Bank lending policies and monetary policy

SUMMARY

What is the long-term impact of negative interest rates on bank lending? To answer this question, we construct a unique summary measure of negative rate exposure by individual banks based on exclusive survey data and banks' balance sheets and couple it with the credit register of Spain and firms' balance sheets to identify this impact on the supply of credit to firms. We find that only when deposit rates reached the zero lower bound did affected banks (relative to non-affected banks) decrease their supply, especially when undercapitalized and lending to risky firms. The adverse effects of the negative rates on banks' intermediation capacity only took place after a protracted period of time.

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Bank lending policies and monetary policy: some lessons from the negative interest era

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1. INTRODUCTION

In June 2014, against a backdrop of low inflation and low economic growth, the European Central Bank (ECB) became the first major central bank to implement negative interest rates by cutting its deposit facility rate (DFR) by 10 basis points (bps) into negative territory.[1] This decision was part of a credit-easing package, which also comprised targeted long-term refinancing operations (TLTROs) and, eventually, a large-scale asset purchase programme (APP) of private and public sector bonds. Further rate cuts of 10 bps each followed in September 2014, December 2015, March 2016 and September 2019, setting the DFR at −0.50% where it remained until July 2022, when the ECB raised it to zero.

Policy rate cuts into negative territory are unlikely to work in the same fashion as positive rate cuts because of banks' reluctance to charge negative interest rates on their retail deposits due to the existence of cash as an alternative store of value (Heider et al., 2019, Schelling and Towbin, 2020; Eggertsson et al., 2020; Heider et al., 2021). Therefore, negative rates may especially harm the net interest income of banks with a high deposit share because of the asymmetric response of returns versus funding costs *if* deposit rates are at the zero lower bound (Bittner et al., 2021). Based on these ideas, Heider et al. (2019) show that banks with more deposits provide less syndicated loans and to riskier borrowers after the ECB's policy rate entered negative territory. Eggertsson et al. (2020) also find that Swedish banks that relied more heavily on deposit financing had lower loan growth once the deposit rate reached its lower bound, although their lack of firm-level data makes it difficult to distinguish between shifts in credit supply and credit demand. While negative interest rates also have positive effects on banks' profitability (e.g. through revaluation of bond portfolios, lower credit provisions and higher credit demand),[2] the bank lending channel may operate differently under negative rates than under positive rates, especially for banks that rely heavily on deposit funding.

However, as banks with excess liquidity earn a negative return, they have incentives to increase their lending to the private non-financial sector in a bid to reduce their excess liquidity holdings (Basten and Mariathasan, 2018; Demiralp et al., 2019; Eisenschmidt and Smets, 2019; Bottero et al., 2021[3]). This portfolio-rebalancing channel may imply higher risk taking, as risk-free excess liquidity is converted into bank

1 Before that, the Danish central bank had introduced negative policy rates in July 2012. Subsequently, the Swiss National Central Bank and the Swedish Riskbank implemented negative policy rates in January 2015 and February 2015, respectively. The Bank of Japan followed suit in January 2016.

2 There is no consensus in the literature on the net effect of negative interest rates on bank profitability. See, *inter alia*, Altavilla et al. (2018), Claessens et al. (2018), Coleman and Stebunovs (2019) and López et al. (2020). Nevertheless, such analysis is not the focus of this article**.

3 However, as Italian banks essentially did not hold reserves in excess of the amount required by regulation during the sample period, Bottero et al. (2021) must use two proxies of liquidity, the net interbank position and the ratio of securities to total assets, which can be contaminated by other factors apart from liquidity.

lending.[4] However, prudential bank capital regulations may prevent greater risk taking in response to negative rates, especially by banks with low capital ratios (Brunnermeier and Koby, 2019; Imbierowicz et al., 2019; Bongiovanni et al., 2021). The argument is simple: a binding capital constraint limits banks' ability to grant loans and take on risk.[5]

Our paper aims to contribute to the literature on the transmission of monetary policy to bank credit and lending rates (bank lending channel) and banks' risk taking behaviour (risk-taking channel) under negative interest rates. In particular, we study the effect of the ECB's negative DFR on the supply of credit by Spanish banks to non-financial corporations (henceforth firms), during a protracted time period, 2014–2019. We do not include the year 2020 to avoid the coronavirus disease 2019 (COVID-19) crisis and the policy responses to the pandemic. The Spanish economy is an ideal laboratory because its financial system is strongly bank-based, even when compared to most other European countries, which also exhibit a 'bank bias' (Langfield and Pagano, 2016). The analysis of the impact of negative interest rates on banks' credit supply and risk taking in a 'negative-for-long' scenario is of particular relevance because, as documented by Eggertsson et al. (2020), negative interest rates may have contractionary effects only when retail deposit rates are very low, which was not the case in many euro area economies in 2014, including Spain. Accordingly, Bittner et al. (2021) show that the introduction of negative interest rates in the euro area had very different effects on the credit supply and risk taking of Portuguese and German banks, as deposit rates were above the zero lower bound (ZLB) in Portugal but close to the ZLB in Germany in 2014.[6]

We assemble a unique dataset that comprises the universe of loans granted to Spanish firms from the Credit Register of the Bank of Spain, banks' and firms' balance sheets and confidential survey data from the ECB's Bank Lending Survey (BLS). Our identification strategy relies on estimating the probability that a bank is adversely affected by the negative interest rates (affected for short), based on the confidential answers to the BLS. In particular, we assume that a bank is affected if the probability that it reports that the ECB's negative DFR decreased its net interest income is higher than 75% (i.e. the median of the distribution in 2014). As previously explained, while negative interest rates may also have positive effects on other components of banks' profits, there is no doubt that negative interest rates squeeze net interest margins. Since the literature suggests several channels through which a negative interest rate policy (NIRP) affects banks (i.e. retail

4 Bubeck et al. (2020) also find that the ECB's negative interest rates induced banks with more customer deposits to reach-for-yield by investing more in securities, especially in those yielding higher returns.

5 The relationship between bank capital and risk taking is a priori ambiguous. The risk-shifting hypothesis (Jensen and Meckling, 1976) implies stronger risk taking by less capitalized banks because, as their skin in the game is low, they may take more risk (Holmstrom and Tirole, 1997; Freixas and Rochet, 2008). In contrast, the risk-bearing capacity hypothesis (Gambacorta and Mistrulli, 2004; Adrian and Shin, 2010; Kim and Sohn, 2017)** suggests that higher bank capital allows more risk taking because of its loss-absorbing capacity.

6 Using a macroeconomic DSGE model, Ulate (2021) compares the effect of negative interest rates in two different scenarios, one in which deposit rates are well above the ZLB and another one in** which deposit rates are close to the ZLB.

deposits, excess liquidity, short-term interbank positions, liquid assets), the BLS provides a summary measure of exposure to negative interest rates.

However, banks' self-assessment of the impact of negative interest rates on their balance sheets may pose an identification challenge, as weak banks with problems with their business models may have incentives to strategically misreport their evaluation of the policy in order to 'blame' the NIRP for their poor performance. Survey respondents may also misunderstand the question, not being able to distinguish between the effects of the negative interest rates from those of the asset purchase programme (APP; which was also launched in 2014), as both policy tools may some detrimental impact on banks' intermediation margins as they flatten the yield curve. However, the fact that banks' answers are consistent with hard data mitigate this concern to a great extent, as we find that banks with more deposits and more liquid assets have a higher probability of reporting being affected by the negative DFR. In particular, during the last years of our sample (i.e. the period in which we find a contractionary effect on credit supply by some banks), the reliance on deposit funding and, to a lesser extent, the weight of short-term loans are the main channels through which negative interest rates affect banks adversely, while the effect of liquid assets is negligible. In addition, we obtain similar results in several robustness analyses in which we classify banks as affected by the negative interest rates according to their deposit ratios, their share of credit at floating rates or the sensitivity of their net interest margin to monetary policy. These alternative metrics are solely based on hard data, which rules out concerns about banks' self-assessment of the impact on negative interest rates on their balance sheets in our baseline identification strategy.

Importantly, we allow for different effects in different periods by interacting our key regressor with time dummies, so that we can analyse the dynamic impact of negative interest rates between 2014 and 2019, a period in which deposit rates in Spain exhibited a downward trend until reaching the ZLB. We also address two key identification challenges. First, we disentangle credit supply from credit demand by including firm-time fixed-effects *à la* Khwaja and Mian (2008). Therefore, we compare lending decisions of multiple banks to the same firm within the same period. Second, we take into account other confounding events, such as the Targeted Long-Term Refinancing Operations (TLTRO) and the expanded asset purchase programme (APP), by including relevant controls in our regressions. In particular, we control for the effect of TLTRO-I and TLTRO-II on banks' credit supply by using banks' uptakes over the eligible credit and for the impact of the APP on banks' balance sheets, using banks' holdings of sovereign bonds that are eligible under the sovereign debt APP-leg, called Public Sector Purchase Programme (PSPP; announced in January 2015), over total assets.

In addition, following previous arguments about the relationship between capital, credit growth and risk taking, we differentiate between high-capital and low-capital banks depending on their capital ratio immediately before the DFR turned negative. This enables us to study whether affected banks with a low capital ratio cut credit supply to a higher extent than non-affected banks, so that undercapitalization may generate an amplification effect. Thus, we contribute to the stream of the literature that analyses the capital channel of monetary policy (Van den Heuvel, 2006; Gambacorta and Shin 2018).

Our results indicate that banks adversely affected by the negative interest rates contracted their lending supply to firms (*relative* to non-affected banks) only during the last sub-sample period (2018–2019), while there is no effect during the earlier periods.[7] This finding may be explained by the fact that deposit rates were high in Spain at the time of the introduction of the NIRP, so they had plenty of room to decline before reaching the ZLB in 2018. This evidence is consistent with Bittner et al. (2021), who show that in Germany, where the pass-through of policy rates to banks' cost of funding was impaired in 2014, especially for those banks relying on deposit funding, the overall effect of the introduction of negative interest rates on the credit supply to firms was essentially zero. In particular, high-deposit German banks expanded their credit supply to risky firms, but the overall effect on the credit supply to all firms was statistically indistinguishable from zero. In contrast, in Portugal, where the pass-through of the rate cut to the cost of funding was strong in 2014, banks increased their credit supply. Therefore, both our study and Bittner et al. (2021) highlight the important role of the initial conditions: As deposit rates were well above the ZLB in Spain and Portugal in 2014, there was not an asymmetric response of returns versus funding costs of banks from those countries, as policy rate cuts into negative territory still reduced their funding costs. Hence, the case of Spain is an ideal experiment because deposit rates were well above the ZLB when negative interest rates were introduced in the euro area and it took them several years to reach that level.

