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\* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

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# Differentiated deleveraging: How do banks respond to capital ratios and capital requirements?\*

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**Abstract** We study the heterogeneous relationship between bank capital ratios, capital requirements, bank lending and loan pricing using data on portfolios and bank characteristics for a sample of large European banks in the period 2014-2025. Exploiting dynamic panel data models with parameter heterogeneity, we relate time-varying bank capital ratios and bank capital requirements to portfolio exposures and loan rates. We establish a pattern of differentiated deleveraging whereby higher capital ratios are associated with smaller portfolio sizes, but only for high-risk portfolios and banks with low leverage ratios. On the pricing side, higher capital requirements are associated with only a small increase in portfolio loan rates. The empirical evidence suggests that, once banks are adequately capitalized, capital requirements can be varied without causing substantial changes in bank loan supply and loan pricing.

**Keywords** Bank lending, capital ratio, capital requirement, loan pricing, panel data model.

**JEL codes** C23, C54, G21, G28.

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# 1 Introduction

In this paper we empirically analyze the impact of capital ratios and time varying capital requirements on both the quantity and pricing of loans for a sample of large European banks in the period 2014-2025. In the wake of the Global Financial Crisis, regulators have substantially increased risk-weighted capital requirements for banks, aiming to create a financial system more resilient to shocks. While studies have shown the positive welfare effects of higher capital ratios and capital requirements (Basel Committee on Banking Supervision 2019), there are ongoing concerns that banks reduce credit and increase lending rates to achieve higher capital ratios in response to higher capital requirements.

Throughout the empirical analysis we exploit panel data models with heterogeneous slope coefficients to allow for heterogeneous responses of portfolio<sup>1</sup> exposures and loan rates to capital ratios and capital requirements. Earlier studies (Carlson et al. 2013, Juelsrud and Wold 2020, Lang and Menno 2025) find that allowing for heterogeneous pass-through of regulatory changes across portfolios and banks is quantitatively relevant. There is evidence of portfolio rebalancing, i.e. substitution of assets with high risk weights for low-risk assets, and of bank lending responsiveness mediated by bank capitalization. To study how banks adjust their balance sheets in response to capital ratios and capital requirements, we combine portfolio-level data and capital ratios obtained from the EBA Transparency Exercises with hand-collected information on bank-specific capital requirements. The level of aggregation of the portfolio data lies between aggregate balance sheet measures (such as total lending or total assets) and loan-level observations.

The empirical analysis in this study provides three key findings. First, we document a relationship between bank capital and portfolio exposure that is consistent with differentiated

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<sup>1</sup>A portfolio is defined as a collection of credit exposures grouped by their regulatory classification, product type and, in some cases, borrower type; a typical example is retail mortgage exposures on an internal model approach.

deleveraging: increases in capital ratios are associated with reductions in portfolio size that are systematically larger for (i) portfolios with higher average risk-weights and (ii) banks with lower leverage ratios. Apart from this "between-portfolio" differentiated deleveraging, we also find evidence of "within-portfolio" differentiated deleveraging: the reductions in portfolio size are more pronounced for risk-weighted assets (RWAs) than for unweighted exposures. By contrast, time-varying capital requirements have little additional explanatory power for portfolio volumes once we control for capital ratios. This nuances the degree to which the more substantial findings in specific countries, portfolios and time periods found in other studies can be generalized to all banks and portfolios.

Second, we document a positive association between lending rates and capital requirements - and not so much between lending rates and higher capital ratios - but the magnitude of the estimated effect is relatively small: about 9 basis points (bp) for a 1 percentage point increase in the capital requirement for new lending. This is higher than one would expect based on the back-of-the-envelope calculation by Lang and Menno (2025) resulting in 3 bp, but it is in the mid-range of previous empirical estimates, such as 3 bp estimate in Bichsel et al. (2021), the 8.5 bp increase found by Glancy and Kurtzman (2022) for US commercial real estate and the 15-20 bp range reported by Lambertini and Mukherjee (2016) for US banks.

Third, we examine how capital requirements affect capital ratios. Because we do not find direct effects of capital requirements on portfolio volumes, controlling for a bank's capital ratio, any influence of requirements on lending must operate through a requirement-capital-ratio channel. We show that, on average, requirement increases are largely absorbed by lower headroom rather than by higher capital ratios. This findings adds to the emerging literature on the muted and heterogeneous pass-through of capital requirements to capital ratios (Couaillier 2021, Abbondanza et al. 2025). A caveat to this finding is that capital requirements are measured at implementation date, and at announcement date, leaving open the possibility for stronger

behavioral effects between announcement and implementation dates.

There is a large literature on the relationship between capital ratios and bank balance sheets (Berrospide and Edge 2010, Carlson et al. 2013, Buch and Prieto 2014, Altunbaş et al. 2016, Tracey and Sowerbutts 2018), on capital requirements and bank lending (Bridges et al. 2014, Mesonnier and Monks 2015, Martynova 2015, Imbierowicz et al. 2018, Cappelletti et al. 2019, De Jonghe et al. 2020, Fraisse et al. 2020, Juelsrud and Wold 2020, Malovaná and Ehrenbergerová 2022, Conti et al. 2023), and on capital requirements and loan pricing (Lambertini and Mukherjee 2016, Bichsel et al. 2021, Glancy and Kurtzman 2022). Most of these studies focus on a single country or specific regulatory change and either exploit very detailed loan-level data for narrowly defined portfolios or rely on highly aggregated lending measures. Many studies also concentrate on crisis or pre-crisis episodes or on single policy interventions. It is therefore not clear how well these findings extend to the current European regulatory regime.

Our contributions to this literature are as follows. First, we provide cross-country estimates for a sample of large European banks and, hence, we move beyond country-level studies for, among others, Belgium, Denmark, France, Germany, Italy, Portugal, Switzerland, UK and the US (Bridges et al. 2014, Buch and Prieto 2014, Lambertini and Mukherjee 2016, Imbierowicz et al. 2018, Tracey and Sowerbutts 2018, De Jonghe et al. 2020, Fraisse et al. 2020, Bichsel et al. 2021, Degryse et al. 2021, Glancy and Kurtzman 2022, Conti et al. 2023). Second, for our sample of banks we employ an unusually detailed portfolio-level data set that covers all banking-book credit exposures classified by regulatory treatment, customer type and product type. This set up is broader than loan-level studies that focus on specific segments (Tracey and Sowerbutts 2018, De Jonghe et al. 2020, Bichsel et al. 2021, Degryse et al. 2021, Glancy and Kurtzman 2022, Couaillier et al. 2025) and more granular than aggregate lending statistics (Mesonnier and Monks 2015, Imbierowicz et al. 2018, Conti et al. 2023). Third, we observe banks over 2014-2025, a period in which Basel III was implemented and voluntary buffers built

up, allowing us to study the effects of capital ratios and time-variation in capital requirements in an environment that closely resembles the current policy regime, rather than in crisis or transition periods (Berrospide and Edge 2010, Bridges et al. 2014, Altunbaş et al. 2016, Mayordomo and Rodríguez-Moreno 2018, Tracey and Sowerbutts 2018, Cappelletti et al. 2019, Juelsrud and Wold 2020, Degryse et al. 2021, Conti et al. 2023, Couaillier et al. 2025). Finally, our work contributes to the literature on heterogeneous pass-through of regulatory changes across portfolios and banks (Carlson et al. 2013, Juelsrud and Wold 2020, Lang and Menno 2025, Abbondanza et al. 2025, Couaillier et al. 2025).

The remainder of this paper is structured as follows. In Section 2 we describe the data with a focus on the portfolio exposures, bank capital ratios and bank capital requirements. In Section 3 we describe our empirical framework, i.e. a dynamic panel data model with slope parameter heterogeneity. In Section 4 we use this empirical model to explain the development of portfolio exposures and lending rates by capital ratios, capital requirements and a host of control variables. We focus on differentiated deleveraging, i.e. the heterogeneous effects that changes in capital ratios and capital requirements have across portfolios, banks and over time. Additionally, we analyze the pass-through from capital requirements to capital ratios. We include a large number of robustness checks, details can be found in the Annex. Section 5 concludes.

## **2 Data**

We construct a semi-annual panel by compiling data from several sources, most notably the series of EBA Transparency Exercises (TEs) and stress tests conducted since 2012. These EBA TEs contain detailed, granular information from regulatory reports submitted by banks, which makes the data highly comparable across institutions. From these disclosures we obtain unweighted portfolio exposures and risk-weighted assets, as well as capital ratios, leverage ratios, and various balance-sheet and profitability metrics. Macroeconomic data are collected

from Eurostat.<sup>2</sup> Data on capital requirements are typically hard to collect, as they are widely considered confidential supervisory information. However, since 2015 European banks with listed securities have been required to disclose their capital requirements, because these affect payouts on those securities. We exploit this disclosure regime to construct a new data set of bank-specific capital requirements, hand-collected from public disclosures.

