Unloading NPLs, unlocking credit? Evidence from the ECB provisioning guidelines*

Soner Baskaya † Jose E. Gutierrez ‡ Jose-Maria Serena § Serafeim Tsoukas ¶

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Abstract

This paper studies how supervisory resolution tools, namely provisioning requirements regarding non-performing loans (NPLs), affect banks' NPL disposal and lending behavior, as well as the real economy. Using the supervisory intervention announced by the European Central Bank in the first quarter of 2018 as a quasi-natural experiment, we show that banks disposed of old NPLs at a higher rate after the policy. In addition, banks with stronger fundamentals were more keen on disposing NPLs and less restrained on lending. Furthermore, banks that were more heavily exposed to the policy tightened their lending standards, especially for risky firms. We also find that firms borrowing from banks affected by the policy intervention experienced a decline in the growth rates of their total assets, investment, employment, and sales. Our results highlight the importance of timely recognition of NPLs as a factor that can affect credit allocation. We also shed light on the importance of strong bank fundamentals in unloading NPLs without disrupting credit intermediation.

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†University of Glasgow, UK. e-mail: soner.baskaya@glasgow.ac.uk

‡Banco de España, Spain. e-mail: josee.gutierrez@bde.es

§Banco de España, Spain. e-mail: josemaria.serena@bde.es

¶University of Glasgow, UK. e-mail: serafeim.tsoukas@glasgow.ac.uk

1 Introduction

A common feature of previous financial crises and the recent pandemic is the accumulation of non-performing loans (NPLs) on banks' balance sheets (Aiyar et al., 2015; Fell et al., 2016; Alessi et al., 2021; Ari et al., 2021; Kasinger et al., 2023). High levels of NPLs bear important consequences for the soundness of the banking sector. They can lead to impaired bank balance sheets, hamper economic growth, and reduce lending capacity (Barseghyan, 2010; Draghi, 2017; Kalemli-Özcan et al., 2022). Yet, banks have ample discretion in their management of NPLs and may keep them at inefficiently high levels, because writing them off requires increasing loan loss provisions, which depresses profits in the short run. This highlights the need for supervisors to monitor banks' asset quality closely, and assess whether adopted practices are appropriate for managing NPLs.

In light of these concerns, the European authorities undertook specific supervisory initiatives to reduce banks' NPLs. In March 2017, the ECB introduced guidelines under which banks with high NPLs recognize loan losses via the so-called ECB guidance. This document was more of a moral suasion; there were no quantitative instructions about when and how much to provision NPLs. In 2018, however, the ECB published concrete requirements urging banks to increase provisions for NPLs and "comply or explain" the disposal of bad loans. The updated policy clearly stated supervisory expectations with respect to the age and degree of collateralization of the NPLs. Provisioning requirements were stricter for uncollateralized NPLs and loans that remained classified as NPLs for longer ("vintage NPL", hereafter). The criteria in the provisioning requirements were largely unanticipated by the banks. This is evident by the drop in the European banks' share price index of more than 3% on the day of the announcement.

We use the release of the ECB prudential provisioning for NPLs in March 2018 as a quasi-natural experiment to study whether changes in NPL oversight affect (i) NPL dynamics and disposals, (ii) bank lending, and (iii) firm outcomes. Our empirical analysis proceeds in three steps. First, to examine the propensity of banks to dispose of NPLs, we utilize loan-level data from the Spanish Credit Register (CIR), enhanced with bank and firm-level data from regulatory filings and the Central Balance-Sheet Data Office, respectively. We exploit an important feature of the policy that differentially affects NPLs. In particular, the policy prompted banks to increase the provisioning level of vintage NPLs. Thus, the differences in NPLs vintages allow us to construct a treatment at the loan level, offering a clear identification of the causal effect of the policy on NPL disposals.

Next, we study how the policy affects banks' lending behavior and the key mechanisms through which banks react to the policy change. For our lending analysis, we employ comprehensive credit information at the bank-firm level from the CIR. To examine whether an increase in vintage NPL disposal matters for banks' credit supply, we compute the weighted average vintage of the NPL in the pre-policy period. This variable measures the degree of banks' exposure to the treatment. Furthermore, to account for potential time-invariant and time-varying observed and unobserved factors that would potentially bias our results, we employ a comprehensive set of bank-firm and bank controls and a wide set of fixed effects thanks to the granularity of our data.

In the final empirical step, we explore whether the effect of the policy change is transmitted to the real sector. In doing so, we conduct a firm-level analysis to examine whether firms that rely more on lending from banks with higher NPL vintage underperform relative to firms that rely less on such banks. In our analysis, we focus on firms' uptake of bank debt, employment, investment, size, and sales. Furthermore, we argue that the policy does not affect all firms in the same manner. In particular, we test whether the effects are stronger for riskier firms, which reveals how the policy change affects the allocative efficiency in the credit market.

For a number of reasons, Spain provides a unique setting in which to conduct the empirical analysis. First, back in 2017, the Spanish banking sector exhibited one of the highest NPL ratios in Europe - around 10% after the sovereign debt crisis of the euro area. Second, the Spanish credit register provides rich loan-level data, which is key for identifying the banks affected by the policy, as well as controlling for a wide range of time-varying and time-invariant firm and bank characteristics that may affect how the ECB's policy impacts NPL disposal and bank lending. Furthermore, the dataset includes all commercial loans in Spain; thus our analysis does not suffer from concerns about the representativeness of the data.

We reach a number of novel results that shed light on how the policy intervention affects lending and real outcomes. Our first set of findings suggests that the introduction of the ECB policy affects banks' propensity to dispose of bad loans with higher vintages. Compared to the pre-policy period, a 1% increase in the loan vintage doubles the probability of disposing the NPL in the post-policy period. We also confirm that there are no differential pre-trends in our analysis. Moreover, we investigate whether the propensity to dispose of NPLs after the policy implementation is heterogeneous across banks. Our findings suggest that more profitable banks are more likely to remove NPLs because they are better positioned to take advantage of the increase in the provisioning of vintage NPLs.

These findings set the stage for our analysis of bank lending. We find that banks more heavily exposed to the policy tighten their lending standards, thereby suggesting bank-driven (credit supply) restrictions due to the policy. In particular, affected banks decrease lending and require higher levels of collateral in the aftermath of the policy. We also show that banks are more likely to terminate a lending relationship following the policy change. As part of the mechanism, we find that more profitable banks can better sustain lending.

Finally, we investigate whether exposure to banks with high NPLs jeopardises financial and real outcomes at the firm level. We find that firms borrowing from banks with higher NPL vintages before the policy experience a decrease in total borrowing, sales, number of workers, investment, and size. More precisely, increasing the value of NPLs by one standard deviation reduces employment and investment growth by 0.7 % and 1.3 %, respectively. In addition, this effect is more pronounced for risky firms.

We contribute to the literature in four main ways. First, we investigate whether ECB supervisory measures affect banks' NPL management. There is a wide body of literature on the determinants of NPLs; it identifies the macroeconomic conditions and bank-specific characteristics as the two main driving factors (Berger and DeYoung, 1997; Balgova et al., 2016). We go beyond these studies and analyze the effectiveness of the ECB policy in disposing NPLs. Moreover, we explore whether the link between NPLs and the policy introduction is heterogeneous among different types of NPLs. Consistent with the objectives targeted by the ECB, not all NPLs were affected in a proportional manner, and vintage NPLs were affected the most.

Second, we offer new evidence on whether bank supervision affects bank behavior.[1] Asset quality reviews, on-site inspection programs, or guidance and instructions may affect bank decisions. Previous studies find that more intense supervision of exposed banks results in lower risk but is also associated with a reduction in credit supply or slower loan growth, at least in the period immediately following the introduction of the new regime (see Abbassi et al., 2023; Ivanov and Wang, 2023). Moreover, focusing on the role of specific policy measures in decreasing NPLs, Accornero et al. (2017) find that banks' lending behavior is not causally affected by the level of NPL ratios. Compared with those papers, our focus is on the ECB intervention and its impact on different types of firms and banks. In doing so we examine the effect of concrete and stringent provision requirements, as set out in the ECB provisioning requirements.

Third, our paper relates to the literature on the implications of inefficient financing, such as sustained lending to non-viable (zombie) firms. Prior work shows that zombie lending affects the allocation of credit (Blattner et al., 2021; Bonfim et al., 2023). The effective recognition and resolution of NPLs are of grave importance to avoid the risk of zombie lending, which has implications for productivity and economic growth (Caballero et al., 2008; Schivardi et al., 2020). In our setting, lending to zombie firms is likely to generate vintage NPLs, thereby increasing the cost of lending to this particular segment of firms. We document that following the policy, banks tend to derisk in the sense that they reallocate their resources by lending less to firms with high ratios of interest payments to cash inflows and with a default history.

[1] For a detailed review, see Hirtle and Kovner (2022).

Finally, our paper is related to the literature analyzing the transmission of disruptions in credit markets to the real economy (see Bonaccorsi and Sette, 2016; Cingano et al., 2016; Bentolila et al., 2018; Farinha et al., 2019; Serena et al., 2022). We document a significant decline in employment, sales, and fixed investment in tangible assets for firms borrowing from banks exposed to the policy. Therefore, we show that the effects of the policy intervention matter for firm-level outcomes.

The rest of the paper is structured as follows. Section 2 presents an overview of the ECB NPL resolution measures and offers a review of the existing literature. Section 3 contains our data-set description. Section 4 presents our methodology and results. Section 5 provides conclusions and policy implications.