Nevertheless, since policy rates in the euro area were lowered several times since 2014, we cannot rule out a complementary explanation, namely that policy rates reached the reversal rate (Brunnermeier and Koby, 2019), which is the rate at which accommodative monetary policy 'reverses' its intended effect and becomes contractionary for lending. But crucially, one of the determinants of the reversal rate is the degree of pass-through of the policy rates to deposit rates, which depends on their distance to the ZLB (the other three determinants are banks' fixed-income holdings, the strictness of capital constraints and the initial capitalization of banks). In addition, according to Repullo (2020), lower policy rates can only lead to a contraction in bank lending if the bank is a net investor in debt securities, a condition typically only satisfied by banks that take a high amount of deposits.

Importantly, we also find that the effect of negative interest rates on banks' credit supply was heterogeneous and depended on the level of banks' capitalization.[8] In

7 Note that we emphasize the word *relative* because, given our identification strategy (a diff-in-diff estimator), we cannot rule out the possibility that affected banks did not reduce credit at all, while nonaffected banks could expand it by lending out their excess reserves.

8 This result is in line with previous studies that show that the heterogeneity in banks' financial conditions matter for the transmission of monetary policy (e.g. Ciccarelli et al., 2013). In particular, their analysis reveals that the monetary transmission mechanism is time-varying and influenced by the financial fragility of the sovereigns, banks, firms and households.

particular, we observe that affected banks with low capital ratios reduced their lending supply to firms relative to non-affected banks. However, they only did so during the last period 2018–2019, which is again in line with the findings of Bittner et al. (2021) and the role of the initial conditions. Consistent with these results, Molyneux et al. (2019) find that banks in countries that adopted a NIRP reduced lending significantly compared to those in countries that did not adopt this policy. Crucially, the previous adverse effect was stronger for banks that were more dependent on retail deposits and were less well capitalized.

We also split our sample into safe and risky firms and find that affected low-capital banks reduced their credit supply to risky firms in the last two sample periods, 2016–2018 and 2018–2019, although the effect is much stronger in the latter period.[9] In contrast, there is only a marginally significant effect on safe firms in the last period, and its size is substantially smaller than that for risky firms.[10] Therefore, our findings indicate that affected low-capital banks contracted their credit supply to risky firms prior to restricting it to safe firms and in a greater magnitude, arguably because loans to the former consume more regulatory capital. To put it differently, we find a positive relationship between capital ratios and risk taking for those banks adversely affected by the negative interest rates, which suggests that affected low-capital banks took less risk because of their lack of capital buffers to absorb losses and the need to meet capital requirements. These findings are in line with those of Bongiovanni et al. (2021), who document an overall reduction in banks' holdings of risky assets in countries where negative rates were introduced. In particular, bank responses to monetary policy were heterogeneous according to their level of capitalization. For undercapitalized (overcapitalized) banks, the introduction of the NIRP implied a reduction (increase) in risk taking. Thus, our results should not be interpreted based solely on the risk taking channel of monetary policy, but also on the interaction between monetary and macroprudential policies. For instance, Cozzi et al. (2020) find that banks' capital buffers are best augmented during times of affluence, when banks can issue new equity and an accommodative monetary policy can mitigate the negative effects of increasing capital requirements on lending.

In addition, affected banks with low capital did not charge higher interest rates to firms than non-affected banks during the period 2018–2019 (there is no available information on interest rates at the loan level before 2018). This finding suggests that low-capital affected banks did not transmit their higher funding costs to their borrowers, arguably because firms borrowing from those banks could substitute away from them (i.e. loan demand was highly elastic).

9 Note that our results are not at odds with those of Heider et al. (2019) and Bittner et al. (2021), who find that high-deposit banks increased their risk taking in the euro area and Germany, respectively, because we also take into account the role of bank capital in the transmission of negative interest rates to credit supply.

10 Similarly, Boungou (2020) finds that risk taking has been lower among banks operating in countries where negative rates have been introduced.

Finally, we aggregate our dataset at the firm level to investigate whether the companies operating with affected banks experienced a contraction in their total bank credit. We assume that a firm is affected by the negative interest rates if its main bank is affected and has a low capital ratio.[11] However, we do not find significant effects on the supply of credit to affected firms. This evidence suggests that the lower supply of credit by affected low-capital banks was offset by the higher lending supply by non-affected banks, with capacity for taking additional risks thanks to their higher capital buffers. Therefore, while the reversal rate might have been reached by some affected undercapitalized banks, there seems to be no aggregate effect on the supply of lending to firms. Nevertheless, caution is warranted when drawing conclusions about aggregate effects with difference-in-differences (diff-in-diff) identification strategies and firm-time fixed effects. In particular, if there is an effect of the negative interest rates that is common across all lenders, then such an effect would be absorbed by the firm-time fixed effects and it will not be reflected in the estimates.

We contribute to the literature along four lines. First, we analyse the impact of negative interest rates on banks' credit supply and risk taking in a 'negative-for-long' scenario, which allows us to study the role of the initial conditions. In particular, deposit rates in Spain were well above zero in 2014 but reached that level in 2018. Our goal is similar to Bittner et al. (2021), but with a different identification strategy. While they exploit the difference in the levels of deposit rates in Portugal and Germany around the introduction of negative policy rates in 2014, we study the behaviour of Spanish banks during the period 2012–2019 in order to have the two different scenarios in one single country.

Second, we explore whether the transmission of negative interest rates to banks' credit supply was heterogeneous and depended on the level of banks' capitalization, while most of the evidence on the subject (e.g. Jiménez et al., 2012, 2014) pertains to pre-crisis times and conventional monetary policy. In particular, we study whether there was an amplification effect, so that affected low-capital banks were the ones that contracted the supply of credit the most. We also investigate the pass-through of negative interest rates to banks' lending rates according to their capital ratios, while previous studies (e.g. Amzallag et al., 2019; Eggertsson et al., 2020) have analysed how this pass-through depends on the reliance on deposit financing.

Third, since the literature suggests several channels through which negative interest rates affects banks (retail deposits, excess liquidity, short-term interbank positions, liquid assets, credit at floating rates, short-term loans), the BLS provides a summary measure of exposure to negative interest rates. Reassuringly, these survey data are corroborated with hard data: Banks with higher deposit ratios and more liquid assets have a higher probability of reporting being affected by the negative rates. In fact, we obtain similar

11 We obtain similar results when using a more stringent definition. In particular, we consider that a firm is affected by the negative interest rates if its main bank is affected, it has a low capital ratio and more than 25% of the firm's outstanding credit has been granted by low-capital affected banks.

results if we consider banks as affected by the negative interest rates according to their deposit ratios, their share of credit at floating rates or the sensitivity of their net interest margin to monetary policy.

Finally, we find a positive relationship between capital ratios and risk taking for those banks adversely affected by the negative interest rates. This evidence suggests that affected undercapitalized banks took less risk because of their lack of capital buffers to bear losses and the need to meet capital requirements. Therefore, our results on banks' risk taking behaviour and capital highlight the interaction between monetary and macroprudential policies.

Regarding the policy implications of our findings, our study offers new evidence about potential unintended consequences of a protracted period of negative interest rates, especially when bank capital is scarce and costly. It is well-known that the build-up of capital buffers, while essential for the resilience of the banking system, may have some short-run costs in terms of lower credit supply and output. While an accommodative monetary policy may mitigate those costs through various channels (by, e.g. stimulating aggregate demand, raising asset prices or favoring lower loans delinquency rates), maintaining negative rates for a long period may also unchain some contractionary effects. Here we document that the interaction of binding capital constraints and a zero lower bound on deposits may unchain such negative effects on the supply of credit.

2. DATA

Our paper combines several different datasets that enable us to observe the universe of bank–firm credit relationships and the balance sheets of both firms and banks. The information on credit is obtained from the Banco de España's Central Credit Register (CCR). The CCR contains information on all bank loans granted to non-financial corporations above 6,000 euro, including credit lines. As corporate loans are normally much larger than this reporting threshold, we are confident that we have the whole population of loans to non-financial corporations. For each loan, we know the size of the credit instrument and other characteristics such as its creditworthiness, its maturity, its interest rate of reference (fixed, floating, etc.), the type of contract (financial credit, commercial credit, leasing, factoring) and the type of guarantee (no guarantee, collateral, or personal guarantee).[12] We aggregate the outstanding amount of credit of each firm in each bank on a monthly basis to obtain its total credit. In the case of credit lines, we include both drawn and undrawn amounts to better capture the supply of credit by banks, as credit drawn is largely affected by the borrower's need for funds and, consequently, it is also determined by demand shifts. In addition, the dataset contains the

12 Personal guarantee refers to the commitment of the firm's owner (or its partners) to honor the firm's debt with her wealth or personal assets in case of default by the company. Collateral refers to specific assets (real estate, financial or movable assets, other assets) that can be seized by the lender in case of default by the firm.

fiscal identity of the borrower and the lender, which enables us to construct a matched bank-firm dataset.

We then merge the CCR with banks' balance sheet data, which are collected by the Banco de España in its role as banking supervisor. In our baseline analyses we use unconsolidated banks' financial statements in order to maximize sample size. In addition, in the case of large multinational banks, the use of consolidated financial statements may lead to include overseas business activities, some of them in economies characterized by (very) high interest rates. Our sample consists of 23 financial institutions including commercial banks, savings banks and credit cooperatives in Spain (hereafter banks). The banks in our sample accounted for 83% of the outstanding credit to Spanish firms as of June 2014.

