1.744**	0.613	−1.131	−1.371*	−0.240
	(0.882)	(0.420)	(0.767)	(0.766)	(0.202)
Contribution	100.0%	35.1%	64.9%	78.6%	−13.7%
Bank FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N clusters	134	134	134	134	134
N	468	468	468	468	468
R^2	0.089	0.273	0.150	0.176	0.107

[5]The coefficient on total *Capital savings* differs from Table 2 because in Table 4 the sample is restricted to banks with observable capital ratio and is not winsorized such that the contributions add up to 100%. Moreover, all regressions in Table 4 include year fixed effects to control for common trends in capital ratio and its components in the period of the sample.

5.1 Robustness to alternative measures, samples, and model specifications

In this section, I discuss several robustness tests to the finding that *Capital savings* is countercyclical. All tests are shown in Appendix B. First, note that in Tables 2 and 3, the regressions do not include year fixed effects. The reason is that their inclusion would remove common variations across banks that are important to explain the cycle within banks across time. However, there could also be time-varying common factors that explain both *Capital savings* and GDP growth rate which the omission would bias my estimates. Panel A of Table 9 shows that the result that the countercyclical nature of *Capital savings* is mostly driven by corporate portfolio is robust to the inclusion of year fixed effects.

Second, in Tables 2 and 3, I regress the change in *Capital savings* on the contemporaneous GDP growth rate. Because I use year-on-year growth rates, it is reasonable to expect that most of the lag from changes in risk profile (GDP growth rate) to changes in risk modeling (*Capital savings* growth rate) is captured with contemporaneous correlations. Nevertheless, in Panel B of Table 9, I included the one and two years lags together with the contemporaneous GDP growth rate. Relative to the benchmark regressions in Tables 2, the signs of contemporaneous correlations remained as expected but the magnitudes are smaller. The signs of the one-year-lag coefficients are also as expected but none of the coefficients is statistically significant. The two-year-lag coefficient for retail and corporate portfolios are negative and positive, respectively, and statistically significant. While the first correlation might reflect the time that it takes for economic shocks to affect the mortgage market, which is the biggest component of retail portfolios, the second might reflect corrections to overreactions of the impact of GDP on corporate portfolio credit risk.

Next, I test the robustness of the main results to alternative measures of *Capital savings*. In Panel A of Table 10, the dependent variable measures the amount of *Capital savings* in US dollars, following equation 5. As before, the estimated coefficients suggest that the countercyclical effect is mostly driven by wholesale portfolios. In panel B of Table 10, the measure of *Capital savings* is the ratio of the average component of RWA to actual RWA following equation 6. This measure, therefore, defines *Capital savings* as the rate at which banks save capital. For instance, column 1 shows that a 1.7% GDP growth rate (one standard deviation) decreases the growth rate of *Capital savings* by 0.6 percentage points on average. In other words, given an average PD, banks have to increase capital by 0.6% to keep their capital ratio constant during a standard expansion of the economy. In Panel C of Table 10, I use the Gini coefficient as an alternative measure of *Capital savings*. Again, the results in Panel B and C support the evidence from Table 2, i.e., *Capital savings* are countercyclical and mostly driven by the effect of GDP growth rate on *Capital savings* from corporate portfolios.

Table 11 shows the results of replacing the GDP growth rate as the measure of the business cycle. In Panel A, I use the growth rate of the industrial production index, in Panel B, the growth rate of the business confidence index, both indexes from the OECD database, and in Panel C, the growth rate of world GDP taken from the World Bank's World Development Indicators. In each Panel, the coefficients for total, wholesale and corporate portfolios are negative and statistically significant. Furthermore, the coefficients for sovereign exposures are negative and statistically significant when the growth rate of industrial production or the world GDP are used as the measure, and the coefficient for retail exposures when the business confidence measure is used, reinforcing the evidence of the countercyclical nature of *Capital savings*.

Lastly, the results are robust to including only banks with at least 10 observations (Panel A of Table 12), to winsorizing the sample to the 1% level instead of the 5% (Panel B of Table 12), to aggregating *Capital savings* at the country-level (Panel C of Table 12), and to the addition of several bank-level controls (Table 13).

6 PD distribution's moments and capital savings

In this section, I study the changes of the PD distribution moments during the business cycle and their relationship with *Capital savings*. According to the theoretical framework presented in section 2.3, an increase in average PD reduces the amount of *Capital savings*, holding other moments constant. This relationship is illustrated in Figure 2 and empirically tested in Table 5. In all columns of this table, average PD is negatively associated with *Capital savings*. Note that, in Table 5, not only the explained but also explanatory variables are replaced across regressions by the respective portfolio j.

Table 5: PD moments and Capital savings

The table shows estimates for the following model:

$$\Delta\text{Log RWA}_{i,t}^{s,j} = \beta\Delta\text{Log mean}(\text{PD}_{i,t}^{j}) + \gamma\Delta\text{Log var}(\text{PD}_{i,t}^{j}) + \kappa\Delta\text{Log skew}(\text{PD}_{i,t}^{j}) + \alpha_i + \alpha_t + \varepsilon_{i,t}.$$