2 Institutional background and related literature

2.1 ECB's NPL provisioning expectations

Supervisors and regulators play a major role in how banks manage NPLs by taking a number of measures, such as asset quality reviews, on-site inspection programs, or guidance and instructions regarding NPL management. To deal with the significant amount of NPLs in European banks following the euro area sovereign debt crisis, the ECB shared a set of documents starting in March 2017. As part of the Single Supervisory Mechanism (SSM) with the European Banking Union, the ECB first released a set of best practices for NPL management, titled "Guidance to Banks on Non-Performing Loans" on March 20, 2017. These measures target entities with NPL ratios that are considerably higher than the EU average, which stood at 5.1% at the end of 2016. The overall objective of this tighter supervisory oversight on NPLs was to enhance the management of NPLs, particularly for entities with NPL ratios considerably higher than the EU average.[2]

However, as the ECB pointed out, "the guidance contains predominantly qualitative

[2]The ECB policy addresses all non-performing exposures (NPEs) following the EBA definition. Hence, this guidance uses the terms "NPL" and "NPE" interchangeably.

elements". It did not make any recommendations about NPL prudential provisioning. To enhance the timeliness of provisions and write-offs, on March 23, 2018 the ECB specified prudential provisioning levels for NPLs, hereafter "ECB NPL Provisioning Expectations."[3] Such provisioning levels depend on the exposure time in a non-performing status (i.e., vintage) and its collateral; see Table 1. In particular, NPLs should be fully provisioned within two to seven years after being classified as NPLs. The provisioning speed depends on whether loans are secured by collateral, as well as the collateralization ratio. Although these rules were initially for new NPLs (classified as such since April 1, 2018), they also served as a supervisory benchmark for the NPL stock, which was explicit in a press release on July 11, 2018.[4]

The NPL resolution measures applied to significant institutions (SI) within the SSM, including their international subsidiaries. The ECB NPL Provisioning Expectations have a potentially stronger effect on the provisioning practices of banks with a larger stock of vintage NPLs (i.e., the loans that have been categorized as NPLs for a long time). They are expected to facilitate NPL disposals for such banks, which in turn affects their short-term profitability, and ability to originate new loans.[5]

In the Spanish context, owing to the higher than EU average NPL ratios, the ECB NPL Provisioning Expectations are more relevant. Specifically, from the fourth quarter of 2015 to fourth quarter of 2019, the NPL ratio in Spain declined from 6.5% to 3.1%. Nevertheless, this figure was considerably higher than the EU average throughout this period, indicating that NPLs remained a matter of concern for Spanish banks. Figure 1 shows the vintage distribution of NPLs for Spain over time. The median vintage decreases, mainly supported by the exit of NPLs with higher vintage. However, the decline in both

[3]For the document, see https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.npl_addendum_201803.en.pdf.

[4]In such press release, the ECB indicated that it aimed to achieve the same coverage of NPL stock and flow over the medium term. However, it would also consider banks' initial NPL ratios to guide expectations regarding the provisioning coverage of NPL stock.

[5]We acknowledge that the guidance was published in March 2017 and that one can argue that banks were not caught by surprise. However, the complex nature of the process and the fact that the draft was not finalized means that banks were unlikely to be able to predict the final policy document accurately, especially with regards to provisioning requirements.

the median and maximum value of NPL vintage accelerates after the second quarter of 2018 with the introduction of quantitative aspects of supervisory expectations presented in Table 1.

As is evident from the discussion above, it is fair to assume that Spanish banks were compelled to clean their balance sheets of bad loans following the ECB policy change. Moreover, this effect could influence lending and the real economy. It is therefore necessary to test these hypotheses using data from the loan market.

2.2 The context of the literature

Previous literature on NPLs mainly focuses on factors that determine the build-up of bad loans, highlighting the relevance of both macro and micro determinants. For example, adverse macroeconomic conditions associated with sluggish economic activity can boost NPLs through their negative effect on borrowers' wealth, income flows, and debt service capacity (Bernanke and Gertler, 1989; Bernanke et al., 1999; Berger and DeYoung, 1997; Kiyotaki and Moore, 1997). On the banks' side, factors related to profitability, capitalization, or concentration can affect the level of NPLs (Balgova et al., 2016; Bischof et al., 2022).

The implications of high levels of NPLs is of great interest to financial markets, policymakers, and academics due to their potential effects on the growth and stability of the financial sector and the real economy. Therefore, accurately identifying NPLs, provisioning, and ultimately resolnving NPLs is on the top of the list for European authorities, especially after the expiry of the moratoria on loans amid the COVID-19 pandemic (Kasinger et al., 2023). The supervisory approach is to help banks resolve their NPLs and improve their lending capacity.

Although the high NPL stock is one of the key factors in hindering banks' lending capacity in Europe, empirical evidence is scarce mainly due to lack of detailed data. Access to granular data is important for achieving stronger identification and establishing causality with a higher degree of confidence. In this vein, Bruno and Marino (2018) use the AQR in 2014 and data from European banks. They find that reviewed banks with higher unexpected changes to their NPLs deleverage and reduce their lending more than non-reviewed banks. Likewise, Accornero et al. (2017) use the supervisory intervention associated with the 2014 AQR to show that banks' lending behavior is not causally affected. Finally, using German loan and security data, Abbassi et al. (2023) show that banks reviewed by the ECB in the 2014 AQR reduce their exposure to riskier securities and credit.

Considering on-site bank inspections as a type of bank supervision, Passalacqua et al. (2021) show that financial intermediaries are more likely to reclassify loans as nonperforming after an audit. Moreover, they reduce lending following the inspection, but this drop reverts to pre-inspection levels after seven quarters. In a similar setting, Bonfim et al. (2023) show that inspections of the largest Portuguese banks reduce zombie lending.[6] Finally, Ivanov and Wang (2023) explore the impact of less lenient supervisors on lending supply, causally linking stricter supervisory evaluations to reduced lending using quasi-random assignment of supervisors to Shard National Credit (SNC) reviews.

These studies provide a helpful background for linking supervisory expectations and bank lending. In this paper, we ask how important a policy intervention regarding NPL provisioning is for NPL disposals, bank lending, and firm-level real outcomes using rich datasets. In the following sections, we turn to our data and estimation strategy.

3 Data and descriptive statistics

Our datasets combine information from three sources available at the Bank of Spain: (i) the Spanish Central Credit Register (CIR), (ii) supervisory bank balance sheets and income statements, and (iii) firms' balance sheets from the Spanish Mercantile Register.

The Spanish Central Credit Register contains confidential information on all outstand-

[6]Other approaches by the financial sector to address NPLs include the introduction of asset management companies (Hallerberg and Gandrud, 2015), macroprudential regulation (Cerutti et al., 2015), changes to loan classification, and changes to provisioning stringency (Barth et al., 2004).

ing loans to non-financial firms granted by all credit institutions operating in Spain. In particular, banks are required to report all loans on their balance sheets to the CIR. It includes loan-level information about the type of loan, amount (drawn and undrawn), type of collateral, maturity, currency, days past due, whether it was forborne or refinanced, the lender, and the borrower. The database also offers borrower-related information, such as firm size. Furthermore, the possibility of identifying both firms and banks enables us to merge the credit register with supervisory bank quarterly balance sheets and annual firm balance sheets, thereby acquiring bank and firm characteristics.

A particular characteristic of the CIR is that it enables us to identify all NPLs (more than 90 days past due) on banks' balance sheets every month. If a bank ceases to report a loan more than 90 days past due in a particular month, we can also identify the exit of an NPL from the CIR, which might have been due to a write-off or a sale of a loan. This information is of great importance for our analysis on whether the ECB's supervisory provisioning rules for vintage NPLs facilitate the exit of NPLs from the CIR.

Using the CIR, we also compile comprehensive data on the credit exposure of all firms with their respective banks, allowing us to analyze how the ECB's provisioning rules affect bank credit supply. In particular, this bank-firm database allows us to investigate whether banks with higher exposure to vintage NPLs reduce their lending more than banks with lower levels of exposure do, as a result of policies aimed at reducing NPLs from banks' balance sheets.

To analyze firms' real outcomes, we combine our credit database with the annual balance sheets of the firms from the Spanish Mercantile Register, which the Central Balance Sheet Office collects. This database permits us to assess whether the ECB's policies affect firms whose loans came primarily from banks with higher NPL vintage. In addition, we follow standard sample selection criteria in the literature and exclude companies with missing data, negative sales, or negative assets.[7]

[7]We winsorize the regression variables at the 1st and 99th percentiles to control for the potential influence of outliers.

Table 2 presents the summary statistics for the data. Our analysis centers on Spanish non-financial firms and banks operating in Spain, covering the period 2017q1 to 2019q4. We report figures across the levels of analyses we conduct: loan level (Panel A), bank-firm level (Panel B panel), bank-level (Panel C), and firm level (Panel D). Over the entire sample, the average NPL exit rate is 10.8% and the average NPL vintage is approximately three years.

The bank-level summary statistics show that the average value for the ratio of NPLs to total loans is 6.8% and the median is 5.4%. Moving to the liquidity indicator, we observe that the mean liquidity ratio is 10.5%, with a median of 6.6%. Finally, the mean and median values of RoA are 0.47 and 0.51 percent, respectively, possibly reflecting the low profitability in the European banking sector in the aftermath of the euro area debt crisis (Elekdag et al., 2020).

Turning to the firm-level dataset, the average growth rate of bank credit between 2017 and 2019 is 4%. Over the same period, employment increased by 6.6%, investment increased by 7.5%, and total assets increased by 8.5%. Finally, the average firm is well collateralized and liquid, with ratios of 35% and 59%, respectively.

4 Empirical strategy and results

Our analysis focuses on how the ECB's supervisory expectations affect three interrelated outcomes, namely NPL dynamics, bank lending, and firms' financial and real outcomes. In particular, we ask the following questions. First, to what extent do the ECB NPL Provisioning Expectations, released in the first quarter of 2018, affect NPL disposals in Spain? Second, do bank fundamentals matter for their capacity to dispose of NPLs? Third, does balance sheet cleansing affect banks' credit supply and lending standards? Finally, do banks treat the firms the same when originating loans after the policy change?

It is empirically challenging to identify the direct impact of supervision on both NPLs and loan outcomes, as many observed and unobserved factors can simultaneously drive

NPLs, loan outcomes, and supervisory initiatives. For instance, Altavilla et al. (2020) argue that regulatory and disciplinary effects of higher capital ratios can also reduce banks' NPL ratios. Moreover, several factors may jointly determine lending and NPLs at the bank level, such as governance, business model, bank capital, or macroeconomic conditions (Hajja, 2020; Louzis et al., 2012). Therefore, any improvement in bank regulation and/or recovery in economic activity could lead to a negative correlation between NPLs and bank lending. Finally, unobserved shocks at the firm and sector level can affect NPLs and loan dynamics, which can contaminate the analysis of how policy shocks affect NPLs and loans.