Panel A of Table 1 contains descriptive statistics on the main characteristics of the banks in the sample. In view of the 1st and 99th percentiles of total assets and its large standard deviation, we confirm that there is a high degree of heterogeneity in terms of bank size. A similar dispersion is observed in banks' profitability (ROA), which is even negative for some banks. The average ratio of non-performing loans to total credit (NPL ratio) is relatively high because of the effects associated to the Great Recession in Spain,[13] with the riskier banks exhibiting an NPL ratio close to 15%. Moreover, although the banks in our sample are, on average, well capitalized, the dispersion in the capital ratios (CET1 over risk-weighted assets) suggests that not all of them can take risks to the same extent because of a lower loss-absorbing capacity. Regarding banks' business models, they are mainly focused on the traditional deposit-based intermediation activity, as the average loan-to-deposit ratio is 1:1. Similarly, the average deposit ratio (i.e. deposits over total assets) is 57.5%, but there is substantial heterogeneity, as the standard deviation of this variable is 23.3%. Finally, we observe that the vast majority of the loans have a floating rate and that the share of sovereign bonds in the portfolios of Spanish banks is substantial (it reaches a maximum value of almost 30%). For reasons of confidentiality, we cannot provide summary statistics on the TLTRO uptakes over eligible credit.

Panel B of Table 1 displays the means of the aforementioned characteristics for affected and non-affected banks,[14] where the statistical significance of the difference between the means of the two groups is assessed according to two-sample t tests. The average deposit ratio of affected banks (68.6%) is much higher than that of non-affected banks (42.6%), which is consistent with previous literature (e.g. Heider et al., 2019). The stronger reliance of affected banks on deposit funding also leads to a lower loan-to-deposit ratio compared to non-affected banks (0.9 and 1.5, respectively). Affected banks

13 According to García-Posada and Vegas (2018), in Spain, during the Great Recession (2008–2013), real housing prices dropped by 35%, real GDP fell by more than 8%, the unemployment rate reached 26% (from 10%) and credit to the nonfinancial private sector fell by more than 18%.

14 A bank is assumed to be adversely affected by the negative interest rates when the estimated probability that its net interest income decreased because of the negative DFR is higher than 75%. See Section 3 for details.

Table 1. Descriptive statistics

	Mean	Median	SD	P1	P99
Panel A					
Total assets (TA) (€ bn.)	107.0	43.6	135.0	7.0	497.0
ROA (%)	0.2	0.2	0.2	−0.2	0.8
NPL ratio (%)	5.3	5.0	3.2	0.1	14.9
Loan-to-deposit ratio	1.1	1.0	0.9	0.5	6.2
Deposit ratio (%)	57.5	62.8	23.3	1.9	95.2
CET1/RWA (%)	12.3	11.9	1.4	8.6	16.1
Sovereign bonds/TA (%)	8.3	8.1	7.0	0	29.4
Prob. affected negative DFR (%)	76.8	78.6	16.4	24.0	98.7
Floating rate loans/Total loans (%)	84.6	91.1	17.1	9.9	100.0

	Non—affected (1)	Affected (2)	Difference (1)–(2)
Panel B			
Total assets (TA) (€ bn.)	134.0	91.3	42.7
			(40.9)
ROA (%)	0.2	0.3	0.0
			(0.0)
NPL ratio (%)	4.8	5.7	−0.9
			(0.7)
Loan-to-deposit ratio	1.5	0.9	0.6***
			(0.2)
Deposit ratio (%)	42.6	68.6	−26***
			(4.3)
CET1/RWA (%)	12.6	12.4	0.2
Sovereign bonds/TA (%)	4.9	10.9	(0.5)
			−6.1***
			(1.4)
Prob. affected negative DFR (%)	62.5	87.4	−24.9***
			(2.4)
Floating rate loans/Total loans (%)	73.2	93.2	−20***
			(3.1)

	Mean	Median	SD	P1	P99
Panel C					
Δlog(credit affected banks)	−0.06	−0.08	0.85	−2.54	2.61
Δlog(credit non–affected banks)	−0.05	−0.08	0.92	−2.66	2.89

Panel A of this table contains banks' descriptive statistics for our sample period. All the variables are expressed in percentages except for total assets (TA), which is in billions of euros. Panel B displays the means of those variables for affected and non–affected banks (a bank is assumed to be adversely affected by the negative interest rates when the estimated probability that it reports that its net interest income decreased because of the negative DFR is higher than 75%, see Section 3 for details). The statistical significance of the difference between the means of the two groups has been evaluated according to two-sample t tests on the equality of means, in which the population variances are not assumed to be equal, where the null hypothesis is no difference. Standard errors are displayed in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Panel C reports descriptive statistics for the log change of credit at the bank-firm level during the four sub-periods considered in our sample period. ROA is the ratio of net income to total assets. NPL ratio is the ratio of non-performing loans to total outstanding loans. Loan-to-deposit ratio is the ratio of total credit to deposits. Deposit ratio is the ratio of deposits to total assets, in percentage terms. CET1/RWA is the ratio of Common Equity Tier 1 to risk-weighted assets. Sovereign bonds/TA is the ratio of sovereign bonds to total assets. Prob. affected negative DFR is the estimated probability that a bank reports that its net interest income decreased because of the negative DFR. Floating rate loans/Total loans is the share of credit that is granted at a floating rate.

also have a higher ratio of sovereign bonds to total assets than non-affected banks (10.9% and 4.9%, respectively), along the lines of Bottero et al. (2021), who consider that banks adversely affected by the negative interest rates are those with a high share of liquid assets. As expected, affected banks also have a higher share of floating-rate loans, which are repriced at a lower rate following a reduction in the official interest rate, than non-affected banks (87.4% and 62.5%, respectively). Finally, Panel C of Table 1 reports descriptive statistics of the variation of credit at the firm-bank level for both affected and non-affected banks. On average, affected banks exhibited a higher decline in their lending to Spanish firms than non-affected banks. All variables are winsorized at the 1st and 99th percentiles.

Finally, the CCR is also merged with a dataset that comprises the Spanish firms that are respondents to the Integrated Central Balance Sheet Data Office Survey (CBI), which includes information from the accounts deposited at the Mercantile Registers for almost 900,000 firms as of December 2015. The coverage of this dataset is quite extensive and contains detailed information of firms' balance sheets. In addition, it is also a representative sample of the whole population of Spanish firms, as a high share of the companies are micro-firms[15] and SMEs, which account for the vast majority of Spanish businesses. We use the combined datasets to conduct a series of analyses aimed to identify the risk taking behaviour of Spanish banks. In particular, we define risky firms as those whose leverage ratio is above the median of the distribution of the leverage ratio of the firms in our sample, while safe firms are those whose leverage ratio is below the median of that distribution.

In addition, in some analyses we aggregate the dataset at the firm-level in order to study the effect of negative interest rates on the total supply of credit to firms. Descriptive statistics of several firm characteristics are reported in Supplementary Appendix Table A1.

3. MEASURING THE EXPOSURE OF BANKS TO NEGATIVE INTEREST RATES

In this section, we explain how we construct our measure of exposure to negative interest rates, so that we can differentiate between more affected and less affected banks (for simplicity, affected and non-affected banks) using information from the iBLS and IBSI datasets on a sample of 123 banks from the euro area.

The Individual Bank Lending Survey (iBLS) and the Individual Balance Sheet Items (IBSI) database are used to classify banks depending on how the negative interest rates affect their net interest income. The iBLS database contains confidential, non-anonymized replies to the ECB's BLS for a subsample of banks participating in the

15 According to the European Commission definition, micro-firms are those that have less than 10 employees and a turnover of less than € 2 million or total assets less than € 2 million. The definitions of micro, small and medium companies can be found at: https://ec.europa.eu/growth/smes/sme-definition_es

BLS. The BLS is a quarterly survey through which euro area banks are asked about developments in their respective credit markets since 2003.[16] Currently, the sample comprises more than 140 banks from 19 euro area countries, with coverage of around 60% of the amount outstanding of loans to the private non-financial sector in the euro area. While preference is given to including the largest banks of each country, smaller and specialized banks are also included in the sample if their lending behaviour represents an important feature of the national banking system. However, there are six countries that do not share the confidential, non-anonymized replies to the BLS, so they are excluded from the iBLS. Spain contributes to the iBLS with ten banks, which account for 78% of the total stock of loans to firms. IBSI contains balance-sheet information of more than 300 of the largest banks in the euro area, which is individually transmitted on a monthly basis from the national central banks to the ECB since 2007. We have matched this dataset with the iBLS and restricted the sample to the period spanning from 2014Q2 to 2018Q2. The resulting sample contains 1,528 observations corresponding to 123 banks from 13 countries (see Supplementary Appendix Table A2).

Our methodology consists of estimating the probability that a bank reports to the BLS to be adversely affected by the negative interest rates based on a probit regression. We first construct the dependent variable NDFR, which is a dummy variable that equals 1 if the bank reported that the ECB's negative deposit facility rate contributed to a decrease of its net interest income (NII) in the past six months and 0 otherwise. The variable is constructed using a semi-annual question of the BLS. The exact wording of the question is: 'Given the ECB's negative deposit facility rate, did this measure, either directly or indirectly, contribute to a decrease/increase of your bank's net interest income over the past six months?'[17] In our sample, NDFR equals 1 in 73% of the observations. This figure is representative of the share of outstanding credit associated with banks with NDFR = 1. For instance, in June 2014 this share was 80%. Moreover, the vast majority of observations for which NDFR equals 0 correspond to banks that responded that the negative DFR had no impact on their NII, since just around 1% of the banks reported a positive impact.

The regressors are bank characteristics that capture transmission mechanisms through which negative interest rates affect banks. Following studies such as Heider et al. (2019) Schelling and Towbin (2020), Eggertsson et al. (2020), Heider et al. (2021) and Bittner et al. (2021), we use the deposit ratio, the ratio of the deposits by households

16 For more detailed information about the survey, see Köhler-Ulbrich et al. (2016). Visit also https://www.ecb.europa.eu/stats/ecb_surveys/bank_lending_survey/html/index.en.html.