The dependent variable is the change in the logarithm of *Capital savings* from portfolio j. In all regressions, the measure of *Capital savings* follows equation 6, the ratio of the average component of RWAs to actual RWAs. ΔLog mean($\text{PD}_{i,t}^{j}$) is the change in the logarithm of the average of the portfolio j's PD distribution. ΔLog var($\text{PD}_{i,t}^{j}$) is the change in the logarithm of the variance of the portfolio j's PD distribution. ΔLog skew($\text{PD}_{i,t}^{j}$) is the change in the logarithm of the skewness of the portfolio j's PD distribution. All regressions include bank and year fixed effects. Robust standard errors adjusted for clustering at the bank and year level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

	j = Total (1)	j = Retail (2)	j = Wholesale (3)	j = Corporate (4)	j = Sovereign (5)	j = Banks (6)
ΔLog mean($\text{PD}_{i,t}^{j}$)	−0.159***	−0.374***	−0.110*	−0.240***	−0.248**	−0.085
	(0.046)	(0.038)	(0.053)	(0.035)	(0.082)	(0.047)
ΔLog var($\text{PD}_{i,t}^{j}$)	0.125***	0.221***	0.090***	0.133***	0.142***	0.090***
	(0.023)	(0.016)	(0.019)	(0.011)	(0.036)	(0.010)
ΔLog skew($\text{PD}_{i,t}^{j}$)	−0.049**	−0.112***	−0.041	−0.073***	−0.020	−0.085***
	(0.019)	(0.024)	(0.025)	(0.020)	(0.041)	(0.014)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	58	53	58	48	35	43
N	509	435	509	455	302	403
R^2	0.373	0.447	0.335	0.484	0.316	0.611

Panel A in Table 6 reports how average PD moves during the business cycle. As expected, in most of the regressions, changes in average PD are negatively associated with GDP growth. This association is the driver of the procyclical character of the current model-based capital regulation. The only exception is the sovereign portfolio. Column 5 of Panel A shows that the coefficient of GDP growth rate on changes in the average PD of sovereign portfolios is positive, although not statistically different from zero. A possible explanation for the positive and insignificant result is that during economic downturns banks may search for safe assets mostly in the form of safe-haven government bonds. According to column 5 of Panel A, this portfolio reallocation appears to be sufficient to compensate for any deterioration of the portfolio held before a negative shock.

Table 5 also shows that, in line with the theoretical framework, an increase in PD variance is positively associated with *Capital savings* for all portfolios. And in line with the evidence from Tables 2 and 3, Panel B in Table 6 shows that the effect of the business cycle on the PD variance is concentrated on corporate portfolios. In sum, the estimated coefficients of the average PD and the PD variance in Table 5 and Panels A and B in Table 6 provide strong empirical support to the theoretical framework presented in Section 2.3.

Next, Panel C in Table 6 shows the relationship between PD distribution skewness and the business cycle. All the statistically significant coefficients are positive. The positive coefficients are consistent with banks responding to the deterioration of their portfolios' credit quality by reducing risk taking on new loans.[6] Consider a negative shock to a continuous PD distribution, such that we can measure its skewness. Assuming a credit quality shock equivalent to the scenario in Figure 2, the shock would not affect the skewness of the distribution. In this case, only a change in the location parameter occurs as the credit quality of all assets is affected equally. Conversely, if the shock is equivalent to the case in Figure 3, the PD distribution should become more skewed to the right. Even if we think that some assets will become safer during bad times, it is reasonable to expect a larger effect on the right tail than on the left tail of the PD distribution. Consequently, without portfolio reallocation, we should expect the skewness of the PD distribution to be negatively associated with the GDP growth rate. The combination of these two movements—higher PD of existing exposures and lower PD of new assets—results in a less skewed PD distribution during recessions.

[6]Ideally, for this purpose, I would track individual assets during the cycle and compare their PD estimates evolution to the PD estimates of new loans. Unfortunately, in my dataset, I only observe assets aggregated by PD bands without knowledge if amount changes in a band are due to new loans or changes in the credit quality of assets already held.

Table 6: PD moments and the business cycle

The table shows estimates for the following model:

$$\Delta \mathrm{Y}^{j}_{i,t} = \beta \Delta \mathrm{Log\ GDP}_{i,t} + \alpha_i + \varepsilon_{i,t}.$$

The dependent variable is the change in the logarithm of the mean in Panel A, of the variance in Panel B, and of the skewness in Panel C of the portfolio j's PD distribution. ΔLog GDP$_{i,t}$ is the real GDP per capita growth rate. All regressions include bank fixed effects. Robust standard errors adjusted for clustering at the country-year level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

Panel A: $\mathrm{Y} = \Delta \mathrm{Log\ mean}(\mathrm{PD}^{j}_{i,t})$

	j = Total (1)	j = Retail (2)	j = Wholesale (3)	j = Corporate (4)	j = Sovereign (5)	j = Banks (6)
ΔLog GDP$_{i,t}$	−4.259***	−1.731***	−5.001***	−5.382***	0.754	−3.205***
	(0.790)	(0.494)	(1.026)	(0.975)	(2.662)	(1.128)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	145	142	145	143	101	132
N	509	435	509	456	315	409
R^2	0.177	0.154	0.139	0.210	0.039	0.049

Panel B: $\mathrm{Y} = \Delta \mathrm{Log\ var}(\mathrm{PD}^{j}_{i,t})$

	j = Total (1)	j = Retail (2)	j = Wholesale (3)	j = Corporate (4)	j = Sovereign (5)	j = Banks (6)
ΔLog GDP$_{i,t}$	−6.650***	−1.780	−9.498***	−10.178***	−1.294	−5.555
	(1.329)	(1.088)	(1.820)	(1.751)	(7.985)	(4.386)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	145	142	145	143	97	132
N	509	435	509	455	302	405
R^2	0.136	0.107	0.150	0.189	0.034	0.023