The data are reported at a semi-annual frequency at either the bank or bank-portfolio level. Our sample covers the period 2014:12-2025:6. The data set has a large cross-section (many portfolios and banks) but a relatively short time dimension for each portfolio-bank pair. The panel is unbalanced: the maximum number of semi-annual observations per portfolio-bank is 22, with a mean (median) of 15 (17). In total, the sample comprises 26 portfolios for 94 banks, yielding 1,726 portfolio-bank combinations and 21,976 observations for which the capital ratio, capital requirement and portfolio exposure are jointly observed. We removed observations with negative exposures (854 observations) and risk weights larger than 2.5 (533 observations). The banks in the sample are the largest banks per country, with all directly supervised banks by the European Central Bank (ECB) included. The countries include both countries that are European union (EU) member states, but also some of the European Economic Area (EEA) member states such as Iceland. Note that not all of these banks have listed equity instruments; some banks are privately held, publicly owned, or constitute cooperative banks.

The main dependent variable (labeled  $Y$ ) is the logarithm of the exposure value,<sup>3</sup> which is the amount on which the bank incurs credit risk and against which capital requirements are defined. Exposures are recorded at the portfolio level, where a portfolio is a collection of exposures that (i) share the same method for calculating risk-weights (standardized or internal models), (ii) have similar product characteristics, and (iii) in some cases the same customer type. Table 1 reports

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<sup>2</sup>The data are downloadable at: <https://doi.org/10.5281/zenodo.19109425>

<sup>3</sup>Formally defined as the “accounting value remaining after specific credit risk adjustments, additional value adjustments in accordance with Articles 34 and 110 and other own funds reductions related to the asset item have been applied” per Article 111(1) of the Capital Requirements Regulation Council of the European Union (2013).

Table 1: Descriptive statistics

	$Y$	$X$	$H$	$R$	$LR$	$PRW$
Mean	7.513	0.177	0.079	0.098	0.068	0.479
SD	2.923	0.101	0.102	0.017	0.043	0.503
p50	7.850	0.153	0.054	0.095	0.059	0.309
Min	-18.229	0.015	-0.078	0.045	0.005	0.000
Max	13.540	1.077	0.970	0.180	0.995	2.500

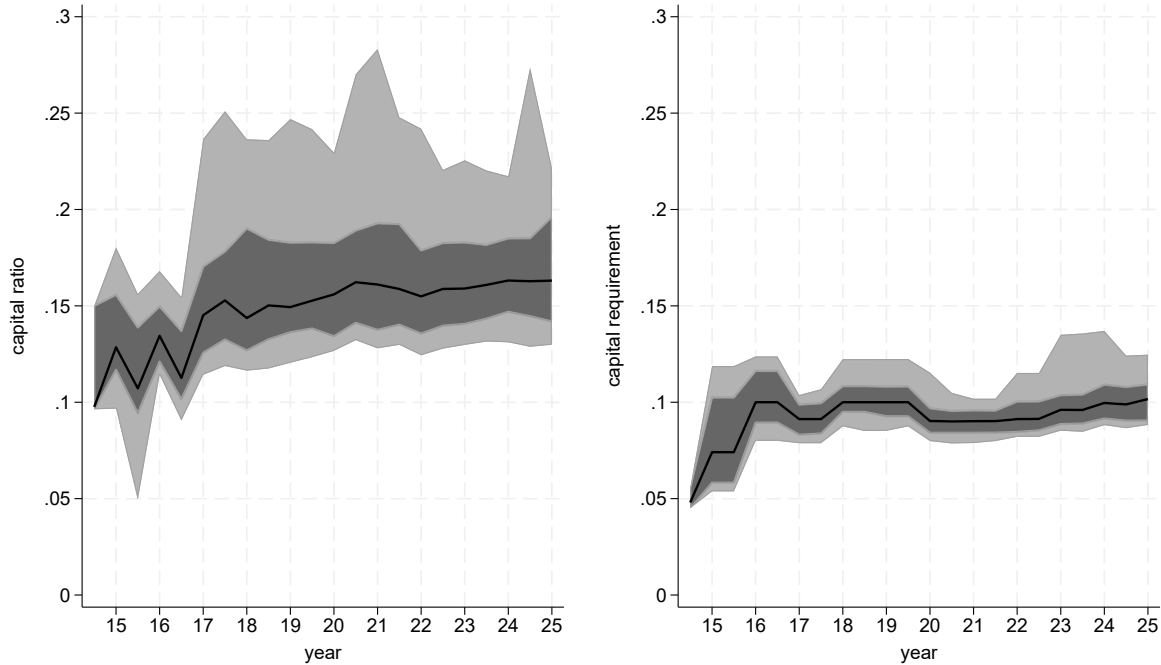
Note:  $Y$  is log portfolio exposure,  $X$  is bank capital ratio,  $H$  is headroom,  $R$  is regulatory capital requirement,  $LR$  is leverage ratio,  $PRW$  is average portfolio risk weight

descriptive statistics for log exposures as well as their average risk weights (labeled  $PRW$ ).

Regarding bank capital, we distinguish between the capital ratio (labeled  $X$ ), the regulatory capital requirement (labeled  $R$ ) and headroom (labeled  $H$ , also referred to as capital surplus). Throughout, we use ‘capital ratio’ to refer to the CET1 capital ratio relative to RWAs, unless stated otherwise. We consider the sum of Pillar 1 requirements (P1R), Pillar 2 requirements (P2R) and the combined buffer requirement (CBR) as the regulatory capital requirement. Since 2015, banks with listed instruments have been required to disclose their capital and buffer requirements; this study relies on data collected from these disclosures. See Annex 1 for a detailed exposition of these separate components. Headroom is defined as the difference between the capital ratio and the capital requirement ( $H = X - R$ ), i.e. the amount of excess capital expressed as a percentage of RWAs. All three variables are measured at the bank level. In the empirical analysis we also exploit the bank leverage ratio (labeled  $LR$ ), which is a measure of capital to unweighted assets, and as such does not depend on risk-weights.

Table 1 reports descriptive statistics for the bank capital variables. The average capital ratio is 0.177 (17.7%), which is around 80% higher than the average capital requirement of 0.098 (9.8%). On average, headroom is 0.079 (7.9%) and it is negative for only 3% of the observations. The dispersion in the regulatory capital requirement is much lower than for the capital ratio and headroom; its standard deviation is more than five times smaller. Unreported

Figure 1: Distribution of capital ratio and regulatory requirements across banks and over time



Note: The black line plots the median. The dark (light) grey areas represent the 25th to 75th (10th to 90th) percentiles, respectively.

panel autoregressions with bank and time fixed effects suggest that all variables are stationary but display significant autocorrelation.

Figure 1 shows the distribution of both the capital ratio and the regulatory capital requirement over time. The sample size is very small in the earliest three periods (2014-2015), so these years should be interpreted with caution. It is clear from the figure that capital ratios are considerably larger than capital requirements throughout the sample, implying that headroom is almost always positive. The large and positive voluntary capital buffers are key for interpreting the empirical results, as we shall see.<sup>4</sup> Furthermore, the dispersion of the capital ratio across banks is large

<sup>4</sup>Note that when changing the definition of capital and associated capital requirement, for example from transitional to fully loaded or from CET1 to Total Capital, we observe some small changes in the levels of the voluntary buffers, but the stylized fact of large voluntary buffers remains.

compared with the capital requirement. Since 2016, the median requirement has remained more or less constant until 2020. This is somewhat surprising, as capital requirements were supposed to be phased in over 2014-2019. One reason for this pattern is that the ECB and some EU member states, such as Italy and Cyprus, decided to apply the full capital conservation buffer already in 2015, instead of a phased-in approach. Later, the ECB and these member states reversed this decision, resulting in a moderate decrease in the requirement during the phase-in period. Due to the Covid-19 pandemic there was also a further drop in capital requirements in 2020, after which there has been a small increase on average, with some countries showing substantial increases, as can be seen from the upper half of the confidence interval.

### 3 Empirical framework

Our empirical analysis is based on dynamic panel regressions at the bank-portfolio-time level that relate portfolio exposures to bank-level capital ratios and regulatory capital requirements. The unit of observation is a portfolio  $p$  of bank  $b$  observed at semi-annual time  $t$ , and the main dependent variable is the logarithm of the portfolio exposure. We include both the bank's capital ratio and its regulatory requirement as key regressors, alongside macroeconomic controls and bank-portfolio and time fixed effects. This common framework underpins all subsequent specifications; in later subsections we adjust the dependent variable (e.g. to risk-weighted assets or loan rates).