17 In additional analysis, we find that banks' answers to the BLS have substantial predictive power about the evolution on banks' lending margins. In particular, we compute the correlation over time (quarters) between the average margins (both on average loans and riskier loans), computed with the banks' answers to the BLS, and the bank lending spread, defined as the difference between the composite bank lending rate and the 3-month Euribor (smoothed by a two-quarter moving average). While the highest correlations are contemporaneous (close to 0.7 in the case of riskier loans and 0.6 in the case of average loans), the correlations between lagged BLS margins and the bank lending spread are sizeable, especially in the case of lags of 1 or 2 quarters.

and firms to total assets. We also include a liquidity ratio, which is the sum of cash, holdings of government securities and Eurosystem deposits over total assets.[18] In addition, affected banks may have a high share of floating-rate loans or short-term loans, which are repriced at a lower rate following a reduction in the official interest rate. Therefore, we also include the weight of loan overdrafts and loans with a maturity up to one year in the total stock of loans, respectively. This may be an important, additional and orthogonal channel because Kirti (2020) shows that banks with more deposits also tend to have more fixed-rate or long-term loans. We then estimate a probit model of NDFR on the aforementioned regressors, as shown in the following equation:

$$NDFR_{it} = \beta_0 + \beta_1 Liquidity\ \ Ratio_{it} + \beta_2 Deposit\ \ Ratio_{it} + \beta_3 Weight\ \ Loan\ \ Overdrafts_{it} + \beta_4 Loans\ \ up\ \ 1y_{it} + X_{it}^{'}\beta_5 + \varepsilon_{it} \quad (1)$$

where $X_{it}^{'}$ denotes a vector of control variables that capture banks' solvency (ratio of capital and reserves to total assets), profitability (ROE), size (log of total assets) and Eurosystem borrowing (ratio of total borrowing from the Eurosystem to total assets). Size is included because there is a growing literature that highlights its importance as a determinant of banks' response to monetary policy shocks (Kashyap and Stein, 1995, 2000; Kishan and Opiela, 2000) and because there is substantial heterogeneity in the sample. The reason is that large banks, compared to small and stand-alone banks, can use the structure of their banking groups and their affiliates to smooth shocks, manage their liquidity through their internal capital markets and diversify their income and funding sources. Bank capital also plays a crucial role in the transmission of monetary policy (Van den Heuvel, 2006; Jiménez et al., 2012). Descriptive statistics of these variables are presented in Supplementary Appendix Table A3. Needless to say, Equation (1) does not have a causal interpretation, as it only aims to predict the out-of-sample probability that a bank is adversely affected by the negative interest rates using balance-sheet variables that are correlated with the variable NDFR. This will allow us to extend our econometric analyses beyond the 10 Spanish banks that participate in the BLS to a larger sample of credit institutions from this country.

The average marginal effects are reported in Table 2. In column (1), as expected, we find that banks with more deposits and more liquid balance sheets are more likely to report an adverse effect of the negative interest rates on their NII. In contrast, the shares of overdraft and short-term loans are not significant predictors, and neither is size. Regarding the rest of controls, banks with low capital ratios, more borrowing from the Eurosystem and lower ROE (although the coefficient of ROE is only marginally significant) are also more likely to report an adverse effect. This suggests that weaker banks, in

18 We do not include excess liquidity (Basten and Mariathasan, 2018; Demiralp et al., 2019) in our regressions because this information is missing for a non-negligible number of banks. However, we obtain similar results for the subsample of banks for which this variable is available when it is included in our analyses. In our sample, the correlation between liquidity ratio and excess liquidity is 0.54.

Table 2. Bank characteristics correlated with the probability that its net interest income is adversely affected by negative interest rates

	(1)	(2)	(3)
Liquidity ratio	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)
Deposit ratio	0.001**	0.001***	0.002***
	(0.001)	(0.000)	(0.001)
Weight loan overdrafts	0.200	0.071	0.223
	(0.136)	(0.116)	(0.139)
Weight loans up to 1 year	−0.155	−0.116	−0.092
	(0.113)	(0.097)	(0.114)
Capital ratio	−0.009***		−0.009***
	(0.002)		(0.002)
ROE	−0.002*		−0.002*
	(0.001)		(0.001)
Eurosystem borrowing	0.020***		0.020***
	(0.005)		(0.005)
Size	0.009		0.012
	(0.009)		(0.009)
Average deposit rate			−0.017
			(0.039)
Deposit ratio × Average Deposit rate			−0.001***
			(0.001)
Observations	1,528	1,756	1,528
Number of banks	123	129	123

Column (1) shows the average marginal effects of the probit model in Equation (1) in which the dependent variable NDFR is a dummy that equals 1 if the negative DFR decreased the bank's net interest income and 0 otherwise. Column (2) displays a variation of Equation (1) in which we exclude some control variables. Column (3) presents another variation of Equation (1) in which we add the Average Deposit rate (i.e. the interest rate on deposits by households) in each country, as well as the interaction between that variable and the deposit ratio. The regressors are bank characteristics. Liquidity ratio is the sum of cash, holdings of government securities and Eurosystem deposits over total assets. Deposit ratio is the sum of deposits by firms and households over total assets. Weight loan overdrafts and Weight loans up to 1 year are the loans with their respective maturities over the total stock of loans to the private non-financial sector. Capital ratio is capital and reserves over total assets. ROE is net income over total equity. Eurosystem borrowing is the ratio of total borrowing from the Eurosystem to total assets. Size is the logarithm of total assets. Average Deposit rate is the average retail deposit rate (i.e. the interest rate on deposits by households) in each country. The sample spans from 2014Q2 to 2018Q2. Heteroscedasticity–robust standard errors in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

terms of lower capital, higher need of Eurosystem funding and lower profitability, are more likely to report a negative impact of the negative interest rates on their NII. As this may lead to some endogeneity problems (e.g. low net interest margins reduce profitability and consequently retained earnings and capital), we check the robustness of our results in column (2) by dropping those controls. The average marginal effects of the key regressors and their statistical significance are remarkably similar, suggesting that we do not face a 'bad control' problem that could bias our estimates (Angrist and Pischke, 2009). Finally, in column (3) we present the results of another robustness check, in which we add to Equation (1) the average retail deposit rate (i.e. the interest rate on deposits by households) in each country, as well as the interaction between that variable and the deposit ratio. As expected, the average marginal effect of that interaction is negative. This means that, while an increase in a bank's deposit ratio is associated with an increase in the probability that it reports an adverse effect on its NII, an increase in the average retail deposit rate of the country where the bank operates reduces such positive association. Hence, in countries and times in which deposit rates are well above (close to) the ZLB, the positive relation between the deposit ratio and the probability of reporting a decline in NII due to the negative interest rates is weaker (stronger). In contrast, the average marginal effect of the average retail deposit rate is not statistically different from zero. This suggests that low deposit rates (arguably, close or at the ZLB) only harm the NII of banks with a high deposit ratio.

We then use the estimates from Equation (1) to predict the probability of NDFR = 1 (henceforth score). The model correctly classifies 73.2% of the observations, understood as predicting a score greater than or equal to 0.5 when NDFR = 1 and a score lower than 0.5 when NDFR = 0. The area under the ROC curve[19] is close to 0.8, which indicates that the accuracy of the model is good. Finally, we keep the score of the 23 Spanish banks in 2014Q2. The median score of the Spanish banks is 75%, its first quartile is 63% and its third quartile is 84%.[20] Therefore, we assume that banks with a score above 75% are the group of affected banks ($Affected_b = 1$), while banks with a score below 75% are the group of non-affected banks ($Affected_b = 0$).

Supplementary Appendix Table A4 displays the means of the variables used in Equation (1) to predict the scores of two groups of Spanish banks, the 10 banks that participate in the BLS and the remaining 13 banks that do not participate in the survey, as of 2014Q2. The table also shows the difference between the means of the two groups for each variable, as well as the *p*-values of two-sample *t* tests on the equality of means. According to those tests, only the means of size (log of total assets) are statistically different between the two groups of banks at a 10% significance level; in particular, BLS banks are, on average, larger than non-BLS banks. In addition, although their means are not statistically different between the two groups, BLS banks exhibit, on average, a higher ROE, a higher capital ratio and a lower deposit ratio, and those differences are sizeable. In any case, as it will be explained in Section 4.1, in all our regression analyses we will control for these and other bank characteristics (size, solvency, profitability, liquidity, reliance on retail deposits, etc.) to avoid an omitted variable bias.

In order to obtain a deeper understanding of the several determinants of reporting being affected by the negative interest rates, Figure 1(A) shows the Shorrocks–Shapley decomposition of the R^2 (Shorrocks, 1982) that is obtained from the estimation of Equation (1) by OLS. In particular, it reports the percentage of the R^2 that is explained by the characteristics that define the banks that are adversely affected by the negative

19 The ROC curve is created by plotting the Sensitivity (the True Positive Rate) against (1-Specificity) (the False Positive Rate). It can also be regarded as a plot of the Power of a test as a function of the Type I Error of the test.

20 In the original sample of ten Spanish banks that participate in the BLS, five banks reported that the ECB's negative deposit facility rate contributed to a decrease of their net interest income (NDFR=1) and 5 banks reported a null effect (NDFR=0) in 2014Q2.