Our research design tackles these concerns in a number of ways. First, we identify how the policy affects NPL disposals by utilizing the clearly stated quantitative aspects of the ECB's supervisory expectations explained in section 2. This policy incentivizes banks to dispose of NPLs with longer histories, (i.e vintage NPLs). Second, the granularity of our data allows us to include a comprehensive set of time-invariant and time-varying fixed effects to insulate our estimates from potential unobserved omitted factors. Finally, we observe multiple loans to the same firm from different banks, which allows us to offer a supply-side interpretation of our findings.

When undertaking these analyses, we explore whether policy's effect on NPL disposals and lending differs among banks with different characteristics. These results shed light on the mechanisms through which the policy affects the supply of lending. We further test whether the policy change affects lending to firms with different degrees of riskiness, which provides evidence about the policy's effect on allocative efficiency in the market for loanable funds.

4.1 ECB NPL Provisioning Expectations and NPL Disposals

The ECB NPL Provisioning Expectations set specific and tighter provisioning requirements on NPLs. This includes a set of quantitative criteria on the timeline for provisioning NPLs in line with their vintage and collateralization. Specifically, unsecured NPLs required being fully provisioned after two years of classification as an NPL ("vintage"). In contrast, secured NPLs require a certain level of provisioning after three years, increasing until year seven at the latest. As NPL vintage is one of the key determinants of how the ECB policy facilitates the exit of vintage NPLs, we measure the effectiveness of the policy by testing whether disposals of high vintage NPLs are more likely after the introduction of the policy.

To that aim, we analyze how vintage NPLs affect the propensity of NPL exit using loan-level information from the second quarter of 2017 to third quarter of 2019, (i.e. five quarters before and after the release of the policy in the second quarter of 2018). The dataset contains 1,654,107 observations from 356,775 loans to 73,422 firms. We track each NPL's presence in the CIR in the subsequent quarter, along with past-due days, outstanding amount, collateral, loan type, and the bank and firm associated with the loan. Specifically, we estimate the following linear probability model:

$$Exit_{l,b,f,t+1} = \alpha_1 Vint_{l,f,b,t} + \alpha_2 Policy_t \times Vint_{l,f,b,t} + \gamma_{f,t} + \gamma_{b,t} + \gamma_{f,b} + \gamma_{k(l)} + \varepsilon_{l,b,f,t+1} \qquad (1)$$

where $Exit_{l,b,f,t+1}$ is a dummy variable that equals 1 if loan l from bank b to firm f, exits the CIR as an NPL in the next quarter (i.e. t+1), and 0 otherwise.[8] $Policy_t$ is a dummy variable equal to 1 for observations in the post-policy period ($t >$ 2018q1) and 0 otherwise. The loan vintage variable, $Vint_{l,f,b,t}$, is the natural logarithm of 1 plus the number of months since the loan was categorized as NPL. Therefore, α_1 measures the probability that an NPL exits the bank's balance sheet in the next quarter in response to a 1% increase in the number of months since the loan became an NPL in the pre-policy period. The coefficient of interest, α_2, measures the change in how NPL vintage affects exit probability in the aftermath of the ECB's policy. Therefore, $\alpha_2 > 0$ implies that the effect of the NPL vintage on the exit probability increases in the post policy period.

Due to the richness of our dataset, the treatment takes place at the loan level rather

[8] NPLs refer to loans more than 90 days past due. Our definition follows previous literature (Ari et al., 2021; Jiménez et al., 2023) and regulatory definitions (IMF, 2019).

than the bank level. This further permits us to control for various loan-level heterogeneity in addition to bank-level heterogeneity that would matter for our results. First, different loans have different recovery rates for many reasons, such as having different collateral types and amounts. These may affect banks' incentives to dispose differently of NPLs backed by collateral versus unsecured NPLs. Similarly, secured loans backed by different types of collateral may also have characteristics, such as liquidity, that cause banks to treat them differently when it comes to disposing of them. Finally, as discussed in section 2, the supervisory expectations of the ECB for vintage NPLs, revealed in detail in July 2018, entail different provisioning rules for different NPL vintages. In our saturated models, we account for such heterogeneity using loan-characteristics fixed effects ($\gamma_{k(l)}$), which is the interaction between a category indicator defining loan types (commercial loans, term loans, credit lines, and leasing), and a category indicator that specifies the collateral type (real estate, financial asset, movable collateral, or uncollateralized). This renders 16 categories.

The models include additional controls as follows: bank×quarter fixed effects ($\gamma_{b,t}$) to account for unobserved time-varying bank heterogeneity, firm×quarter fixed effects ($\gamma_{f,t}$) to account for time-varying firm heterogeneity and firm-bank fixed effects ($\gamma_{f,b}$) to account for endogenous matching between firms and banks. $\varepsilon_{l,b,f,t+1}$ is the error term. Finally, we cluster standard errors at the bank-quarter level to allow for correlation across NPLs from the same bank.

Table 3 presents the results on how the exit probability of NPLs with different vintages in the next quarter changes before and after the release of the quantitative aspects of the ECB's supervisory expectations. Our key variable of interest is $Policy_t$ and $Vint_{l,f,b,t}$ ($Policy_t \times Vint_{l,f,b,t}$). Columns 1 to 3 show that the exit probability of NPLs with different vintages did not change following the policy change.

In column 4 we control for the time-invariant unobserved characteristics of the bank-firm match. Our results indicate that banks are more likely to dispose of older NPLs in $t{+}1$ both before and after the policy. Importantly, banks dispose of older NPLs at a significantly higher rate after the policy shift. To put the numbers into perspective, a 1%

increase in the months of a loan classified as an NPL increases the exit probability of NPL in $t+1$ by 1.3 percentage points before the policy change and by 3.2 percentage points after the policy change. In column 5, we show our estimation results for our preferred specification; it saturates the model with the richest set of fixed effects. The estimated coefficient for α_1 suggests that before the ECB's policy, a 1% increase in months classified as an NPL increases the probability of exit by 1.5 percentage points. There is a significant change after the policy, as the estimated coefficient for α_2 is positive and significant. More important, the estimated effect for the post-policy period, measured as $\alpha_1 + \alpha_2$, suggests that a 1% increase in months classified as an NPL increases the exit probability by 3.2 percentage points.

One potential concern with our findings thus far is that banks may reduce their exposure to vintage NPLs before the ECB initiative. This pattern would violate the parallel-trends assumption, rendering the estimates biased for the effect of the policy. To assess whether any trends before the policy may influence our identification strategy, we investigate the dynamic behavior of our dependent variable over our sample window. Specifically, in Figure 2, we plot the series of coefficients and corresponding 95% confidence intervals from estimating regressions analogous to equation 1, in which we replace $Policy_t$ with a sequence of time dummies spanning our entire estimation period. Overall, the graph suggests that NPLs with higher vintage exited the CIR at the same rate in the run-up to the ECB initiative. Hence, the absence of pre-trends corroborates a causal interpretation of our results.

4.1.1 Robustness checks

We conduct a series of robustness tests for the results in the previous sub-section. Table 4 shows the results of the tests. First, as a refinement of the data, on column 1, we exclude NPLs whose outstanding debt decreases by more than 10% of the last outstanding debt (at its final quarter in the CIR) at any moment before their exit. This test retains NPLs that remain constant or increase. The results are consistent with those in column 5 of

Table 3, which is our preferred specification. Yet, they indicate a slightly higher degree of NPL disposals following the policy change.

In addition, our findings could arise from a lagged effect of the ECB guidance released in 2017q1. As pointed out, the guidance aimed to affect the NPL management of high-NPL banks relative to low-NPL banks. However, to deal with such a concern, we add bank-quarter fixed effects in our preferred specification, allowing us to exploit NPL vintage variation within the same bank and quarter to explain NPL disposals. Additionally, to better isolate the impact of the provisioning supervisory expectation, we keep high NPL banks in the sample, as the ECB guidance should affect them homogeneously. We estimate our preferred specification for this smaller sample as robustness. In particular, we drop banks with NPLs below 5%, which is the cut-off the EBA uses to define high-NPL banks. The results of this exercise, presented in column 2, remain consistent with our baseline results.

One could also argue that rural banks and foreign credit institutions operating in Spain could contaminate our analysis. The former has a very different business model compared to other banks. The parent bank could "bail out" the latter in case of possible distress. To address this potential concern, we rerun our models without rural banks and foreign credit institutions. We report the outcome of this exercise in column 3. We confirm the positive impact of the policy on the rate of NPL disposal.

Finally, we address a potential concern that a particularly vulnerable sector in Spain drives our results. We argue that the real estate and construction sectors were affected the most during the sovereign debt crisis and could have contributed to the accumulation of NPLs. Therefore, we re-estimate our regressions excluding the NPLs that belong to firms in the real estate and construction sectors. The results are in column 4 and hold using that sub-sample.

4.1.2 The role of bank-level characteristics

The NPL vintage has a direct effect on the probability of its disposal after the policy. However, other characteristics may attenuate or exacerbate this effect. Specifically, disposal of a high amount of NPLs potentially generates a burden on bank capital and profitability (Altavilla et al., 2018; Elekdag et al., 2020). Therefore, banks' ability to act in line with intended policy outcomes can be closely related to predetermined bank characteristics at the time of the introduction of the policy. In addition, from a broader policy perspective, it is important to assess whether other bank-level factors affect banks' ability to dispose of bad loans and extend new loans in the aftermath of the policy. Further, banks' financial health has been affected significantly by a set of prudential policies in the aftermath of the euro area debt crisis. This provides suggestive evidence of the complementarities between policies to improve bank soundness and policies targeting NPL resolution.

In light of this discussion, we take into account how certain bank-level characteristics affect the relationship between NPL vintage and NPL disposal. For this, we estimate equation (1) for our preferred specification (column 5 in Table 3) augmented with interaction terms among the $Policy_t$, $Vint_{l,f,b,t}$, and bank-level indicators, such as size, ROA, book capital ratio, and NPL ratio. The results are in Table 5. Each column corresponds to one of the bank-level alternative indicators, with the last column presenting the model with all interaction terms.

