Do capital requirements really reduce the riskiness of banks?

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Abstract

This paper investigates the response of banks to an increase in capital requirements using loan-level data from the European Credit Register. In addition to the two ways to comply with more restrictive capital requirements already studied in the literature, namely reducing risk-weighted assets and increasing capital reserves, this paper highlights a new response from banks: Following an increase in the countercyclical capital buffer, banks report lower risk parameters in order to reduce the costs associated with tighter financial regulation. This optimisation of risk-weights has implications for the effectiveness of macroprudential policy, as this practice is more pronounced for banks that are most in need of it, when it is most effective and when it is easier to hide the pattern.

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While regulators and market participants want to ensure that banks are financially resilient, the complexity of large bank's business model makes it difficult to observe the bank's true risks at a reasonable cost. One solution to this problem, almost two decades ago, was the introduction of the Basel II Accord: a risk-based framework that allows most large banks to self-report their risks based on internal models. As a result, banks may have incentives to under-report their risks, since regulators will judge their compliance with financial regulation on this basis. These incentives will be even stronger if the regulator increases the stringency of the capital requirements with which the banks have to comply. Do banks under-report their risk parameters when faced with higher capital requirements? In this paper, we examine the extent to which European banks increase the bias in their reported risk estimates when faced with higher countercyclical capital buffers.

To understand bank risk, it is essential to understand the concept of bank capital and its importance in financial regulation. When a commercial bank makes a loan to an individual or a company, the amount of the loan is credited to the customer's bank account: Money has been created. Legally, this amount should be destroyed by the repayment of the loan over time. If the debtor defaults, the bank cannot repay this amount and fails. In order to survive, banks must have their own resources, i.e. capital to cover possible losses: the capital ratio corresponds to the capital held by banks divided by their assets, weighted by their level of risk, calculated with a certain level of granularity. To ensure banks' solvency, the regulator monitors banks and imposes regulatory capital requirements to ensure they have sufficient capital for the risks they take: In 2022, the average amount of total capital requirements and guidance in Common Equity Tier 1 (CET1, the highest quality of regulatory capital) ratio was around 10.6% of risk-weighted assets.

The public debate on bank solvency ratios has been mainly about the amount of capital banks should have and the definition of what is capital in the 2000s. Since the Great Financial Crisis, as Acharya and Richardson (2009) argues that the use of regulatory arbitrage by banks to evade capital requirements imposed by regulators is what made this event a financial crisis, a new debate has opened up among economists and regulators about the definition of the denominator of the ratio: risk-weighted assets. Under Basel I, on-balance-sheet assets were grouped into broad categories, and each category was assigned a standard risk weight, which determined the amount of capital that banks were required to set aside to compensate for the risks they posed. Under Basel II, after 2008, banks could use an internal ratings-based approach to determine their capital requirements if they met a number of conditions. Under this approach, the risk weight of a loan is a function of the bank's internally generated estimates of the borrower's probability of default (PD), the bank's loss given default (LGD), and the bank's exposure at default (EAD).

While the internal-ratings based approach has been touted to allow more flexibility and has allowed for more complex risk measurement models, the literature on regulatory arbitrage and the identification and quantification of risk underreporting practices by banks has grown significantly since the Great Financial Crisis (e.g., see Behn et al., 2022; Plosser and Santos, 2018; Boyson et al., 2016; Abbassi and Schmidt, 2018; Begley et al., 2017; Berg and Koziol, 2017). The conclusion is that banks systematically underestimated the level of credit risk in banks' loan portfolios when they have the opportunity to do it. Despite the risk of sanctions from the supervisory authorities, this practice allows banks to lend more and to riskier debtors, and thus to make more profit, giving them an advantage over more cautious and law-abiding rivals.

Regulators are responding. In 2014, Sweden set a floor of 25% for the risk weights banks can use for their mortgage books under Article 458 of the Capital Requirements Regulation (CRR). In addition to the capital requirements, the regulator imposes a maximum leverage ratio, which is defined as the ratio between the capital detained by a bank and its total assets, without taking into account their riskiness to avoid optimization. The Single Supervisory Mechanism was introduced in 2014, and central banks around the world are organizing consultations on the final Basel banking reform package which will make important changes to the way banks calculate their risk-weighted assets, the denominator of their capital ratio. Scheduled for implementation in January 2025, it is designed to stop the downward drift in risk reporting and reduce the variation in risk weights that larger banks assign to assets using their own internal models.

While one might have expected all the studies on the subject and the strengthening of banking supervision in the 2010s, a major supervisory review in 2021 (European Central Bank, 2021) concludes that euro area banks still repeatedly artificially inflated the strength of their balance sheets by underestimating the riskiness of their assets. The central bank found more than 5,800 deficiencies in the way 65 of the biggest lenders used internal models to calculate their capital requirements: 67% of the investigations ended with serious findings on the calculation of the probability of default. This led to more than 253 supervisory decisions by the ECB that increased banks' risk-weighted assets by €275 billion, a 12% increase in the models examined. As this review shows, this practice is more widespread than just a few large banks. The Supervisory Review and Evaluation Process (SREP) 2022 exercise confirmed that deficiencies in the risk controls of supervised institutions persist and that addressing them has been identified as a priority for 2023-2025.

One hypothesis to explain why this practice is still so widespread and has even intensified in the last few years, as noted by Calza et al. (2021), is that the incentives to minimize the level of reported risk parameters may have increased. Our study analyzes the impact of higher capital requirements policies on the level of risk under-reporting in corporate credit portfolios. Since higher capital requirements reduce the profitability of banks, they may have an additional incentive to minimize their risk reporting in order to maintain their profits.

To examine how the accuracy of reported credit risk estimates evolves following an increase in regulatory capital requirements, we exploit the cross-sectional and time-series variations in countercyclical capital buffers in the Euro Area between 2018 and 2022. Since 2016 in Euro Area, macroprudential authorities can activate countercyclical capital buffer (CCyB) to require up to 2.5% of additional capital from banks in good times when credit supply is high and capital is cheap. These funds can be used in bad times to absorb losses and maintain the financing of the economy. In our sample, we observe 55 changes in countercyclical capital buffers in twelve countries of the Euro Area. This macroprudential tool is the buffer that has contributed most to the change in the overall capital requirement rate over the past five years.

To identify underreporting, we make use of Anacredit, the comprehensive euro area credit register, and the fact that all banks using the internal ratings-based approach report the probability of default (PD) they assign to each firm in their corporate loan portfolio every month. We are able to detect the impact of countercyclical capital buffers on the incidence of underreporting by exploiting firms with loans granted by different banks located in different countries, and thus exposed to different CCyB. We then compare the probability of default reported by banks with high CCyB and those reported by banks with low CCyB. Since the firm is the same, we should not expect a significant difference if the risk reporting is coherent in a situation where there is no information asymmetry. Our sample consists of more than 120,000 non-financial corporations with loans from at least two different banks in two different countries, which corresponds to 400,000 credit relationships with 579 banks for which we observe the probability of default and track monthly from October 2018 to May 2022.

To analyze how capital requirements affect banks' reporting of corporate risks, we first address three identification challenges in this literature: Reverse causality, policy anticipation and cofounding factors. To account for these endogenous forces, our analysis builds on the fiscal and monetary policy shock literature to extract a measure of the deviation of capital requirements from a "macroprudential Taylor rule" (Chari et al., 2022). This new measure of the macroprudential stance, estimated with high explanatory power, is critical to our identification strategy. Our other causal identification strategies rely on the estimation of high-frequency macroprudential announcement surprise shocks (Bluwstein and Patozi, 2022), a narrative approach identification based on countries that decided to implement a positive neutral rate of countercyclical capital buffer (Rojas et al., 2022), the use of granular instrumental variable as suggested by (Gabaix and Koijen, 2021) – the difference between weighted and unweighted exposure to countercyclical capital buffer rates– and the analysis of the impact on very small banks for which CCyB decisions are truly exogenous as they do not influence the estimation of adequate CCyB rate by macroprudential authorities.

We rule out the hypothesis that banks with higher countercyclical capital buffers are simply less good at estimating risk parameters by introducing bank, bank x firm, and bank x year fixed effects. Our results are not driven by the COVID period alone, as we validate them separately for each year. Moreover, a decrease in the reported probability of default is not associated with a less risky portfolio rebalancing as our identification method analyzes the reported probabilities of default by different banks for the same firm at the same time. The within-firm analysis also mitigates concerns about omitted variables (such as sectoral and macroeconomic factors) that may differentially affect banks depending on the composition of their portfolios. We also ensure that our results are not driven by better access to information or lower credit seniority that would enable to identify a default more quickly by restricting the sample to the least risky firms. Finally, we introduce date-interacted consolidated banking group fixed effects to control for a set of time-varying factors that would not be related to CCyB.

First, we find that the probabilities of default estimated for corporate loans under the internal ratings-based approach are significantly lower when a bank is subject to higher capital requirements through an increase in the countercyclical capital buffer. These probabilities of default are also less correlated with observed defaults over the next twelve months and less correlated with the interest rate charged by the bank, more specifically the spread, which includes the risk premium that the bank charges the firm to cover the risk of default: This suggests that banks were aware of the inherent riskiness of these loans. The size of this effect is statistically and economically significant, a one percentage point increase of CCyB reduces probabilities of default reported by banks by -2.5 to -5% (-0.9pp) in most of the specifications. This result is robust to all causal identification strategies presented above.

To further strengthen our analysis, we exploit differences in incentives to underreport default probabilities. Following an increase in the countercyclical capital buffer, we show that banks underreport their risks more when they need to, such as when banks are more capital constrained. Banks optimize the probability of default more when the practice is effective: they do it for exposures in their portfolio, such as credit relationships based on standard credit rather than credit line, and they do not optimize for transferred loans, as the bank no longer bears the risk. We also observe that the underestimation of default probabilities is most pronounced when it is easier for banks to hide the pattern: they do not underestimate the default probability for syndicated loans, as a deviation from the consensus would be immediately visible, and they do it more when there is less consensus on the true default probability: when the firm does not have many different banks and when the standard deviation on the default probability for a firm has already been in previous periods.

Our paper contributes to two strands of the literature. The first one is the study on risk reporting by banks. The literature on financial regulation has already identified that banks that self-report their risks based on internal risk models tend to under-report them. Behn et al. (2022) shows that the introduction of model-based capital regulation in Germany enables banks to under-report their risks. Begley et al. (2017) shows that banks with low equity capital have more violations of their self-reported risk levels. Plosser and Santos (2018), Faria-e Castro (2021) and Berg and Koziol (2017) also found that low-capital banks also report downward biased risk estimates. Although these studies identify precisely that the transition from the standard approach to the IRB approach has led to a decrease in the level of risk carried forward by banks, as well as investigating the link between capital surplus and under-reporting, these analyses do not study the causal and dynamic impact of an exogenous modification of the level of capital requirements. The results of these studies are primarily driven by the cross-section of banks or are identified during periods where capital requirements were also increasing, making it difficult to distinguish capital requirements and time fixed effects. To the best of our knowledge, our paper is the first to demonstrate causally that higher capital requirements lead to lower risk estimates reported by banks. We are also the first to study more broadly the impact of countercyclical capital buffer on the consistency of risk reporting, and to have such a large sample including all the banking relationships in the Euro Area from 2018 to 2022. Our paper also provides answers to how banks operate to understate their risks, while the literature to date has mainly focused on what are the drivers of risk understatement. For example, Calza et al. (2021) finds that banks underestimate the credit risk of their corporate loans when the latter are used as collateral for monetary policy operations. Our identification strategy, combined with the richness of our data set, allows us to identify how banks make this practice as invisible as possible to regulators and as profitable as possible for them. By increasing the PD of firms that are unimportant to their portfolios and for which it is easy to identify a consensus on the probability of default, they gain additional leeway to understate the probability of default of firms that are really important to the banks.

Our paper also contributes to the literature on the effectiveness of macroprudential policies to improve financial stability and the identification of their impacts on risk taking by banks. Juelsrud and Wold (2020) suggests that a rise of capital requirement of 10pp in Norway in 2013 leads to a reduction of risk-weighted assets by -3.3% for low-capitalized banks. Gropp et al. (2019) shows that Capital Exercise banks had to increase their capital requirements by 1.82pp on average, and they did it mostly by reducing their levels of risk-weighted assets by 10%. Mayordomo and Rodriguez-Moreno (2021) identifies that an increase of capital requirements by 1pp leads to a reduction of the risk-weights reported by 1.5%. By identifying that increasing capital requirements by 1pp leads to a decrease in the risk carried by banks from 2.5 to 5% with no change in the actual risk borne, our study offers a new perspective on the results of this literature knowing that the impact of an increase in capital requirements on RWAs that the literature found is similar in magnitude to the under-reporting effect that we identify.

The remainder of this paper is organized as follows: Section 2 presents our data. The methodology is reported in Section 3. Section 4 presents our results and Section 5 concludes.

1 Data description

Loan Information from the Euro Area Credit Register

Our principal source of data on loan information and credit relationships is the Euro Area credit register Anacredit. It is a regulatory database covering harmonized loan-level data granted by euro area financial institutions. As part of their supervisory role, all Euro Area central banks collect data each month on all credit relationship if the total exposure to a borrower exceeds 25.000 euros. From Anacredit, we obtain information since October 2018 on banks and their borrowers, which allows us to obtain the probability of default of firms reported by banks with the internal ratings-based approach. The probability of default is defined as the probability that, in the following year, (1) the borrower is unlikely to pay its credit obligations to the bank in full and (2) the obligator is past due more than 90 days on any material credit obligation to the bank, according to the Basel Commitee. The probability of default reported in Anacredit is computed in accordance with the the Capital Requirements Regulation (CRR), the value have to be between 0.03% and 100% and it has to be computed at the borrower-level rather than at the loan-level[1]. Because of the high level of the quality control on this variable, we do not apply a trimming or a winsorizing on this variable, but our results are robust to such treatments as presented after in robustness checks. We also obtain information on the characteristics of all loans such as the interest rate, the maturity, the transferred amount, the stage of default, ..