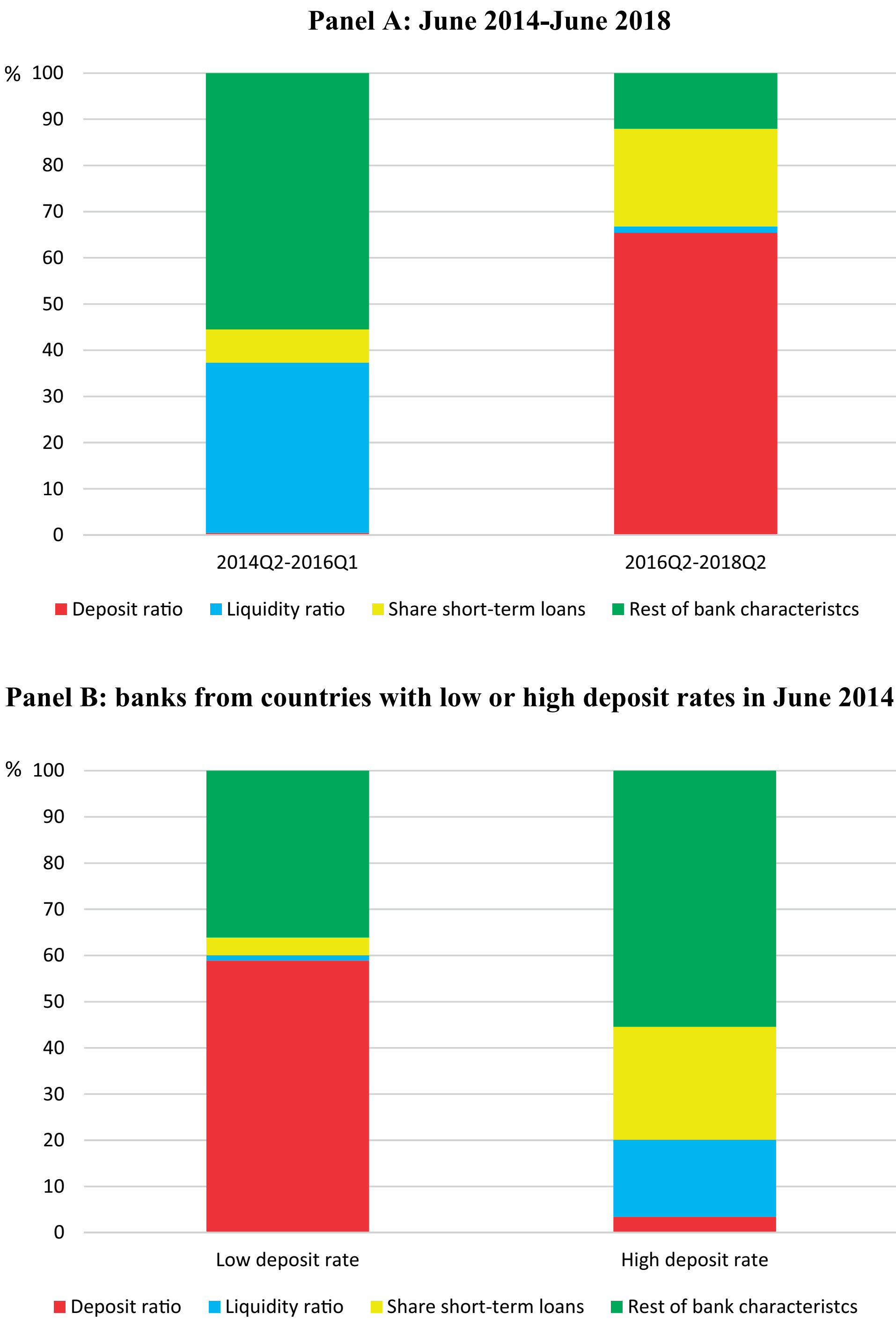

Figure 1. Percentage of R^2 explained by each group of variables (Shorrocks–Shapley decomposition). (A) June 2014 to June 2018; (B) banks from countries with low or high deposit rates in June 2014. This figure contains the percentage of the R^2 explained by the characteristics that define the banks adversely affected by the negative interest rates: deposit ratio (ratio of the deposits by households and firms to total assets),

(Continued)

interest rates: deposit ratio, liquidity ratio and share of short-term loans (overdraft loans and loans with a maturity up to 1 year). We consider an additional category that comprises the control variables of Equation (1): log of total assets, ROE, capital ratio and ratio of total borrowing from the Eurosystem to total assets. The first bar summarizes the percentage of the R^2 explained by each of these bank characteristics based on a sample period that spans from June 2014 to March 2016. During that period, the group of control variables accounts for the highest proportion of the R^2, followed by the liquidity ratio. This evidence is consistent with Bottero et al. (2021), who characterize exposed banks as those with a high share of liquid assets.

The second bar corresponds to the sample period between June 2016 and June 2018. During this period, the interest rates of deposits by households and firms (aggregate deposit rates) gradually approached zero and eventually reached the ZLB in most euro area countries (in Spain, aggregate deposit rates were 0.09% in June 2018, while the interest rate on household deposits was 0.06%, as shown in Figure 2). Accordingly, during that period, the variable that explains by far the highest percentage of the R^2 is the deposit ratio, which corroborates the findings of Heider et al. (2019), Schelling and Towbin (2020), Eggertsson et al. (2020) and Bittner et al. (2021), followed by the share of short-term loans and the group of control variables. In contrast to the previous period (June 2014 to March 2016), the liquidity ratio explains a very small percentage of the R^2.

This evidence suggests that the variable $Affected_b$ allows us to disentangle the effects due to the 'negative for-long' environment (in which the NII of banks with a high deposit share declines if the deposit rate is at the ZLB) from the 'low-for-long' environment (in which the NII of banks with a high deposit share does not necessarily decrease because the deposit rate is above the ZLB). In addition, the share of short-term loans plays a higher role than in the previous period because the persistently negative interest rates could erode net interest margins in a 'negative-for-long scenario'.

In addition, to analyse the role of the so-called initial conditions, i.e. whether deposit rates were well above the ZLB or close to it in the different economies of the euro area when negative interest rates were introduced, we estimate Equation (1) by OLS only with data on June 2014 and for two subsamples, banks from countries with low or high

Figure 1. Continued
liquidity ratio (sum of cash, holdings of government securities and Eurosystem deposits over total assets) and the share of short-term loans (both overdraft loans and loans with a maturity up to 1 year) in the total stock of loans. We consider an additional category that comprises the rest of bank characteristics: size (log of total assets), profitability (ROE), solvency (ratio of capital and reserves to total assets) and borrowing from the Eurosystem (ratio of total borrowing from the Eurosystem to total assets). The results are obtained from the estimation of Equation (1) by OLS. In Panel A, the first bar summarizes the percentage of the R^2 explained by each of these bank characteristics in the period between June 2014 and March 2016. The second bar corresponds to the period between June 2016 and June 2018. In Panel B, the first (second) bar corresponds to banks from countries with low (high) average deposit rates (lower or higher than the median, respectively) in June 2014.

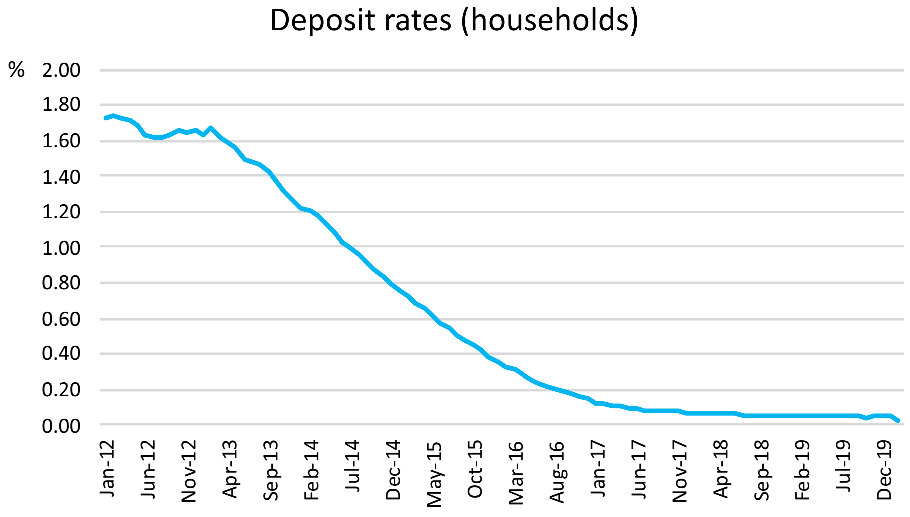

Figure 2. Evolution of interest rates on deposits by households in Spain. This figure depicts the evolution of the interest rates on deposits by households in Spain from January 2012 to February 2020, in percentage terms.

average deposit rates (below or above the median, respectively) and apply the Shorrocks–Shapley decomposition of the R^2. Figure 1(B) shows the results, where the first (second) bar corresponds to banks from countries with low (high) average deposit rates. As expected, in banks from countries with low deposit rates, the variable that explains the highest percentage of the R^2 is by far the deposit ratio, followed by the group of control variables. In contrast, in banks from countries with high deposit rates, the group of control variables accounts for the highest percentage of the R^2, followed by the share of short-term loans and the liquidity ratio, while the deposit ratio only explains a tiny proportion of the R^2. Hence, initial conditions matter, as the deposit ratio was only a strong predictor of the probability of reporting a decline in NII due to the negative interest rates in banks from countries with low average deposit rates in June 2014.

Therefore, the variable $Affected_b$ may be regarded as a summary measure that comprises the several channels (retail deposits, liquid assets, short-term loans) through which the negative interest rates have an adverse effect on banks' net interest income. Nevertheless, in further analyses we will also examine each channel separately.

Finally, note that the variable $Affected_b$ is time-invariant. There are two main reasons for this choice. First, our measure of exposure to negative interest rates exhibits high persistency. To illustrate this phenomenon, we compute the correlation matrix of the bank scores (i.e. the estimated probability that a bank reports that its net interest income decreased because of the negative DFR) in five moments of our sample period: 2014Q2 (Score14q2), 2015Q2 (Score15q2), 2016Q2 (Score16q2), 2017Q2 (Score17q2) and 2018Q2 (Score18q2). The correlation matrix is displayed in Supplementary Appendix Table A5. The correlations are always very high, most of them between 0.8 and 0.95 and some close to 1. Second, as further rate cuts into negative territory cumulated over our sample period 2014Q4–2018Q2, banks could adopt several strategies to mitigate the adverse impact of the negative interest rates on their net interest income (e.g. substituting wholesale funding for funding from retail deposits). Hence, these banks' responses would cause a time-varying variable $Affected_{bt}$ to be endogenous, while the time-invariant variable $Affected_b$, as it is computed with the scores in 2014Q2, at the inception of the negative interest rates era, is not subject to such concern.

4. EMPIRICAL STRATEGY AND RESULTS

4.1. Analysis of banks' credit supply at the bank–firm level

4.1.1. Credit supply of affected banks in a 'negative-for-long' scenario: the role of the zero lower bound. Our identification strategy relies on three pillars. First, as explained in the previous section, a bank is assumed to be affected by the negative interest rates when the estimated probability that it reports that its net interest income decreased because of the negative DFR is higher than 75% (the median probability of the 23 Spanish banks in 2014Q2). It is important to note that, while negative interest rates may also have positive effects on other components of banks' profits, there is no doubt that they squeeze net interest margins. Second, we allow for different effects in different periods by interacting our key regressor, $Affected_b$, a dummy variable that equals 1 for banks affected by the negative interest rates, with time dummies. Therefore, we analyse the dynamic impact of negative interest rates over a protracted period (2014–2019) that comprises two scenarios, a first one with deposit rates above the ZLB (2014–2017) and a second one with deposit rates very close to the ZLB (2018–2019). Third, we control for credit demand by including firm-time fixed-effects *à la* Khwaja and Mian (2008). Therefore, we compare the lending decisions of multiple banks to the same firm within the same time period. While the long time period examined leaves more room for other confounding shocks, the use of firm-time fixed-effects ameliorates this identification problem by controlling for aggregate shocks and the business cycle, as there is a strong correlation between business cycles and credit cycles (e.g. Rünstle and Vlekke, 2018).