Our results show that, following the policy, higher vintage level is associated with a higher probability of NPL disposal, especially for more profitable banks. In particular, one-standard-deviation change in RoA increases the probability of an older NPL exiting at t+1 by 3.7 percentage points in the aftermath of the ECB policy. This figure implies that, compared to a bank with zero profitability, a bank with profitability one standard deviation higher is approximately twice as much likely to dispose of an older NPL in the next quarter (3.96 percentage points vs 7.7 percentage points, ceteris paribus). We also find that smaller banks are more likely to dispose of NPLs compared to larger banks.

For example, compared to a bank that is larger by one standard deviation, following the policy change, a smaller bank's probability of disposing of an NPL in the next period is one percentage point higher. On the other hand, we find that capital ratio and NPL ratio do not influence the propensity to dispose of an NPL following the policy change.

4.2 ECB NPL Provisioning Expectations and Bank Lending

We now aim to understand whether banks with more significant vintage NPLs tightened their lending standards after the ECB policy. To do so, we use bank-firm level data from the first quarter of 2017 to third quarter of 2019. This dataset includes 6,776,491 observations from 954,097 firm-bank relationships and 305,965 firms. We exploit the data at the firm-bank-quarter level and strategy proposed by Khwaja and Mian (2008) to identify how the ECB policy affects bank credit supply, considering the observed and unobserved factors affecting credit demand. Specifically, we estimate the following equation:

$$y_{f,b,t+1} = \theta_1 Policy_t \times NPL\ vintage_b + Controls_{f,b,t} + \gamma_{f,t} + \gamma_{f,b} + \varepsilon_{f,b,t+1} \quad (2)$$

where the dependent variable $y_{f,b,t+1}$ can be either (i) the natural logarithm of outstanding credit from bank b to firm f, or (ii) a dummy that equals 1 if bank b extends a new credit to firm f and 0 otherwise, or (iii) a dummy that equals 1 if bank b terminates the lending relationship with firm f and 0 otherwise, or (iv) the ratio of collateralized credit that firm f has with bank b, or (v) the ratio of credit with residual maturity beyond three years that firm f has with bank b.

The exposure of the bank to the policy is represented by $NPL\ vintage$, which is the weighted average of NPL vintage (number of months since the loan became an NPL) of loans by bank b to non-financial firms as the end of the fourth quarter of 2017. More concretely, we define $NPL\ vintage$ as:

$$NPL\ vintage_b = \frac{\sum_{l=1}^{N_b} vintage_{l,b} \times C_{l,b}}{\sum_{l=1}^{N_b} C_{l,b}} \tag{3}$$

In this expression, the NPL vintage of each loan in the fourth quarter of 2017 is weighted by its outstanding credit (i.e., $C_{l,b}$), in the same period across all the loans in the loan portfolio of bank b (i.e., $l \in \lceil 1, 2, 3, ..., N_b \rceil$). By definition, performing loans have a vintage of zero. Thus, banks with more significant amounts of vintage NPL before the policy have higher $NPL\ vintage$ values, making them more sensitive to the ECB NPL Provisioning Expectations. We also control for a vector of bank-firm level factors denoted by $Controls_{f,b,t}$, which are lagged to limit endogeneity concerns. At the firm-bank level,the vector includes the share of NPL, collateralized loans, forborne/refinanced loans, long-term loans to firm f from bank b, and the ratio of loans from bank b to firm f total debt to banks. We also add bank-level controls such as the logarithm of total assets, ROA, NPL, liquidity, and leverage ratios. Additionally, we include firm-time fixed effects to control for all (un)observed heterogeneity (firm-level credit demand, firm quality, growth opportunities, riskiness, etc.). This is particularly important to give a supply-side interpretation of the effects: the inclusion of firm-time fixed effects ensures we are comparing the same borrower with at least two different banks and, therefore, absorbing any demand factors.

In addition, we saturate our models with firm-bank fixed effects to control for a persistent (non-random) firm-bank specific match, such as geographical distance and relationship lending (Petersen and Rajan, 1995). Finally, we add bank type-quarter fixed effects to account for different shocks that could have distinctly affected different types of banking institutions, which our set of bank controls does not capture. In particular, we consider three types of banking institutions: banks directly supervised by the ECB, rural banks, and other banks.

The coefficient θ_1 indicates the extent to which banks with different levels of vintage NPLs reduce their lending standards to the same borrower, following the ECB policy. Given that the policy caused a decrease in NPL balances, we only consider firms with performing credit greater than zero to avoid a mechanical decay in our credit variables. We cluster standard errors at the bank-quarter level.

Table 6 shows the estimation results for the model presented in equation 2. Columns 1 to 5 show the results when considering the natural logarithm of credit, the new credit dummy, the termination dummy, the share of collateralized credit, and the share of long-term credit, respectively. The general finding is that lending standards tightened for banks with higher levels of vintage NPL. According to column 1, one-standard-deviation increase in NPL vintage, which roughly corresponds to 1.9 months, causes credit to decrease by 2.7% (-0.0061×4.503). These findings echo Abbassi et al. (2023), who show that credit supply is lower for banks subject to the ECB's asset quality review (AQR). Also, Altavilla et al. (2020) find that supranational supervision reduces credit supply to firms with high ex-ante and ex-post credit risk. We further document that the probability of ending a lending relationship increases by 0.32 percentage points, and the tendency to collateralize loans increases by 0.78 percentage points in the aftermath of the ECB policy. On the other hand, we do not find a significant change in the probability of obtaining a new loan or an increase/decrease in the share of long-term loans.

As in the case of NPL disposals, Figure 3 shows no trends before the introduction of the policy for our main specifications. This supports our identifying assumption that the banks did not anticipate the details of the policy regarding the quantitative aspects of the supervisory expectations on NPL disposal. This figure also provides visual evidence that the effect of the policy change on the credit occurred with a time lag, with the effect increasing over time.

In sum, the results are economically important and suggest that affected banks curtail the supply of credit after the ECB policy. Hence, we postulate that more exposed banks were forced to recognize risky loans and increase loan disposal, thereby creating pressure on their lending capacity.

4.2.1 Robustness checks

In Table 7, we present five additional robustness tests for the results in column (1) of table 6. We first allow for differential time fixed effects for the group of banks that participated in the 2018 EU-wide stress test. In particular, the stress test might cause less sound banks to deleverage to preserve capital for the test. However, only the four largest Spanish banks participated, showing significant resilience against the adverse stress scenario. Yet, in column 1 we include a bank group dummy (1 if the bank took part in the stress test and 0 otherwise) interacted with quarter dummies to deal with the possibility of different trends between participating and non-participating banks in the 2018 EU-wide stress test. In column 2, we interact all bank controls with quarter dummies to control for variations across time. As in our analysis of NPL disposals, we also include the following robustness checks: we drop from the sample banks with NPL ratios below 5% (column 3), we exclude rural banks, and foreign credit institutions operating in Spain (column 4). Finally, we remove firms belonging to the construction or real estate sectors (column 5). We conclude that our findings are robust to all the above modifications.

4.2.2 Heterogeneous effects with respect to bank characteristics

As the next step, we explore whether bank characteristics such as profitability, NPL ratios, NPL coverage ratios, size, and capital, affect the degree to which bank lending standards respond to the policy change. For this, we estimate the model in Equation 2 but include the interaction terms among NPL vintage, the policy dummy, and the various bank-level characteristics.

We first find that the banks at the mean of the corresponding distributions of these bank characteristics do not experience any change in lending behavior. However, we surface significant heterogeneities across banks, which also reveals important insights into how the policy affects the credit market.

Our findings in general reveal that the banks with weak fundamentals do reduce lending following the tighter policy, which requires disposal of vintage NPLs. For example, consistent with our analysis of NPL disposals, Table 8 shows that bank profitability is one of the factors that interact with the effect of the policy on bank lending. In particular, the policy negatively affects lending by banks with low profitability. For example, a bank with profitability two standard deviations lower profitability than the average bank significantly reduces lending compared to a bank with average profitability and the same degree of NPL vintage. We also find that bank asset affects how bank lending responds to the tighter NPL provisioning requirements. In particular, the banks with higher NPL ratios and lower NPL coverage ratios than the average bank reduce their lending following the policy. For example, keeping everything else constant, for a bank with an NPL- coverage ratio of two or more standard deviations lower, the effect of the NPL provisioning policy on bank lending was contractionary. In other words, banks with a higher share of NPLs that are not provisioned by the time of the policy reduce their lending in response to tighter provisioning requirements.

These results highlight the importance of strengthening bank fundamentals. Our results provide evidence of a potential complementarity across different regulations, which improve banks' profitability and asset quality. In particular, policies aiming to increase banks' financial health in the aftermath of a crisis may be a pre-condition to guarantee a prompt resolution of NPLs without significantly disrupting financial intermediation. Thus, the success/failure of regulatory and supervisory efforts aiming to improve banks' asset quality may depend on the initial soundness of the banking system. Finally, a similar conclusion can be made for the different countercyclical macroeconomic policies that limited the deterioration in the profitability and asset quality of the banking sector in Europe in the aftermath of the euro area debt crises.

4.3 ECB's NPL Provisioning Expectations and firm level outcomes

Thus far, we have shown that Spanish banks with more significant vintage NPLs cut credit to their borrowers more after the ECB policy. In this section, we first reaffirm the decline in credit volume from the firms' perspective. We then explore the impact of the policy on firm real outcomes, such as growth of total assets, employment, investment, and sales.

The firm-level analysis requires us to match our previous dataset with the Spanish Mercantile Register to obtain firm balance-sheet variables. As a consequence, our sample size decreases to 113,081 firms (38.6% of the original sample), particularly biased toward larger firms (representing 51% of the outstanding debt at the end of 2017). For this analysis, we estimate the following empirical model:

$$Firm\ Outcome_{17:19,f} = \theta_1 Weighted\ NPL\ vintage_{17,f} + Controls_{17,f} + \gamma_{P,I,Size} + \varepsilon_f, \tag{4}$$

where the dependent variable $Firm\ Outcome$ measures a firm's real variable growth between the end of 2017 and 2019 (i.e. before and after the introduction of the ECB policy). As the outcomes of interest, we focus on the growth in banks' credit commitments including both drawn and undrawn amounts, total assets, number of employees, tangible fixed assets, and sales.