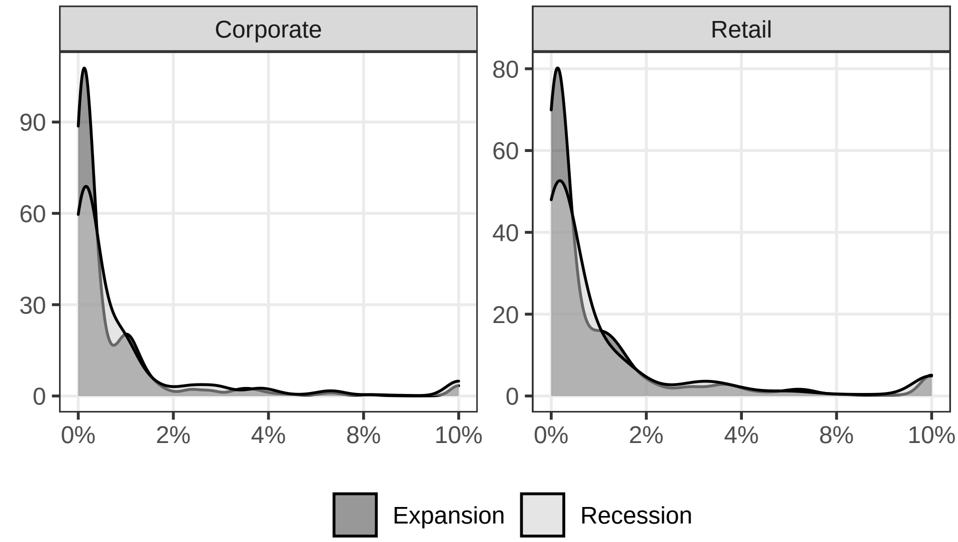
Panel C: $\mathrm{Y} = \Delta \mathrm{Log\ skew}(\mathrm{PD}^{j}_{i,t})$

	j = Total (1)	j = Retail (2)	j = Wholesale (3)	j = Corporate (4)	j = Sovereign (5)	j = Banks (6)
ΔLog GDP$_{i,t}$	3.841***	1.628***	4.299***	4.296***	−0.241	1.586
	(0.701)	(0.435)	(1.039)	(1.021)	(2.556)	(1.767)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	145	142	145	143	97	132
N	509	435	509	455	302	403
R^2	0.141	0.117	0.113	0.123	0.032	0.030

Table 5 shows that lower skewness translates into higher *Capital savings*. The effect is statistically significant for all except sovereign portfolios. According to column 1, an increase of 18.2 percentage points in PD distribution skewness growth rate (one standard deviation) decreases total *Capital savings* growth rate by 0.9 percentage points on average, representing 20% of total *Capital savings* standard deviation. The effect is even stronger on corporate portfolio accounting for 42% of its *Capital savings* standard deviation.

The evidence of Panel C in Table 6 and Table 5 suggest that part of the increase in *Capital savings* in economic recessions is consistent with a portfolio reallocation effect. This countercyclical effect, driven by the skewness of the PD distribution, is on top of any gain from a lower average PD, which is also a result of the reduced risk taking.

Figure 9: PD distribution during the business cycle



Notes: The figure plots the density of PD among all banks in the sample. The dark-shaded density considers PDs when the GDP growth rate is positive. The light-shaded density considers PDs when the GDP growth rate is negative.

Figure 9 illustrates the results of Table 6 for the corporate and retail portfolios. The figure plots, for each portfolio, the density of PDs across all banks in the sample when the GDP growth rate is positive (expansions) and when it is negative (recessions). During expansions, PDs are more concentrated at low values and there are fewer extreme values. In line with the results of Table 6, from expansions to recessions the average PD for corporate portfolios increases from 0.9% to 1.3%, the standard deviation increases from 1.7% to 2.3%, and the (scaled) skewness decreases from 3.7% to 2.7%. For retail portfolios, the pattern is the same but with smaller changes.

6.1 Selection and reallocation across portfolios

In this section, I show that selection into IRB is not driving my results. Although banks cannot opt out of IRB approach once it has been approved, they can try to (re)allocate assets to portfolios under the less risk-sensitive standardized approach. If banks can reallocate assets across approaches, then my reasoning that *Capital savings* varies due to changes in the credit quality of the portfolios is at least partially invalid. The countercyclical effect of *Capital savings* would be the result of this reallocation across approaches.

Table 7: Other RWA components and the business cycle

The table examines the relationship between the business cycle and other components of RWA. The dependent variable is the change in the logarithm of risk-weighted assets for portfolios under the standardized approach in column 1, the change in risk-weights for portfolios under the standardized approach in column 2, the change in the ratio of exposure under the standardized approach to total exposure in column 3, the change in the wholesale share of the IRB portfolio in column 4, and the change in the retail share of the IRB portfolio in column 5. ΔLog GDP$_{i,t}$ is the real GDP per capita growth rate. All regressions include bank and year fixed effects. Robust standard errors adjusted for clustering at the country level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

	ΔLog RWA$^{SA}_{i,t}$	ΔLog RW$^{SA}_{i,t}$	Δq$^{SA}_{i,t}$	Δq$^{Wholesale}_{i,t}$	Δq$^{Retail}_{i,t}$
	(1)	(2)	(3)	(4)	(5)
ΔLog GDP$_{i,t}$	0.626	0.270	0.154	−0.179	0.294
	(1.387)	(0.304)	(0.141)	(0.181)	(0.181)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N clusters	142	142	155	145	142
N	465	465	506	509	435
R^2	0.219	0.103	0.315	0.150	0.178

Table 7 provides little support for cross-approach reallocation during the business cycle. The growth rate of the total amount of RWA (column 1), the average risk-weight (column 2), and the share under the standardized approach (column 3) are all statistically insignificant. The positive coefficient in column 1 is most likely driven by the balance sheet expansion during economic booms while the positive coefficient in column 2 is reflecting portfolio reallocation within the standardized approach during the business cycle, for instance, from sovereign to corporate lending.

Lastly, I test if banks reallocate across portfolios under the IRB approach during the business cycle. According to columns 4 and 5 in Table 7, it seems that banks increase retail exposure at the expense of wholesale exposure during periods of economic expansion. However, I find this reallocation to be statistically insignificant.

Overall, Table 7 supports ruling out selection concerns with the result that *Capital savings* are a countercyclical component of capital requirements.