In order to implement our identification strategy, we extract information for all firms borrowing from at least two different banks in two different countries, and thus exposed to different countercyclical capital buffers shocks. We focus on both term loans and credit lines granted by banks to non-financial institutions, and we non-standard credit instruments such as credit card debt or revolving credit, as they could give information on the financial stability of a firm. Term credit and credit lines represent 70% of total credit in Euro Area, and corresponds to 89% of all firms having credit.

The dataset we analyze consists of 400 000 credit relationships between 120.000 unique non financial corporations and 579 unique European banks, from October 2018 to May 2022 (44 months). Firms are distributed across 20 countries (Austria, Belgium, Cyprus, Germany, Estonia, Spain, Finland, France, Greece, Ireland, Italy, Lithuania, Latvia, Luxembourg, the Netherlands, Portugal, Slovenia and Slovakia), 92 2-digit NACE industries

[1] While the rule in Anacredit is to report the PD of the borrower and not the product, this can happen in some exceptional cases. We cannot identify in Anacredit if the PD was produced at the instrument level (product PD). In this case, the counterparty PD reported in Anacredit is the exposure weighted average PD of all instruments of the counterparty reported whenever possible. This mostly happen for small firms and specialised lending as referred to in Article 147(8) of the CRR, such as ship finance or project finance. However, the probability that we observe such cases in our database is rare as usually debtors that are small firms or special purpose entities do not have as least two banks in two different countries.

out of 96 and 430 NUTS2 locations. There is 38 banking groups at the highest level of consolidation in our dataset, using RIAD group structure (based on foreign branches and ownership with control relationships, and SSM relationships) reported in Anacredit, with an average of 15 banks in a banking group.

We do not consolidate banking groups –or corporate groups– for our analyses as the probability of default could be very different for different entities of a same group, but this variable is used for additional analyses supporting our results. Every loans are reported separately but we consolidate the database at a date-credit relationship level as the probability of default reported by a bank at a certain date is the same for all the loans of a unique debtor.

Although information in the credit register is available on a monthly basis, reported PDs tend to be sticky and are adjusted only infrequently, except for cases in which a new loan is granted to the firm and the banks has to reasses the firm's credit risk.

Figure 1 presents the distribution of the firm's probability of default reported by banks (in logarithm. One was added to probabilities of default, that is then comprise between 1 and 101). We see a concentration towards zero. The average is 2.3% and the median 1.57%. We observe a high disparity in the probabilities of default reported by banks for the same firm at the same date, as presented in Figure 2, with a standard deviation of 0.3 for probability of default in logarithm. Table 3 presents the number of observations in Anacredit for each credit relationships observed, by countries of banks and firms. We observe that we have more observations in France, Germany in Italy compared to other countries.

Data on banks

We complement Anacredit with bank level information from EBA transparency exercises in order to exploit bank characteristics that may change over time. It is a regulatory database maintained by the EBA, which reports the main asset and liability items of 100 banks resident in the euro area at quarterly frequency. This database provides information on the total amount of outstanding loans, household and corporate deposits, and other relevant bank balance sheet information. We also obtain bank stock prices and CDS spreads from Bloomberg. We use the consolidated banking groups from RIAD in order to match tables from EBA's transparency exercise.

ESRB countercyclical capital buffer database

We identify the announced countercyclical capital buffer rates of each Euro Area jurisdiction through the ESRB database. Figure 3 shows the countries that had positive CCyBs. While banks banks are granted a lead time of up to twelve months to prepare for a countercyclical buffer increase, reductions are takng effect immediately after the announcement of the competent authority. The CCyBs have been released for the first time as the COVID-19 crisis unfolded rapidly, but not all coutries released their CCyB completely: Burgaria, Norway and Sweden decided to keep their positive CCyB rate during 2020 for example.

In some regressions, we calculate the bank-specific capital requirement by using the credit exposure weighted sum of the CCyB rates in each jurisdiction banks invest in. Unfortunately, there exists no information on the monthly total exposure of each bank across countries. Facing this problem, two solutions are tested: first, we use only the repartition of credit exposure of each bank across countires as a proxy for the repartition of total exposure. Second, we use quarterly EBA transparency exercises to have information about the repartition of total exposure of large banks between the eight countries with the most exposure. usually, these eight countries represent more than 99% of total exposure.

To ensure that there is no confounding from changes in other macroprudential or microprudential policies during our study, we analyze how these changed between 2018 and 2022. Pillar 1 minimum capital requirement have not change during our study (always 8% for all banks in all countries), so as the capital conservation buffer (2.5%, it can vary from 0 to 2.5%). The Pillar 2 requirement (P2R, up to 5%) is a bank-specific capital requirement which applies in addition to, and covers risks which are underestimated or not covered by, the minimum capital requirement (known as Pillar 1). A bank's P2R is determined on the basis of the Supervisory Review and Evaluation Process (SREP). This capital requirement vary very little through time but we take it into account as a control variable as it can vary yearly. In some specifications, we eliminate the risk of confounding effect with bank x date fixed effects. Finally, some countries have implemented a systemic risk buffers in our sample. Most of them concern retail exposures secured by residential property (Slovenia, Lithuania, Liechtenstein, Germany, Belgium), and for the others their sizes as a percentage of common equity tier 1 are currently very small. According to SREP, systemic risk buffers went from 0.8% in 2019 to 0.7% in 2021. As systemic risk buffer are revised yearly, we take it into account with bank x year fixed effects. Finally, no countries have adopted borrower-based measure on corporate exposures up to now (multiple countries have implemented borrower-based measures on residential real estate but our study concentrate on corporate risk), and no risk-weight measures were taken before December 2021 (Romania, Poland, Norway, Latvia and Croatia took risk-weight measures on commercial real estate after December 2021).

2 Estimation methodology

2.1 Main tests

Our empirical analysis assesses whether reported probabilities of default (PDs) reported by banks adequately reflect the credit risk of the firms they lend to when they are exposed to different level of capital requirements. As we do not observe the true probability of default of all firms in the Euro Area, we first compare the reported PD of a firm f by a bank b at a date t to the average consensus on the probability of default reported for the same firm f by all banks at a date t, as suggested by Plosser and Santos (2018). Theoretically, since all banks must judge the risk of the same company on the same date, they are supposed to report a similar probability of default. Differences may exist because each bank may have slightly different information about the firm, but if the probabilities reported by one bank are systemically lower than the consensus, then this would indicate underreporting. By focusing on the fact that different companies assess the risk parameters of the same company, the question of the difference in credit portfolios is ruled out. As we want to calculate the percentage deviation from the average, we apply a logarithmic transformation on the probability of default. For example, the deviation in log(PD) reported by a bank b for a firm j at time t is:

$$\Delta log(PD)_{b,f,t} = log(PD)_{b,f,t} - log(PD)^{Mean}_{f,t} \tag{1}$$

Our main regression estimates the consistency of reporting of the probability of corporate default by banks following an increase in the countercyclical capital buffer. Practically speaking, this consists of regressing the announced level of CCyB on the probability of default reported of firms while including a set of fixed effects: first, we include firm x date fixed effects to analyse the deviation of a reported PD from the average consensus as presented just before. These firm x date fixed effects also take into account the difference of firm financial robustness through the financial cycle. We also assume that some banks may be better to forecast the probability of default of their debtors, that could impact the accuracy of the reported PD. Some banks may also structurally report lower PDs based on some incentives they may have, as demonstrated by several papers in the literature. We thus integrate bank fixed effects to control for this. In some specifications, we further saturate our regression with bank x year fixed effects to address the fact that the ability to correctly estimate risk may vary over the financial cycle: some banks may have credit risks models that perform well during calm periods but not financial stressed periods. Applying such fixed effects severely constrains the ability to identify the impact of an increase in CCyB on the reporting of the PD: the evolution of the PD before and after the month in which an increase in CCyB was announced is then compared within the same calendar year. Finally, we implement in some specifications firm x bank fixed effects in order to clean the estimation from the fact that some banks may structurally have a different quality of information on a firm's probability of default, which we are not interested about as we want to focus on how the PD reported changes following an increase of CCyB. As presented before, our main strategy of identification of the impact of CCyB on the consistency of PD reporting requires us to consider only European firms that have loans from at least two different banks located in two different countries.

In practice, there are multiple other reasons why banks might differ in their risk assessments through time that is not capture by bank or bank x year. For example, some banks may possess more private information about a borrower, resulting in a more accurate and/or more up to date forecast relative to other banks at a specific date t. As we are interested in the impact of an increase in capital requirements, we would like to check for all other reasons that could explain the reported differences in PD. For example, as presented by Granja et al. (2022), the distance between the bank and the company can strongly impact the access to information that a bank has regarding the companies to which it lends. We thus include in the control variables a dummy if the firm is in the same country as the bank. We also include as a control variable the share of outstanding amount granted at a given date to take into account the fact that a bank have more information on a firm when granting new credits. As discussed in Section 1, the PD reported in Anacredit should be the PD of the borrower, not of the loan. However, this can theoretically happen in such specific cases: we include the average characteristics of the loans of a bank-firm relationship in the control variables to deal with this possible source of noise. This includes the share of loans with a variable interest rate, the percentage of credit line (off-balance sheet amount) in the total authorised amount of credit given by the bank to a firm, the interest rate, the maturity of a loan and the average share of protection (collateral). Finally, we also include a list of quarterly control variables linked to the financial situation of banks knowing that the financial situation of a bank can impact the reported PDs as demonstrated by Plosser and Santos (2018). The variables from the EBA transparency exercises are detailed in Table 1. We do not include firm control variables as we already control for all the information related to a company at each period with the firm x date fixed effects.

To assess whether a rise of capital requirements impact the consistency of the PD reported by banks, we then estimate different version of the following regression:

$$log(PD)_{f,b,t} \sim \quad \alpha_{f,t} + \alpha_{b,f} + \beta_1 \text{CCyB}_{b,t-1} + \eta_{b,t-1} + \theta_{f,b,t-1} + \varepsilon_{f,b,t} \tag{2}$$

where $\alpha_{f,t}$ are firm x date fixed effects, $\alpha_{b,f}$ are bank x firm fixed effects, $\eta_{b,t-1}$ are monthly or quarterly control variables concerning the bank and $\theta_{f,b,t-1}$ are monthly control variables concerning the banking relationship between a firm and a bank. The variable of interest is $\text{CCyB}_{b,t}$, the announced countercyclical capital buffer rate that a bank b is exposed to at a date t. We consider the CCyB rate announced in the country of the banks and not the one in the country of the firms as a our identification strategy assumes that different banks are exposed differently to an increase in CCyB. If the increase in CCyB were at the level of a country of firms, it would be totally absorbed by firm x date fixed effects.

We consider the CCyB rate announced in the country of the banks and not the one in the country of the firms as a our identification strategy assumes that different banks are exposed differently to an increase in CCyB. If the increase in CCyB were at the level of a country of firms, it would be totally absorbed by firm x date fixed effects. However, even if the announced CCYB rate increase is identified according to the country of the banks, it may have an impact on the consensus among banks on the true probability of default of a company: Bluwstein and Patozi (2022) shows that a rise of CCyB reduce the systemic risk of the financial system, which in turn may reduce the risk of corporate default by reducing the likelihood of a financial crisis, protecting the firms borrowing from banks with a high CCyB. The risk of corporate default could also be reduced by the fact that the existence of a countercyclical buffer protects firms from a credit crunch in times of financial stress, guaranteeing that the banks will always be able to provide liquidity to a firm. However, these mechanisms should not impact the coefficient $\beta 1$ as they reduce the true probability of default of firms and not the incentives for some banks to deviate from the consensus, as all banks are aware of all the CCyB rates announced in the Euro Area. All else equal, a CCyB rise could lead to an upward deviation from the consensus on the true PD ($\beta 2 > 0$) if the CCyB rise in a bank's country is perceived by this bank as a disclosure of information that the central bank believes that banks in its jurisdiction are offering too much credit too easily, or are offering credit that is deemed too risky. In this case, banks in this jurisdiction may wish to revise upward their self analysis of their debtors' riskiness. On the contrary, a rise of a CCyB in a country could lead to banks in this jurisdiction to reduce their reported probabilities of default ($\beta 2$) to reduce the impact they suffer from this macroprudential tightening: an increase in capital requirements should theoretically lead banks that have little voluntary capital buffer to increase their capital reserve, and lead other banks that wish to maintain their voluntary capital buffer to also increase their capital reserve (announced capital targets by banks increase with capital requirements and adverse macroeconomic environment according to Couaillier (2021)). This would be coherent with the trade-off theory according to which banks balance the expected cost of higher risk of regulatory breach due to lower reported probabilities of default, versus the additional cost of higher capital ratios[2]. To allow for potential correlation among the probability of default reported by banks for a same firm, standard errors of the regression are clustered at the firm x date level as done by

[2]Whether or not capital is actually costly has produced a vast literature and is beyond the scope of this paper. The simple fact that many investors and bank managers perceive capital to be costly rationalises this trade-off approach.

In the literature, some papers already show that a low voluntary capital buffer over the common equity Tier 1 (CET1) requirement decreases the probabilities of default reported by banks. As an increase of countercyclical capital buffer increase total capital requirements, our hypothesis is thus that $\beta 1$ may be negative.

2.2 Causal identification strategies

Our main regression would be adequate if the announcement of countercyclical capital buffer was perfectly exogeneous. In practice, this variable is perfectly endogenous to the situation in the financial cycle, the level of credit risk in the economy and the financial situation of the banks. This perennial challenge in this literature can be problematic in our analysis for three different reasons: (1) there is a risk of reverse causality: macroprudential authorities can decide to increase countercyclical capital buffer is they believe that banks in their jurisdictions do not realize/report correctly the extent of the risk they are bearing. (2) Time-variant observable variables could be correlated with an increase of countercyclical capital buffer, driving our results. This can be for example two things: first, as countercyclical capital buffer is increased when cyclical risks of the financial system are increasing, perhaps the position in the financial cycle is the element explaining the result. Second, a tightening of the countercyclical capital buffer may be simultaneously accompanied by other regulatory or supervisory measures, such as tighter on-site monitoring of reporting practices. (3) Finally, our result may be biased if banks anticipate the rise of CCyB rate and adjust their behavior in advance.