Because we are focusing on the firm level, we construct the exposure of firm f to its banks with different levels of vintage NPLs as:

$$Weighted\ NPL\ vintage_{17,f} = \sum_{b=1}^{N_f} w_{17,f,b} NPL\ vintage_b \tag{5}$$

The $Weighted\ NPL\ vintage$ is the weighted average NPL vintage for each firm, considering the NPL vintage of each bank b and the share of loans from each bank in the total outstanding bank debt of firm f. In particular, it uses weights, $w_{17,f,b}$, equal to the amount each bank b lends to firm f considering the number of all banks in a lending relation with firm f (i.e., N_f by 2017). Thus, a higher NPL vintage indicates that firm f has a higher exposure to banks with high-vintage NPLs, as its lending mainly comes from such institutions.

Our parameter of interest is θ_1, which captures the extent to which banks with high NPL vintage affect firm-level outcomes for the average firm. We control for a set of variables for accommodating sources of credit and investment/growth opportunities measured as of the end of 2017. First, we include firm-level characteristics such as size, book-to-capital ratio, liquidity ratio, ROA, tangible assets to total assets, age, and riskiness (measured as the share of credit that is either forborne or NPL). In addition, we control for bank-level characteristics, such as the logarithm of bank assets, bank capital ratio, bank liquidity ratio, ROA, and share of lending from significant institutions (SI) weighted by credit from each bank to firm f. We also include bank-firm contractual characteristics, such as the share of long-term debt, the share of collateralized debt, and the share of credit from the main bank. Finally, we control for province-industry-size fixed effects denoted by $\gamma_{P,I,Size}$. Standard errors are clustered at the main bank level.

The results of estimating equation 5 are in Table 9. In column 1 we find a reduction in the growth rate of bank debt for firms that rely more heavily on exposed banks. In particular, a one-standard-deviation increase in NPL vintage decreases the growth rate of committed loans by 2.3 percentage points. These results also indicate that the average firm is not capable of smoothing the decrease in credit supply, which complements our earlier results from the banks' perspective. In other words, the higher value of vintage NPLs before the policy is associated with a decline in bank lending in the aftermath of the ECB intervention.

According to columns 2 to 4, lower access to credit following the policy has implications for firms' real decisions. For instance, we show that more exposed firms (a one-standard-deviation increase in the weighted NPL vintage) experience 0.7% lower employment growth if they obtain loans from more exposed banks. The results also document a deterioration in firms' investment in tangible assets by 1.3%. Finally, we find that firms' size (proxied by total assets) and sales grew at a slower rate following the policy if their lending comes from banks with higher exposure to the policy. Our results suggest that firms' bank debt and outcomes respond to changes in the vintage of the NPLs for firms borrowing from banks exposed to the ECB policy shift.

4.3.1 Firm riskiness

In order to enrich our findings about the supply of credit and firm-level outcomes, we now turn our attention to the role of firm riskiness. Specifically, we determine whether borrowing from an exposed bank has a stronger effect on firms that are likely risky in the pre-policy period. One of the potential outcomes associated with the supervisory and regulatory policy interventions is the change in banks' risk exposure in the aftermath of the policy change. In particular, by introducing tighter provisioning requirements for NPLs, policymakers may increase banks' incentives to reduce credit risk exposure in the aftermath of the policy change.

To this end, we interact our variables of interest in equation (2) with a variable measuring firm riskiness. In the spirit of Gertler and Gilchrist (1994) and Yang et al. (2022), *Risky* is a dummy variable that equals 1 if the firm's interest coverage ratio is above the median of the distribution of the variable as of the end of 2017. This exercise is based on the consideration that, when the policy was implemented, risky firms responded more strongly in terms of credit uptake compared to their counterparts. The estimation results in Table 10 show that banks cut lending after the policy change. Notably, this effect is more potent if a firm is risky. To put the numbers into perspective, we find that after the policy, a bank with a one-standard-deviation increase in NPL vintage cut lending to non-risky firms by 1.08%. On the other hand, the effect on the risky firms is statistically significant, with a 1.6% decline.

In terms of the mechanism, we next ask whether this decline stems from a drop in the origination of new loans to risky firms, an increase in the termination of banking relationships with risky firms, or both. Results in columns 5 and 6 suggest that banks decrease their tendency to originate new loans to risky firms after the policy change. On the other hand, columns 8 and 9 suggest that there is no significant difference between risky and non-risky firms in terms of changes in the probability of experiencing a banking relationship termination. Nevertheless, these results suggest that the policy's focus on reducing the NPL stock might increase banks' sensitivity to lending relationships that carry risk for contributing to higher NPLs and thereby to a higher likelihood of NPL provisioning.

Finally, we assess the differential role of firm riskiness on firm-level financial and real outcomes using equation 4. In particular, we focus on how borrowing from exposed banks affects financial choices and outcomes for different firm types, namely those that are risky. The results, reported in Table 11, show that risky and non-risky firms differ in borrowing outcomes significantly. However, the effect on the former group is significantly higher than the effect on the latter. Moreover, risky firms perform significantly worse than non-risky firms in terms of employment and investment growth. Depending on the specification, we find that the rate of slowdown in employment, associated with exposure to affected banks in the aftermath of the ECB's policy, is two-to-four times higher for risky firms. Likewise, following the policy, risky firms exposed to affected banks experience a slowdown in investment growth at a rate about two-to-three times higher than their non-risky counterparts.

All in all, we find that the policy brings about an improvement in allocative efficiency in the economy. In particular, we observe emergence of derisking behavior for banks exposed to the new regulations concerning NPLs, as they have a significantly lower tendency to originate loans to risky firms after the introduction of the ECB's supervisory expectations.

5 Conclusion

We use the release of the ECB prudential provisioning for NPLs as a quasi-natural experiment to study how changes in NPL oversight affect (i) NPL dynamics and disposals, (ii) bank lending, and (iii) firm outcomes. For our analysis of NPL disposals, we utilize loan-level data from the Spanish Credit Register (CIR), enhanced with bank and firm-level data from regulatory filings and the Central Balance-Sheet Data Office, respectively. Our findings indicate that the ECB initiatives were effective at reducing NPLs. Specifically, in the post-policy period, banks are more likely to dispose of vintage NPLs. We also show that banks with better bank fundamentals dispose of their NPLs at a higher rate.

In terms of credit supply, we find that banks with higher levels of vintage NPLs reduce lending more in the aftermath of the policy. In other words, lending from exposed banks was constrained after the policy, thereby suggesting bank-driven tightening in the credit market due to the policy. However, when we introduce, bank-level heterogeneity, banks with higher profitability and asset quality at the date of the release are more capable of smoothing the effect of the policy change on the credit market.

Finally, we show that firms exposed to high-vintage banks experience a decline in borrowing, cut employment, and reduce their investment in fixed assets. Moreover, we observe that the reduction in bank debt and employment is more pronounced for the risky firms. All in all, we conclude that the ECB's policy is effective in reducing NPLs. On the other hand, consistent with recent papers focusing on improving asset quality at banks, this was associated with a decline in bank lending in the short term as well as real effects. However, the medium- and long-run effects are beyond the scope of this paper, as the period between the first quarter of 2020 and afterward are associated with the COVID-19 crisis.

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A Figures and tables

Table 1: ECB's quantitative expectations on NPL provisioning

Vintage	Unsecured part	Secured part
2 years	100%	
3 years		40%
4 years		55%
5 years		70%
6 years		85%
7 years		100%

Source: European Central Bank (ECB)