7 Conclusion

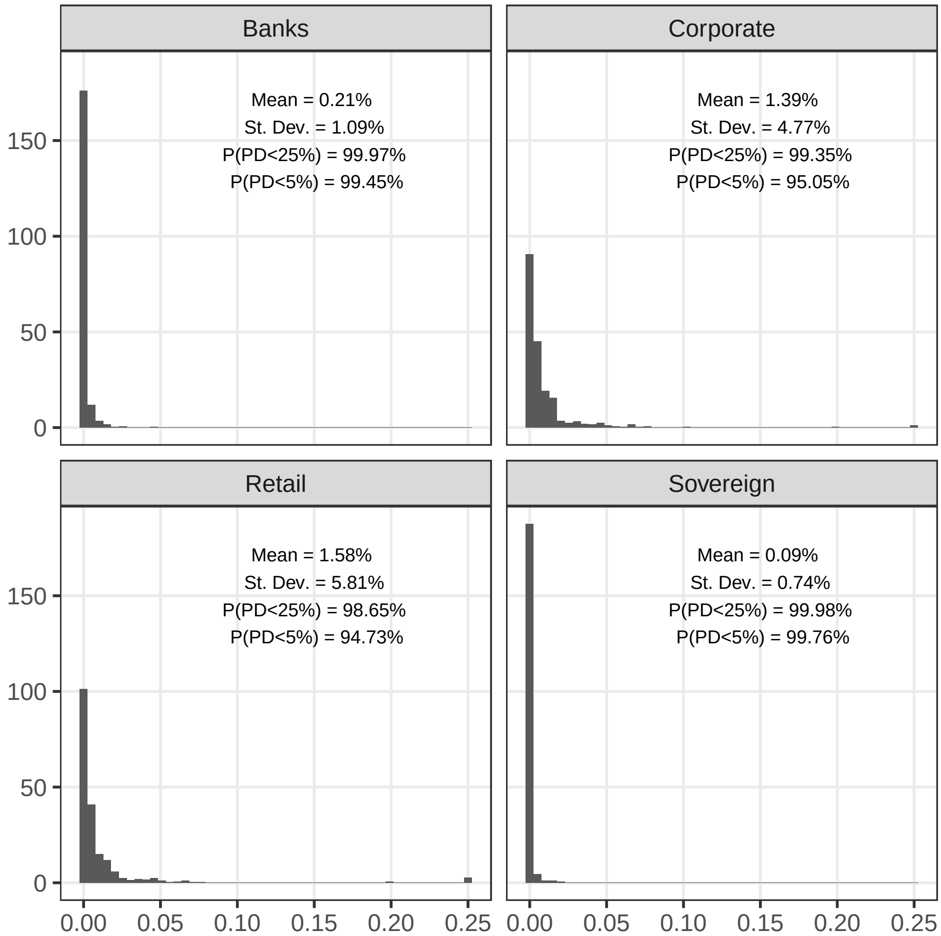
This chapter contributes new knowledge about the cyclicality and variability of capital requirements by identifying the effects of an unexplored feature of the IRB framework on capital requirements, namely, *Capital savings*. Using a hand-collected dataset, I find *Capital savings* to be countercyclical and economically relevant. My preferred regression shows that a 1.7% GDP growth rate decreases the growth rate of *Capital savings* by 0.5 percentage points on average. The variation of *Capital savings* during the business cycle reduces the procyclicality of the capital ratio by 13.7% on average. The results also suggest that the countercyclical relationship between GDP and *Capital savings* is mostly driven by wholesale portfolios, particularly corporate portfolios.

I further analyze the relationship of the PD distribution moments with GDP growth and find that during economic recessions the average and the variance of PD distributions increase while the skewness decreases. Although the effect of the average PD is stronger, which characterizes capital requirements as procyclical, both the higher variance and the lower skewness of the PD distribution mitigate the increase of capital requirements during recessions. I argue that the change of skewness during the business cycle is consistent with a within-portfolio reallocation effect on *Capital savings*.

To conclude, this chapter provides evidence that moments of the PD distribution other than the average explain a substantial variation of RW across time and banks. This finding is significant in light of the literature on RW manipulation (Berg and Koziol, 2017; Cannata et al., 2012; Ferri and Pesic, 2017; Mariathasan and Merrouche, 2014) and the policy efforts to reduce the variability of RW across banks (BCBS, 2016; EBA, 2019b; ECB, 2021) as it highlights the importance of considering the entire RW distribution within banks, not just the average PD, to understand the drivers of RW variability. Moreover, my results suggest that *Capital savings* can be used to reduce the procyclicality of capital regulation. From a policy perspective, this unexplored feature of the IRB approach could enhance financial stability in light of the evidence that countercyclical policy instruments are effective in supporting lending during crisis periods (Avezum et al., 2021; Bergant and Forbes, 2021; Jiménez et al., 2017).