In order to identify the causal impact of an increase in countercyclical capital buffer on corporate risk reporting, the identification strategy should be adapted to take into account these three limitations. Our main causal strategy is macroprudential policy surprise shocks, which are an adaptation to the CCyB of high-frequency monetary policy announcements surprise shocks. To complement this approach, we test four additional causal strategies to avoid or reduce these three potential bias: (1) deviation from a macroprudential Taylor rule (2) use of a narrative approach based on positive neutral CCyB rate (3) use of a Granular Instrumental Variable following Gabaix and Koijen (2021), defined as the difference between weighted exposures and unweighted exposures to CCyB, and (4) analysis of the impact on very small banks as CCyB decisions are truly exogenous for them.

2.2.1 High-frequency macroprudential policy surprise shocks

For our identification strategy, we borrow from the monetary policy literature and turn to financial market data to identify unanticipated macroprudential policy "surprises" shocks[3]. We then study the impact of these surprises on the corporate risk reported by banks using a local projection method Jordà (2005). Using a high-frequency approach for identification and daily data on credit default swap on all available banks in the Euro Area allows us to control for any anticipatory effects that financial markets might have already factored in before the policy was announced, and endogeneity problems where macroprudential policy might have responded to market conditions. The approach is similar to the one used by Bluwstein and Patozi (2022) and Couaillier and Henricot (2021). Credit Default Swap are used to identify unanticiped macroprudential policy

[3]Some examples for high-frequency identification for monetary policy shocks are Gürkaynak et al. (2005); Cesa-Bianchi et al. (2020); Jarociński and Karadi (2020)

surprises as thery are most closely related to expected probability of bank default: since CDS spreads price in a firm's probability of default and loss given default, we use CDS spreads as a proxy for bank default probability. The CDS spread is a relatively pure pricing of default risk of the underlying entity Zhang et al. (2009).

We use the countercyclical capital buffer database proposed by ESRB to obtain all daily announcements of CCyB rate changes between 2018 and 2022 in the Euro Area. We look at each announcement and pin down the exact date when they were first made public: for some countries, the date of publication of the official press release of the decision is not the same as the date of announcement of the decision in itself. For these countries (like France), we use the dates of the announcement of the decision and not the date of introduction in the government journal. In total, we collect 44 CCyB rates announcements in 16 different countries present in our database: 30 of them represent a tightening of the CCyB rate and 14 of them are CCyB release.

To examine whether the CCyB announcements in our dataset were unanticipated by financial markets, we assess the CDS spread of the 26 banks in the Euro Area against the CDS spread of a broad CDS market index, the Markit iTraxx Europe Non-Financials Series 38 Version 1. This index comprises the 95 non-financial entities from the Markit iTraxx Europe index. Our sample contains 26 banks in Euro Area as they are the only banks with CDS and less than half missing values available in Refinitiv Eikon. However, among those 26 banks, only 15 are located in a country with a CCyB that was non-null: BNP Paribas, Societe Generale, Credit Agricole in France, Deutsche Bank, Commerzbank and Unicredit in Germany, ING Bank, Rabobank , Aegon bank in Netherlands, Svenska, Swedbank and SEB group in Sweden, OTP Bank in Hungary, Danske Bank in Denmark and DNB in Norway.

Macroprudential policy aims to reduce the probability of default of banks and increase the resilience of the financial system to future shocks, and thus reduce banks' CDS spread. However, a pessimistic communication of the financial risks that motivated the macroprudential authority to introduce a new policy measure may send panic signals in the markets, increasing these CDS spread. The way in which countercyclical capital buffer announcements affect stock prices will depend on which of these channels dominates. In this paper, wto identify CCyB shocks we empoy event study technique, which bracket a short window before and after a CCyB announcement. The event study methodology allow us to think of macroprudential policy shocks as days where CDS spreads of a portfolio that consists of stocks from the 15 european banks are significantly different from zero. In other words, our CCyB shocks are days when financial markets were significantly surprised in the aftermath of a CCyB tightening announcement. Using this definition, we remove CCyB announcements which are being interpreted as non-binding or non-effective by market participants. Although the CCyB is intended to reduce the risk of default by banks, it is not intended to impact the probability of default by the companies that these banks finance. And even if it did, CCyB should impact the banks' consensus on the true probability of corporate default, and not induce a deviation in the analysis of this risk by banks exposed to a higher CCyB. All banks in the market have access to information about an increase in CCyB in each country of the euro zone, so the increase in CCyB does not generate information asymmetry that would lead to a systemic underestimation by some banks of the corporate risk in their portfolio.

For our event study, we follow a standard methodology and compare CDS preads in the event window versus an estimation window: the estimation windows represents CDS spreads during "normal times". We designate the date of each macroprudential policy as $t = 0$, the estimation window covers the period from 261 days before the publication to 2 days before the publication. The event window brackets the window before and after the announcement. The event window is chosen to be sort enough to exclude any non-macroprudential policy related news, and long enough for the information to be assimilated by the markets. The estimation windows is chosen following Bruno et al. (2018). We use a CAPM model to estimate abnormal CDS spread evolution. The α and β coefficients are estimated from an ordinary least squares (OLS° regression of each bank's daily CDS spread $CDS_{b,t}$ on the daily CDS spread of the iTraxx index $CDS_{m,t}$. Cumulative abnormal change in CDS spread are computed over the event window ($t - 1$, $t + 1$)).

$$\widehat{\text{Abnormal CDS}}\ \text{change}_{b,t} \sim \quad CDS_{b,t} - \widehat{\alpha}_{b,t} + \widehat{\beta}_{b,t} \times CDS_{m,t} \tag{3}$$

2.2.2 Deviation from a macroprudential Taylor rule

The risk of reverse causality is plausible but unlikely, simply because underreporting risk, whether by reducing it by more aggressively exploiting the margin of conservatism or by actually reporting lower probabilities than reality, reduces the risk perceived by the macroprudential authorities. Therefore, it is even the contrary: macroprudential policy have a higher probability of not increasing the ccyb as they perceive banking portfolio as less risky. Moreover, according to BCBS (2010) and ESRB (2014) providing a recommendation on guidance for setting countercyclical capital buffer rates, Detken et al. (2014) from ESRB providing operational guidance on setting CCyB in accordance with the preceding recommendation and BIS (2017) analysing how countries are calibrating CCyB, macroprudential institutions do not rise CCyB because they think that banks are under-reporting credit risks. Macroprudential institutions usually follow a list of "core systemic risks indicators" and decide CCyB rates based on these indicators. The main indicator is the credit-to-GDP gap, also called Basel gap, which is the deviation of the ratio of non-financial private debt over GDP in one country from the long-term trend, captured through a Hodrick-Prescott filter. This practice is in line with ESRB and BCBS guidance. Other indicators are also used to calibrate CCyB, such as the evolution of credit growth for firms and households, housing price growth, banks' capital ratio,and external imbalances.

Our second identification strategy of the causal impact of countercyclical capital buffer on corporate risk reporting by banks is based on the methodology proposed by Chari et al. (2022) and the macroeconomics literature assessing the impact of policy shocks, such as papers constructing exogenous fiscal policy shocks Auerbach and Gorodnichenko (2012) and exogenous monetary policy shocks Furceri et al. (2018). Chari et al. (2022) constructs exogenous macroprudential policy-shocks by estimating a first-stage regression of the macroprudential stance on a group of variables that could affect the implementation of macroprudential policy. The residual from this first-stage equation is defined as a macroprudential policy shock, which is a more exogenous measure of a country's macroprudential stance in each period. This variable is then used as the explanatory variable in a second stage regression. The idea is that the residual from the first stage regression correspond to the deviation of a macroprudential institution decision from what could be anticipated by the market if this institution had follow a sort of "macroprudential Taylor rule", as proposed by Bianchi and Mendoza (2018). We adapt the first-stage to predict what level of CCyB could be anticipated by the market if macroprudential authorities were following a quantitative rule.

$$\text{CCyB}_{b,t} = \beta_0+\beta_1\times\text{Basel gap}_{b,t}+\beta_2\times\text{financial}_{b,t}+\beta_3\times\text{macroeconomic}_{b,t}+\beta_4\times\text{real estate}_{b,t}+\varepsilon_{b,t} \tag{4}$$

To predict the optimal level of CCyB according to European macroprudential institutions, we use a dataset with 36 variables that can be used at one stage of the calibration of the CCyB rate, either via an estimate of the position of the financial cycle, via an estimate of the level of credit growth, or via the estimate of an early warning system to identify the risk of a financial cycle reversal. These are stationarized by calculating an annual growth rate or a first difference when necessary. The variables and their sources are presented in Table 4. From this dataset, we use three different models to predict the optimal level of CCyB according to the European macroprudential institutions: an OLS, a Lasso whose constraint on the L1 norm is obtained with the elbow rule, and a random forest. the random forest is our preferred model since the relationship between the credit gap and the recommended ccyb rate is not linear in the formula recommended by international institutions. Special care is taken to reduce the risk of overfitting: the hyper-parameters of the latter are optimized with a grid search on a test sample over 2018-2020, and tested over 2021-2022. Four specifications are proposed of the first-stage regression: one with each model and an additional one estimated with a random forest by including in the dataset three additional variables that the macroprudential authorities themselves report quarterly to the ESRB to justify their calibration of the CCyB rate deemed optimal: the level of credit gap reported with the Baloise formula recommended by the guidelines, the level of credit gap calculated with the preferred formula of each macroprudential institution, and finally the main additional indicator that institutions use most to help calibrate the CCyB, generally a financial cycle indicator. A three-month lag is applied to all explanatory variables in order to be sure of that they are not impacted by CCyB announcement or discussion.

Each deviation from the "target" given by the rules estimated with these four specifications represents a surprise for market participants of the level of CCyB rate announced. The risk of reverse causality or anticipation is lower as banks cannot thus anticipate them, and the integration of 39 macroeconomic, financial and real-estate variables reduce the risk of the existence of time-variant observable variables that could be correlated with an increase of countercyclical capital buffer.

$$log(PD)_{f,b,t} \sim \quad \alpha_{f,t} + \alpha_{b,f} + \beta_1 Resid_{b,t-1} + \eta_{b,t-1} + \theta_{f,b,t-1} + \varepsilon_{f,b,t} \tag{5}$$

2.2.3 Narrative approach: positive neutral CCyB rate

Third, in terms of the identification of exogenous countercyclical capital buffers shocks, we analyse the narrative behind each CCyB changes, similarly to what Richter et al. (2018) and Rojas et al. (2022) already did for other macroprudential policies. We use changes in countercyclical capital buffers that are exogenous to the financial cycle by using a narrative approach to analyse its impact on credit risk reporting, as opposed to changes in CCyB that are decided based on the position in the financial cycle as it is recommended originally by the proposed policy reaction function of all the international institutions.

To the best of our knowledge, this is the first instance in the literature on countercyclical capital buffer in which a narrative approach has been used. Using historical documents, including IMF, ESRB and central banks reports, we classify changes in countercyclical capital buffers in (1) endogenous changes, which were mainly motivated by current or prospective credit fluctuations and (2) exogenous changes, which were triggered by reasons exogenous to the financial cycle. These exogenous changes are identified through the decisions of some countries to adopt a positive neutral CCyB rate. Under this approach, authorities aim for a positive CCyB rate when risks are judged to be neither subdued nor elevated, instead of a rate of zero in a "normal" situation as most countries. The move from a zero percent neutral rate to a positive neutral rate is a policy decision that is, by definition, unrelated to the position in the financial cycle.

To this day, six countries have decided to implement a positive neutral CCyB rate: Ireland have decided to implement a 1% neutral CCyB rate before 2022 and 1.5% after, Sweden 2%, Netherlands 2%, Lithuania 1% and Denmark 2.5% but the decision was taken in 2022. The situation of Czech Republic is less clear, they indicate having a neutral rate of 1% but also applying a policy of a perpetual rise of the CCyB rate by 0.5% per quarter as long we are not in an economic or financial crisis.

We define the endogenous CCyB rate as the share of the CCyB rate exceeding the neutral rate decided by the country, and the exogenous CCyB rate as the share of the CCyB that does not depend on the financial cycle but on the positive neutral rate policy decided by the country.

$$\text{Exogenous CCyB}_{b,t} = min(\text{neutral CCyB}_{b,t}, \text{announced CCyB}_{b,t})$$

$$\text{Endogenous CCyB}_{b,t} = max(\text{announced CCyB}_{b,t} - \text{neutral CCyB}_{b,t}, 0)$$

By regressing Basel credit-to-gdp gaps in every euro area countries with exogenous and endogenous CCyB rate (without fixed effects), we validate that exogenous CCyB rate does not explain Basel gaps (p-value = 0.58), contrary to endogenous CCyB rate (p-value $<$ 0.01%). This validates the exogenous nature of the CCyB increases resulting from the political decision to adopt a positive neutral CCyB rate.

2.2.4 Granular Instrumental variable

The first three strategies for causally identifying the impact of capital requirements on banks' risk reporting are based on the idea of finding a countercyclical increase in the domestic capital buffer that is truly exogenous and not anticipated by banks. However, one can always imagine that banks in countries that implement a countercyclical capital buffer are structurally different from others and react differently throughout the financial cycle. While the various robustness tests already conducted have already refuted this argument (setting up bank x year or banking group x date fixed effects), we propose here to go further and take advantage of the cross-section between banks in a same country to identify the impact of an increase in the countercyclical capital buffer.

The effective CCyB level that applies to a bank is the weighted average of the CCyB rates of the countries in which all of a bank's borrowers are located, based on the size of the exposures. Thus, two banks located in the same country are exposed differently to an increase in CCyB in another country of the euro zone, depending on the distribution of their exposures. If a large firm exposed to a high CCyB decides to draw on a credit line granted by a bank, then this increase in exposure to that firm does represent an exogenous CCyB shock for the bank.