The baseline specification takes the form of a dynamic panel regression of the logarithm of portfolio exposure ( $Y_{pbt}$ ) on bank level capital ratio ( $X_{bt}$ ) and capital requirement ( $R_{bt}$ ):

$$Y_{pbt} = \beta X_{bt} + \rho R_{bt} + \gamma Y_{pb,t-1} + \delta' W_{pbt} + \alpha_{pb} + \lambda_t + \varepsilon_{pbt}, \quad (1)$$

with  $p = 1, 2, 3, \dots, P$  indexing portfolios,  $b = 1, 2, 3, \dots, B$  banks and  $t = 1, 2, 3, \dots, T$  the semi-annual periods. Our sample includes  $P = 26$  portfolios,  $B = 94$  banks and  $N = 1726$

distinct bank-portfolio combinations, while the maximum number of time periods is  $T = 22$ .

We follow De Jonghe et al. (2020) and include both actual and required capital ratios in equation (1). Because  $H_{bt} = X_{bt} - R_{bt}$ , this can also be rewritten into a model with the headroom and required capital ratio. The parameters  $\beta$  and  $\rho$  measure the amount of portfolio deleveraging associated with a change in the bank's capital ratio and capital requirement, respectively. There is potential multicollinearity between  $X_{bt}$  and  $R_{bt}$ , i.e. capital ratios may be responsive to (expected) increases in capital requirements. The sample correlation coefficient is very low ( $< 0.01$ ), however, confirming the absence of multicollinearity. In Section 4.3 below we further assess the pass-through from capital requirements to capital ratios.

We initially estimate equation (1) under the restriction of common slope coefficients for all portfolios, banks and periods. To accommodate differentiated deleveraging, we next allow for slope parameter heterogeneity, i.e.  $\beta = \beta_{pbt}$  and similar for the other slope parameters, as the impact of capital ratios and capital requirements likely differs across portfolios, banks and over time. Specifically, in equation (1) the slope parameters are allowed to have systematic heterogeneity across portfolios, banks and over time using a threshold model of the form:

$$\beta_{pbt} = \beta_1 I(Z_{pbt} < v) + \beta_2 I(Z_{pbt} > v), \quad (2)$$

and similar specifications for the other slope parameters ( $\rho$ ,  $\gamma$  and  $\delta$ ). The effect of  $X_{bt}$  on  $Y_{pbt}$  depends on whether the variable  $Z_{pbt}$  is below or above the threshold  $v$ . As a baseline, we use a known threshold  $v$  based on the sample median of an observed portfolio or bank characteristic, resulting in split sample estimation of equation (1). Regarding heterogeneity at the portfolio level, we use the average risk-weight of the portfolio ( $Z_{pbt} = PRW_{pbt}$ ). At the bank level, we exploit the leverage ratio ( $Z_{pbt} = LR_{bt}$ ). We assess the sensitivity of the empirical results to alternative sample splits in Annex 2.4.

We include the lagged dependent variable regressor ( $Y_{pb,t-1}$ ) because exposures are autocor-

related. A single exposure typically has a maturity that is longer than the observation period (6 months). Once an exposure is incurred, it will remain on the balance sheet for a relatively long time, making current exposure values dependent on past exposure values. Additionally, we include lagged capital ratios and capital requirements ( $X_{b,t-1}$  and  $R_{b,t-1}$ , which are elements of  $W_{pbt}$ ) as additional regressors because *a priori* we do not want to restrict the dynamic relationship. In estimating an Autoregressive Distributed Lag (ADL) model we do not restrict the data and use all information available both in the levels and first differences. We have assessed empirically that this specification of the short-run dynamics in exposures is adequate. The baseline model also includes a number of other control variables (embedded in  $W_{pbt}$ ), which include the annual inflation rate and real GDP growth, to control for country-time macroeconomic conditions.

To model unobserved heterogeneity in exposures across portfolios and over time, we include a bank-portfolio specific effect  $\alpha_{pb}$  and a time specific effect  $\lambda_t$ . Regarding the latter, our sample includes several major events affecting the entire European continent, e.g. Covid-19, Russia's war on Ukraine and higher economic policy uncertainty. Additionally, the monetary policy stance and time variation in financial conditions have an impact on bank credit. The included time fixed effects control for the common or aggregated impact of these developments. We assess the sensitivity of the empirical results to the use of country-time specific effects in Annex 2.2. We exploit fixed effects (FE) estimation, i.e. allowing for correlation between observed and unobserved heterogeneity. With a maximum  $T = 22$  and an average number of periods well into double digits, we rely on large  $T$  asymptotics and assume that the finite-sample Nickell (1981) bias in the fixed effects Ordinary Least Squares (OLS) estimator is moderate only. In Annex 2.6 and 2.7 we further assess this and report Maximum Likelihood (ML) and Generalized Method of Moments (GMM) estimates respectively. Standard errors are clustered at the bank-portfolio level, i.e. regarding the idiosyncratic error term  $\varepsilon_{pbt}$  we allow for heteroskedasticity and autocorrelation within the bank-portfolio time series.

Finally, we treat capital requirements as weakly exogenous, following Aiyar et al. (2016). A central identification challenge is that banks may adjust both their capital ratios and their portfolios in response to common shocks, and portfolio changes mechanically affect risk-weighted assets. Initially, we also assume weak exogeneity of capital ratios, i.e. within a semi-annual period portfolio exposures do not have instantaneous feedback into capital ratios. Under this weak exogeneity assumption and with sufficiently large  $T$ , fixed effects OLS yields consistent estimates of the conditional association between capital ratios, capital requirements and portfolio exposures. We assess the sensitivity of this assumption using GMM estimation allowing for endogenous capital ratios in Annex 2.7. The GMM estimates reported in Annex 2.7 suggest that endogeneity is unlikely to overturn the main pattern of the OLS results. We additionally estimate equation (1) with only lagged regressors to mitigate endogeneity issues.

In summary, this empirical framework allows us to estimate the conditional association between portfolio exposures and bank capital ratios and requirements, allowing for “differentiated deleveraging” and flexibly accounting for persistence, macroeconomic conditions and unobserved heterogeneity across banks and portfolios.

## **4 Results**

We exploit the empirical framework outlined in Section 3 to study three different outcomes: (i) portfolio quantities (exposures and risk-weighted assets), (ii) loan pricing for outstanding and new loans, and (iii) the pass-through from capital requirements to bank capital ratios and headroom.

### **4.1 Differentiated deleveraging**

We study how the association between bank capital and portfolio exposures and risk-weighted assets varies across portfolios and banks. We find that higher capital ratios are associated with

smaller portfolios, but this deleveraging is concentrated in high-risk portfolios and in banks with low leverage ratios, and is more pronounced for risk-weighted assets than for exposures.

The OLS estimation results of equation (1) are displayed in Table 2, with the threshold for the split sample estimation set at the sample median of either the average portfolio risk-weight or bank leverage ratio. From the first column of Table 2 it is clear that, on average, the relationship between a bank's capital ratio or capital requirement on portfolio exposures is moderate and only weakly significant. In contrast, the split sample estimates in the other columns show substantial heterogeneity across portfolios and banks, at least for the capital ratio. A higher capital ratio is associated with significantly smaller portfolios if these portfolios have higher average risk-weights. No such association is found for portfolios with relatively low risk-weight exposures. For banks with a low leverage ratio (high leverage), a higher capital ratio is associated with significantly smaller portfolio exposure, while for stronger banks with a higher leverage ratio we find no significant relationship. These results are consistent with "between-portfolio" differentiated deleveraging: in response to higher capital ratios, associations are stronger for high risk-weight portfolios and low leverage ratio banks. For this cross-country sample of banks, the regulatory capital requirement does not have additional explanatory power for portfolio exposures on top of capital ratios. The capital requirement coefficient has rather large standard errors and the coefficients are not significantly different from zero.

When banks adjust their balance sheets to boost their capital ratios, the largest effects can be obtained not by reducing exposure value of its portfolios, but from a reduction in portfolio RWAs. We therefore estimate specification (1) also with portfolio risk-weighted assets as the dependent variable. The results are reported in Table 3 and show that the impact of a capital ratio change is stronger compared to the regressions with unweighted exposures as dependent variable. This is consistent with "within-portfolio" differentiated deleveraging. It indicates that, apart from a deleveraging process that results in the decrease of exposure, banks also adjust

Table 2: Estimation of equation (1), log exposures

	(all)	(low prw)	(high prw)	(low lr)	(high lr)
$Y_{pb,t-1}$	0.690*** (0.024)	0.700*** (0.030)	0.608*** (0.041)	0.621*** (0.041)	0.720*** (0.025)
$X_{bt}$	-0.527* (0.284)	-0.066 (0.378)	-1.529*** (0.449)	-0.939** (0.464)	-0.350 (0.408)
$R_{bt}$	-0.311 (1.379)	-1.728 (1.690)	0.783 (2.153)	0.818 (2.396)	-1.807 (1.813)
total obs	19926	9961	9880	9786	9941
$R^2$	0.956	0.959	0.956	0.949	0.963

Note: Dependent variable is log unweighted exposures; FE OLS with macro controls, bank-portfolio and time FE included; sample splits based on median portfolio risk-weight (prw) and bank leverage ratio (lr); Standard errors in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

risk-weighted assets. Two alternative channels could in principle generate similar patterns: reallocating exposures from high- to low-risk products and customers, and optimization of risk-weights (‘regulatory arbitrage’). Both mechanisms would tend to keep total exposure roughly constant while reducing risk-weighted assets. We find that changes in capital ratios are associated with declines in both exposures *and* risk-weighted assets, with a larger elasticity for RWAs than for exposures. This pattern is more consistent with banks shedding relatively risky borrowers within existing portfolios than with pure risk-weight optimization or portfolio shifts across products. While we cannot fully rule out these alternative channels, the joint behavior of exposures and RWAs suggests that within-portfolio rebalancing toward safer borrowers is the dominant adjustment margin, consistent with the portfolio rebalancing channel emphasized by Juelsrud and Wold (2020) and related work.