Figure 1: NPL vintage distribution over time

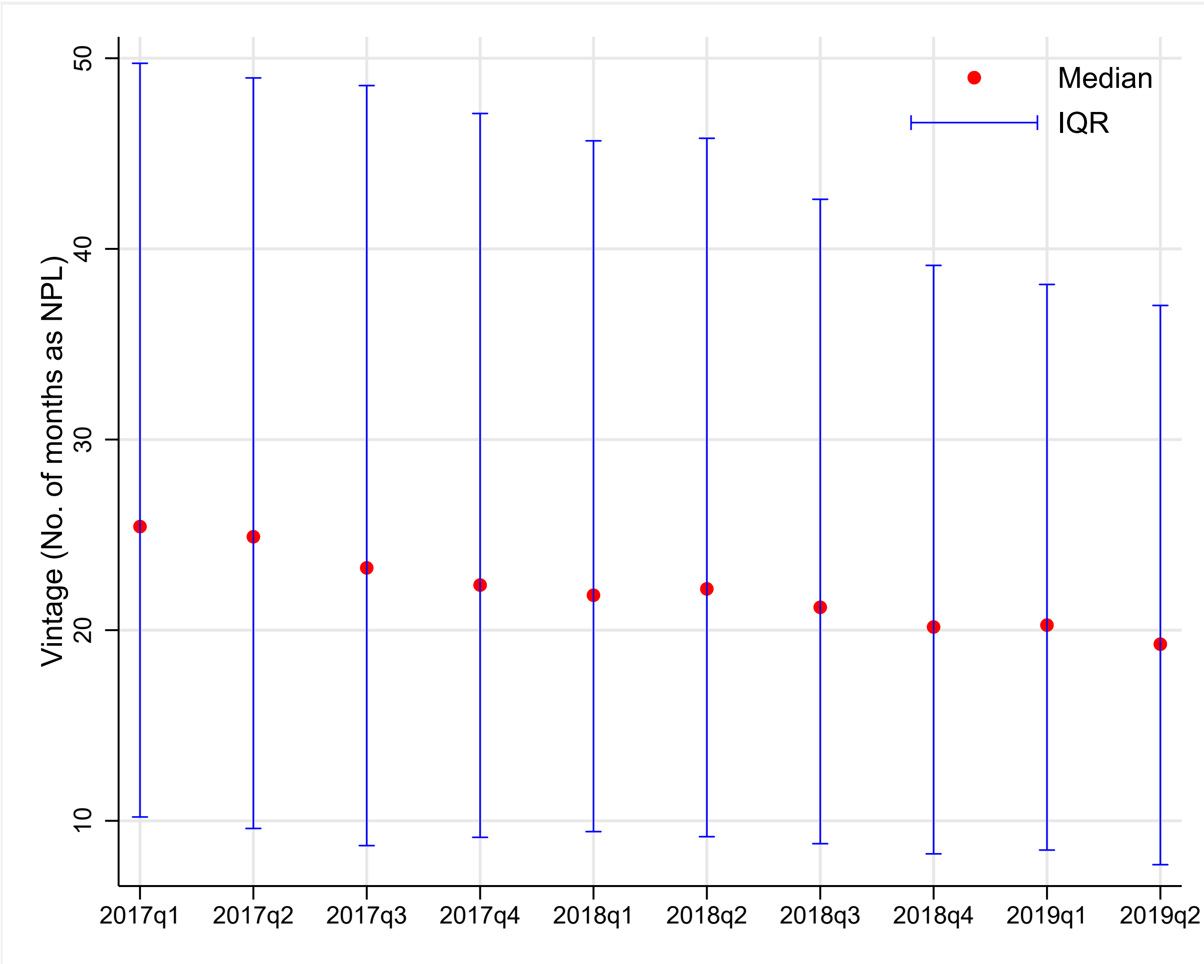


Table 2: Summary statistics

Panel A: NPL-level variables						
	Obs.	Mean	sd	p25	Median	p75
Exit	1,654,107	0.108	0.311	0.000	0.000	0.000
Policy	1,654,107	0.501	0.500	0.000	1.000	1.000
Loan size	1,654,107	8.463	2.905	6.265	8.798	10.784
Log(1+Vintage)	1,654,107	2.969	1.064	2.303	3.105	3.804
Real estate collateral	1,654,107	0.253	0.435	0.000	0.000	1.000
Financial asset collateral	1,654,107	0.006	0.078	0.000	0.000	0.000
Movable collateral	1,654,107	0.004	0.062	0.000	0.000	0.000
Uncollateralized	1,654,107	0.737	0.440	0.000	1.000	1.000
Commercial loan	1,654,107	0.046	0.210	0.000	0.000	0.000
Leasing	1,654,107	0.039	0.193	0.000	0.000	0.000
Credit line	1,654,107	0.469	0.499	0.000	0.000	1.000
Term loans	1,654,107	0.446	0.497	0.000	0.000	1.000
Panel B: Bank-firm-level variables						
	Obs.	Mean	sd	p25	Median	p75
Log(Credit)	6,776,491	10.897	2.014	9.703	10.988	12.164
New credit dummy	6,776,491	0.217	0.412	0.000	0.000	0.000
Termination dummy	8,284,342	0.039	0.195	0.000	0.000	0.000
Collateralized loan share	6,776,491	0.189	0.372	0.000	0.000	0.000
Long-term loan share	6,776,491	0.644	0.418	0.161	0.928	1.000
NPL share	6,776,491	0.007	0.080	0.000	0.000	0.000
Forborne loan share	6,776,491	0.021	0.133	0.000	0.000	0.000
Credit share	6,776,491	0.331	0.285	0.089	0.249	0.522
Panel C: Bank-level variables						
	Obs.	Mean	sd	p25	Median	p75
Log(Assets)	1,051	14.296	2.150	12.625	14.135	15.309
Capital ratio	1,051	0.070	0.147	0.057	0.077	0.097
NPL ratio	1,051	6.879	7.185	2.734	5.473	8.151
Liquidity ratio	1,051	10.478	13.189	2.793	6.604	11.876
ROA	1,051	0.477	1.080	0.282	0.512	0.771
NPL vintage	106	2.743	4.503	0.260	1.325	3.739

Table 2 (cont'd): Summary statistics

Panel D: Firm-level variables						
	Obs.	Mean	sd	p25	Median	p75
Bank credit growth	113,081	0.040	0.926	-0.313	-0.023	0.357
Employment growth	113,081	0.066	0.477	-0.063	0.025	0.211
Investment growth	113,081	0.075	0.718	-0.152	-0.015	0.214
Firm growth	113,081	0.085	0.310	-0.066	0.043	0.206
Sales growth	113,081	0.081	0.345	-0.067	0.074	0.233
Weighted NPL vintage	113,081	3.757	1.892	2.153	3.692	5.159
Risky-1	113,081	0.033	0.147	0.000	0.000	0.000
Risky-2	113,081	0.502	0.500	0.000	1.000	1.000
Log(Assets)	113,081	6.686	1.607	5.573	6.501	7.611
Capital ratio	113,081	0.353	0.278	0.160	0.339	0.550
Liquidity ratio	113,081	0.588	0.281	0.369	0.626	0.834
ROA	113,081	0.031	0.078	0.004	0.020	0.056
Tangible assets to total assets	113,081	0.349	0.272	0.111	0.293	0.545
log(1+age)	113,081	2.663	0.760	2.303	2.833	3.178

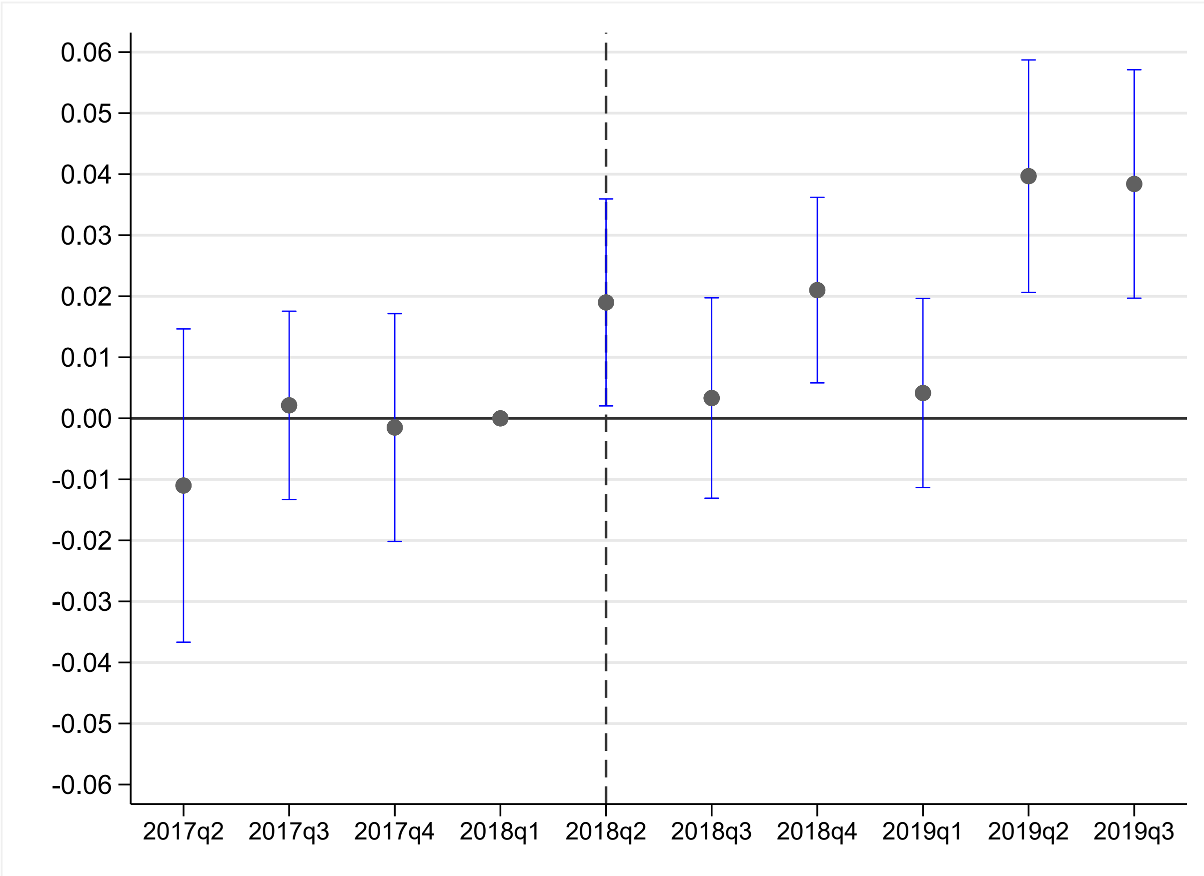
The table provides basic descriptive statistics. See online appendix B for precise definitions of the variables.

Table 3: Policy and NPL disposals

	(1)	(2)	(3)	(4)	(5)
log(1+Vintage)	0.0071	0.0072	0.0155***	0.0128***	0.0153***
	(0.0054)	(0.0048)	(0.0033)	(0.0046)	(0.0049)
Policy × log(1+Vintage)	0.0172	0.0171	0.0008	0.0191***	0.0166***
	(0.0124)	(0.0108)	(0.0049)	(0.0055)	(0.0057)
Bank-Time FE	N	Y	Y	Y	Y
Firm-Time FE	N	N	Y	Y	Y
Firm-Bank FE	N	N	N	Y	Y
Loan Type FE	N	N	N	N	Y
Observations	1,654,107	1,654,107	1,654,107	1,654,107	1,654,107
R-squared	0.01	0.06	0.60	0.66	0.66

Notes: The table presents regressions results of a linear probability model at the NPL level, where the dependent variable is a dummy variable that equals 1 if the loan exists the CIR the next quarter as NPL, and 0 otherwise. *Policy* is a dummy variable that equals 1 for observations in the post-policy period ($t >$2018q1) and 0 otherwise. $Vintage$ is the number of months the NPL has been classified as such. The fixed effects that are included in each regression are noted in the lower part of the table. Standard errors are clustered at the bank-quarter level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure 2: Policy and NPL disposals: Parallel trends



Notes: This figure uses quarterly data for the period 2017q1 to 2019q3. The dotted line corresponds to the introduction of the ECB NPL Provisioning Expectations (2018q2). The graph plots period-by-period coefficients and 95% confidence intervals that we obtain by replacing in equation 1 the variable *Policy* by a sequence of period (quarter) dummies spanning all periods used in the estimation window. Standard errors are clustered at the bank-quarter level.