Based on this, the third causal identification strategy we use is the "Granular Instrumental Variable" (GIV) approach, developed by Gabaix and Koijen (2021). We estimate the model by instrumenting bank CCyB shocks by the GIV. Denoting $s_{f,b,t}$ the loan share of firm f in portfolio b at time t, it can be written as the difference between the weighted and equally-weighted sum of firm CCyB shocks, using bank b loan shares:

$$GIV_{b,t} = \sum_f s_{b,f,t} \times CCyB_{f,t} - \frac{1}{N_f}\sum_f CCyB_{f,t} \tag{6}$$

Intuitively, the GIV extracts variation in the exposure-weighted borrower countercyclical capital buffer rate that can be attributed to "granular" borrowers. Specifically, the instrument is the difference between exposure-weighted and unweighted aggregated borrower CCyB rate, each aggregated to the bank level. Conditional on the distribution of credit shares being fat-tailed, which was proven by Baena et al. (2022), idiosyncratic rise of CCyB to large borrower allow us to achieve identification. The GIV purges away any bank x year factor, which is potentially correlated with the rise of countercyclical capital buffer, as shown by Galaasen et al. (2020). With this methodology, we compare how two banks in the same country are differently exposed to an increase in CCyB in another country based on the evolution of their exposure distribution.

An important identifying assumption is that CCyB shocks are exogenous to the loan share. We have empirical evidence of exogeneity when computing the correlation between these two variables: firm's country CCyB shocks are independent to loan shares when controlling for firm, bank and date fixed effects. We do two robustness checks: first, we reproduce the methodology of Galaasen et al. (2020) and compute the residuals from a regression explaining the countercyclical capital buffer with the loan share, in order to be sure that the residuals is exogeneous to the loan share. Secondly, we instrument the loan share with the portion of credit lines drawn by the company: as the credit lines have a maturity of several years, they are granted before the announcement of ccyb, and the fact that the company decides to use this credit line is purely exogenous to the bank's behavior and it increases the loan share for the bank.

2.2.5 Countercyclical capital buffer exogenous to small banks behaviour

Macroprudential institutions define the appropriate CCyB rate based primarily on credit aggregates. In 2019, 5 banks accounted for 23% of total assets held by the sector. In France, the 4 largest banks account for more than 90% of all bank loans to businesses. Thus, these large banks have the greatest impact on the total amount of credit granted in each country, which in turn influences the rate deemed adequate by the macroprudential authorities. On the contrary, the smallest banks have little influence on this decision because of their size: for them, the ccyb rate is not subject to a risk of reverse causation and is therefore more exogenous. Their small size also reduces their ability to anticipate future CCyB rates, and they are more affected by financial cycles at the local geographic level.

Knowing this, we analyze the impact of an increase in CCyB on risk reporting by small euro area banks. We thus interact the CCyB variable with a dummy if the size of the bank (defined as the total amount of credit granted) is smaller than 10% of the sample, 50%, and then interact the CCyB rate with a continuous variable of the logarithm of the total amount of credit granted. The sample is composed of 578 unique banks, it is thus largely enough to realise this analysis without suffering from a small sample bias.

3 Empirical results

3.1 Impact of countercyclical capital buffer on the consistency of reported probability of default

3.1.1 Baseline results

Table 5 presents the results on the estimation for the baseline specification detailed in Equation 3. The table is composed of eight columns where we progressively saturate the specification with fixed effects and control variables: all specification include firm x date fixed effects, the specifications in columns (3) and (6) include bank fixed effects, the specification in column (4) includes bank x year fixed effects, the specifications in columns (5) and (7) include bank x firm fixed effects, and the specification in column (8) include bank x firm x year fixed effects. While specification (1) do not have control variables, specifications (2) to (8) have loans-related variables and specifications (6) to (8) have in addition bank control variables. While the introduction of firm x date fixed effects is strictly required to control for the actual financial situation of each firm at each period and thus identify the deviation of reported probability of default from the consensus of all banks, we believe that a robust analysis should also account for the characteristics of the loan as it can affects the quantity or quality of information a bank have on the debtor, as well as bank balance sheet controls as well as variable describing the position in the financial cycle in the country of the creditor. Specification (6) is our benchmark specification and the inclusion of firm x bank and firm x bank x year fixed effects adds further robustness by controlling for characteristics of the lending relationships at the firm x bank level.

The results show that the increase of capital requirements through a rise of countercylical capital buffers in a country conducts to a reduction of the probabilities of default reported by banks in this country that are directly exposed to it. Specifically, a 1% increase of countercyclical capital buffer reduces reported probabilities of default by 2.6-6.3% depending on the econometric specification (coefficient $AnnouncedCCyB$, p-value $< 0.1\%$ in specifications (5) and (8), 0.01% otherwise). This result suggests that the evolution of the level of risk-weighted assets seems to be a particularly biased indicator for analyzing the impact of capital requirements on the risk level of banks' portfolios. The risk level of a portfolio may appear to decrease after an increase in capital requirements only because banks have a stronger incentive to reduce the risk level of the assets they report to regulators.

Regarding the control variables, our results are in line with expectations. Banks consider that firms that borrow with variable interest rate, with long loan maturity and through credit lines are riskier. The most a bank lend to a debtor (relative size of the loan, duration of the credit relationship, new loans granted recently), the more confidence the bank have towards the firm's ability to pay back. As found by the literature, banks with a low voluntary capital buffer tend to report lower probabilities of default, and so are large banks and bank with high leverage.

3.1.2 Robustness tests

To begin with, we ask whether our result is robust to changes in the variable of interest, namely the logarithm of the probability of default of a firm at a date assigned by a bank in deviation from the consensus on all banks. In Table 6, we analyze column (1) whether the result is robust to the removal of Firm x Date fixed effects and the analysis of the variable *PD gap* proposed by Plosser and Santos (2018), which, which is the difference between the log average probability of default given by all the banks to the same firm at the same date and the log probability of default given by one specific bank. We analyse column (2) whether the result is robust when using the probability of default without applying a logarithm as the variable of interest. In column (3), we replicate the test proposed by Plosser and Santos (2018) on the explicability of the interest rate spread. Loan prices provide an alternative benchmark by which to gauge the information content of risk estimates. We estimate loan pricing models for banks by relating the spreads on loan originations to loan characteristics and the borrowers' probability of default. A key concern with internal estimates is that bank's exert discretion over the information they use to produce risk estimates and that this information is less complete than it otherwise could be. To test this we compare the explanatory power of PD-based loan pricing models across banks. Low explanatory power relative to other banks implies that spreads are chosen using information that is not reflected in risk estimates, consistent with low quality estimates that incorporate less relevant information. Finally, in column (4) we apply the test of xxx, which consists on comparing estimation biases of corporate loans based on the ex-post analysis of the realisation of default. We define the variable "precision" as the difference between a dummy for actual default one year after the report (at time $t + 12$) and the reported PD of a bank for a firm at time t. By doing that, we have to remove from our sample all credit risk reporting taking place less than twelve months before the end of our sample. If the precision is reducing, it means that the probability of default reported by banks are less informative to predict actual default in the following year. As presented in Table 6, our result is robust to all different versions of the dependent variable.

Our sample includes the COVID-19 period. While this period is very interesting because it represents a countercyclical buffer shock exogenous to the financial condition of banks and firms, COVID-19 and the resulting restrictions on the economy in Europe may also have impacted the probability of bank defaults and reduced the ability of some banks to estimate them correctly. To ensure that our results are not driven by an artifact related to COVID-19 or the support provided by individual states, we estimate our main regression by removing observations from each year sequentially. As presented in Table 7, we reject the hypothesis that our result are explained by the observations of one specific year, as it the impact remains significantly every year.

The third robustness check is to ensure that the results are not driven by firms in default. It is possible that a company stops repaying one bank before another, either by hazard or because several credits may have different seniorities. In this case, it is normal for one bank to report a higher probability of default than another, having not yet noticed the default. This effect may be even stronger in times of increased risk in the financial system, justifying an increase in countercyclical capital buffer. Although defaults are very much in the minority in our database (about 5.4% of the firms in the sample have already been late in payment or defaulted on), we remove from the sample all the observations when a firms have defaulted for at least one bank, and then all the firms with an average default probability of more than 50%, 10% and 2%. As presented in Table 8, our result is robust to removing all firms that could have appeared in difficulty to at least one creditor, even with the most restrictive definition reducing the sample size by 24%.

It is possible that our results are driven by time-varying unobservable variables at the bank level. Although we have already validated that our results hold even when controlling for bank x year fixed effects, by playing on the fact that the CCyB can be updated every quarter, it is not excluded that bank level variables varying every month are confounding our results. To exclude this hypothesis, we take advantage of the fact that most banks are part of banking groups and that some of them are located in several countries at the same time. We thus add bank group x date fixed effects to look at how, within the same bank group at the same date, the exposure of certain entities to CCyB affects their reporting of default probabilities. Knowing that the control variables were at the banking group level, they are totally absorbed by the introduction of these additional fixed effects. With these fixed effects, there are only 21% (48) banking groups with more than two bank entities, and 16% (30) (banking groups that are located in more than two countries at a time, so the degree of freedom of our regressions is much less important with these fixed effects. Despite this limit, we observe in Table 9 that our result still holds with banking group x date fixed effects, combined with bank fixed effects column (1), bank x firm fixed effects column (2), or when we use this variable to cluster the standard errors column (3) if we consider that the banking group can have an impact on the probability of default decided by the banks belonging to the group.

3.2 Causal inference strategies

Our results appear robust to the list of robustness checks and alternative tests done in Section 3. However, as indicated in Section 2, we cannot rule out with this first approach that the results are driven by reverse causality or time-variant confounding factors. The probability that banks anticipate CCyB rate still exists but is estimated low as it would pull down the estimated coefficient of the announced CCyB rate if it was the case, however this coefficient is significantly high in our estimations.

To identify more precisely the impact of countercyclical capital buffer on risk reporting by banks, we first rely on the identification of high-frequency macroprudential policy shocks and the impact on risk reporting with an event-study approach. Then, we estimate the deviation of countercyclical capital buffer rate from a macroprudential Taylor rule, and use the residuals as proxy for unanticipated and exogenous CCyB changes. We then rely on a narrative approach based on countries deciding to have a positive neutral CCyB rate, the use of a Granular Instrumental Variable (GIV) and finally we analyse the impact of CCyB on small banks; for whom CCyB is truly exogenous.

High-frequency macroprudential surprise shocks

Our tests show that five countercyclical capital buffer announcements days significantly affected banks' credit default swap spreads after removing all CCyB changes that took place during the COVID-19 periods where the volatility of the market was high and the number of cofounding factors elevated. Our final sample of unanticipated countercyclical capital buffer events are presented. We observe that, as identified by Bluwstein and Patozi (2022) and Couaillier and Henricot (2021), tightening countercyclical capital buffers decrease credit default swap spreads. This is in line with the objective of macroprudential policy which is to pursue financial stability by ensuring banks are resilient enough to withstand financial shocks.

We then create a dummy equal to one for each month of countercyclical capital buffer change that was unanticipated by the markets and reduced CDS spreads, and we regress in on the risk reporting of banks with an event study methodology. Figure 3 presents the dynamic effects of an unexpected countercyclical capital buffer tightening announcement on the reporting by banks of firms' probabilities of default. Our results indicate that CCyB policy significantly impact risk reporting by banks after eight months (coefficient 0.042, p-value < 0.01). This suggests that banks know that there is a 12-month legal delay between the announcement of the CCyB increase and its effective implementation, they have the time to adapt their probability of default reported downwards in order to reduce the additional supported cost due to this new regulation before this cost become effective. This effect seems to be durable because it is present for several periods. However, it is difficult to go beyond this in terms of the duration of the projection, knowing that the COVID crisis is in the middle of our sample and may affect the results, and on top of that our study period is only 42 months.

CCyB deviation from a "macroprudential Taylor rule"

Table 10 presents the impact of countercyclical capital buffers on credit risk reporting by banks using as main independent variable the residual from a macroprudential Taylor rule to decide the adequate rate for CCyB. *CCyB residuals* is the main independent variable and is computed as the residual from a regression predicting the adequate rate of CCyB based on historical experiences and data on the financial, economic, monetary situation, as well as variables on the real estate and commodities market. This function is called "macroprudential Taylor rule" as a reference to what is done in monetary policy. Specification (1) computes the macroprudential Taylor rule with an OLS regression, specification (2) with a LASSO regression, specifications (3) to (5) with a Random Forest regression. Specifications (4) and (5) have additional variables reported directly by the macroprudential authorities as variables that are used principally to calibrate the CCyB rate: the additional variables are the "additional [credit-to-gdp] gap" (in addition to the classic Basel gap) and the "additional benchmark", usually a financial cycle composite indicator developped by these macroprudential authorities.

We observe that the impact of CCyB residuals is significantly negative in all specifications (p-value < 0.01), confirming the results found in the previous analyses. This result could be expected given that the Basel gap (the main variable that have to be used to calibrate the CCyB rate according to all financial international institution, as BCBS and ESRB) was already a control variable and was never significant. The firm x date fixed effects were already strongly capturing the position in the financial cycle in the country of the firm, while knowing that the financial cycles of the different countries of the euro zone are strongly correlated as demonstrated by Oman (2019) and Fidrmuc and Korhonen (2006). This result indicates that the difference between the CCyB rate anticipated by the banks and the actual rate applied has a substantial impact on the reporting behavior of the banks: a decrease in the probability of default carried forward from 8.5 to 16% for one percentage point more of non anticipated CCyB. This figure is to be compared with the average difference between the adequate rate indicated by the Random Forest regression with all additional variables (specification 4 and 5), which is on average 0.2pp. The impact on reporting would therefore be much smaller in reality, between 1.5 and 3.2%.

Narrative approach: positive neutral CCyB rate

Six countries have decided to implement a positive neutral CCyB rate, which mean that these countries decided to increase their CCyB rate not because of an increase in the level of vulnerability in the financial system, but because the national macroprudential authorities feel that the mechanism is more effective with a higher rate even in calm times, so as to release more capital in times of crisis and increase their macroprudential space. It is thus a choice based on considerations unrelated to the position in the financial cycle and the cyclical level of risk to banks. We use these political considerations on how to use the countercyclical capital buffer tool to identify exogenous shocks to the capital requirements.