We address the robustness of these baseline empirical results on differentiated deleveraging in many directions, see Annex 2 for more details. First, the portfolio risk-weights and bank leverage ratios used to split the sample may themselves be affected by portfolio adjustments, and the choice of median thresholds is somewhat arbitrary. We address these concerns by defining

Table 3: Estimation of equation (1), risk-weighted assets

	(all)	(low prw)	(high prw)	(low lr)	(high lr)
$Y_{pb,t-1}$	0.701*** (0.014)	0.673*** (0.024)	0.700*** (0.020)	0.702*** (0.018)	0.679*** (0.022)
$X_{bt}$	-0.914*** (0.267)	-0.695* (0.357)	-1.632*** (0.386)	-1.635*** (0.505)	-0.508 (0.396)
$R_{bt}$	-0.059 (0.805)	-1.366 (1.056)	0.620 (1.226)	-1.011 (1.286)	-0.426 (1.140)
total obs	19926	9961	9880	9786	9941
$R^2$	0.978	0.982	0.962	0.978	0.978

Note: Dependent variable is risk-weighted assets; FE OLS with macro controls, bank-portfolio and time FE included; sample splits based on median portfolio risk-weight (prw) and bank leverage ratio (lr); Standard errors in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

sample splits using lagged values of risk weights and leverage, and exploit estimated threshold values. Second, the dynamic specification in the level of exposures may be sensitive to the treatment of macroeconomic conditions and persistence. We address this by estimating equation (1) with country-time fixed effects and exposure growth as dependent variable, respectively. Third, the estimated heterogeneity in slope coefficients could be an artifact of the particular sample splits, rather than reflecting genuine slope heterogeneity. We address this by allowing for richer patterns of slope heterogeneity through split sample regressions along the different data dimensions and estimating (correlated) random coefficient models (Pesaran and Smith 1995, Keane and Neal 2020). Fourth, we address endogeneity concerns in various ways. We estimate equation (1) by the transformed ML estimator (Hsiao et al. 2002) to address the Nickell (1981) bias of the fixed effects OLS estimator and by GMM (Arellano and Bond 1991, Blundell and Bond 1998) allowing for endogeneity of the capital ratio. In addition, we estimate equation (1) by fixed effects OLS including only lagged values of the capital ratio and capital requirements to mitigate endogeneity issues. Annex 2 shows that, to a large extent, our empirical results on differentiated deleveraging are robust.

## 4.2 Loan pricing

Turning to pricing, we find little evidence that capital ratios affect loan rates, but higher capital requirements are associated with modest increases in rates on new lending. These findings corroborate existing empirical evidence that banks increase loan interest rates in response to higher requirements (Lambertini and Mukherjee 2016, Bichsel et al. 2021, Glancy and Kurtzman 2022). However, Lang and Menno (2025) show that the pricing channel of capital requirements is quantitatively small. Under conditions where banks can retain profits in order to meet capital requirements, bank funding costs and, hence, lending rates will increase with a few basis points in response to a 1 percentage point increase in the capital requirement. We consider this effect quantitatively small.

We have bank-portfolio loan rate data that covers the period 2014-2023, so the pricing analysis uses a slightly shorter sample period than the analysis on exposures. Average loan rates for a portfolio are constructed as volume-weighted interest rates on outstanding exposures and on new lending over each semi-annual period. We observe loan rates only for a selection of aggregated portfolios. Included are corporate, retail mortgage and other retail and we observe both standardized approach (SA) and internal ratings based (IRB) types resulting in 6 aggregated portfolios. We estimate equation (1) for this sample with loan rates ( $P_{pbt}$ ) as dependent variable. We furthermore distinguish between existing exposures and new loans. The latter amounts to around 10 percent of the former in terms of loan volume. Regarding the sample splits, we estimate the threshold by the median portfolio risk-weight and bank leverage ratio, as before.

From Table 4 it is clear that, controlling for a host of explanatory factors, the impact of changes in the capital ratio or capital requirement on loan rates is quantitatively small. Loan rates on outstanding exposures do not show a significant change, as expected. Increased capital requirements do lead to increased loan rates for new business, as indicated by the lower panel of Table 4. In the full sample, a one percentage point increase in the capital requirement is

associated with an increase of about 9 basis points in the loan rate on new lending. While this magnitude is modest in economic terms, it is about three times larger than the 3 basis point (bp) benchmark in Lang and Menno (2025). It sits in the mid-range of previous estimates, including the 3 bp estimate in Bichsel et al. (2021), the 8.5 bp increase for Glancy and Kurtzman (2022) for US commercial real estate and the 15-20 bp range reported by Lambertini and Mukherjee (2016) for US banks.

We have also estimated equation (1) for this sample with log exposure ( $Y_{pbt}$ ) as dependent variable. This provides an additional sensitivity check on differentiated deleveraging exploiting more aggregated portfolios. The results for existing exposures in Table 5 do show a negative impact of capital ratios, in line with the earlier results using the more refined classification of bank portfolios. Compared to Table 2 the differentiated deleveraging is less pronounced across portfolios and banks, however. The main difference with the earlier results is that low risk-weight portfolios also show a significant decrease. This may be due to the higher level of aggregation in this sample. New loans do not show significant deleveraging, which is somewhat counterintuitive.

Table 4: Estimation of equation (1), loan rates

	(all)	(low prw)	(high prw)	(low lr)	(high lr)
	outstanding exposures				
$P_{pb,t-1}$	0.762*** (0.052)	0.790*** (0.040)	0.735*** (0.085)	0.777*** (0.046)	0.731*** (0.104)
$X_{bt}$	0.320 (0.690)	0.747 (0.476)	-0.021 (1.242)	-0.935 (1.007)	2.268* (1.150)
$R_{bt}$	-4.383 (2.791)	-6.348 (5.077)	-2.200 (3.393)	-3.210 (2.983)	-5.256 (4.867)
total obs	2448	1229	1219	1333	1115
$R^2$	0.676	0.681	0.674	0.692	0.655
	new loans				
$P_{pb,t-1}$	0.594*** (0.037)	0.570*** (0.056)	0.613*** (0.056)	0.521*** (0.068)	0.625*** (0.049)
$X_{bt}$	0.325 (0.890)	0.060 (1.137)	1.036 (1.074)	-2.096* (1.192)	3.003 (2.381)
$R_{bt}$	9.168*** (3.093)	6.956* (4.097)	11.712** (4.854)	5.908* (3.476)	8.670* (4.951)
total obs	2586	1413	1173	1422	1164
$R^2$	0.732	0.757	0.714	0.742	0.728

Note: The dependent variable  $P_{bpt}$  is the average loan rate. We distinguish outstanding exposures and new loans. FE OLS with macro controls, bank-portfolio FE and time FE included; sample splits based on median portfolio risk-weight (prw) and bank leverage ratio (lr); Robust standard errors in parentheses, \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 5: Estimation of equation (1), log exposures

	(all)	(low prw)	(high prw)	(low lr)	(high lr)
outstanding exposures					
$Y_{pb,t-1}$	0.742*** (0.026)	0.719*** (0.034)	0.752*** (0.036)	0.764*** (0.045)	0.691*** (0.030)
$X_{bt}$	-1.044*** (0.330)	-1.111*** (0.379)	-1.020** (0.506)	-1.809*** (0.394)	-0.577 (0.553)
$R_{bt}$	0.133 (0.722)	-0.726 (0.984)	0.274 (0.944)	-0.633 (0.904)	1.197 (0.813)
total obs	4527	2341	2186	2170	2357
R <sup>2</sup>	0.549	0.512	0.573	0.583	0.479
new loans					
$Y_{pb,t-1}$	0.422*** (0.098)	0.458*** (0.118)	0.291** (0.142)	0.462*** (0.126)	0.279*** (0.101)
$X_{bt}$	-0.397 (0.745)	-0.828 (0.886)	0.371 (1.242)	-2.583 (1.704)	0.566 (1.002)
$R_{bt}$	0.459 (2.811)	-2.206 (4.969)	4.453 (2.763)	-3.221 (4.363)	6.447** (2.761)
total obs	2663	1446	1217	1475	1188
R <sup>2</sup>	0.185	0.252	0.101	0.215	0.167

Note: The dependent variable  $Y_{pb,t}$  is the log unweighted exposures. We distinguish outstanding exposures and new loans. FE OLS with macro controls, bank-portfolio FE and time FE included; sample splits based on median portfolio risk-weight (prw) and bank leverage ratio (lr); Robust standard errors in parentheses, \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

### 4.3 The pass-through of capital requirements to capital ratios

The adjustment of banks to higher capital requirements can operate through many channels. We already assessed whether banks choose to reduce exposures - and, if so, which assets. In this section we analyze the pass-through of capital requirements to capital ratios and its separate components, i.e. bank equity and risk-weighted assets. We find that changes in capital requirements are largely absorbed by headroom, with limited pass-through to capital ratios.