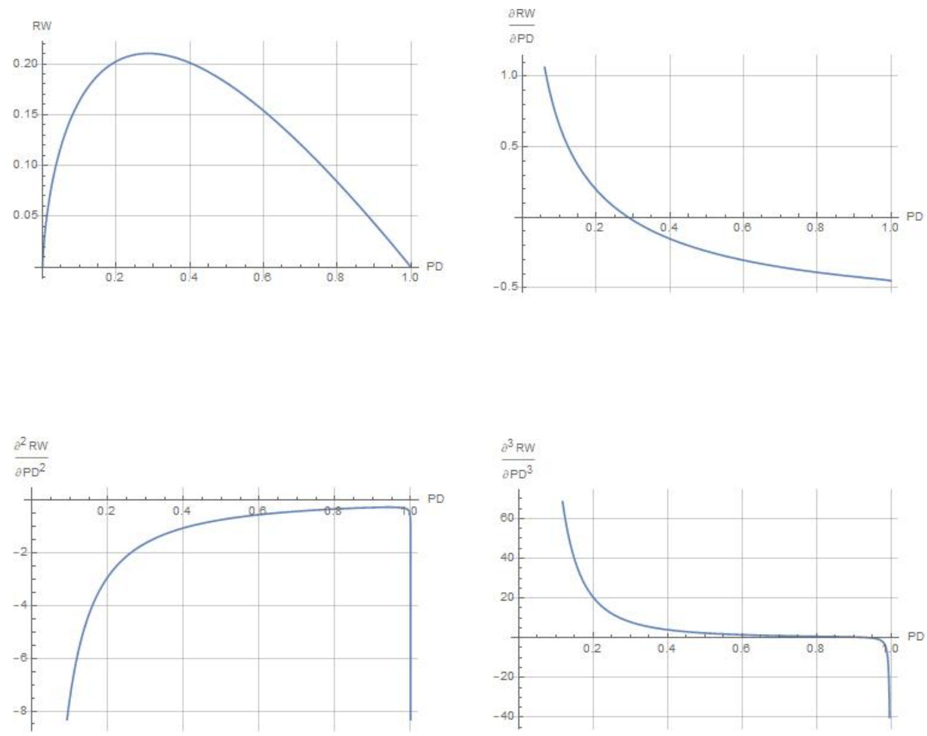
A Figures

Figure 10: PD histograms by portfolio



Notes: The figure plots probability of default histograms by portfolio for all banks and years. The last bin contains all observations with PD higher or equal to 25%. Defaulted exposures are excluded.

Figure 11: RW function and its derivative with respect to PD



Notes: The figure plots risk-weights as a function of probabilities of default (top-left) and its first, second, and third derivative with respect to probabilities of default (top-right, bottom-left, and bottom-right, respectively).

B Tables

Table 8: Summary statistics

The table shows summary statistics for banks that have introduced the IRB approach between 2007 and 2018. All variables are winsorized at 5th and 95th percentiles.

Statistic	N	Mean	St. Dev.	Min	Max
Panel A: Main dependent variables					
RW^s total	648	0.139	0.076	0.000	0.237
RW^s retail	486	0.130	0.070	0.040	0.309
RW^s wholesale	560	0.189	0.075	0.061	0.344
RW^s corporate	499	0.251	0.077	0.113	0.399
RW^s sovereign	366	0.060	0.058	0.001	0.210
RW^s banks	447	0.096	0.070	0.010	0.244
ΔRW^s total	509	−0.003	0.024	−0.052	0.050
ΔRW^s retail	435	−0.003	0.022	−0.056	0.038
ΔRW^s wholesale	509	−0.003	0.032	−0.070	0.064
ΔRW^s corporate	456	−0.005	0.037	−0.082	0.071
ΔRW^s sovereign	318	−0.0001	0.035	−0.081	0.076
ΔRW^s banks	409	−0.001	0.048	−0.108	0.103
ΔLog RWA^s total	509	0.002	0.044	−0.092	0.093
ΔLog RWA^s retail	435	0.004	0.048	−0.075	0.121
ΔLog RWA^s wholesale	509	0.001	0.045	−0.096	0.095
ΔLog RWA^s corporate	456	0.001	0.039	−0.082	0.080
ΔLog RWA^s sovereign	322	0.026	0.294	−0.454	0.859
ΔLog RWA^s banks	409	−0.005	0.118	−0.265	0.232
Panel B: Alternative measures					
ΔLog RWA^S total	509	−0.019	0.193	−0.425	0.362
ΔLog RWA^S retail	435	0.027	0.211	−0.341	0.518
ΔLog RWA^S wholesale	509	−0.037	0.206	−0.486	0.328
ΔLog RWA^S corporate	456	−0.042	0.205	−0.514	0.348
ΔLog RWA^S sovereign	318	0.028	0.764	−1.634	1.694
ΔLog RWA^S banks	409	−0.109	0.602	−1.440	1.133
Δ Log Gini total	509	0.001	0.026	−0.053	0.062
Δ Log Gini retail	435	0.003	0.025	−0.040	0.067
Δ Log Gini wholesale	509	−0.001	0.031	−0.064	0.066
Δ Log Gini corporate	455	0.0004	0.030	−0.064	0.063
Δ Log Gini sovereign	308	0.006	0.135	−0.268	0.354
Δ Log Gini banks	408	−0.0002	0.114	−0.224	0.263
Panel C: Other dependent variables					
ΔLog capital ratio	468	0.025	0.159	−0.315	0.327
ΔLog capital	537	0.021	0.111	−0.175	0.295
ΔLog RWA^{IRB}	509	−0.020	0.146	−0.301	0.273
ΔLog RWA^c	509	−0.021	0.150	−0.315	0.277
ΔLog RWA^{SA}	476	−0.090	0.290	−0.735	0.506
ΔRW^{SA}	476	−0.019	0.066	−0.171	0.112
Δq^{SA}	588	−0.013	0.035	−0.088	0.027
$\Delta q^{\text{IRB, Wholesale}}$	509	−0.008	0.033	−0.097	0.052
$\Delta q^{\text{IRB, Retail}}$	435	0.007	0.031	−0.052	0.077