Table 11 presents the results of the impact of CCyB on credit risk reporting with this identification methodology. The variable *Exogenous CCyB* corresponds to the rise of CCyB because of the decision to have a positive neutral CCyB rate. *Endogenous CCyB* corresponds to the share of CCyB rate that was decided above the positive neutral rate, when the national macroprudential authority identify a rise of vulnerabilities in the financial system. We observe in all specifications that increasing the CCyB rate not because of the position in the financial cycle but following a decision to have a positive neutral rate reduces significantly the risk reported by banks (coefficient of *Exogenous CCyB* between 4.4 and 16.3%, p-value $< 0.01\%$. Dummy variable Exogenous country interacted with *Announced CCyB* significantly positive at 5%). We also identify that the impact of CCyB is stronger when the decision to increase it is exogenous to the level of risk in the financial system, which may seem logical given that the CCyB is increased when macroprudential authorities consider that the level of financial risk is increasing, analyzed either through the exposure at default (EAD) or through the probability of default (PD).

Granular Instrumental Variable

Table 13 presents the result of the impact of countercyclical capital buffer on credit risk reporting based on the Granular Instrumental Variable proposed by Gabaix and Koijen (2021). The Granular Instrumental Variable is the prediction of a first stage regression where we explain countercyclical capital buffer as the difference between the weighted and unweighted announced countercyclical capital buffer rate announced of all debtors. In specification (2), the GIV is computed based on the residuals of a regression explaining the loan share by the announced rate of countercyclical capital buffer, in order to be sure to respect the exogeneity condition of the loan shares. If the loan share is correlated to the CCyB, then the instrument would not be exogenous to the behaviour of the bank. However, we validate with a regression that these two variables are not significantly correlated. In specification (3), the GIV is computed as in specification (2) but with outstanding amount changes due to credit lines utilisation only. The idea of this change is to say that the bank can always choose to stop lending to certain companies and this can indirectly impact the probability of default of the company. Based on the evolution of the outstanding amount, and therefore of the loan share, which depends solely on the firm via the share of the credit lines granted to it that it decides to draw, we obtain an indicator that is totally exogenous to the bank's behavior.

Within the same country with the same CCyB rate applied, banks are exposed differently to an increase in CCyB in some eurozone countries through the difference in the composition of their portfolios. These differences between banks – cross-section rather than over time– are used to identify the impact of CCyB with this method, and the finding further confirms the results identified with the other methodologies: we observe in all specifications that the GIV significantly reduce the risk reported by banks (coefficients between -0.547 and 0.386, p-value 0.01).

Countercyclical capital buffer exogenous to small banks behaviour

Finally, we analyse how small banks react to a rise of CCyB. As CCyB rate is defined based on financial aggregates, such as the aggregate quantity of credit granted by banks, small banks do not have a large influence, if not none, on the decision of the macroprudential authority. For them, the decision is truly exogenous. This is especially true since these banks are less sophisticated and therefore less able to anticipate changes in the CCyB rate than large international banks.

Table 12 presents the results. We observe that small banks, defined as banks with less total outstanding amount than the average bank, are not less significantly sensible to the evolution of CCyB than large banks. It could even be the contrary according to specification (1). However, this impact is not statistically significant when introducing bank fixed effects. It seems that small banks react the same way to CCyB than large banks, this supports the results of our study: banks exposed to an increase in CCyB seem to under-report their credit risk to avoid bearing the burden of this new regulation.

3.3 Additional results

In the previous sections of the paper, we saw that an increase of capital requirements, through a tightening of the countercyclical capital buffer rate, leads to a reduction of the probability of default of firms reported by banks. We now try to identify how banks are doing to under-report their risks while minimizing the risk of being flagged by microprudential authorities as under-reporting risk. The results are presented in Table 14. First, we test an hypothesis that was already demonstrated multiple time in the literature, which is that banks with lower capital buffer under-report lower risks Plosser and Santos (2018); Behn et al. (2022); Berg and Koziol (2017). In column (1), we interact the announced rate of CCyB with the distance between the CET1 ratio of a bank and the average CET1 ratio of all other banks in the same country at the same date. We observe that banks with low CET1 ratio report less risk when CCyB rise than other banks, they seem to react more to the change of capital requirement. This result confirms what had already been identified in the literature: banks under-report more risks when they need it the most, in this case when the increase of regulatory requirements is the most likely to impact them directly, limiting their ability to distribute dividends if this would lead them to fall below the Maximum Distributable Amount (MDA) limit.

In some cases, banks have less incentive to report lower-than-usual probabilities of default, this is for example the case when the bank does not bear the risk of the credit. This could be the case for two reasons: first, the bank got rid of the exposure to the company by transferring the risk to other financial institutions willing to take it. This can be done by the securitization, the use of Special Purpose Vehicule and the emission of mortgage-backed securities or collateralised debt obligation. Second, the bank could not be exposed to a company if the credit relationship is mostly credit lines and the company does not have use it yet. Our hypothesis is that banks do not have incentive to report lower PD in these case as the impact on the risk-weighted assets and thus on the capital requirements will be lower if not null. In column (2) we interact the announced CCyB rate with the share of the outstanding amount of a credit relationship that was transferred by the banks to other creditors. We observe that when the loan is transferred, the bank do not under-report the probability anymore when the CCyB rate increases. In column (3), we interact the announced CCyB rate with the share of off-balance-sheet amount in the commitment amount of the credit relationship. Here again, we find the same result:

banks under-report less the risk when the practice is less effective. This result seems to indicate that banks are aware of cases where it would be profitable to carry over a lower level of risk, and cases where the potential risk is not worth the gain from doing so.

Finally, we analyse whether banks try to hide the pattern. Indeed, the under-reporting of risk is more visible to the regulator in some cases than in others. One hypothesis would be that banks try to reduce the probability of default of companies for which it is harder for the regulator to have an accurate view of the real probability of default. One situation where the comparison of deferred default probability is highly visible and easy to do is syndicated loans. In these loans, multiple creditors work together to grant jointly the same loan to the same firm to realise the same project with the same amount of information given to all the creditors. In column (4), we identify that banks exposed to a rise of the announced CCyB rate do not report lower risk parameter for firms to which they lend through syndicated loans, contrary to the other firms. The more loans a company has with a large number of banks, the greater the number of default probabilities that will be reported for this same firm, which can increase the precision of the consensus on the true value of the probability of default that can emerge around this company. Column 5 we interact the advertised rate of CCyB with the number of banks lending to the same firm at a certain date. We find that the more statistically accurate can be the concensus on the probability of default of a bank through a high number of banks analyzing the firm, the less a bank exposed to an increase in CCyB will tend to reduce the PD carried forward for that same company. Similarly, we find in column (6) that the less consensus there is on a firm's probability of default, analyzed via the variance of the distribution of the probability of default in the previous period, the more banks will tend to report low probabilities of default when exposed to a rise in CCyB (p-value $< 10\%$).

4 Conclusion

Using data from the European credit register from 2018 to 2022, we investigate how the tightening of capital requirements through the increase of countercyclical capital buffer (CCyB) affected banks' reporting of the probability of default (PD) of their corporate debtors. We find that banks report lower PDs when they are exposed to a higher CCyB, as compared with banks in other countries without CCyB. The size of this effect is statistically and economically significant, a one percentage point increase of CCyB reduces probabilities of default reported by banks by -2.5 to -5% (-0.9pp) in most of the specifications. This effect is not a statistical artifact: the predictive power of observed default rates after one year is reduced, and the relationship between the credit spread and the reported borrower's probability of default is altered. This finding is robust to five different causal identification strategies adapted from the literature on monetary and fiscal policy and to a diversity of robustness tests.

To understand better this mechanism, we analyze which banks reduce their risk reporting and how are they doing it. We find that this effect is stronger for banks that have higher incentives to underreport, such as banks that need it as they have lower capital surplus above the regulatory minimum. Banks report lower risk parameters when the practice effectively reduces their risk-weights. This is the case when the bank supports the firm's risk of default, i.e. the loan is not transferred and the credit relationship is not predominantly off balance sheet. Finally, banks also report lower risk parameters when the practice is less visible, for example when the credit relationship is not predominantly composed of syndicated loans, when the number of banks lending to a company is small, and when the consensus between banks on the true value of a firm's probability of default is already low.

Our result suggests a significant risk to financial stability as most studies in the literature identified that banks raise capital ratios mainly by reducing their average risk-weights[4]: the fact that this decline in average risk-weights is largely related to an under-reporting of risk parameters by banks rather than to a reallocation of the portfolio to less risky assets raises questions about the effectiveness of macroprudential capital policies. Our findings have important policy implications. They reveal that banks optimize risk and thus regulatory risk weights to reduce the costs associated with more stringent capital requirements. They suggest that regulators should continue to encourage a comprehensive view of the different dimensions of bank risk as part of their ongoing supervisory role, and increase monitoring of the risks reported by banks in times of rising systemic risk as several elements suggest that banks try to conceal their under-reporting through different methods.

[4] Juelsrud and Wold (2020) suggests that a rise of capital requirement of 10pp in Norway in 2013 leads to a reduction of risk-weighted assets by -3.3% for low-capitalized banks. Gropp et al. (2019) shows that Capital Exercise banks had to increase their capital requirements by 1.82pp on average, and they did it mostly by reducing their levels of risk-weighted assets by 10%.

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Table 1: Definition of main variables

Variable	Definition
PD	Probability of default (PD) which bank b assigns to borrower f at monthly date t. Source: Anacredit.
Announced CCyB	Countercylical capital buffer (CCyB) rate announced by a macroprudential institution in the country of a bank b at a date t. The CCyB rate become effective twelve months after the announcement. Source : ESRB.
Same country	Dummy equal to one if a firm f and a bank b are in the same country. Proxy for the distance between the two entities. Source : RIAD.
Instrument	Share of the total commitment amount by a bank b to a firm f at a date t that is in form of credit line (rather than standard credit). Source: Anacredit.
Interest rate type	Share of the total outstanding amount of debt granted by a bank b to a firm f at a date t that is at fixed rate (rather than variable or mixed rate). Source: Anacredit.
Interest rate spread	Average interest rate spread of a credit relationship between a bank b and a firm f at a date t. Source: Anacredit.
Relative firm size	Share of the total banking debt of a firm f contracted to a bank b at a date t. Source: Anacredit.
Relative bank size	Share of the total banking debt the country of a bank b, granted by a bank b at a date t. Source: Anacredit.
New credit (%)	Share of the new outstanding amount of debt granted by a bank b to a firm f at a date t. Source: Anacredit.
Duration relationship	Duration of the credit relationship between a bank b and a firm f, in number of months. Source: Anacredit
Maturity loan	weighted average maturity at origination of credit loans granted to a firm f by a bank b. Source: Anacredit.
CET1 ratio	Corresponds to "Common equity tier 1 capital ratio (fully loaded) in EBA transparency exercise. The variable is quarterly and reported consolidated by banking group.
Risk weight	Corresponds to risk-weighted assets (RWA) divided by "Total assets" in EBA transparency exercise. Risk-weighted assets are computed based on "Common equity tier 1 capital (fully load)" and "common equity tier 1 capital ratio (fully loaded)", as CET1 rato = CET1 capital divided by RWA. The variable is quarterly and reported consolidated by banking group.
Share credit	Corresponds to "Credit risk" divided by total risk-weighted assets in EBA transparency exercise. The variable is quarterly and reported consolidated by banking group.
Provisions ratio	Corresponds to "Provisions" divided by "Total assets" in EBA transparency exercise. The variable is quarterly and reported consolidated by banking group.
Total assets	"Total assets" in EBA transparency exercise. The variable is quarterly and reported consolidated by banking group.
Leverage ratio	"Leverage ratio - using a fully phased-in definition of Tier 1 capital" in EBA transparency exercise. The variable is quarterly and reported consolidated by banking group.
Retained earnings	"Retained earnings" divided by "Total assets" in EBA transparency exercise. The variable is quarterly and reported consolidated by banking group.
Credit gap	Credit-to-gdp Basel gap reported by macroprudential institution to ESRB every quarter in CCyB database. It corresponds to the decomposition of the credit-to-GDP ratio of the country of a bank b into a long-run trend and a cyclical component using a statistical filter. In particular, the Basel methodology proposes the use a real-time (one-sided) version of the Hodrick–Prescott filter (HP), with a lambda parameter of 400 000.
Transferred loans (%)	Share of the outstanding nominal amount of debt in a credit relationship between a bank b and a firm f that has been transferred to another creditor at a date t. The bank reduces its exposure to the company in question, and therefore bears a smaller share of the default risk. Source: Anacredit
Syndicated loans (%)	Share of the outstanding nominal amount of debt in a credit relationship between a bank b and a firm f that is a syndicated loan at a date$t$. In the context of AnaCredit, syndicated loans are single loan agreements, in which several institutions participate as creditors. Source: Anacredit
Number of banks	Number of creditors granting credit to a firm f at a date t.