Table 4: Effect of policy on NPL disposals - Robustness tests

	Drop NPLs > 10% decline	Drop low-NPL banks	Drop rural banks & foreign credit institutions	Drop construction & real estate sector
	(1)	(2)	(3)	(4)
log(1+vintage)	0.0135***	0.0179***	0.0174***	0.0127**
	(0.0049)	(0.0053)	(0.0057)	(0.0052)
Policy × log(1+vintage)	0.0206***	0.0147**	0.0133**	0.0132**
	(0.0060)	(0.0062)	(0.0065)	(0.0058)
Bank-Time FE	Y	Y	Y	Y
Firm-Time FE	Y	Y	Y	Y
Firm-Bank FE	Y	Y	Y	Y
Loan Type FE	Y	Y	Y	Y
Observations	1,394,607	1,494,992	1,431,013	1,158,527
R-squared	0.69	0.67	0.67	0.62

Notes: This table presents robustness tests for the estimation results of the specification in column (5) of Table 3. The dependent variable is a dummy variable that equals 1 if the loan exists the CIR the next quarter as NPL, and 0 otherwise. *Policy* is a dummy variable that equals 1 for observations in the post-policy period (t >2018q1) and 0 otherwise. $Vintage$ is the number of months the NPL has been classified as such. Column (1) excludes NPLs whose outstanding debt decreased by more than 10% (at its final quarter in the CIR) at any moment before their exit. Column (2) presents results with a sample of banks with NPL ratios above 5%. Column (3) presents results where rural banks and foreign credit institutions operating in Spain are excluded from the sample. Column (4) presents results without NPLs belonging to construction or real estate firms. The fixed effects that are included in each regression are noted in the lower part of the table. Standard errors are clustered at the bank-quarter level and reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5: Accounting for bank-level heterogeneity in NPL disposal

	(1)	(2)	(3)	(4)	(5)
Policy×log(1+Vintage)	0.0300**	0.0396***	0.0302***	0.0254**	0.0392***
	(0.0116)	(0.0121)	(0.0117)	(0.0116)	(0.0121)
Policy×log(1+Vintage)×Size	-0.0065	-0.0109**	-0.0067	-0.0041	-0.0100*
	(0.0053)	(0.0054)	(0.0053)	(0.0051)	(0.0052)
Policy×log(1+Vintage)×ROA		0.0373***			0.0366**
		(0.0135)			(0.0152)
Policy×log(1+Vintage)×Capital			0.0115		-0.0008
			(0.0187)		(0.0201)
Policy×log(1+Vintage)×NPL ratio				-0.0239*	-0.0022
				(0.0143)	(0.0168)
Bank-Time FE	Y	Y	Y	Y	Y
Firm-Time FE	Y	Y	Y	Y	Y
Firm-Bank FE	Y	Y	Y	Y	Y
Loan Type FE	Y	Y	Y	Y	Y
Observations	1,654,107	1,654,107	1,654,107	1,654,107	1,654,107
R-squared	0.66	0.66	0.66	0.66	0.66

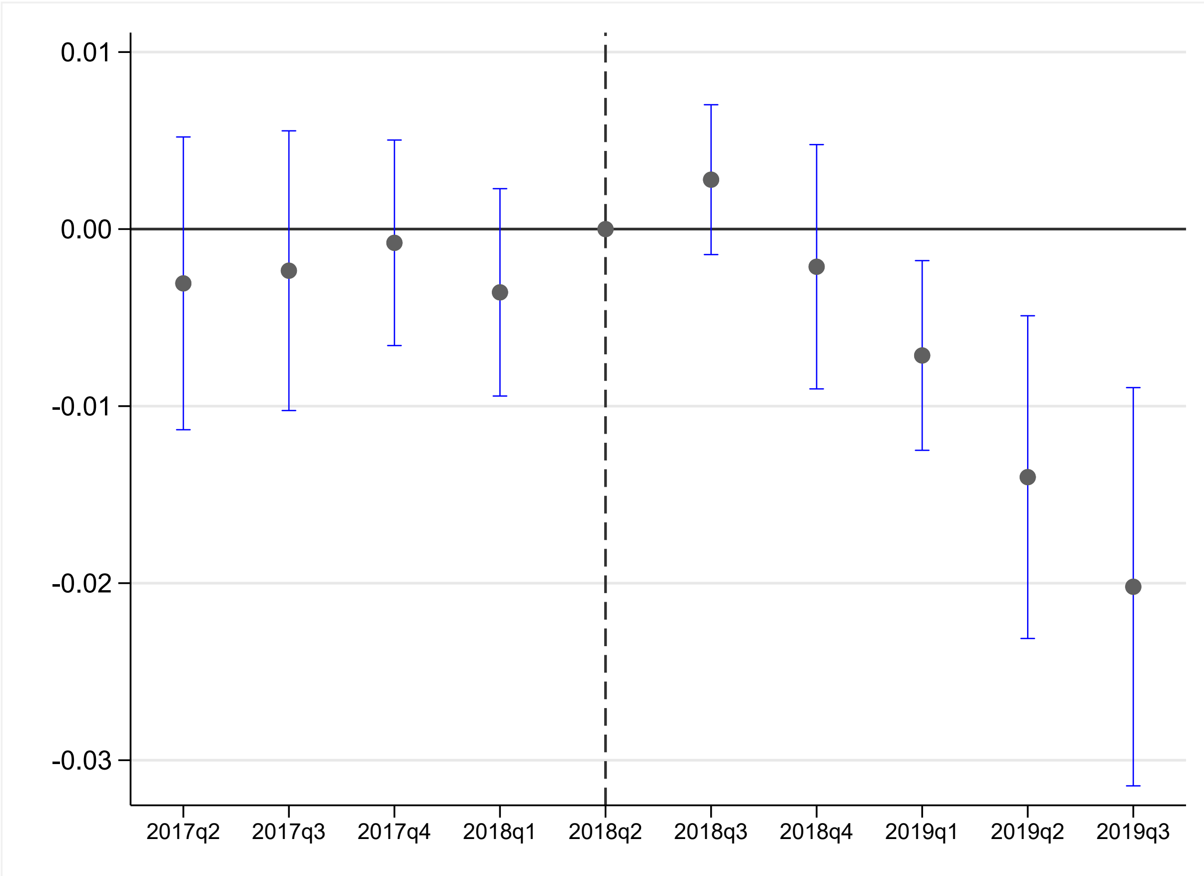
Notes: The table presents regressions results of a linear probability model at the NPL level, where the dependent variable is a dummy variable that equals 1 if the loan exists the CIR the next quarter as NPL, and 0 otherwise. *Policy* is a dummy variable that equals 1 for observations in the post-policy period ($t >$2018q1) and 0 otherwise. $Vintage$ is the number of months the NPL has been classified as such. We interact *Policy* and $log(1 + Vintage)$ with bank characteristics to account for bank heterogeneous effects. The fixed effects that are included in each regression are noted in the lower part of the table. Standard errors are clustered at the bank-quarter level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6: Policy and bank lending standards

	Log credit	New credit dummy	Termination dummy	Collateralized loan ratio	Long-term loan ratio
	(1)	(2)	(3)	(4)	(5)
Policy×NPL vintage	-0.0061***	0.0002	0.0007*	0.0017***	0.0002
	(0.0019)	(0.0011)	(0.0004)	(0.0003)	(0.0019)
Bank controls	Y	Y	Y	Y	Y
Relationship controls	Y	Y	Y	Y	Y
Bank-Firm FE	Y	Y	Y	Y	Y
Firm-Time FE	Y	Y	Y	Y	Y
Bank Type-Time FE	Y	Y	Y	Y	Y
Observations	6,776,491	6,776,491	8,284,342	6,776,491	6,776,491
R-squared	0.95	0.65	0.57	0.97	0.86

This table contains a set of regressions in which the dependent variables are the natural logarithm of outstanding credit from bank b to firm f (column 1), a dummy that equals 1 if bank b extended a new loan to firm f (column 2), a dummy that equals 1 if bank b terminates the lending relationship with firm f (column 3), the ratio of collateralized credit that firm f has with bank b (column 4), and the ratio of bank debt with residual maturity above three years that firm f has with bank b (column 5). *Policy* is a dummy variable that equals 1 for observations in the post-policy period ($t > 2018q1$) and 0 otherwise. $NPL\ vintage$ is a bank's weighted average vintage of the loan portfolio to non-financial firms as of the end of 2017. The fixed effects that are included in each regression are noted in the lower part of the table. Standard errors are double clustered at the bank and firm levels and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure 3: The effect of policy on log credit: Parallel trends



Notes: This figure uses quarterly data for the period 2017q1 to 2019q3. The dotted line corresponds to the introduction of the ECB NPL Provisioning Expectations (2018q2). The graph plots period-by-period coefficients and 95% confidence intervals that we obtain in Equation 2 by replacing the variable *Policy* by a sequence of period (quarter) dummies spanning all periods used in the estimation window. Standard errors are double clustered at the bank and firm level.