We estimate the following dynamic panel model for the capital ratio at the bank level:

$$X_{bt} = \beta R_{bt} + \gamma X_{b,t-1} + \delta' W_{bt} + \alpha_b + \lambda_t + \varepsilon_{bt}, \quad (3)$$

with  $b = 1, 2, 3, \dots, B$  indexing banks and  $t = 1, 2, 3, \dots, T$  indexing the semi-annual periods. Our estimation sample includes  $B = 91$  banks, while the maximum number of time periods is  $T = 22$ . The parameter  $\beta$  measures the pass-through, i.e. the impact of a change in the bank level capital requirement on the capital ratio. We conduct common coefficient and split sample estimation based on the median bank leverage ratio, i.e. similar to specification (2) with  $Z_{bt} = LR_{bt}$ . The vector of control variables  $W_{bt}$  includes the same macro controls as before as well as the lagged value of capital requirements ( $R_{b,t-1}$ ). The specification furthermore includes bank and time fixed effects.

Table 6 shows the empirical results from common effect and split sample FE OLS estimation of equation (3). Although not significantly different from zero, we find in the short-run counter-intuitive results in the sense that higher capital requirements are associated with lower capital ratios. The autoregressive coefficient for banks with low leverage ratio is much higher suggesting strong state dependence, i.e. shocks to the capital ratio have persistent effects. To provide further evidence, we also estimated equation (3) separately for bank equity and bank RWA as dependent variables, which amount to the numerator and denominator of the capital ratio respectively. Table

Table 6: impact of capital requirements on the capital ratio

	(all)	(low lr)	(high lr)
$X_{b,t-1}$	0.782*** (0.032)	0.958*** (0.110)	0.442*** (0.093)
$R_{bt}$	-0.263* (0.154)	-0.383 (0.325)	-0.076 (0.155)
total obs	1232	612	620
$R^2$	0.709	0.708	0.420

Note: The dependent variable  $X_{bt}$  is the capital ratio; FE OLS with macro controls, bank FE and time FE included; sample splits based on median bank leverage ratio (lr); Robust standard errors, \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

7 shows the empirical results from common effect and split sample estimation. These results also indicate that banks do not significantly adjust their equity and risk-weighted assets following changes in capital requirements. Summarizing, for this sample of banks and time period there does not seem a significant pass-through from capital requirements to capital ratios.

All in all, these findings suggest that banks mostly use their headroom to accommodate changes in capital requirements. There is no clear evidence in favor of widespread pass-through of capital requirements to capital ratios. However, this should not be taken as definitive evidence. A caveat to this finding is that capital requirements are measured as implemented capital requirements, and do not reflect the date of announcement, leaving open the possibility that a majority of the bank response to capital requirements occurs (shortly) after the announcement, ahead of the implementation.

Table 7: impact of capital requirements on bank equity and RWA

	equity			RWA		
	(all)	(low lr)	(high lr)	(all)	(low lr)	(high lr)
$X_{b,t-1}$	0.602*** (0.117)	0.769*** (0.132)	0.523*** (0.173)	0.843*** (0.022)	0.790*** (0.035)	0.851*** (0.028)
$R_{bt}$	-1.575 (1.077)	-2.077 (2.287)	-0.574 (1.727)	0.318 (0.845)	0.871 (1.663)	-0.324 (0.499)
total obs	1232	612	620	1232	612	620
$R^2$	0.589	0.583	0.585	0.801	0.740	0.819

Note: The dependent variable is either equity or RWA; FE OLS with macro controls, bank FE and time FE included; sample splits based on median bank leverage ratio (lr); Robust standard errors, \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## 5 Conclusion

This paper investigated how bank portfolios respond to changes in capital ratios and regulatory capital requirements for a sample of large European banks over the period 2014-2025. We combined portfolio-level data on exposures, risk-weighted assets and loan rates with bank capital ratios and hand-collected data on bank- and time-specific capital requirements. We have estimated dynamic panel data models that allow for heterogeneous effects across banks and portfolios, while controlling for bank-portfolio and time fixed effects and macroeconomic conditions.

Our first main result is that of differentiated deleveraging: higher capital ratios are associated with smaller portfolio sizes, but the deleveraging pattern is differentiated across portfolios and banks. Between portfolios, the association is much stronger for high risk-weight portfolios and for banks with low leverage ratios. Within portfolios, the effect on risk-weighted assets is larger than the effect on unweighted exposures, which suggests that banks shed relatively risky customers rather than cutting exposures proportionally.

Second, we do not find a separate impact of regulatory capital requirements on portfolio

exposures once we control for the capital ratio. Nor do we find a strong or systematic pass-through from higher capital requirements to higher capital ratios at the bank level. In most cases, changes in capital requirements are absorbed by changes in headroom.

Third, the impact of capital requirements on loan rates is small. For outstanding loans we do not find a clear effect of either capital ratios or requirements on average loan rates. For new lending we do find that higher requirements are associated with higher loan rates, but the effect is of moderate magnitude only. Capital requirements therefore do not seem to have a large impact on the overall cost of credit in this sample.

Taken together, our results imply that in a period with sizable voluntary capital buffers, time-varying capital requirements, such as the countercyclical capital buffer and bank-specific add-ons, are less likely to have strong effects on the quantity and pricing of credit. Banks mainly respond to changes in requirements by managing their headroom and by adjusting riskier parts of their portfolios, rather than by a broad contraction in their credit supply. Our empirical evidence is consistent with a regime in which capital requirements can be adjusted over time with limited consequences for aggregate credit supply, as long as banks maintain substantial capital buffers above the regulatory minimum. These conclusions are specific to large European banks over 2014-2025, a period characterized by the build-up of substantial voluntary buffers and the phase-in of Basel III. They may not generalize to smaller institutions or to periods of acute systemic stress in which capital ratios come much closer to regulatory minima.

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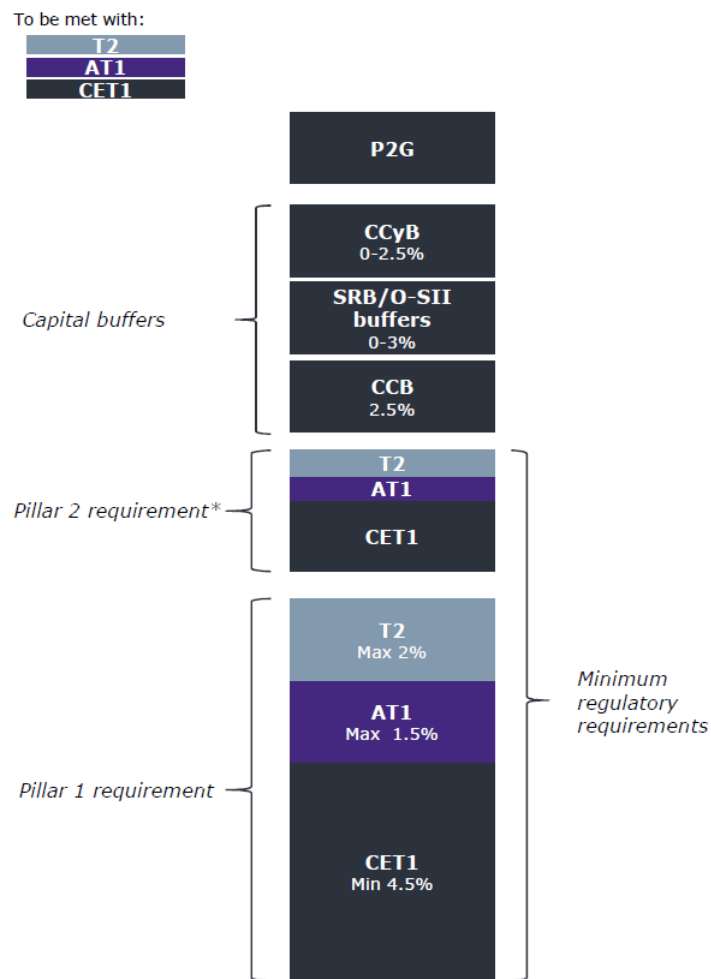
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# 1 Annex - Capital requirements overview

Banks face a number of capital requirements, and can meet these requirements with different types of capital instruments. This section describes these requirements and instruments. Figure 2 provides an overview.