Table of results

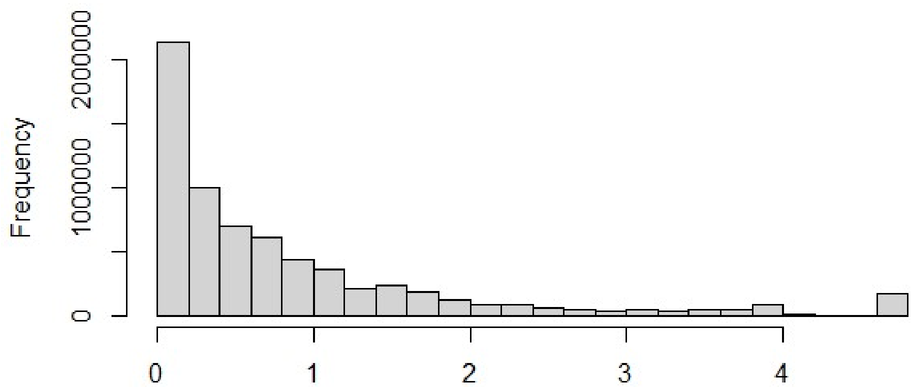
Data

Table 2: Descriptive statistics of variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Log(PD)	6,710,141	0.840	1.046	0.000	0.140	0.457	1.097	4.615
Announced CCyB	6,710,141	0.086	0.308	0.000	0.000	0.000	0.000	2.500
Number of banks	6,710,141	2.768	3.155	1	1	2	3	76
Log(outstanding amount)	6,710,141	12.361	2.272	7.356	10.721	12.002	13.667	18.372
Same country	6,710,141	0.834	0.372	0	1	1	1	1
Type instrument: term credit	6,710,141	0.839	0.362	0.000	1.000	1.000	1.000	1.000
Type interest: Fixed	6,710,141	0.470	0.479	−0.001	0.000	0.240	1.000	1.002
Relative firm size	6,710,141	0.594	0.380	0.00000	0.211	0.612	1.000	1.000
Relative bank size	6,710,141	0.024	0.004	0.009	0.022	0.023	0.025	0.092
New credit	6,710,141	0.049	0.188	−0.019	0.000	0.000	0.000	1.785
Length relationship	6,710,141	3.471	3.681	−3.000	1.000	2.000	4.000	20.000
Maturity	6,710	1,418	1,663	0	559.800	1,126	1,747	66,230
CET1 ratio	6,710,141	0.165	0.040	0.065	0.135	0.155	0.205	0.670
Risk weight	6,710,141	0.370	0.085	0.058	0.335	0.370	0.390	0.680
Share credit	6,710,141	0.805	0.058	0.209	0.802	0.805	0.826	0.940
Provisions ratio	6,710,141	0.113	0.057	0.002	0.085	0.113	0.113	0.391
Total assets	6,710,141	462,074.200	357,329.700	2,230.435	167,735.100	462,074.200	539,619.900	1,907,554.000
Leverage ratio	6,710,141	0.059	0.017	0.019	0.050	0.059	0.059	0.139
Retained earnings	6,710,141	0.503	0.327	−1.034	0.448	0.503	0.655	1.601
Credit gap	6,710,141	−16.337	17.593	−96.000	−17.700	−16.337	−5.800	24.200
Interest rate spread	6,710,141	1.161	1.759	0.000	0.000	0.238	1.900	11.500

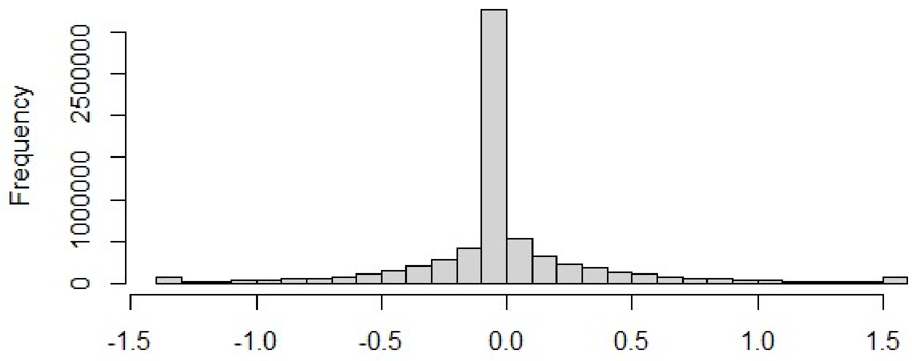
Note: This table reports the summary statistics of the variables used in the paper, across our sample of all credit relationships in Euro Area for firms that have credit in at least two banks located in two different countries, that report risks with internal rating-based models, from 2018:Q3 to 2022:Q2. The definition of the variables can be found in Table 1. Source: European credit register, Anacredit. authors' own calculations.

Figure 1: Distribution of the firm's probability of default reported by banks (log)



Note: This figure shows the distribution of the logarithm of the probabiity of default by banks of their borrowers during our sample period 2018:Q3 to 2022:Q2, computed monthly based on internal rating-based models. The probability of default vary between 0 and 100 percent. The x-axis refers to the logarithm of the probability of default. Source: European credit register Anacredit.

Figure 2: Distribution of the firm's probability of default gap reported by banks (log)



Note: This figure shows the cross-sectional variation in probability of default (relative to the mean probability of default) reported by banks for the same borrower at the same time during our sample period 2018:Q3 to 2022:Q2. The probability of default for the same borrower in the same month vary around the mean value (i.e., the spread between the probability of default and the mean probability is not zero). The x-axis refers to the spread between the logarithmic reported probability of default minus the average of the logarithmic probability of default of a given borrower at the same time, across all banks. The distribution was winsorized at 1%. Source: European credit register Anacredit, authors' own calculations

Table 3: Number of observations for each credit relationships observed, by countries

	AT	BE	CZ	DE	DK	EE	ES	FI	FR	GR	IE	IT	LT	LU	LV	MT	NL	PT	SE	SK
AT	29868	410	333	21327	301	43	1494	500	2857	38	75	1462	95	379	116	43	719	99	181	332
BE	247	70783	0	4164	57	0	3957	295	8963	115	520	470	19	4186	0	39	2891	437	164	107
CZ	0	0	54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15896
DE	8296	3007	1140	514175	1017	93	152812	1463	27751	582	2020	5677	130	1387	44	463	9134	3223	1505	856
DK	31	0	0	475	20	1180	0	70496	0	0	397	0	2036	0	251	0	4	10	103	0
EE	0	0	0	0	0	4811	0	43	0	0	0	0	10	9	60	0	0	0	0	0
ES	325	855	52	2154	49	0	1170129	87	7026	273	774	2647	3	481	0	0	1064	24426	75	344
FI	42	7	0	269	221	218	85	1181510	22	0	65	42	1529	9	109	39	25	0	946	0
FR	825	19561	225	105648	413	2	9161	424	544125	161	1760	116033	20	4177	0	146	2771	3716	472	5288
GR	0	0	0	0	0	0	0	0	0	36559	0	0	0	26	0	106	0	0	0	0
IE	364	196	30	1443	149	0	4714	469	4373	90	55866	1862	0	84	0	0	739	187	1108	122
IT	188	157	43	1762	0	0	2500	33	3244	45	220	1546999	0	178	0	0	278	314	52	58
LT	0	0	0	0	0	50	0	0	0	0	0	0	18913	0	112	0	0	0	0	0
LU	650	3381	73	58985	220	4	1716	447	7337	4331	463	959	0	11181	0	25	2219	204	447	0
LV	0	0	0	0	0	51	0	0	0	0	0	0	66	0	7362	0	0	0	0	0
MT	0	0	0	0	0	0	83	0	0	4589	66	11	0	24	0	0	0	0	0	43
NL	185	3060	64	8727	179	0	25112	77	8794	12	566	40543	21	197	0	109	31778	2001	302	121
PT	0	0	0	0	0	0	149	0	4	0	0	0	0	0	0	0	0	344831	0	0
SE	1	1	0	260	7	20	198	101930	242	0	1	2	2	0	0	1	0	0	147	0
SK	143	4	281	239	0	0	0	86	114	0	0	27	0	27	0	0	92	0	0	26132

Note: This table presents the distribution of observations between the countries of the banks (creditors) and the firms (debtors). The x-axis indicates the country of firms and the y-axis indicates the country of banks. The diagonal of the matrix represents loans granted by banks to the firms in the same country.

Table 4: Source of variables used to predict countercyclical capital buffer

Category	Variable	Source	Frequency
Financial	Credit to non financial-corporations, USD	BIS, total credit	Quarterly
Financial	Credit to households, USD	BIS, total credit	Quarterly
Financial	Credit to the private non-financial sector, USD	BIS, total credit	Quarterly
Financial	Credit-to-gdp gap	BIS, total credit	Quarterly
Financial	Shares price, national index	OECD, MEI	Monthly
Financial	VIX Stoxx 50	Stoxx	Monthly
Financial	Average risk-weight	EBA transparency exercise	Monthly
Economic	Gross Domestric Product	OECD, MEI	Quarterly
Economic	Productivity index	OECD, EO	Quarterly
Economic	Unemployment rate	OECD, EO	Quarterly
Economic	Consumption price index	OECD, MEI	Monthly
Economic	Consumption index	OECD, EO	Quarterly
Economic	Investment index	OECD, EO	Quarterly
Economic	Saving rate	OECD, EO	Quarterly
Economic	Manufacturing confidence	OECD, KEI	Monthly
International	Import volume	OECD, MEI	Monthly
International	Export volume	OECD, MEI	Monthly
International	Exchange rate, national currency per USD	OECD, EO	Quarterly
International	Terms trade	IMF, PCTOT	Monthly
Monetary	M3	OECD, KEI	Monthly
Monetary	Long-term interest rate	OECD, KEI	Montly
Monetary	Short-term interest rate	OECD, KEI	Monthly
Real estate	Real estate price index	OECD, HOUSE PRICES	Quarterly
Real estate	Real estate rent index	OECD, HOUSE PRICES	Quarterly
Real estate	Real estate price to rent index	OECD, HOUSE PRICES	Quarterly
Real estate	New permits for real estate construction	OECD, KEI	Monthly
Real estate	Production of construction, index 2015=100	OECD, MEI	Monthly
Commodities	Oil price index	OECD, EO	Quarterly
Commodities	Gold price	LBMA	Monthly
Commodities	Silver price	LBMA	Monthly

Baseline results

Table 5: Impact of countercyclical capital buffer on reported probabilities of default

	Dependent variable:							
	Reported probability of default (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Announced CCyB	-0.042^{***}	-0.115^{***}	-0.048^{***}	-0.049^{***}	-0.026^{**}	-0.063^{***}	-0.032^{***}	-0.029^{**}
	(0.015)	(0.017)	(0.012)	(0.012)	(0.012)	(0.014)	(0.011)	(0.011)
Same country		-0.121^{***}	0.016	0.016		0.014		
		(0.015)	(0.011)	(0.011)	(0.000)	(0.011)	(0.000)	
Instrument: Credit line		0.059^{***}	0.105^{***}	0.105^{***}	0.096^{***}	0.073^{***}	0.053^{***}	0.056^{***}
		(0.013)	(0.013)	(0.013)	(0.020)	(0.012)	(0.019)	(0.018)
Interest rate: Fixed		-0.046^{***}	-0.018^{***}	-0.018^{***}	-0.031^{***}	-0.032^{***}	-0.022^{**}	-0.022^{**}
		(0.007)	(0.006)	(0.006)	(0.009)	(0.006)	(0.009)	(0.008)
Relative firm size						-0.400^{***}	-0.376^{***}	-0.374^{***}
						(0.009)	(0.013)	(0.012)
Relative bank size						5.296	2.228	2.071
						(3.224)	(1.642)	(1.499)
New credit (%)						-0.069^{***}	-0.019^{***}	-0.019^{***}
						(0.007)	(0.004)	(0.004)
Duration relationship		-0.010^{***}	-0.012^{***}	-0.012^{***}	-0.020^{***}	-0.010^{***}	-0.021^{***}	-0.021^{***}
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Maturity loan		0.00000^{***}	0.00001^{***}	0.00001^{***}	0.00001^{***}	0.00003^{***}	0.00002^{***}	0.00002^{***}
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
CET1 ratio						0.683^{*}	0.858^{**}	0.825^{**}
						(0.343)	(0.343)	(0.332)
Risk weight						0.635^{***}	0.604^{***}	0.562^{***}
						(0.187)	(0.201)	(0.198)
Share credit						0.169	-0.040	0.029
						(0.203)	(0.219)	(0.232)
Provisions ratio						-0.192^{**}	0.069	0.062
						(0.087)	(0.078)	(0.078)
Total assets						-0.00000^{***}	-0.00000^{***}	-0.00000^{***}
						(0.00000)	(0.00000)	(0.00000)
Leverage ratio						-2.895^{**}	-2.587^{***}	-2.617^{***}
						(1.097)	(0.939)	(0.935)
Retained earnings						-0.020	0.015	0.010
						(0.023)	(0.016)	(0.017)
Credit gap						0.002	0.001	0.001
						(0.001)	(0.001)	(0.001)
Firm x Date FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank FE			*Yes*			*Yes*		
Bank x Year FE				*Yes*				
Bank x Firm FE					*Yes*		*Yes*	
Bank x Firm x Year FE								*Yes*
Observations	6,710,141	6,710,141	6,710,141	6,710,141	6,710,141	6,710,141	6,710,141	6,710,141
Adjusted R^2	0.575	0.578	0.639	0.639	0.860	0.651	0.863	0.854
Note:								*p<0.1; **p<0.05; ***p<0.01

Note: This table presents the regression results of OLS regression estimates for which the dependent variable is $log(PD)$, the logarithm of the probability of default reported by a bank b to a firm f at a date t. All specifications (1 to 8) have firm x date fixed effects, specifications (3) and (6) have bank fixed effects, specification (4) have bank x year fixed effects, specifications (5) and (7) have bank x firm fixed effects and specifications (8) have bank x firm x year fixed effects. For all regressions, independent variables include $AnnouncedCCyB$, the countercyclical capital buffer rate announced in the country of the bank b at a date t. Two set of control variables are added as regressors: specifications (2) to 5) have a dummy if the bank and the firm arein the same country, the share of credit line in the credit relationship, the share of outstanding amount with a fixed interest rate, the duration of the credit relationship in months and the average maturity at origination. Columns (6) to (8) add as control variables the relative firm size, relative bank size, the share of new credit, the CET1 ratio of the bank, the risk-weight, the share of credit, the provisions ratio, the amount of total assets of the bank, the leverage ratio, retained earnings and the credit gap of the country of the bank. Errors are clustered by firm and date. There is one observation by credit relationship between a firm and a bank every month. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Robustness tests

Table 6: Robustness check, alternative explained variables

	Dependent variable:			
	PD gap	PD	Spread	Precision
	(1)	(2)	(3)	(4)
Announced CCyB	-0.019^{***}	-0.869^{***}	0.125^{***}	-0.004^{**}
	(0.004)	(0.204)	(0.038)	(0.002)
Log(PD)			0.075^{***}	
			(0.014)	
Announced CCyB $\times$ log(PD)			0.112^{***}	
			(0.031)	
Firm x Date FE		Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	6,710,141	6,710,141	6,710,141	6,710,141
Adjusted R^2	0.842	0.597	0.488	0.028
Note:			*p<0.1; **p<0.05; ***p<0.01	

Note: This table presents the regression results of OLS regression estimates for which the dependent variable is $PDGap$ (the difference between the reported probability of default (logarithm of the PD) by a bank for a firm at a certain date, and the average of all the PD for the same firm at the same date reported by all creditors) in the specification (1), the probability of default without logarithmic transformation in the specification (2), the interest rate spread in specification (3) and the difference between a dummy equal to one if the firm is in default twelve month later and the (one-year) probability reported by a bank for a firm at a date t in specification (4). All specifications (1 to 4) have firm x date fixed effects, specifications (2) and (4) have bank fixed effects. For all regressions, independent variables include $AnnouncedCCyB$, the countercyclical capital buffer rate announced in the country of the bank b at a date t. The control variables are a dummy if the bank and the firm are in the same country, the share of credit line in the credit relationship, the share of outstanding amount with a fixed interest rate, the duration of the credit relationship in months and the average maturity at origination, the relative firm size, relative bank size, the share of new credit, the CET1 ratio of the bank, the risk-weight, the share of credit, the provisions ratio, the amount of total assets of the bank, the leverage ratio, retained earnings and the credit gap of the country of the bank. Errors are clustered by firm and date. There is one observation by credit relationship between a firm and a bank every month. *p<0.1; **p<0.05; ***p<0.01.