Table 8 – continued from the previous page

Statistic	N	Mean	St. Dev.	Min	Max
Panel D: PD distribution moments					
Δ Log PD mean total	509	−0.017	0.177	−0.333	0.391
Δ Log PD mean retail	435	−0.023	0.133	−0.265	0.274
Δ Log PD mean wholesale	509	−0.034	0.230	−0.510	0.465
Δ Log PD mean corporate	456	−0.034	0.207	−0.430	0.424
Δ Log PD mean sovereign	315	−0.002	0.586	−1.210	1.385
Δ Log PD mean banks	409	0.027	0.352	−0.615	0.774
Δ Log PD variance total	509	−0.004	0.333	−0.578	0.795
Δ Log PD variance retail	435	−0.018	0.252	−0.479	0.573
Δ Log PD variance wholesale	509	−0.033	0.447	−0.837	0.995
Δ Log PD variance corporate	455	−0.030	0.433	−0.814	0.937
Δ Log PD variance sovereign	302	−0.055	1.391	−2.749	3.136
Δ Log PD variance banks	405	−0.045	1.288	−3.016	2.504
Δ Log PD skewness total	509	0.023	0.182	−0.359	0.441
Δ Log PD skewness retail	435	0.021	0.133	−0.258	0.311
Δ Log PD skewness wholesale	509	0.031	0.229	−0.461	0.536
Δ Log PD skewness corporate	455	0.034	0.225	−0.442	0.519
Δ Log PD skewness sovereign	302	0.039	0.552	−1.086	1.183
Δ Log PD skewness banks	403	−0.034	0.498	−1.046	0.951
Panel E: Independent variables					
ΔLog GDP$_{i,t}$	649	0.007	0.016	−0.027	0.041
ΔLog assets$_{i,t}$	616	0.009	0.111	−0.183	0.290
ΔLog income$_{i,t}$	485	0.019	0.439	−0.959	0.917
ΔLog LLR$_{i,t}$	602	0.023	0.217	−0.346	0.463
ΔLog NPL$_{i,t}$	596	0.055	0.354	−0.472	0.897
ΔLog deposits$_{i,t}$	608	0.033	0.110	−0.146	0.298
ΔLog loans$_{i,t}$	611	0.015	0.111	−0.165	0.290
ΔLog NII$_{i,t}$	597	0.013	0.138	−0.238	0.319
Log GDP$_{i,t}$	649	10.790	0.748	9.994	12.787
Log assets$_{i,t}$	619	13.142	0.983	11.183	14.648
NPL / loans$_{i,t}$	610	0.036	0.034	0.003	0.119
LLR / loans$_{i,t}$	612	0.020	0.017	0.003	0.063
ROA$_{i,t}$	613	0.006	0.005	−0.004	0.017
Equity / assets$_{i,t}$	616	0.063	0.022	0.025	0.105
Deposit / assets$_{i,t}$	614	0.442	0.155	0.198	0.702
NII / oper. rev.$_{i,t}$	610	0.541	0.165	0.171	0.799
Loans / assets$_{i,t}$	616	0.501	0.179	0.127	0.785

Table 9: Robustness to alternative model specifications

The table shows estimates for the following model:

$$\Delta Y^{j}_{i,t} = \beta \Delta \text{Log GDP}_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}.$$

The dependent variable is the change in *Capital savings* from portfolio j. In both panels, the measure of *Capital savings* is in terms of risk-weights following equation 4. All regressions in Panel A include bank and year fixed effects. In Panel B, all regressions include two lags besides the contemporaneous ΔLog GDP$_{i,t}$, the real GDP per capita growth rate. The regressions in Panel B and C include bank fixed effects. Robust standard errors adjusted for clustering at the country-year level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

Panel A: Including year fixed effects α_t

	j = Total (1)	j = Retail (2)	j = Wholesale (3)	j = Corporate (4)	j = Sovereign (5)	j = Banks (6)
ΔLog GDP$_{i,t}$	-0.185^{*}	-0.028	-0.206	-0.377^{**}	0.114	-0.218
	(0.100)	(0.096)	(0.145)	(0.148)	(0.271)	(0.236)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	145	142	145	143	99	132
N	509	435	509	456	318	409
R^2	0.116	0.159	0.119	0.175	0.074	0.067

Panel B: Including GDP growth rate lags

	j = Total (1)	j = Retail (2)	j = Wholesale (3)	j = Corporate (4)	j = Sovereign (5)	j = Banks (6)
ΔLog GDP$_{i,t}$	-0.315^{***}	-0.136	-0.389^{***}	-0.551^{***}	-0.274	-0.282
	(0.083)	(0.105)	(0.110)	(0.134)	(0.184)	(0.191)
ΔLog GDP$_{i,t-1}$	-0.082	-0.043	-0.152	-0.103	0.057	0.026
	(0.068)	(0.084)	(0.095)	(0.119)	(0.138)	(0.173)
ΔLog GDP$_{i,t-2}$	-0.055	-0.204^{***}	0.111	0.292^{***}	-0.114	-0.095
	(0.072)	(0.074)	(0.108)	(0.099)	(0.165)	(0.158)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	145	142	145	143	99	132
N	509	435	509	456	318	409
R^2	0.087	0.137	0.088	0.141	0.042	0.027

Table 10: Robustness to alternative Capital savings measures

The table shows estimates for the following model:

$$\Delta Y^j_{i,t} = \beta \Delta \text{Log GDP}_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}.$$

The dependent variable is the change in the logarithm of *Capital savings* from portfolio j. In Panel A, *Capital savings* are measured in monetary units as RWAs, following equation 5. All regressions in Panel A include bank and year fixed effects. In Panel B, the measure of *Capital savings* follows equation 6, the ratio of the average component of RWAs to actual RWAs. In Panel C, the Gini coefficient is used as an alternative measure of the shape of the PD distribution. ΔLog GDP$_{i,t}$ is the real GDP per capita growth rate. All regressions in Panel B and C include bank fixed effects. Robust standard errors adjusted for clustering at the country-year level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

Panel A: Y = Log RWA$^{S,j}_{i,t}$

	j = Total	j = Retail	j = Wholesale	j = Corporate	j = Sovereign	j = Banks
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog GDP$_{i,t}$	−1.700**	−0.508	−2.069**	−1.441	−0.415	−1.867
	(0.848)	(0.833)	(1.016)	(0.977)	(5.198)	(2.969)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	145	142	145	143	99	132
N	509	435	509	456	318	409
R^2	0.223	0.258	0.224	0.270	0.070	0.118