Figure 2: Capital requirements and buffers according to the Capital Requirements Regulation



\* Depending on regulatory and supervisory requirements, this can be met with CET1, AT1 and T2 in proportion to the minimum requirement. For example, a bank needs to meet at least at least  $4,5/8=56.25\%$  of the P2R with CET1.

The regulatory minimum requirement that is common to all banks is the Pillar 1 capital requirement (P1R), laid down in the Basel accords. This requirement is 8% (percentage points) of risk-weighted assets, of which 4.5% should at least be met with Common Equity Tier 1 capital. Up to 1.5% of it can be met with Additional Tier 1, which is convertible or contingent debt that is converted or written down if the CET1-ratio hits a trigger level. Up to 2% of the 8% can be met with Tier 2 capital, which is deeply subordinated debt. Essentially, a bank can optimize its capital structure by issuing AT1 and T2 bonds, but mainly banks also maintain their Pillar 1 requirement fully in CET1.

The Pillar 2 requirement (P2R) is set by the supervisor, and varies by bank, and is meant to address risk not captured by Pillar 1. Together with P1R, this requirement functions as the regulatory minimum; sustained breaches of P2R can result in insolvency or resolution of the bank. Over time and by jurisdiction, the type of capital to be used to meet the Pillar 2 requirement varies. Currently, most supervisors allow banks to meet their Pillar 2 requirement with AT1 and T2 in proportion to the Pillar 1 requirement. Previously, it was more common to require the P2R to be fully met with CET1.

Banks are also subjected to so-called "buffer" requirements. Banks are allowed to draw on these buffers, but doing so will limit the amount of dividends, bonuses and AT1-coupons they can distribute. In practice, banks rarely breach their buffer requirement. Each buffer requirement serves another purpose. The capital conservation buffer (CCB) acts to create distance from the regulatory minimum, and is equal to 2.5%, with a gradual phase-in over the 2014-2019 period. The systemic risk buffer (SRB) aims to address structural risks in national banking sector, the countercyclical buffer (CCyB) aims to address cyclical risks, while the other and globally systemically important institution buffers aim to address the risk from systemic institutions. On top of these buffers, supervisors sometimes issues Pillar 2 guidance, which is not a hard requirement but essentially a recommendation.

## 2 Annex - Detailed robustness results

To assess the robustness of the results, a number of robustness checks of equation (1) have been performed. The details of those additional regressions are reported in this Annex. Across these checks, the main patterns of differentiated deleveraging and the limited additional role of capital requirements remain broadly unchanged.

### 2.1 Previous period splits

There is a concern that the variables used to define the sample splits may be affected by portfolio exposures themselves leading to concerns of endogeneity. In Table 8 we report estimation results using median sample splits exploiting the average portfolio risk-weight and bank leverage ratio from the previous period ( $PRW_{pb,t-1}$  and  $LR_{b,t-1}$  respectively). The pattern of the estimates is similar, but the empirical evidence on differentiated deleveraging is weaker for the sample split based on the bank leverage ratio.

Table 8: Estimation of equation (1), sample split based on previous period value

	(all)	(low prw)	(high prw)	(low lr)	(high lr)
$Y_{pb,t-1}$	0.690*** (0.024)	0.720*** (0.030)	0.625*** (0.043)	0.604*** (0.045)	0.739*** (0.025)
$X_{bt}$	-0.527* (0.284)	-0.142 (0.369)	-1.392*** (0.418)	-0.809* (0.436)	-0.412 (0.421)
$R_{bt}$	-0.311 (1.379)	-1.396 (1.627)	0.491 (2.117)	-0.779 (2.414)	-1.497 (1.762)
total obs	19926	9944	9910	9468	10119
$R^2$	0.956	0.959	0.953	0.950	0.964

Note: Dependent variable is log unweighted exposures; FE OLS with macro controls, bank-portfolio and time FE included; sample splits based on previous period median portfolio risk-weight ( $PRW_{pb,t-1}$ ) and bank leverage ratio ( $LR_{b,t-1}$ ); Standard errors in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 9: Estimation of equation (1), country-time fixed effects

	(all)	(low prw)	(high prw)	(low lr)	(high lr)
$Y_{pb,t-1}$	0.685*** (0.024)	0.695*** (0.030)	0.596*** (0.040)	0.620*** (0.041)	0.714*** (0.026)
$X_{bt}$	-0.980*** (0.336)	-0.586 (0.455)	-2.000*** (0.513)	-1.041 (0.727)	-1.488** (0.734)
$R_{bt}$	0.969 (1.740)	-0.574 (2.392)	1.571 (2.447)	5.527** (2.697)	-2.133 (2.298)
total obs	19926	9961	9880	9786	9941
$R^2$	0.957	0.961	0.958	0.950	0.964

Note: Dependent variable is log unweighted exposures; FE OLS with bank-portfolio and country-time FE included; sample splits based on median portfolio risk-weight (prw) and bank leverage ratio (lr); Standard errors in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## 2.2 Country-time fixed effects

In Table 9 we report estimation results substituting the macroeconomic control variables and time fixed effects in equation (1) by country-time fixed effects  $\lambda_{ct}$ . There are some differences seen compared to the estimation results from the specification with only time effects. First, the common effect becomes twice as large (in absolute value). Second, the heterogeneity along the bank leverage ratio dimension is reversed, i.e. banks with higher leverage ratio deleverage more. Third, banks with a low leverage ratio expand bank lending due to the larger capital requirement. This last result should be treated with some care, however, as the variation in capital requirements is largely captured by the country-time fixed effects.

## 2.3 Loan growth instead of levels

In contrast to other studies (Bridges et al. 2014, Imbierowicz et al. 2018, Cappelletti et al. 2019, De Jonghe et al. 2020), we take the level of log exposure as the dependent variable instead of the log first difference (or growth rate). In Table 10 we report estimates from the baseline specification in first differences, i.e. regressing loan growth on the change in the capital ratio.

Table 10: Estimation of equation (1), loan growth

	(all)	(low prw)	(high prw)	(low lr)	(high lr)
$\Delta X_{bt}$	-0.605** (0.274)	-0.131 (0.368)	-1.542*** (0.403)	-0.811 (0.503)	-0.502 (0.365)
$\Delta R_{bt}$	-0.500 (1.479)	-2.030 (1.495)	1.167 (2.575)	0.382 (2.764)	-1.374 (1.551)
total obs	19926	9961	9880	9786	9941
$R^2$	0.071	0.085	0.090	0.075	0.103

Note: Dependent variable is change in log unweighted exposures ( $\Delta Y_{pbt}$ ); FE OLS with macro controls, bank-portfolio and time FE included; sample splits based on median portfolio risk-weight (prw) and bank leverage ratio (lr); Standard errors in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Qualitatively the estimation results from the loan growth specification are similar to the baseline model in levels, but no significant heterogeneity along the bank leverage dimension is found.

## 2.4 Alternative sample splits

In the specifications that we have estimated so far, sample splits were set based on the median value of portfolio risk-weights and bank leverage ratios. In the analysis below, we do not define sample splits exogenously, but use the threshold regression model of Ditzen et al. (2026) and estimate a single, common threshold. Regarding portfolio risk-weight and bank leverage ratio the threshold estimates are 0.095 and 0.050, respectively. Table 11 reports estimation results using these thresholds instead of the median sample splits. The pattern of the estimates using portfolio risk-weights is similar, but the empirical evidence for the leverage ratio is opposite and indicates that banks with a high leverage ratio have substantially smaller portfolios and higher capital ratios. However, these estimates cannot be seen independently of the number of observation in each split; the high leverage ratio group has substantially more observations.

In a further sensitive check, we base sample splits on the median value of headroom and capital requirement instead of portfolio risk-weights and bank leverage ratio. We expect larger effect on exposures when there is little headroom or capital requirements are relatively high.

Table 11: Estimation of equation (1), estimated thresholds for sample splits

	(all)	(low prw)	(high prw)	(low lr)	(high lr)
$Y_{pb,t-1}$	0.690*** (0.024)	0.648*** (0.046)	0.632*** (0.032)	0.591*** (0.048)	0.700*** (0.029)
$X_{bt}$	-0.527* (0.284)	-0.157 (0.499)	-0.749** (0.299)	-0.688 (0.631)	-0.860** (0.361)
$R_{bt}$	-0.311 (1.379)	-4.754 (2.960)	0.994 (1.441)	4.226 (3.966)	-0.944 (1.572)
total obs	19926	4593	15278	5371	14435
$R^2$	0.956	0.942	0.966	0.947	0.961

Note: Dependent variable is log unweighted exposures; FE OLS with macro controls, bank-portfolio and time FE included; sample splits based on estimated threshold values for portfolio risk-weight (prw) and bank leverage ratio (lr); Standard errors in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 12 reports estimation results using these median sample splits. There is no obvious heterogeneity depending on either headroom or capital requirement. Note that median headroom is around 5 percent, which is large enough to accommodate changes in capital requirements without affecting exposures. There are only few observations with headroom close to zero, hence it is difficult to identify the effect on exposures of capital ratio close to capital requirement.