Table 7: Robustness check, subsamples on different years

	Reported probability of default (log)			
	(1)	(2)	(3)	(4)
Announced CCyB	-0.043***	-0.044**	-0.047***	-0.042***
	(0.014)	(0.018)	(0.014)	(0.012)
Firm x Date FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Year removed	2019	2020	2021	2022
Observations	4,887,732	4,814,991	4,781,921	6,235,206
R^2	0.855	0.849	0.854	0.853
Note:				*p<0.1; **p<0.05; ***p<0.01

*Note: This table presents the regression results of OLS regression estimates for which the dependent variable is $log(PD)$, the logarithm of the probability of default reported by a bank b to a firm f at a date t. All specifications (1 to 4) have firm x date fixed effects and bank fixed effects. For all regressions, independent variables include $AnnouncedCCyB$, the countercyclical capital buffer rate announced in the country of the bank b at a date t. Specification (1) is estimated after removing all observations during 2019, specification (2) all observations during 2020, specification (3) during 2021 et specification (4) during 2022. The control variables are a dummy if the bank and the firm are in the same country, the share of credit line in the credit relationship, the share of outstanding amount with a fixed interest rate, the duration of the credit relationship in months and the average maturity at origination, the relative firm size, relative bank size, the share of new credit, the CET1 ratio of the bank, the risk-weight, the share of credit, the provisions ratio, the amount of total assets of the bank, the leverage ratio, retained earnings and the credit gap of the country of the bank. Errors are clustered by firm and date. There is one observation by credit relationship between a firm and a bank every month. *p<0.1; **p<0.05; ***p<0.01.*

Table 8: Robustness check, subsamples of different risk level

	Reported probability of default (log)			
	(1)	(2)	(3)	(4)
Announced CCyB	-0.045^{***}	-0.013^{*}	-0.005^{**}	-0.003^{**}
	(0.011)	(0.006)	(0.003)	(0.001)
Firm x Date FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Sample	$Nodefault$	PD¡50%	PD¡10%	PD¡2%
Observations	6,429,636	4,869,963	2,888,540	1,070,546
Adjusted R^2	0.582	0.226	-0.021	-0.197
Note:				*p<0.1; **p<0.05; ***p<0.01

Note: This table presents the regression results of OLS regression estimates for which the dependent variable is $log(PD)$, the logarithm of the probability of default reported by a bank b to a firm f at a date t. All specifications (1 to 4) have firm x date fixed effects and bank fixed effects. For all regressions, independent variables include $AnnouncedCCyB$, the countercyclical capital buffer rate announced in the country of the bank b at a date t. Specification (1) is estimated on a sample comprising all firms that are not in default with at least one bank, specification (2) is estimated on a sample comprising all firms with an average default probability lower than 50%, specification (3) lower than 10% and specification (4) lower than 2%. The control variables are a dummy if the bank and the firm are in the same country, the share of credit line in the credit relationship, the share of outstanding amount with a fixed interest rate, the duration of the credit relationship in months and the average maturity at origination, the relative firm size, relative bank size, the share of new credit, the CET1 ratio of the bank, the risk-weight, the share of credit, the provisions ratio, the amount of total assets of the bank, the leverage ratio, retained earnings and the credit gap of the country of the bank. Errors are clustered by firm and date. There is one observation by credit relationship between a firm and a bank every month. *p<0.1; **p<0.05; ***p<0.01.

Table 9: Robustness check, controling for banking groups

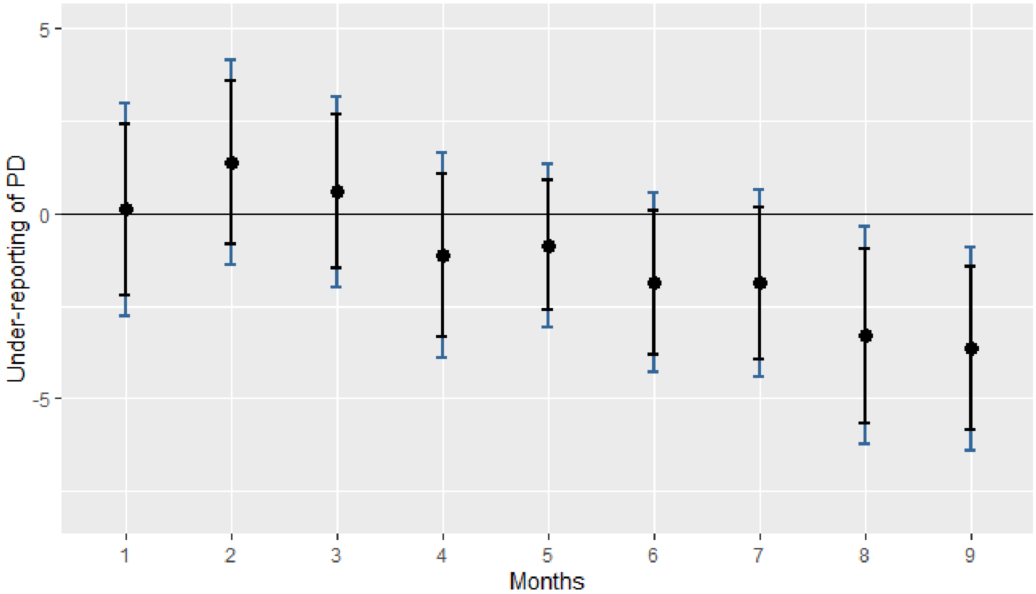
	Reported probability of default (log)		
	(1)	(2)	(3)
Announced CCyB	-0.026**	-0.114***	-0.046**
	(0.012)	(0.032)	(0.020)
Firm x Date FE	Yes	Yes	Yes
Group x Date FE	Yes	Yes	
Bank FE	Yes		Yes
Bank x Firm FE		Yes	
Controls	Yes	Yes	Yes
Yes			
Clustering	Firm/date	Firm/date	Firm/date/group
Observations	6,710,141	6,710,141	6,710,141
R^2	0.894	0.727	0.149
Note:		*p<0.1; **p<0.05; ***p<0.01	

Note: This table presents the regression results of OLS regression estimates for which the dependent variable is $log(PD)$, the logarithm of the probability of default reported by a bank b to a firm f at a date t. All specifications (1 to 4) have firm x date fixed effects. Specifications (1) and (2) have banking group x date fixed effects, specifications (1) and (3) have bank fixed effects and specification (2) has bank x firm fixed effects. For all regressions, independent variables include $AnnouncedCCyB$, the countercyclical capital buffer rate announced in the country of the bank b at a date t. Specification (1) is estimated after removing all observations during 2019, specification (2) all observations during 2020, specification (3) during 2021 et specification (4) during 2022. The control variables are a dummy if the bank and the firm are in the same country, the share of credit line in the credit relationship, the share of outstanding amount with a fixed interest rate, the duration of the credit relationship in months and the average maturity at origination, the relative firm size, relative bank size, the share of new credit, the CET1 ratio of the bank, the risk-weight, the share of credit, the provisions ratio, the amount of total assets of the bank, the leverage ratio, retained earnings and the credit gap of the country of the bank. Errors are clustered by firm and date in specifications (1) and (2), and firm, date and group fixed effects in specification (3). There is one observation by credit relationship between a firm and a bank every month. *p<0.1; **p<0.05; ***p<0.01.

Causal identification strategy

High-frequency macroprudential policy surprise shocks

Figure 3: Impact of CCyB on reported probability of default (log)



Note: This figure presents the regression results of an event study OLS regression estimates for which the dependent variable is PDgap, the difference between the reported probability of default (logarithm of the PD) by a bank for a firm at a certain date, and the average of all the PD for the same firm at the same date reported by all creditors. The specification presented have bank x firm fixed effects. The independent variable is a dummy equal to one if a rise of the countercyclical capital buffer rate was announced in the country of a bank. Each black dot represents the coefficient of this variable with different number of lag applied. "Month 0" is the relative date of the CCyB announcement. The control variables are a dummy if the bank and the firm are in the same country, the share of credit line in the credit relationship, the share of outstanding amount with a fixed interest rate, the duration of the credit relationship in months and the average maturity at origination, the relative firm size, relative bank size, the share of new credit, the CET1 ratio of the bank, the risk-weight, the share of credit, the provisions ratio, the amount of total assets of the bank, the leverage ratio, retained earnings and the credit gap of the country of the bank. Errors are clustered by firm and date. There is one observation by credit relationship between a firm and a bank every month. Black bars represent 90% confidence intervals and blue bars represent 95% confidence intervals.

Macroprudential Taylor rule

Table 10: Macroprudential Taylor rule

	Dependent variable:				
	Reported probability of default (log)				
	(1)	(2)	(3)	(4)	(5)
CCyB residuals	-0.084^{***}	-0.154^{***}	-0.126^{***}	-0.107^{***}	-0.089^{***}
	(0.020)	(0.037)	(0.029)	(0.027)	(0.028)
Same country	0.014	0.015	0.015	0.015	
	(0.011)	(0.011)	(0.011)	(0.011)	(0.000)
Instrument: Credit line	0.073^{***}	0.073^{***}	0.073^{***}	0.073^{***}	0.053^{***}
	(0.012)	(0.012)	(0.012)	(0.012)	(0.019)
Interest rate: Fixed	-0.031^{***}	-0.032^{***}	-0.031^{***}	-0.031^{***}	-0.022^{**}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)
Relative firm size	-0.399^{***}	-0.400^{***}	-0.400^{***}	-0.400^{***}	-0.376^{***}
	(0.009)	(0.009)	(0.009)	(0.009)	(0.013)
Relative bank size	5.595	5.100	5.646^{*}	5.993	2.558
	(3.339)	(3.083)	(3.328)	(3.610)	(1.808)
New credit (%)	-0.069^{***}	-0.069^{***}	-0.069^{***}	-0.069^{***}	-0.019^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.004)
Duration relationship	-0.010^{***}	-0.010^{***}	-0.010^{***}	-0.010^{***}	-0.021^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Maturity loan	0.00003^{***}	0.00003^{***}	0.00003^{***}	0.00003^{***}	0.00002^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
CET1 ratio	0.699^{**}	0.679^{*}	0.558	0.630^{*}	0.770^{**}
	(0.341)	(0.355)	(0.355)	(0.355)	(0.348)
Risk weight	0.628^{***}	0.647^{***}	0.582^{***}	0.617^{***}	0.560^{***}
	(0.185)	(0.191)	(0.189)	(0.189)	(0.203)
Share credit	0.166	0.153	0.233	0.183	0.021
	(0.206)	(0.196)	(0.206)	(0.205)	(0.219)
Provisions ratio	-0.192^{**}	-0.197^{**}	-0.203^{**}	-0.185^{**}	0.059
	(0.086)	(0.087)	(0.086)	(0.086)	(0.078)
Total assets	-0.00000^{***}	-0.00000^{***}	-0.00000^{***}	-0.00000^{***}	-0.00000^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Leverage ratio	-2.862^{**}	-2.889^{**}	-2.686^{**}	-2.742^{**}	-2.451^{**}
	(1.094)	(1.104)	(1.099)	(1.106)	(0.944)
Retained earnings	-0.019	-0.018	-0.020	-0.016	0.014
	(0.024)	(0.023)	(0.023)	(0.023)	(0.016)
Credit gap	0.002	0.002	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm x Date FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank FE	*Yes*	*Yes*	*Yes*	*Yes*	
Bank x Firm FE					*Yes*
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Taylor rule	*OLS*	*Lasso*	*RF*	*RF+*	*RF+*
Observations	6,710,141	6,710,141	6,710,141	6,710,141	6,710,141
Adjusted R^2	0.651	0.651	0.651	0.651	0.863
Note:					*p<0.1; **p<0.05; ***p<0.01

Note: This table presents the regression results of OLS regression estimates for which the dependent variable is $log(PD)$, the logarithm of the probability of default reported by a bank b to a firm f at a date t. All specifications (1 to 4) have firm x date fixed effects and bank fixed effects. For all regressions, independent variables include $CCyBresiduals$, the residuals of a regression predicting the countercyclical capital buffer rate announced in the country of the bank b at a date t. Specification (1) computes the macroprudential Taylor rule with an OLS regression, specification (2) with a LASSO regression, specifications (3) to (5) with a Random Forest regression. Specifications (4) and (5) have additional variables reported directly by the macroprudential authorities as variables that were used directly to calibrate the CCyB rate: the additional variables are the "additional [credit-to-gdp] gap" (in addition to the classic Basel gap) and the "additional benchmark", usually a financial cycle composite indicator. The control variables are a dummy if the bank and the firm are in the same country, the share of credit line in the credit relationship, the share of outstanding amount with a fixed interest rate, the duration of the credit relationship in months and the average maturity at origination, the relative firm size, relative bank size, the share of new credit, the CET1 ratio of the bank, the risk-weight, the share of credit, the provisions ratio, the amount of total assets of the bank, the leverage ratio, retained earnings and the credit gap of the country of the bank. Errors are clustered by firm and date. There is one observation by credit relationship between a firm and a bank every month. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Narrative approach