Table 7: Policy and bank lending - Robustness tests

	Bank group*quarter dummies	Controls*quarter dummies	Drop low-NPL banks	Drop rural banks & foreign credit institutions	Drop construction & real estate sector
	(1)	(2)	(3)	(4)	(5)
Policy × NPL vintage	-0.0059***	-0.0085***	-0.0060***	-0.0075***	-0.0061***
	(0.0017)	(0.0020)	(0.0011)	(0.0019)	(0.0018)
Bank controls	Y	Y	Y	Y	Y
Relationship controls	Y	Y	Y	Y	Y
Bank x Firm FE	Y	Y	Y	Y	Y
Firm x Quarter FE	Y	Y	Y	Y	Y
Bank Type x Quarter FE	Y	Y	Y	Y	Y
Observations	6,776,491	6,776,491	5,180,135	5,012,521	5,688,858
R-squared	0.95	0.95	0.95	0.95	0.95

Notes: This table presents robustness tests for the estimation results of the specification in column (1) of Table 6. The dependent variable is the logarithm of total credit granted to firm f by bank b. *Policy* is a dummy variable that equals 1 for observations in the post-policy period (t >2018q1) and 0 otherwise. $NPL\ vintage$ is a bank's weighted average vintage of the loan portfolio to non-financial firms as of the end of 2017. In column (1), we include a bank group dummy interacted with quarter dummies, where the bank group dummy takes the value 1 if the banking group participated in the 2018 EU-wide stress test and 0 otherwise. In column (2), we interact all bank controls with quarter dummies. In column (3), we drop from the sample banks with NPL ratios below 5% (*Low-NPL* banks). In column (4), we drop from the sample rural banks and foreign credit institutions operating in Spain. Finally, in column (5), we drop firms belonging to the construction or real estate sectors. The fixed effects that are included in each regression are noted in the lower part of the table. Standard errors are double clustered at the bank and firm levels and reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 8: Accounting for bank-level heterogeneity in bank lending

	(1)	(2)	(3)	(4)	(5)	(6)
NPL vintage×Policy	-0.003	0.000	-0.003	0.001	-0.001	0.006
	(0.003)	(0.004)	(0.003)	(0.004)	(0.002)	(0.00)
NPL vintage×Policy×Size	-0.008***	-0.011***	-0.006***	-0.009***	-0.004**	-0.007***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
NPL vintage×Policy×ROA		0.007**				0.009**
		(0.003)				(0.003)
NPL vintage×Policy×Capital			-0.003			-0.006***
			(0.003)			(0.002)
NPL vintage×Policy×NPL ratio				-0.005**		-0.004**
				(0.002)		(0.002)
NPL vintage×Policy×NPL coverage					0.010***	0.009**
					(0.004)	(0.004)
Bank controls	Y	Y	Y	Y	Y	Y
Relationship controls	Y	Y	Y	Y	Y	Y
Bank-Firm FE	Y	Y	Y	Y	Y	Y
Firm-Time FE	Y	Y	Y	Y	Y	Y
Bank Type-Time FE	Y	Y	Y	Y	Y	Y
Observations	6,776,491	6,776,491	6,776,491	6,776,491	6,776,491	6,776,491
R-squared	0.95	0.95	0.95	0.95	0.95	0.95

The table presents regression results, where the dependent variable is the natural logarithm of outstanding credit from bank b to firm f. *Policy* is a dummy variable that equals 1 for observations in the post-policy period ($t >$ 2018q1) and 0 otherwise. NPL *vintage* is a bank's weighted average vintage of the loan portfolio to non-financial firms as of the end of 2017. The fixed effects that are included in each regression are noted in the lower part of the table. Standard errors are double clustered at the bank and firm levels and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9: Firm-level outcomes

	Growth between the end of 2017 and 2019				
	Bank debt	Employment	Investment	Assets	Sales
	(1)	(2)	(3)	(4)	(5)
Weighted NPL vintage	-0.0153*	-0.0040***	-0.0074***	-0.0021**	-0.0035***
	(0.0083)	(0.0007)	(0.0020)	(0.0010)	(0.0009)
Province-Industry-Size FE	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y
Bank controls	Y	Y	Y	Y	Y
Firm-Bank controls	Y	Y	Y	Y	Y
Observations	113,081	113,081	113,081	113,081	113,081
R-squared	0.12	0.09	0.09	0.17	0.12

Notes: The table presents regression results, where the dependent variable is the growth between the end of 2017 and 2019 (pre and post policy) of a firm's real variable, presented in columns (1) to (5): bank debt, employment (measured as the number of workers), investment (measured as tangible fixed assets), assets, and sales. $Weighted$ $NPL\ vintage$ is the weighted average NPL vintage of banks lending to firm f in 2017, taking as weights the amount granted by each bank to firm f. We include province-industry-size fixed effects and controls. Standard errors are clustered at the main bank level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 10: Effect on log lending, heterogeneous effects based on firm riskiness

	Log credit	New credit	Termination
	(1)	(2)	(3)
Policy×NPL vintage	-0.0061*	-0.0001	0.0019
	(0.0033)	(0.0013)	(0.0015)
Policy× NPL vintage× Risky	-0.0029**	-0.0023**	-0.0005*
	(0.0014)	(0.0011)	(0.0003)
Controls	Y	Y	Y
Bank-Firm FE	Y	Y	Y
Firm-Time FE	Y	Y	Y
Bank Type-Time FE	Y	Y	Y
Observations	2,907,652	2,907,652	3,109,871
R-squared	0.95	0.52	0.54

Notes: The table presents regression results, where the dependent variable is the natural logarithm of outstanding credit from bank b to firm f. *Policy* is a dummy variables that equal 1 for 2018q2 onwards and 0 otherwise. NPL *vintage* is a bank's weighted average vintage of the loan portfolio to non-financial firms as of the end of 2017. *Risky* takes the value 1 if the firm's interest coverage ratio is above the median of the distribution as of the end of 2017, and 0 otherwise. The fixed effects that are included in each regression are noted in the lower part of the table. Standard errors are double clustered at the bank and firm levels and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 11: Firm-level outcomes, heterogeneous effects based on firm riskiness

	Growth between the end of 2017 and 2019				
	Bank debt	Employment	Investment	Assets	Sales
	(1)	(2)	(3)	(4)	(5)
Weighted NPL vintage	-0.0102	-0.0023**	-0.0053**	-0.0015	-0.0033***
	(0.0088)	(0.0010)	(0.0023)	(0.0012)	(0.0010)
Risky	0.0313***	-0.0116	-0.0011	-0.0207***	0.0011
	(0.0116)	(0.0093)	(0.0063)	(0.0045)	(0.0073)
Weighted NPL vintage × Risky	-0.0110***	-0.0030**	-0.0043**	-0.0010	-0.0005
	(0.0034)	(0.0014)	(0.0018)	(0.0008)	(0.0015)
Province x Industry x Size FE	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y
Bank controls	Y	Y	Y	Y	Y
Firm x Bank controls	Y	Y	Y	Y	Y
Observations	113,078	113,078	113,078	113,078	113,078
R-squared	0.1266	0.0917	0.0907	0.1709	0.1192

Notes: The table presents regression results, where the dependent variable is the growth between the end of 2017 and 2019 (pre and post policy) of a firm's real variable, presented in columns (1) to (5): bank debt, employment (measured as the number of workers), investment (measured as tangible fixed assets), assets, and sales. $Weighted$ NPL vintage is the weighted average NPL vintage of banks lending to firm f in 2017, taking as weights the amount granted by each bank to firm f. Moreover, we interact the variable of interest with a firm risk measure. *Risky* takes the value 1 if the firm's interest coverage ratio is above the median of the distribution as of the end of 2017 and 0 otherwise. The fixed effects that are included in each regression are noted in the lower part of the table. Standard errors are clustered at the main bank level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B Variable definitions

Loan-level variables (Source: Credit Register, Bank of Spain)

- $Exit$: A dummy variable that equals 1 if the bank stopped reporting the loan to the CIR, and 0 otherwise.
- $Size$: The natural logarithm of the loan's outstanding debt.
- $Vintage$: The natural logarithm of 1 plus the number of months that the loan is classified as non-performing.

Firm-bank variables (Source: Credit Register, Bank of Spain)

- $log(Credit)$: The natural logarithm of the granted commitment.
- $NewCredit$: A dummy variable that equals 1 if the bank grants a new loan to the firm.
- $Termination$: A dummy variable that equals 1 if the bank terminates the relationship with the firm.
- $Share\ of\ secured\ loans$: The amount of collateralized loans divided by total debt.
- $Share\ of\ short\text{-}term\ loans$: The amount of loans with residual maturity of less than a year divided by total debt.
- $Share\ of\ NPLs$: The amount of non-performing loans divided by total debt.
- $Share\ of\ forborne/refinanced\ loans$: The amount of Forborne/refinanced loans divided by total debt.
- $Share\ of\ loans\ with\ bank\ j$: The total amount of loans from bank j divided by firms' total debt.

Firm-level variables (Source: Spanish Mercantile Register, Bank of Spain)

- *Risky*: A dummy variable that equals 1 if the firm's interest coverage ratio is above the median of the distribution as of the end of 2017, and 0 otherwise.
- *Growth in credit*: The difference in the logarithm of bank committed credit (drawn and undrawn funds) between 2017 and 2019.
- *Growth in no. of employers*: The difference in the logarithm of the number of workers between 2017 and 2019.
- *Growth in tangible fixed assets*: The difference in the logarithm of tangible fixed assets between 2017 and 2019.
- *Growth in assets*: The difference in the logarithm of assets between 2017 and 2019.
- *Growth in sales*: The difference in the logarithm of sales between 2017 and 2019.
- *Weighted average NPL vintage*: The weighted average NPL vintage of the firm's creditors, using as weights the total amount each bank lends to the firm as of the end of 2017.
- *Size*: The logarithm of total assets as of the end of 2017.
- *Capital ratio*: The ratio of book equity to total assets as of the end of 2017.
- *Liquidity ratio*: The ratio of current assets to total assets as of the end of 2017.
- *ROA*: The ratio of earnings in 2017 to total assets as of the end of 2017.
- *Tangible assets to total assets*: The ratio of tangible fixed assets to total assets as of the end of 2017.
- *Age*: The logarithm of 1 plus the age of the firm, measured as the difference between the current year and the date of incorporation.

Bank-level variables (Source: Supervisory Reports, Bank of Spain)

- *Size*: The logarithm of the bank's total assets.
- *Liquidity*: The ratio of liquid assets (cash and balance with central banks, and loans and advances to governments and credit institutions) held by the bank divided by its total assets.
- *NPL ratio*: Loans in default as a proportion of the bank's total credit.
- *NPL coverage*: The ratio of provisions to NPLs.
- *RoA*: Net income divided by assets.
- *Capital*: Book bank equity divided by total assets.
- *NPL vintage*: A bank's weighted average vintage of the loan portfolio to non-financial firms as of the end of 2017.