Table 14 reports estimation results of specification (1) for a variety of alternative sample splits based on the portfolio type. We distinguish (non-financial) corporate, retail and PSE (Public Sector Entities) portfolios, see Table 13 for an overview of portfolios. An important difference are the average portfolio risk-weights (0.68, 0.38 and 0.12 respectively). Furthermore, we distinguish SA (Standardised Approach) and IRB (Internal Ratings-Based) portfolios. The former uses fixed risk-weights defined by regulators, while the latter exploits internal models. While most of the PSE portfolios are SA type, the retail and corporate portfolios are a mix of SA and IRB types. Given that corporate portfolios have the highest average risk-weight, we therefore also estimate separate regressions zooming in on the corporate portfolios.

The results show significant differentiated deleveraging across portfolio types. Deleveraging is

Table 12: Estimation of equation (1), sample splits based on headroom and capital requirement

	(all)	(low $H_{bt}$ )	(high $H_{bt}$ )	(low $R_{bt}$ )	(high $R_{bt}$ )
$Y_{pb,t-1}$	0.690*** (0.024)	0.649*** (0.048)	0.666*** (0.033)	0.681*** (0.039)	0.649*** (0.037)
$X_{bt}$	-0.527* (0.284)	0.505 (0.690)	-0.620* (0.350)	-0.611 (0.382)	-0.326 (0.457)
$R_{bt}$	-0.311 (1.379)	0.068 (1.356)	-2.190 (2.584)	-0.367 (2.220)	-0.926 (1.540)
total obs	19926	9697	9913	9868	9736
$R^2$	0.956	0.955	0.962	0.963	0.952

Note: Dependent variable is log unweighted exposures; FE OLS with macro controls, bank-portfolio and time FE included; sample splits based on median headroom (H) or capital requirement (R); Standard errors in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

largest for corporate portfolios exploiting fixed risk-weights, while PSE portfolios stay more or less unchanged. This is not surprising as corporate portfolios tend to have high(er) risk-weights, while public sector entity portfolios carry (very) low risk-weights. Shedding exposures or adjusting risk-weights is unlikely to produce any substantial effect on the capital ratio.

Table 15 reports estimation results of specification (1) for a variety of alternative sample splits based on the dimensions of the data. The number of resulting sample splits is denoted by  $M$ . We distinguish period, portfolio, portfolio-period, bank and portfolio-bank specific regressions.<sup>5</sup> In other words, we specify  $\beta$  to be  $\beta_t$ ,  $\beta_p$ ,  $\beta_{pt}$ ,  $\beta_b$  or  $\beta_{pb}$  in equation (1) and similarly for the other slope parameters. Because capital requirements vary per year only, we have to use at least two periods to identify their coefficients resulting in 9 estimates. We use at least 100 observations for each sample split except for the portfolio-bank specific regressions, for which we use a minimum of 10 observations per portfolio-bank pair. Because the unit of observation in the cross-section is at the portfolio-bank level, the latter corresponds to the Mean Group (MG) estimator of Pesaran

<sup>5</sup>Because capital ratios and capital requirements only vary across banks and periods, it is not feasible to conduct bank-period regressions.

Table 13: List of portfolios

<i>Corporate portfolios</i>
IRB - Corporates - SME IRB - Corporates - Specialised Lending SA - Corporates
<i>Retail portfolios</i>
IRB - Retail IRB - Retail and Other Retail IRB - Retail and Qualifying Revolving IRB - Retail and Secured by real estate property SA - Retail SA - Secured by mortgages on immovable property
<i>Public Sector Entities portfolios</i>
IRB - Central governments or central banks SA - Central governments or central banks SA - International Organisations SA - Public sector entities SA - Regional governments or local authorities
<i>Other portfolios</i>
IRB - Institutions IRB - Equity exposures IRB - Securitisation SA - Claims in the form of CIU SA - Claims on institutions and corporate with a short-term credit assessment SA - Covered bonds SA - Equity exposures SA - Institutions SA - Items associated with particularly high risk SA - Multilateral Development Banks SA - Other items SA - Securitisation

Table 14: Estimation of equation (1), split sample based on portfolio type

	(all)	(pse)	(ret)	(corp)	(corp IRB)	(corp SA)
$Y_{pb,t-1}$	0.690*** (0.024)	0.718*** (0.035)	0.789*** (0.020)	0.674*** (0.089)	0.611*** (0.108)	0.791*** (0.029)
$X_{bt}$	-0.527* (0.284)	-0.238 (0.621)	-1.448*** (0.397)	-1.505*** (0.550)	-1.104 (0.690)	-1.848*** (0.590)
$R_{bt}$	-0.311 (1.379)	-0.858 (3.167)	-0.076 (0.876)	-0.276 (1.045)	-1.542 (1.435)	1.382 (1.338)
total obs	19926	4636	4939	2677	1459	1218
$R^2$	0.956	0.935	0.987	0.976	0.974	0.978

Note: Dependent variable is log unweighted exposures; FE OLS with macro controls, bank-portfolio and time FE included; sample splits based on portfolio type (PSE, RET, CORP, SA, IRB); Standard errors in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

and Smith (1995). Table 15 shows that both the mean and median coefficients for the capital ratio are mostly negative corroborating the earlier results. Regarding the capital requirement, there is no clear pattern visible. Furthermore, dispersion across subsample estimates is very large as reported by the relatively high standard deviation and interquartile range. This confirms the earlier found lack of significance for this regressor.

## 2.5 Random coefficient model

We estimate a random coefficient model in which regression coefficients can vary more freely across portfolios, banks and over time. We perform mean observation (MO) estimation, i.e.  $\beta = \beta_0 + \mu_{pb} + \theta_t$  (Keane and Neal (2020)) in equation (1) and similar for the other slope parameters. This is an extension of mean group (MG) estimation, i.e.  $\beta = \beta_0 + \mu_{pb}$  (Pesaran and Smith 1995) including a time dimension. Table 16 shows MO-OLS estimates of the mean parameters of equation (1). The MO estimates of the mean impact of the capital ratio and capital requirement are negative, but not significantly different from zero. Just like the common effects estimation in Table 2, the mean effects are not significantly different from zero. Apart from the

Table 15: Estimation of equation (1), split samples based on data dimensions

dimension	M	mean	sd	p25	p50	p75
lagged exposures						
all	1	0.689	0	.	.	.
t	9	0.669	0.062	0.627	0.678	0.714
p	26	0.686	0.177	0.589	0.702	0.801
pt	94	0.726	0.190	0.593	0.758	0.863
b	83	0.653	0.181	0.565	0.711	0.772
pb	1094	0.577	0.602	0.284	0.610	0.877
capital ratio						
all	1	-0.526	0	.	.	.
t	9	-0.700	1.288	-1.845	-0.442	0.424
p	26	-0.637	2.963	-1.792	-0.431	0.361
pt	94	-1.490	4.806	-3.174	-0.756	0.722
b	83	1.779	21.245	-4.589	-0.258	3.381
pb	1094	-1.358	40.585	-7.938	-0.611	5.828
capital requirement						
all	1	-0.310	0	.	.	.
t	9	-0.825	8.018	-3.608	0.305	2.762
p	26	-2.109	8.627	-1.987	-0.375	1.159
pt	94	1.398	32.108	-4.704	0.744	9.811
b	83	13.428	67.444	-6.288	0.000	14.349
pb	1094	0.381	169.940	-16.377	0.151	17.949

Note: Dependent variable is log unweighted exposures; FE OLS with macro controls, bank-portfolio and time FE included; sample splits based on portfolio (p), bank (b) and time (t) data dimensions;  $M$  indicates the number of split sample estimates.