Panel B: Y = Log RWA$^{s,j}_{i,t}$

	j = Total	j = Retail	j = Wholesale	j = Corporate	j = Sovereign	j = Banks
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog GDP$_{i,t}$	−0.356***	−0.132	−0.326**	−0.254**	0.072	−0.339
	(0.132)	(0.166)	(0.143)	(0.115)	(1.310)	(0.425)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	145	142	145	143	101	132
N	509	435	509	456	322	409
R^2	0.060	0.058	0.055	0.048	0.099	0.038

Panel C: Y = Log Gini$^{j}_{i,t}$

	j = Total	j = Retail	j = Wholesale	j = Corporate	j = Sovereign	j = Banks
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog GDP$_{i,t}$	−0.252***	−0.009	−0.346***	−0.342***	−0.359	−0.259
	(0.082)	(0.108)	(0.092)	(0.081)	(0.653)	(0.379)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	145	142	145	143	98	132
N	509	435	509	455	308	408
R^2	0.079	0.079	0.088	0.083	0.045	0.027

Table 11: Robustness to alternative measures of the business cycle

The table shows estimates for the following model:

$$\Delta\text{RW}^{j}_{i,t} = \beta\Delta\text{Y}_{i,t} + \alpha_i + \varepsilon_{i,t}.$$

The dependent variable is the change in *Capital savings* from portfolio j. In all regressions, the measure of *Capital savings* is in terms of risk-weights following equation 4. In Panel A, the independent variable is the change of the industrial production index. In Panel B, the independent variable is the change of the business confidence index. In Panel C, the independent variable is the growth rate of world GDP. All regressions include bank fixed effects. Robust standard errors adjusted for clustering at the country-year level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

Panel A: Industrial production

	j = Total	j = Retail	j = Wholesale	j = Corporate	j = Sovereign	j = Banks
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog IP$_{i,t}$	−0.082***	−0.019	−0.119***	−0.192***	−0.098**	−0.054
	(0.025)	(0.038)	(0.029)	(0.034)	(0.038)	(0.038)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	145	142	145	143	99	132
N	509	435	509	456	318	409
R^2	0.079	0.113	0.075	0.129	0.051	0.025

Panel B: Business confidence

	j = Total	j = Retail	j = Wholesale	j = Corporate	j = Sovereign	j = Banks
	(1)	(2)	(3)	(4)	(5)	(6)
ΔConfidence$_{i,t}$	−0.269***	−0.149*	−0.280**	−0.557***	0.049	−0.246
	(0.086)	(0.088)	(0.114)	(0.143)	(0.162)	(0.150)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	145	142	145	143	99	132
N	509	435	509	456	318	409
R^2	0.073	0.122	0.050	0.095	0.032	0.027

Panel C: World GDP

	j = Total	j = Retail	j = Wholesale	j = Corporate	j = Sovereign	j = Banks
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog GDP$_{t}$	−0.332***	−0.081	−0.526***	−0.825***	−0.378***	−0.213
	(0.104)	(0.135)	(0.129)	(0.138)	(0.138)	(0.191)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	145	142	145	143	99	132
N	509	435	509	456	318	409
R^2	0.077	0.113	0.080	0.132	0.053	0.025

Table 12: Capital savings and the business cycle: robustness to alternative samples

The table shows estimates for the following model:

$$\Delta \text{RW}^{s,j}_{i,t} = \beta \Delta \text{Log GDP}_{i,t} + \alpha_i + \varepsilon_{i,t}.$$

The dependent variable is the change in *Capital savings* from portfolio j. In all regressions, the measure of *Capital savings* is in terms of risk-weights following equation **??**. ΔLog GDP$_{i,t}$ is the real GDP per capita growth rate. In Panel A, only banks with at least 10 observations are included. In Panel B, variables are winsorized at 1% and 99%. In Panel C, *Capital savings* is aggregated at the country level. Regressions in Panel A and B include bank fixed effects and robust standard errors adjusted for clustering at the country-year level are reported in parentheses. In Panel C, regressions include country fixed effects, and robust standard errors for heteroscedasticity are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

Panel A: Balance panel

	j = Total	j = Retail	j = Wholesale	j = Corporate	j = Sovereign	j = Banks
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog GDP$_{i,t}$	-0.312^{***}	-0.062	-0.470^{***}	-0.648^{***}	-0.406^{***}	-0.291
	(0.082)	(0.115)	(0.108)	(0.136)	(0.121)	(0.180)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	123	122	123	123	81	123
N	428	334	428	387	243	357
R^2	0.080	0.063	0.078	0.113	0.053	0.031

Panel B: Sample winsorized at 1%

	j = Total	j = Retail	j = Wholesale	j = Corporate	j = Sovereign	j = Banks
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog GDP$_{i,t}$	-0.307^{***}	-0.111	-0.462^{***}	-0.716^{***}	-0.126	-0.215
	(0.094)	(0.143)	(0.120)	(0.120)	(0.202)	(0.148)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	145	142	145	143	99	132
N	509	435	509	456	318	409
R^2	0.073	0.108	0.076	0.136	0.027	0.022

Panel C: Capital savings at the country-level

	j = Total	j = Retail	j = Wholesale	j = Corporate	j = Sovereign	j = Banks
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog GDP$_{i,t}$	-0.285^{**}	-0.196^{*}	-0.320^{*}	-0.575^{***}	0.138	-0.391^{*}
	(0.133)	(0.114)	(0.189)	(0.127)	(0.567)	(0.232)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
N	145	142	145	143	99	132
R^2	0.101	0.045	0.084	0.362	0.022	0.037

Table 13: Capital savings and the business cycle: control variables

The table shows estimates for the following model:

$$\Delta \text{RW}^{s,j}_{i,t} = \beta \Delta \text{Log GDP}_{i,t} + \gamma \Delta X_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}.$$