Our first empirical model is a type of diff-in-diff estimator with multiple time periods:

$$\begin{aligned}\Delta\ln(Credit)_{ibt} = \alpha_{it} + \alpha_b + \beta_1 Affected_b \times Post.14-16_t + \beta_2 Affected_b \times Post.16-18_t \\ + \beta_3 Affected_b \times Post.18-19_t + \gamma X'_{bt-1} + \varepsilon_{ibt}\end{aligned} \tag{2}$$

where the dependent variable is the growth in the outstanding credit of firm i with bank b at time t. We consider credit growth during four different periods. In particular, we compute credit growth during a period before the interest rates turned negative in June 2014 (between June 2012 and June 2014) and three consecutive periods after this event: June 2014–June 2016, June 2016–June 2018 and June 2018–June 2019. The last period only comprises 1 year in order to avoid the adverse economic effects of the COVID-19 crisis and the measures undertaken by governments and central banks to mitigate such effects (e.g. public credit guarantee programs, debt moratoria, bankruptcy moratoria, central bank lending and asset purchase programs). We do not use another date such as March 2020 or December 2019 to avoid seasonal effects.

Concerning the explanatory variables, *Affected* is a dummy variable denoting banks adversely affected by the negative interest rates, as previously explained.[21] It is interacted with the dummy variables referred to the three periods after June 2014 that are used to define credit growth (*Post.14–16*, *Post.16–18* and *Post.18–19*). In addition, we use firm-time fixed effects (α_{it}) to control for firm-level observed and unobserved heterogeneity in each period (including firms' demand for credit, firms' financial conditions, industry, business model, etc.), bank fixed effects (α_b) to deal with banks' time-invariant heterogeneity and time-varying bank controls (X'_{bt-1}) that are lagged 1 year to avoid a simultaneity bias.[22] Those bank controls are measures of size (log of total assets), solvency (ratio of equity to total assets), profitability (ROA), risk (NPL ratio), liquidity (loan-to-deposit ratio) and reliance on deposit funding (deposit ratio). We also take into account other confounding events that occurred during our sample period and could affect the supply of credit, such as the TLTROs and the APP, by including relevant controls in our regressions. In particular, we control for the effect of TLTRO-I and TLTRO-II by using banks' uptakes over the eligible credit (i.e. credit to firms and credit to households except for loans for house purchase) and by the potential effects of the APP by including banks' holdings of sovereign bonds that are eligible under the PSPP over total assets. This last control mitigates the concern that survey respondents (i.e. loan officers) misunderstand the question and attribute the decline of their NII to the APP rather than to negative rates.[23] The regressors of interest are the three interaction

21 The variable denoting affected banks is a particular type of a generated regressor, given that it has been estimated based on the coefficients obtained from Equation (1) and then transformed to a dummy variable. To deal with this issue, we perform two robustness tests based on resampling techniques. Namely, we estimate Equation (1) and collect the fitted values for the probability of being adversely affected by negative interest rates and the residuals. Then, we randomly scramble the residuals and add them without replacement to the fitted values to obtain synthetic probabilities and estimate Equation (1) using these probabilities as the dependent variable. We repeat this process 100 times such that we end up with 100 estimates for each coefficient to predict 100 scores for our sample of 23 Spanish banks as of 2014Q2. As a first robustness test, we take the average of these scores for each bank and classify banks in our sample as affected if the average score is above 0.75, which corresponds to the same threshold used in our baseline analysis, and as nonaffected if the score is below this figure. We obtain the same categorization for 22 of the 23 banks in our sample. As a second robustness test, we use the new classification of affected and nonaffected banks and estimate Equation (3). Results are reported in Supplementary Appendix Table A6 and support the robustness of our results.

22 The time-invariant variable *Affected* is subsumed into the bank fixed effects and the three dummy variables *Post.14–16*, *Post.16–18* and *Post.18–19* are absorbed by the firm–time fixed effects. The presence of bank fixed effects also precludes the use of an interaction term between *Affected* and a dummy variable denoting the pre-event period June 2012–June 2014.

23 In addition, there is another question of the BLS that specifically asks loan officers about the effect of the APP on banks' balance sheets, including the impact on NII, so that banks must disentangle the effects of the two policies.

terms between *Affected* and the period dummies *Post.14-16*, *Post.16-18* and *Post.18-19*. The estimation of Equation (2) will tell us whether affected banks increased/reduced their credit supply to a given firm (relative to non-affected banks) during each period.[24]

The results are reported in Table 3. Column (1) shows that affected banks reduced their credit supply to firms (relative to non-affected banks) by around 13 percentage points (pp) during the last period (2018–2019). While the coefficient is only statistically significant at the 10% level, it is large and economically significant, as the average credit growth in the sample is −6% for affected banks and −5% for non-affected banks. In contrast, there is no effect during the previous periods. This finding is robust to excluding banks whose probability of reporting that its net interest income decreased because of the negative DFR is close to the threshold (i.e. 75%), as displayed in column (2). In particular, we exclude four banks whose score is in the 73%–77% interval. In fact, the estimated coefficient is slightly larger and it is still statistically significant even though its standard error increases substantially due to the lower number of observations. Our results are also robust to the use of the score (i.e. the estimated probability that a bank reports that its net interest income decreased because of the negative DFR) instead of the dummy variable denoting whether a bank is adversely affected by negative interest rates (see column (3)).

These results are consistent with those of Heider et al. (2019), who find that negative interest rates only become contractionary for lending once deposit rates reach the ZLB. In particular, retail deposit rates were high in Spain at the time of the introduction of the negative interest rates, so they had plenty of room to decline before reaching the ZLB. According to Figure 2, interest rates on deposits by Spanish households were at 1% in June 2014 and reached the ZLB at the end of 2017 (we focus on households' deposits because Altavilla et al. (2021) document that the interest rates on corporate deposits may go negative in the euro area, that is there is no ZLB for corporate deposits). Therefore, the contraction of lending supply by affected banks in the last sample period 2018–2019 was concurrent with the arrival of zero interest rates on households' deposits, even though most of the cuts of the DFR into negative territory took place in previous periods (between June 2014 and March 2016).[25] This result is also in line with the findings of Ampudia and Van den Heuvel (2019), who document a decline in bank equity values of high-deposit banks in Europe in reaction to policy rate cuts into negative territory by the ECB.

24 Standard errors are clustered at the bank-time level. Alternatively, standard errors could be clustered at the bank level to allow for potential heteroskedasticity and serial correlation within banks in the error structure. However, as the asymptotic justification of cluster-robust standard errors assumes that the number of clusters goes to infinity, with a small number of clusters (in our empirical application, 23 banks) cluster-robust standard errors are likely to biased downwards (Bertrand et al., 2004; Angrist and Pischke, 2009), which would overstate the statistical significance of the estimated coefficients.

25 The last DFR cut (by 10 bps) was implemented in September 2019, out of our sample period.

Table 3. Variation in the supply of credit of affected banks to firms

	(1)	(2)	(3)
Affected BLS × *Post.14-16*	−0.037	0.022	0.227
	[0.062]	[0.064]	[0.256]
Affected BLS × *Post.16-18*	−0.046	0.015	0.127
	[0.074]	[0.070]	[0.233]
Affected BLS × *Post.18-19*	−0.128*	−0.138*	−0.568*
	[0.073]	[0.083]	[0.322]
Observations	728,398	583,243	728,398
R^2	0.388	0.402	0.388
Firm–Time FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes

Column (1) of this table reports the results obtained from the estimation of Equation (2), where the dependent variable is the growth in the outstanding credit of a given firm i with bank b at time t. We consider credit growth during four periods: June 2012–June 2014, June 2014–June 2016, June 2016–June 2018 and June 2018–June 2019. The variables of interest are three interaction terms obtained as the product of a dummy variable denoting banks adversely affected by negative interest rates (*Affected*) and a series of dummy variables referred to the three time periods after June 2014 used to define credit growth (*Post.14-16*, *Post.16-18* and *Post.18-19*). A bank is assumed to be adversely affected by the negative interest rates when the estimated probability that it reports that its net interest income decreased because of the negative DFR is higher than 75% (see Section 3 for details). In addition, we use firm-time fixed effects, bank fixed effects and lagged bank controls. Bank controls are measures of size (log of total assets), solvency (ratio of equity to total assets), profitability (ROA), risk (NPL ratio), liquidity (loan-to-deposit ratio) and reliance on deposit funding (ratio of deposits to total assets). We also include banks' TLTRO-I and TLTRO-II uptakes over the eligible credit and holdings of sovereign bonds over total assets. In column (2), we present a variation from the baseline analysis in which we exclude banks whose probability of being adversely affected by negative interest rates is close to the threshold (i.e. 75%). Namely, we exclude banks whose probability of being affected is in the 73%–77% interval. In column (3), we report the results obtained when, instead of using the dummy variable denoting whether a bank is adversely affected by negative interest rates or not, we use its score (i.e. the estimated probability that it reports that its net interest income decreased because of the negative DFR). Standard errors are reported in brackets and are clustered at the bank-time level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

In addition, a complementary explanation is that, in a prolonged period of low/negative interest rates, banks may eventually reduce their intermediation activity, as the persistent negative effect on net interest margins outweighs the potential increase in credit demand (Brei et al., 2019). In fact, as also shown in Figure 2, interest rates on retail deposits were already very low since 2016. According to this hypothesis, affected banks curtailed their credit supply to firms as a consequence of a protracted period of low deposit rates, which squeezed their net interest margins and ended up eroding their profits. Finally, note that, given our identification strategy (a diff-in-diff estimator), we estimate *relative* effects, which implies that we cannot rule out the possibility that affected banks did not reduce credit at all, while non-affected banks could expand it by lending out their excess reserves.

While our key regressor in the previous analyses (*Affected*) may be interpreted as a summary measure of exposure to negative interest rates, our results are robust to alternative ways to gauge the exposure to negative interest rates (i.e. whether banks are adversely affected by them or not). These alternative metrics are solely based on hard data, which rules out concerns about banks' self-assessment of the impact on negative interest rates on their balance sheets in our baseline identification strategy. Moreover, these additional measures of exposure enable us to identify the specific channel through which negative interest rates have a contractionary impact on the credit supply of affected banks in the last sample period 2018–2019. Our analyses are based on the results depicted in Figure 1, which shows the percentage of the R^2, obtained from the estimation of Equation (1) by OLS, which is explained by the characteristics of the banks adversely affected by the negative interest rates (deposit ratio, liquidity ratio and share of short-term loans) and other controls (size, ROE, capital ratio and borrowing from the Eurosystem). The first bar summarizes the percentage of the R^2 explained by each of these bank characteristics between June 2014 and March 2016 (first period), while the second bar corresponds to the time span between June 2016 and June 2018 (second period). During this second period, the variable that explains the highest percentage of the R^2 is the deposit ratio, followed by the share of short-term loans. This means that, during the last years of our sample, the reliance on deposit funding and, to a lesser extent, the share of short-term loans, were the main channels through which negative interest rates affected banks adversely. Therefore, we focus the following analysis on these two dimensions.