Table 11: Impact of CCyB on credit risk reporting based on positive neutral CCyB rate

	Reported probability of default		
	(1)	(2)	(3)
Endogenous CCyB	-0.078^{***}	-0.012	
	(0.024)	(0.023)	
Exogenous CCyB	-0.044^{***}	-0.163^{***}	
	(0.010)	(0.014)	
Announced CCyB			-0.029
			(0.022)
Exogenous country			-0.118^{***}
			(0.033)
CCyB announced x Exogenous country			-0.050^{**}
			(0.024)
Same country	0.014	-0.051^{***}	-0.059^{***}
	(0.011)	(0.014)	(0.014)
Type instrument: Credit line	0.073^{***}	0.050^{***}	0.050^{***}
	(0.012)	(0.013)	(0.013)
Interest rate: Fixed	-0.031^{***}	-0.089^{***}	-0.089^{***}
	(0.006)	(0.006)	(0.006)
Relative firm size	-0.400^{***}	-0.472^{***}	-0.472^{***}
	(0.009)	(0.012)	(0.012)
Relative bank size	5.040	4.337^{***}	3.979^{***}
	(3.233)	(1.490)	(1.413)
New credit (%)	-0.069^{***}	-0.062^{***}	-0.063^{***}
	(0.007)	(0.009)	(0.009)
Duration relationship	-0.010^{***}	-0.008^{***}	-0.008^{***}
	(0.001)	(0.001)	(0.001)
Maturity loan	0.00003^{***}	0.00003^{***}	0.00003^{***}
	(0.00000)	(0.00000)	(0.00000)
CET1 ratio	0.698^{**}	1.126^{***}	1.170^{***}
	(0.345)	(0.240)	(0.240)
Risk weight	0.645^{***}	0.527^{***}	0.545^{***}
	(0.189)	(0.087)	(0.087)
Share credit	0.153	-0.196^{*}	-0.243^{**}
	(0.202)	(0.098)	(0.103)
Provisions ratio	-0.186^{**}	0.589^{***}	0.602^{***}
	(0.087)	(0.105)	(0.107)
Total assets	-0.00000^{***}	0.00000^{***}	0.00000^{***}
	(0.00000)	(0.000)	(0.000)
leverage ratio	-2.921^{**}	-2.374^{***}	-2.495^{***}
	(1.100)	(0.713)	(0.701)
Retained earnings	-0.019	0.022^{**}	0.023^{**}
	(0.023)	(0.010)	(0.010)
Credit gap	0.002	0.005^{***}	0.005^{***}
	(0.001)	(0.0004)	(0.0004)
Firm x Date FE	*Yes*	*Yes*	*Yes*
Bank FE		*Yes*	
Controls	*Yes*	*Yes*	*Yes*
Observations	6,710,141	6,710,141	6,710,141
Adjusted R^2	0.651	0.599	0.600
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: This table presents the regression results of OLS regression estimates for which the dependent variable is $log(PD)$, the logarithm of the probability of default reported by a bank b to a firm f at a date t. All specifications (1 to 4) have firm x date fixed effects. Specification (2) has bank fixed effects. In specifications (1) and (2), independent variables include $ExogenousCCyB$ and $EndogenousCCyB$, based on the decomposition between countercyclical capital buffer rate changes announced as driven by the willingness to have a positive neutral CCyB rate or not. In specification (3), the main independent variable is $AnnouncedCCyB$, the countercyclical capital buffer rate announced in the country of the bank b at a date t. Specification (1) is estimated after removing all observations during 2019, specification (2) all observations during 2020, specification (3) during 2021 et specification (4) during 2022. The control variables are a dummy if the bank and the firm are in the same country, the share of credit line in the credit relationship, the share of outstanding amount with a fixed interest rate, the duration of the credit relationship in months and the average maturity at origination, the relative firm size, relative bank size, the share of new credit, the CET1 ratio of the bank, the risk-weight, the share of credit, the provisions ratio, the amount of total assets of the bank, the leverage ratio, retained earnings and the credit gap of the country of the bank. Errors are clustered by firm and date. There is one observation by credit relationship between a firm and a bank every month. *p<0.1; **p<0.05; ***p<0.01.

Small banks

Table 12: Impact of CCyB on credit risk reporting by small banks

	Log(PD)	PD	Log(PD)	
	(1)	(2)	(3)	(4)
Announced CCyB	0.028	−0.762**	−0.116***	−0.065***
	(0.024)	(0.324)	(0.036)	(0.014)
Small bank	−0.045**	0.339	−0.038	
	(0.021)	(0.256)	(0.027)	
Announced CCyB x Small bank	−0.121***	−0.173	0.063	
	(0.025)	(0.276)	(0.040)	
Bank size				5.040
				(3.233)
Announced CCyB x Bank size				0.000
				(0.000)
Same country	−0.055***	−0.203	0.014	0.014
	(0.014)	(0.241)	(0.011)	(0.011)
Type instrument: credit line	0.051***	0.789***	0.073***	0.073***
	(0.013)	(0.169)	(0.012)	(0.012)
Interest rate: Fixed	−0.089***	−0.403***	−0.032***	−0.032***
	(0.006)	(0.096)	(0.006)	(0.006)
Relative firm size	−0.473***	−3.187***	−0.400***	−0.400***
	(0.012)	(0.138)	(0.009)	(0.009)
New credit (%)	−0.062***	−0.313***	−0.069***	−0.069***
	(0.009)	(0.080)	(0.007)	(0.007)
Duration relationship	−0.008***	−0.104***	−0.010***	−0.010***
	(0.001)	(0.010)	(0.001)	(0.001)
Maturity loan	0.00003***	0.0002***	0.00003***	0.00003***
	(0.00000)	(0.00004)	(0.00000)	(0.00000)
CET1 ratio	1.119***	15.399***	0.746**	0.684*
	(0.239)	(3.975)	(0.347)	(0.343)
Risk weight	0.517***	16.065***	0.642***	0.635***
	(0.086)	(2.915)	(0.186)	(0.187)
Share credit	−0.138	4.110**	0.181	0.172
	(0.090)	(1.575)	(0.200)	(0.203)
Provisions	0.573***	−0.125	−0.184**	−0.193**
	(0.103)	(1.115)	(0.086)	(0.087)
Leverage ratio	−2.408***	−84.006***	−3.086***	−2.905**
	(0.701)	(15.434)	(1.095)	(1.103)
Retained earnings	0.021**	−0.388	−0.022	−0.020
	(0.009)	(0.300)	(0.023)	(0.023)
Credit gap	0.006***	0.009	0.002	0.002
	(0.0005)	(0.006)	(0.001)	(0.001)
Firm x Date FE	*Yes*	*Yes*	*Yes*	*Yes*
Bank FE			*Yes*	*Yes*
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Observations	6,710,141	6,710,141	6,710,141	6,710,141
Adjusted R^2	0.599	0.597	0.651	0.651
Note:				*p<0.1; **p<0.05; ***p<0.01

*Note: This table presents the regression results of OLS regression estimates for which the dependent variable is $log(PD)$, the logarithm of the probability of default reported by a bank b to a firm f at a date t, except in specification (2) when the logarithm transformation is not applied. All specifications (1 to 4) have firm x date fixed effects. Specifications (3) and (4) have bank fixed effects. The main independent variable is $AnnouncedCCyB$, the countercyclical capital buffer rate announced in the country of the bank b at a date t. $Smallbank$ is equal to one if the total outstanding amount of a bank is smaller than the median. The control variables are a dummy if the bank and the firm are in the same country, the share of credit line in the credit relationship, the share of outstanding amount with a fixed interest rate, the duration of the credit relationship in months and the average maturity at origination, the relative firm size, bank size(logarithm of total assets), the share of new credit, the CET1 ratio of the bank, the risk-weight, the share of credit, the provisions ratio, the amount of total assets of the bank, the leverage ratio, retained earnings and the credit gap of the country of the bank. Errors are clustered by firm and date. There is one observation by credit relationship between a firm and a bank every month. *p<0.1; **p<0.05; ***p<0.01.*

Granular Instrumental Variable

Table 13: Impact of CCyB on credit risk reporting based on GIV

	Reported probability of default		
	(1)	(2)	(3)
GIV	−0.547**	−0.504**	−0.386***
	(0.208)	(0.205)	(0.083)
Same country	0.018	0.018	0.017
	(0.011)	(0.011)	(0.011)
Type instrument: credit lines	0.072***	0.073***	0.072***
	(0.012)	(0.012)	(0.012)
Interest rate: Fixed	−0.032***	−0.032***	−0.032***
	(0.006)	(0.006)	(0.006)
Relative firm size	−0.399***	−0.399***	−0.400***
	(0.009)	(0.009)	(0.009)
New credit (%)	−0.069***	−0.068***	−0.069***
	(0.007)	(0.007)	(0.007)
Duration relationship	−0.010***	−0.010***	−0.010***
	(0.001)	(0.001)	(0.001)
Maturity	0.00003***	0.00003***	0.00003***
	(0.00000)	(0.00000)	(0.00000)
CET1 ratio	1.105***	1.091***	0.600**
	(0.398)	(0.396)	(0.293)
Risk weight	0.645***	0.647***	0.371*
	(0.191)	(0.190)	(0.195)
Share credit	0.195	0.189	0.317
	(0.217)	(0.215)	(0.214)
Provisions ratio	−0.153*	−0.151*	−0.135
	(0.085)	(0.085)	(0.082)
Total assets	−0.00000***	−0.00000***	−0.00000***
	(0.00000)	(0.00000)	(0.00000)
Leverage ratio	−3.257***	−3.242***	−2.048**
	(1.179)	(1.175)	(0.947)
Retained earnings	−0.009	−0.010	0.030
	(0.024)	(0.024)	(0.019)
Credit gap	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)
Firm x Date FE	*Yes*	*Yes*	*Yes*
Bank FE	*Yes*	*Yes*	*Yes*
Controls	*Yes*	*Yes*	*Yes*
Observations	6,710,141	6,710,141	6,710,141
Adjusted R^2	0.650	0.650	0.651
Note:			*p<0.1; **p<0.05; ***p<0.01

*Note: This table presents the regression results of OLS regression estimates for which the dependent variable is $log(PD)$, the logarithm of the probability of default reported by a bank b to a firm f at a date t. All specifications (1 to 3) have firm x date fixed effects and bank fixed effects. The main independent variable is GIV, which is an instrumental variable of the countercyclical capital buffer rate announced in the country of the bank b at a date t. GIV is the predictions of a first stage regression where we explain countercyclical capital buffer as the difference between the weighted and unweighted announced countercyclical capital buffer of all debtors. In specification (2), the GIV is computed based on the residuals of a regression explaining the loan share by the announced rate of countercyclical capital buffer, in order to be sure to respect the exogeneity condition of the loan shares. In specification (3), the GIV is computed as in specification (2) but with outstanding amount changes due to credit lines utilisation only. The control variables are a dummy if the bank and the firm are in the same country, the share of credit line in the credit relationship, the share of outstanding amount with a fixed interest rate, the duration of the credit relationship in months and the average maturity at origination, the relative firm size, the relative bank size, the share of new credit, the CET1 ratio of the bank, the risk-weight, the share of credit, the provisions ratio, the amount of total assets of the bank, the leverage ratio, retained earnings and the credit gap of the country of the bank. Errors are clustered by firm and date. There is one observation by credit relationship between a firm and a bank every month. *p<0.1; **p<0.05; ***p<0.01.*

Additional results

Table 14: Practices of risk reporting by banks

	Log(Reported probability of default)					
	Low CET1 ratio	Transferred loans	% credit line	% Syndicated loans	Nb banks	Var(PD)
Announced CCyB	-0.101^{***}	-0.108^{***}	-0.117^{***}	-0.114^{***}	-0.150^{***}	-0.062^{***}
	(0.014)	(0.015)	(0.015)	(0.015)	(0.023)	(0.015)
Var.	-0.146^{***}	-0.134^{***}	-0.063^{***}	-0.010		
	(0.023)	(0.013)	(0.014)	(0.009)		
Announced CCyB x Var.	-0.292^{**}	0.340^{***}	0.046^{***}	0.093^{***}	0.014^{***}	-0.140^{*}
	(0.144)	(0.051)	(0.015)	(0.021)	(0.004)	(0.076)
Firm x Date FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	6,710,141	6,605,883	6,710,141	6,710,141	6,710,141	4,240,219
R^2	0.829	0.829	0.828	0.828	0.828	0.709
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: This table presents the regression results of OLS regression estimates for which the dependent variable is $log(PD)$, the logarithm of the probability of default reported by a bank b to a firm f at a date t. All specifications (1 to 6) have firm x date fixed effects and bank fixed effects. The main independent variable is $AnnouncedCCyB$, the countercyclical capital buffer rate announced in the country of the bank b at a date t. In specification (1), $Var.$ corresponds to the distance between the CET1 ratio of a bank b at a date t and the average CET1 ratio for the same date. In specification (2), $Var.$ corresponds to the share of transferred loans, in specification (3) it is the share of credit line, in specification (4) it is the share of syndicated loans, in specification (5) it is the number of banks lending to the same firm and in specification (6) it is the variance of the probability of default reported by all banks for the same firm in the previous period. The control variables are a dummy if the bank and the firm are in the same country, the share of credit line in the credit relationship, the share of outstanding amount with a fixed interest rate, the duration of the credit relationship in months and the average maturity at origination, the relative firm size, bank size(logarithm of total assets), the share of new credit, the CET1 ratio of the bank, the risk-weight, the share of credit, the provisions ratio, the amount of total assets of the bank, the leverage ratio, retained earnings and the credit gap of the country of the bank. Errors are clustered by firm and date. There is one observation by credit relationship between a firm and a bank every month. *p<0.1; **p<0.05; ***p<0.01.