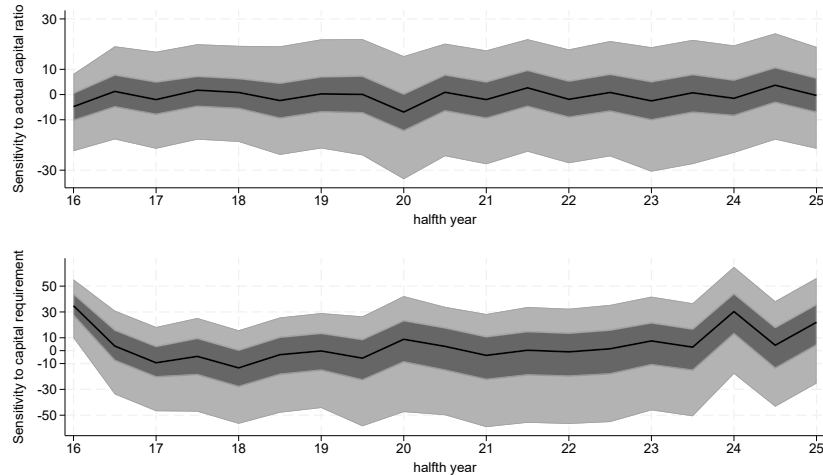
average effect of the capital ratio, we are also interested in the variation in the observation-level coefficients. We therefore plot the cross-sectional distribution of the coefficients over time. Figure 3 shows the results. As can be seen, there is large heterogeneity in the impact of capital ratios across portfolios. While at the median the impact is negative, there are portfolios that grow as a result of a higher capital ratio. Regarding capital requirements, the heterogeneity is even larger with no clear pattern visible.

Table 16: MO-OLS estimates of equation (1)

	mean	median	st dev	p25	p75
$Y_{pb,t-1}$	0.541 (0.084)	0.537	2.425	0.076	0.902
$X_{bt}$	-0.761 (1.409)	-0.465	56.123	-8.090	6.568
$R_{bt}$	-3.510 (6.639)	1.785	221.820	-15.870	17.521

Note: Dependent variable is log unweighted exposures; MO estimation with macro controls, bank-portfolio and time FE included; Standard errors in parentheses, \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Figure 3: Distribution of coefficients across bank-portfolios and time



Note: Upper (lower) panel is capital ratio (capital requirements) coefficient; The black line plots the median coefficient. The dark (light) grey areas represent the 25th to 75th, and 10th to 90th percentiles, respectively.

## 2.6 finite sample bias

We estimate a dynamic panel data model with only a moderately large number of time observations. Nickell (1981) analytically assessed the bias of the fixed effects OLS estimator for dynamic models with fixed individual effects in case the number of time periods is small. To assess

Table 17: Transformed ML estimation of equation (1)

	(all)	(low prw)	(high prw)	(low lr)	(high lr)
$Y_{pb,t-1}$	0.842*** (0.044)	0.781*** (0.069)	0.796*** (0.043)	0.680*** (0.075)	0.993*** (0.044)
$X_{bt}$	-0.646** (0.275)	-0.057 (0.356)	-1.526*** (0.424)	-0.722 (0.539)	-0.478 (0.534)
$R_{bt}$	-0.475 (1.043)	-0.999 (1.363)	1.944 (1.587)	-0.647 (1.704)	-1.434 (3.172)
average T	11.987	11.063	11.249	10.189	9.189
N	1394	709	686	545	592

Note: Dependent variable is log unweighted exposures; Transformed ML with macro controls, bank-portfolio and time FE included; sample splits based on median portfolio risk-weight and bank leverage ratio; Standard errors in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

this finite sample bias, we estimate equation (1) by the transformed ML estimator (Hsiao et al. 2002), which provides a consistent estimator of the slope coefficients when the number of time periods is limited. Compared to fixed effects OLS, it exploits for its asymptotic validity a similar exogeneity assumption regarding the capital ratio and capital requirement. The empirical results in Table 17 show more persistent autoregressive dynamics compared to fixed OLS suggesting that the latter indeed is subject to the Nickell (1981) bias. The estimation results for the capital ratio and capital requirement largely corroborate with the fixed effect OLS estimates, although the sample split based on the leverage ratio is no longer discriminatory.

## 2.7 Endogeneity

It could be that the FE OLS results are biased due to endogeneity issues. We assume weak exogeneity of capital ratios and capital requirements, but especially capital ratios may be jointly determined with portfolio exposures. It is not *a priori* obvious what the direction of simultaneity bias is. Holding constant bank equity and changes in other portfolios, larger exposures with

positive risk-weight lead to higher risk-weighted assets and, hence, a lower capital ratio. There is also the view that banks actively manage their assets to maintain a constant bank capital ratio (Berrospide and Edge 2010).

To accommodate endogenous regressors, we estimate equation (1) by the system GMM estimator (Blundell and Bond 1998), which combines moment conditions for the model in first differences with moment conditions for the model in levels. We assume endogeneity of the capital ratio and, following Aiyar et al. (2016), weak exogeneity of the capital requirement. To economize on the number of overidentifying restrictions, we collapse moment conditions and exploit up to four lagged values only. For most of the GMM specifications in Table 18 the instrument validity test of the overidentifying restrictions (Hansen 1982) is passed. We also report the p-values of Arellano and Bond (1991) test of serial correlation in the first-differenced idiosyncratic errors up to second order, which do not indicate misspecification. The pattern of the system GMM coefficient estimates is not clear due to the relatively large standard errors.

We also consider the alternative sample split based on the portfolio type, see Table 19 . For this sample split the system GMM results are actually qualitatively similar to the OLS results. Although finding suitable instrumental variables is inherently challenging, these results suggest that endogeneity is unlikely to be a primary driver of our baseline OLS results.

We furthermore estimate equation (1) by FE OLS, but only including lagged values of capital ratio and capital requirement. Although a different dynamic model, capital ratios and capital requirements are predetermined in this specification. Table 20 reports the estimation results, which largely corroborate the earlier finding of differentiated deleveraging.

Table 18: System GMM estimation of equation (1)

	(all)	(low prw)	(high prw)	(low lr)	(high lr)
$Y_{pb,t-1}$	0.767*** (0.062)	0.895*** (0.059)	0.879*** (0.096)	0.795*** (0.068)	0.866*** (0.053)
$X_{bt}$	0.625 (0.884)	0.596 (0.814)	-1.049 (2.167)	-0.126 (1.131)	-0.188 (0.788)
$R_{bt}$	-1.117 (2.816)	-0.438 (4.703)	-1.503 (3.560)	-1.631 (4.221)	-2.355 (3.057)
average T	12.343	10.814	10.661	9.401	8.155
N	1618	926	934	1048	1238
OIR p-value	0.318	0.204	0.032	0.290	0.398
AR(1) p-value	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.588	0.224	0.490	0.424	0.640

Note: Dependent variable is log unweighted exposures; System GMM with macro controls, bank-portfolio and time FE included; collapsed IVs for first-differenced equation are  $Y_{pb,t-s}$  and  $X_{b,t-s}$ ,  $s = 2, 3, 4$ , and  $R_{b,t-s}$ ,  $s = 1, 2, 3, 4$ ; sample splits based on median portfolio risk-weight (prw) and bank leverage ratio (lr); Standard errors in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 19: System GMM estimation of equation (1), split sample based on portfolio type

	(all)	(pse)	(ret)	(corp)	(corp IRB)	(corp SA)
$Y_{pb,t-1}$	0.767*** (0.062)	0.894*** (0.074)	0.974*** (0.059)	0.548*** (0.093)	0.511*** (0.089)	0.820*** (0.171)
$X_{bt}$	0.625 (0.884)	1.950 (1.407)	-1.852 (1.911)	-2.754** (1.168)	5.227 (6.178)	-3.240** (1.258)
$R_{bt}$	-1.117 (2.816)	0.439 (7.894)	-3.439 (2.592)	-5.891 (6.441)	-5.343 (16.007)	-3.486 (5.141)
average T	12.343	12.829	13.921	13.679	13.783	13.556
N	1618	362	355	196	106	90
OIR p-value	0.318	0.663	0.123	0.293	0.128	0.731
AR(1) p-value	0.000	0.000	0.000	0.000	0.020	0.002
AR(2) p-value	0.588	0.380	0.625	0.796	0.417	0.297

Note: Dependent variable is log unweighted exposures; System GMM with macro controls, bank-portfolio and time FE included; sample splits based on portfolio type (PSE, CORP, SA, IRB); Standard errors in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 20: OLS estimation of equation (1), lagged regressors only

	(all)	(low prw)	(high prw)	(low lr)	(high lr)
$Y_{pb,t-1}$	0.690*** (0.024)	0.720*** (0.030)	0.625*** (0.043)	0.604*** (0.045)	0.739*** (0.025)
$X_{b,t-1}$	-0.172 (0.197)	-0.059 (0.244)	-0.717** (0.340)	-0.510** (0.250)	-0.522 (0.428)
$R_{b,t-1}$	0.250 (0.635)	0.085 (0.662)	-0.088 (1.108)	-0.096 (1.525)	0.028 (0.697)
total obs	19926	9944	9910	9468	10119
$R^2$	0.956	0.959	0.953	0.950	0.964

Note: Dependent variable is log unweighted exposures; FE OLS with macro controls, bank-portfolio and time FE included; sample splits based on previous period median portfolio risk-weight (prw) and bank leverage ratio (lr); Standard errors in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

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