The estimation results are presented in Table 4. Column (1) replicates our baseline analysis (previously displayed in Table 3), in which a bank is assumed to be affected by the negative interest rates when the estimated probability that it reports that its net interest income decreased because of the negative DFR is higher than 75%. In column (2), following the arguments of Heider et al. (2019), Schelling and Towbin (2020), Eggertsson et al. (2020), Heider et al. (2021) and Bittner et al. (2021), banks are considered to be adversely affected by the negative interest rates when their deposit ratio is above the median of the distribution of the banks in our sample as of December 2013. Therefore, our dummy variable *Affected* now equals 1 for banks with a deposit ratio higher than the median and 0 otherwise. The intuition behind this variable is banks' reluctance to charge negative interest rates on their retail deposits. If interest rates on retail deposits reach the ZLB, then policy rate cuts to negative levels are not transmitted to this funding source, while the rest of banks' liabilities (e.g. wholesale funding) are repriced at lower rates. Thus, banks with high deposit ratios have higher funding costs than banks that rely less on retail deposits and more on wholesale funding. In column (3), banks are classified as adversely affected by the negative interest rates (*Affected* = 1) if their share of credit to firms and households at a floating rate is above the median of the shares of the banks in our sample as of December 2013. The rationale behind this variable is that floating-rate loans are repriced at a lower interest rate following a reduction in the policy rate, which squeezes banks' net interest margins and erodes their net interest income. Finally, in column (4) we classify banks as adversely affected by the negative interest rates if the sensitivity of their net interest income (NIM) to monetary policy (proxied by the 3-month Euribor since 1999 and by the 3-month Mibor between 1995

Table 4. Variation in the supply of credit to firms by affected banks. Alternative measures of exposure to negative interest rates

	(1) High prob. NII decreases because of the negative DFR	(2) High deposit share	(3) High share of credit at floating rates	(4) High sensitivity of NIM to monetary policy
Affected BLS × *Post.14-16*	−0.037	−0.042	−0.021	−0.107
	[0.062]	[0.049]	[0.071]	[0.072]
Affected BLS × *Post.16-18*	−0.046	−0.035	−0.019	−0.179***
	[0.074]	[0.059]	[0.072]	[0.074]
Affected BLS × *Post.18-19*	−0.128*	−0.112*	−0.133*	−0.217***
	[0.073]	[0.059]	[0.074]	[0.075]
Observations	728,398	728,398	728,398	728,398
R^2	0.388	0.388	0.388	0.388
Firm–Time FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Bank controls	YES	YES	YES	YES

This table reports the results obtained from a variation of Table 3 in which we consider alternative channels through which negative interest rates affect banks' net interest income (NII). In column (1) banks are classified as adversely affected by the negative interest rates if the estimated probability that they report that its NII decreased because of the negative DFR is higher than 75% (see Section 3 for details). In column (2), banks are considered as adversely affected by the negative interest rates when the share of deposits over total assets is above the median of the distribution of the banks in our sample as of December 2013. The larger the share of deposits, the larger are banks' funding costs because negative interest rates are not passed on to retail depositors. In column (3), we classify banks as adversely affected by the negative interest rates if a high share of their credit is granted at a floating rate. The larger this share, the larger the income that is adjusted at lower interest rates following a policy rate cut. More specifically, we consider that a bank is affected according to this measure when the share of its credit to firms and households at a floating rate is above the median of the shares of the banks in our sample as of December 2013. In column (4), we classify banks as adversely affected by the negative interest rates if the sensitivity of their net interest income (NIM) to monetary policy (proxied by the 3-month Euribor since 1999 and by the 3-month Mibor between 1995 and 1998) is higher than the median, as explained in the main text. The set of control variables and fixed effects used in this estimation is that used in Table 3. Standard errors are reported in brackets and are clustered at bank-time level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

and 1998) is higher than the median,[26] following the methodology of Drechsler et al. (2021).[27] In the four cases, the coefficient of interest, which is the one of the interaction between *Affected* and *Post.18-19*, is negative and statistically significant. In particular,

26 Mibor stands for Madrid Interbanking Offered Rate. The Mibor was obtained daily by computing a weighted average of the operations of several maturities between banks. It was the main reference interest rate for mortgage loans in Spain. It was replaced by the Euribor since the onset of the euro area on 1 January 1999 (the Euribor was not available before that date).

27 We estimate the sensitivity of a bank's net interest margin (NIM, computed as the ratio of net interest income to total assets) to monetary policy (proxied by the 3-month Euribor since 1999 and by the 3-month Mibor between 1995 and 1998) by running the following regression: $\Delta NIM_{it} = \alpha_i + \delta_t + \sum_{\tau=0}^{1} \beta_{i,\tau} \Delta Euribor_{t-\tau} + \varepsilon_{it}$ where ΔNIM_{it} is the change in bank i's net interest margin from $t-1$ to t, $\Delta Euribor_t$ is the change in the Euribor/Mibor from $t-1$ to t, α_i are bank fixed effects and δ_t are time fixed effects. The sample comprises the 23 banks of our study, with annual observations between 1995 and 2019. Our estimate of bank i's sensitivity is the sum of the beta coefficients in the above equation, that is $\beta_i^{NIM} = \sum_{\tau=0}^{1} \beta_{i,\tau} = \beta_{i,0} + \beta_{i,1}$. When then sort the 23 β_i^{NIM}, so that affected (nonaffected) banks are those with a β_i^{NIM} higher (lower) than the median of the distribution.

affected banks reduced their credit supply to firms (relative to non-affected banks) between 11 pp and 22 pp during the last period (2018–2019). Therefore, regardless of the measure of exposure, affected banks eventually contracted their credit supply when interest rates stayed in negative territory during a protracted period, so that deposit rates ended up reaching the ZLB.

Finally, the use of a diff-in-diff estimator to study the long-run persistence of a shock such as the introduction of the negative interest rates may face an identification challenge if both the treatment and control groups can adjust their exposures to the shock (i.e. their deposit and liquidity ratios) over time. In particular, as affected banks tend to have more deposits and more liquid balance sheets, they could reduce their exposure over time to mitigate the adverse impact on their net interest income. We test this hypothesis in the last section of the Supplementary Appendix, in which we also study the evolution of the market shares of affected and non-affected banks in the segment of loans to NFCs.

4.1.2. Credit supply of affected banks in a 'negative-for-long' scenario: the amplification effect of low bank capital. Following previous arguments about the relationship between capital, credit growth and risk taking, we now differentiate between high-capital and low-capital banks: those whose capital ratio was above/below the median capital ratio in December 2013, i.e. before the DFR turned negative. Therefore, in the following analyses our key regressor will be the interaction between the dummy *Affected* and the dummy *Low Capital*, where *Affected* denotes the banks adversely affected by the negative interest rates according to our baseline definition. Thus, we propose the following empirical model, which is an extension of Equation (2), to analyse the amplifying effect of low capital on the credit supply of affected banks relative to non-affected banks in different periods:

$$\begin{aligned}\Delta\ln(Credit)_{ibt} = {} & \alpha_{it} + \alpha_b + \beta_1 Affected_b \times LowCapital_b \times Post.14-16_t + \beta_2 Affected_b \\ & \times LowCapital_b \times Post.16-18_t + \beta_3 Affected_b \times LowCapital_b \\ & \times Post.18-19_t + \beta_4 Affected_b \times HighCapital_b \times Post.14-16_t \\ & + \beta_5 Affected_b \times HighCapital_b \times Post.16-18_t + \beta_6 Affected_b \\ & \times HighCapital_b \times Post.18-19_t + \gamma X'_{bt-1} + \varepsilon_{ibt} \qquad (3)\end{aligned}$$

where *Low Capital* (*High Capital*) is a dummy variable that denotes whether a bank's CET1 capital ratio was below (above) the median of the CET1 capital ratios of the banks in our sample as of December 2013. The rest of variables are the same as in Equation (2). The estimation of Equation (3) will show whether low-capital affected banks and high-capital affected banks increased/reduced their credit supply to a given firm (relative to non-affected banks) during each period.

The corresponding results are presented in Table 5, which shows that the effect of the negative interest rates on banks' credit supply depends on banks' capitalization levels. In particular, only affected low-capital banks (i.e. banks with capital ratios below the

Table 5. Variation in the supply of credit to firms by affected banks depending on their capital ratio

	(1)	(2)
Affected bank × Low capital × *Post.14-16*	−0.087	−0.029
	[0.061]	[0.064]
Affected bank × Low capital × *Post.16-18*	−0.092	−0.022
	[0.082]	[0.081]
Affected bank × Low capital × *Post.18-19*	−0.150**	−0.153*
	[0.076]	[0.091]
Affected bank × High capital × *Post.14-16*	0.029	0.098
	[0.071]	[0.066]
Affected bank × High capital × *Post.16-18*	0.011	0.070
	[0.080]	[0.068]
Affected bank × High capital × *Post.18-19*	−0.089	−0.100
	[0.078]	[0.092]
Observations	728,398	583,243
R^2	0.388	0.402
Firm–Time FE	Yes	Yes
Bank FE	Yes	Yes
Bank controls	Yes	Yes

Column (1) of this table reports the results obtained from the estimation of Equation (3), in which the group of banks adversely affected by the negative rates is split into two, depending on whether their CET1 capital ratio is above or below the median of the CET1 capital ratios of the banks in our sample as of December 2013 (i.e. before the DFR turned negative). Thus, the control group consists of non-affected banks. The set of control variables and fixed effects used in this estimation is that used in Table 3. In column (2), we present a variation of column (1) and exclude banks whose probability of being adversely affected by the negative interest rates is in the 73%–77% interval. Standard errors are reported in brackets and are clustered at bank-time level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

median in December 2013) exhibited a decline in credit growth between 2018 and 2019 relative to non-affected banks. According to column (1), affected low-capital banks reduced their credit supply to firms (relative to non-affected banks) by around 15 pp during the last period (2018–2019), i.e. when deposit rates reached the ZLB. This effect is somewhat larger than the one obtained with the estimation of Equation (2) for the same period (13 pp), as previously explained and displayed in column (1) of Table 3. This result provides evidence of the amplifying effect of low capital on the credit supply of banks adversely affected by the negative interest rates. In contrast, there is no effect for the group of affected high-capital banks (i.e. banks with capital ratios above the median in December 2013). We obtain similar results when excluding banks whose score is close to the threshold (i.e. 75%), as displayed in column (2). Again, the estimated coefficient is somewhat larger than the one obtained with the estimation of Equation (2) for the last period 2018–2019 (−0.15 versus −0.14, as reported in column (2) of Tables 3 and 4, respectively), which suggests that the contractionary effect of the negative interest rates on the credit supply of affected banks is particularly severe in the case of banks with ex-ante low capital.