The dependent variable is the change in the logarithm of *Capital savings* from portfolio j. The dependent variable is the change in *Capital savings* from portfolio j. In all regressions, the measure of *Capital savings* is in terms of risk-weights following equation **??**. ΔLog GDP$_{i,t}$ is the real GDP per capita growth rate. $X_{i,t}$ is a vector of independent variables: ΔLog total assets$_{i,t}$ is the asset growth rate. ΔLog capital$_{i,t}$ is the capital growth rate. ΔLog income$_{i,t}$ is the earnings before taxes growth rate. ΔLog LLR$_{i,t}$ is the growth rate of the ratio of loan loss reserve to gross loans. ΔLog NPL$_{i,t}$ is the growth rate of the ratio of non-performing assets to total loans. ΔLog deposits$_{i,t}$ is the growth rate of the ratio of deposits to total assets. ΔLog loans$_{i,t}$ is the growth rate of the ratio of loans to total assets. ΔLog NII$_{i,t}$ is the growth rate of the ratio of net interest income to operating revenues. Log GDP$_{i,t}$ is the log of real GDP per capita. Log total assets$_{i,t}$ is the log of total asset. NPL / loans$_{i,t}$ is the ratio of non-performing loans to total loans. LLR / loans$_{i,t}$ is the ratio of loan loss reserve to gross loans. ROA$_{i,t}$ is the ratio of earnings before taxes to total assets. Equity / total assets$_{i,t}$ is the ratio of capital to total assets. Deposit / total assets$_{i,t}$ is the ratio of deposits to total assets. NII / oper. rev.$_{i,t}$ is the ratio of net interest income to operating revenues. Loan / total assets$_{i,t}$ is the ratio of gross loans to total assets. All regressions include bank and year fixed effects. Robust standard errors adjusted for clustering at the country-year level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	j = Total (1)	j = Retail (2)	j = Wholesale (3)	j = Corporate (4)	j = Sovereign (5)	j = Banks (6)
ΔLog GDP$_{i,t}$	−0.270**	−0.085	−0.212	−0.408**	0.006	−0.103
	(0.136)	(0.123)	(0.180)	(0.194)	(0.310)	(0.250)
ΔLog assets$_{i,t}$	0.024	0.072**	−0.006	0.045	0.039	−0.066
	(0.039)	(0.033)	(0.055)	(0.065)	(0.084)	(0.075)
ΔLog capital$_{i,t}$	−0.006	−0.033*	−0.001	−0.025	0.044	0.011
	(0.022)	(0.019)	(0.026)	(0.032)	(0.035)	(0.043)
ΔLog income$_{i,t}$	0.002	0.006*	−0.002	−0.007	0.010	0.001
	(0.004)	(0.004)	(0.006)	(0.007)	(0.008)	(0.009)
ΔLog LLR$_{i,t}$	0.018*	0.001	0.029*	0.014	0.005	0.030
	(0.011)	(0.011)	(0.016)	(0.017)	(0.023)	(0.029)
ΔLog NPL$_{i,t}$	−0.008	0.008	−0.009	0.008	−0.020*	−0.015
	(0.008)	(0.008)	(0.011)	(0.014)	(0.012)	(0.018)
ΔLog deposits$_{i,t}$	−0.032	−0.019	−0.022	−0.021	−0.018	−0.083
	(0.033)	(0.031)	(0.045)	(0.052)	(0.044)	(0.068)
ΔLog loans$_{i,t}$	0.036	−0.047	0.040	0.006	−0.087	0.093
	(0.036)	(0.035)	(0.047)	(0.066)	(0.068)	(0.080)
ΔLog NII$_{i,t}$	−0.025**	0.009	−0.030*	−0.058***	−0.013	0.065*
	(0.012)	(0.018)	(0.018)	(0.018)	(0.030)	(0.038)
Log GDP$_{i,t}$	−0.054	−0.081	0.069	0.089	−0.603**	−0.229
	(0.124)	(0.099)	(0.145)	(0.175)	(0.260)	(0.221)
Log assets$_{i,t}$	0.016	0.031**	0.021	0.020	−0.038	−0.032
	(0.015)	(0.016)	(0.019)	(0.022)	(0.026)	(0.038)

(Continued)

Table 13 – continued from the previous page

	j = Total	j = Retail	j = Wholesale	j = Corporate	j = Sovereign	j = Banks
	(1)	(2)	(3)	(4)	(5)	(6)
NPL / loans$_{i,t}$	0.086	−0.337	0.468	−0.193	0.265	0.295
	(0.356)	(0.299)	(0.511)	(0.607)	(0.654)	(0.778)
LLR / loans$_{i,t}$	0.050	0.545	−0.382	0.927	−0.994	0.708
	(0.738)	(0.579)	(1.064)	(1.326)	(1.385)	(1.682)
ROA$_{i,t}$	0.148	−0.124	−0.312	1.096	−0.022	0.289
	(1.111)	(1.147)	(1.586)	(1.841)	(1.938)	(2.303)
Equity / assets$_{i,t}$	−0.036	0.152	−0.147	0.113	0.440	−1.151
	(0.265)	(0.234)	(0.379)	(0.423)	(0.642)	(0.888)
Deposit / assets$_{i,t}$	−0.018	−0.002	−0.039	0.048	−0.071	−0.080
	(0.051)	(0.050)	(0.067)	(0.074)	(0.082)	(0.113)
NII / oper. rev.$_{i,t}$	0.066*	−0.006	0.099*	0.078	0.139**	0.155
	(0.039)	(0.035)	(0.055)	(0.052)	(0.059)	(0.095)
Loans / assets$_{i,t}$	0.059	0.058	0.090	−0.015	−0.125	0.042
	(0.059)	(0.056)	(0.083)	(0.093)	(0.140)	(0.136)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N clusters	118	115	118	116	73	102
N	363	316	363	313	215	289
R^2	0.227	0.274	0.208	0.254	0.266	0.164

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