This evidence is also in line with the theoretical prediction of Brunnermeier and Koby (2019) on the reversal rate. In particular, following a policy rate cut, if the capital gains from re-evaluation of banks' assets are too low to compensate the loss in net interest margins, then net worth decreases to the point where the capital constraint binds, which limits banks' ability to grant new loans. In that context, monetary policy becomes contractionary for lending. Against this backdrop, our results also suggest that the reversal rate is bank-specific and dependent on banks' initial capitalization levels. The fact that the effect is only significant in the last period (2018–2019) would also be consistent with Brunnermeier and Koby (2019), who show that the reversal rate 'creeps up' over time: Given a fixed policy rate, in a 'low-for-long' scenario banks may end up curtailing lending.[28]

As the estimations include firm-time fixed effects, this method effectively drops all firms that do not borrow from multiple banks in the same year, which may threaten the external validity of the exercise. Hence, as a robustness check, we have replaced firm-time fixed effects by industry-location-size-time fixed effects in the estimation of Equation (3). Industry is defined at the three-digit level and location at the NUTS-3 level (i.e. Spanish provinces), while size is split into ten buckets according to the deciles of firms' total assets and time corresponds to the years between 2012 and 2019. The results, presented in Supplementary Appendix Table A7, are very similar, which indicates that the main findings are not driven by the distinct lending behaviour of banks to firms that borrow from multiple credit institutions in the same year.[29]

Table 6 is a variation of Table 5, in which we conduct a couple of robustness tests regarding the timing of capital requirements and the concept of low/high capital banks. We use column (1), which is identical to column (1) in Table 5, as a benchmark. In column (2) we exclude the period 2014–2016, such that we compare the variation of credit between 2016 and 2018 and between 2018 and 2019 with that between 2012 and 2014, and classify low and high-capital banks depending on their CET1 capital ratio as of December 2015. In other words, while our reference period is still 2012–2014 (i.e. before the introduction of the negative rates), we analyse the impact of the negative DFR from 2016 onwards. The reason for this alternative exercise is that, in the baseline analyses, credit institutions are classified as low-capital and high-capital banks based on their capital ratios as of December 2013. This implies a long time span between our classification and the last period of the estimation sample, 2018–2019, during which capital ratios may have changed substantially because of banks' issuance of new equity, retained earnings or changes in their risk-weighted assets. Therefore, it may be more appropriate

28 The reversal interest rate "creeps up" over time because asset revaluation fades out as fixed-income holdings mature while net interest income stays low.

29 Comparing columns (1) of Table 5 and Table A7 we find that, by including firm–time fixed effects, we lose about 575,000 observations because there are 267,000 firms that borrow from only one bank in some years. The main reason of the high number of firms with a single lending relationship is the consolidation of the Spanish banking sector that started in 2009, in the midst of the Spanish banking crisis (2008–2012). A comprehensive narrative of the crisis of the Spanish banking system can be found in Santos (2018). Cuñat and Garicano (2009) also provide a thorough analysis of the structural problems of the Spanish savings banks.

Table 6. Variation in the supply of credit to firms by affected banks depending on their capital ratio. Alternative measures of banks' capital position

	(1) CET1	(2) CET1	(3) Capital Buffer
Affected bank × Low capital × *Post.14-16*	−0.087		
	[0.061]		
Affected bank × Low capital × *Post.16-18*	−0.092	−0.024	0.014
	[0.082]	[0.062]	[0.057]
Affected bank × Low capital × *Post.18-19*	−0.150**	−0.113*	−0.137**
	[0.076]	[0.067]	[0.068]
Affected bank × High capital × *Post.14-16*	0.029		
	[0.071]		
Affected bank × High capital × *Post.16-18*	0.011	0.001	−0.025
	[0.080]	[0.049]	[0.055]
Affected bank × High capital × *Post.18-19*	−0.089	−0.071	−0.060
	[0.078]	[0.052]	[0.056]
Observations	728,398	726,117	671,436
R^2	0.388	0.388	0.396
Firm–Time FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes

Column (1) of this table reports the results obtained from the estimation of Equation (3), in which the group of banks adversely affected by the negative rates is split into two, depending on whether their CET1 capital ratio is above or below the median of the CET1 capital ratios of the banks in our sample as of December 2013 (i.e. before the DFR turned negative). Thus, the control group consists of non-affected banks. The set of control variables and fixed effects used in this estimation is that used in Table 3. In column (2) we exclude the period 2014–2016, such that we compare the variation of credit between 2016 and 2018 and between 2018 and 2019 with that between 2012 and 2014, and classify low and high-capital banks depending on their CET1 ratio as of December 2015. In column (3) low-capital banks are those whose CET1 capital ratio in excess of micro- and macro-prudential requirements (i.e. capital buffer) is below the median of the distribution of capital buffers as of December 2015. Standard errors are reported in brackets and are clustered at bank-time level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

to classify banks according to their capital ratios as of December 2015, although *Low Capital* and *High Capital* are not predetermined variables anymore.

An additional robustness analysis is presented in column (3), in which we replace the CET1 capital ratio by the banks' capital buffer, i.e. the CET1 capital ratio in excess of micro- and macro-prudential requirements. The latter variable may be a more precise measure of capital constraints, as Aiyar et al. (2014) show that shifts in the supply of credit are mainly driven by changes to banks' minimum capital requirements (see also Peek and Rosengren, 2005; Giannetti and Simonov, 2013; and Schivardi et al., 2022). In particular, now low-capital banks are those whose capital buffer is below the median of the distribution of capital buffers as of December 2015. The capital buffers are obtained using banks' consolidated information because capital requirements are established at the consolidated level. Given that this information is not available for all the banks in our sample, the number of observations in column (3) is lower than that in columns (1) and (2). In particular, we cannot use five banks of our sample, in some cases because we do not have detailed information on their capital requirements and, in other cases, because the bank in our sample is a subsidiary. This is the main reason why, in order to maximize sample size, we use unconsolidated banks' financial statements in our baseline analyses. In addition, in the case of large multinational banks, the use of consolidated financial statements may lead to include overseas business activities, some of them in economies characterized by (very) high interest rates, which would weaken the identification strategy. Nevertheless, the results are robust to these alternative specifications: according to columns (2) and (3) of Table 6, affected low-capital banks reduced their credit supply to firms (relative to non-affected banks) between 11 pp and 14 pp, respectively, during the last period (2018–2019). This finding is of particular significance, owing to the substantial increase in regulatory capital requirements during the period analysed.[30]

We also conduct a falsification test to rule out that most of the previous results are merely driven by the impact of low capitalization on banks' credit supply, as opposed to the effect of the negative interest rates. In other words, if accumulating capital deficits – due to the inability to build up capital organically through retained earnings or by issuing new equity – are an important constraint in their own right, could this alone explain the slower credit growth of low-capital banks in the later part of the sample (rather than negative interest rates)? To answer this question, we propose a modification of Equation (3) in which the variable *Affected* is absent:

$$\Delta \ln(Credit)_{ibt} = \alpha_{it} + \alpha_b + \beta_1 Low\ Capital_b \times Post.14-16_t + \beta_2 \times Low\ Capital_b \times Post.16-18_t + \beta_3 Low\ Capital_b \times Post.18-19_t + \gamma X'_{bt-1} + \varepsilon_{ibt} \quad (4)$$

where *Low Capital* (*High Capital*) is a dummy variable that denotes whether a bank's CET1 capital ratio was below (above) the median of the CET1 capital ratios of the banks in our sample as of December 2013 and the rest of variables are the same as in Equation (3). The estimation of Equation (4) will determine whether low-capital banks increased/reduced their credit supply to a given firm (relative to high-capital banks) during each period, *regardless of being affected by the negative interest rates or not.*

The corresponding results are presented in column (1) of Table 7. The three coefficients of interest are not statistically different from zero at conventional confidence levels, which implies that being a poorly capitalized bank does not have a differential impact on a bank's credit supply, once we control for time-invariant heterogeneity and a wide array of time-varying bank characteristics. We reach the same conclusion when

30 The Capital Requirements Directive (CRD IV) and the Capital Requirements Regulation (CRR), in place since January 2014, envisage several capital-based measures to enhance the resilience of the European financial system and limit the build-up of vulnerabilities. Besides macroprudential capital buffers that should be fully implemented as of January 2022, regulators might also require additional buffers to individual financial institutions under Pillar 2 based on either a macro- or micro-prudential perspective.

Table 7. Falsification test. Variation in the supply of credit to firms by banks depending on their capital ratio

	(1)	(2)
Low capital × *Post.14-16*	−0.041	
	[0.061]	
Low capital × *Post.16-18*	−0.043	−0.008
	[0.065]	[0.065]
Low capital × *Post.18-19*	−0.089	−0.075
	[0.063]	[0.048]
Observations	728,398	558,516
R^2	0.387	0.390
Firm–Time FE	Yes	Yes
Bank FE	Yes	Yes
Bank controls	Yes	Yes

Column (1) of this table reports the results obtained from the estimation of Equation (4), in which banks are classified as high-capital or low-capital banks depending on whether their CET1 capital ratio is above or below the median of the CET1 capital ratios of the banks in our sample as of December 2013 (i.e. before the DFR turned negative). The set of control variables and fixed effects used in this estimation is that used in Table 3. In column (2) we exclude the period 2014–2016, such that we compare the variation of credit between 2016 and 2018 and between 2018 and 2019 with that between 2012 and 2014, and classify low and high-capital banks depending on their CET1 ratio as of December 2015. Standard errors are reported in brackets and are clustered at bank-time level. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

inspecting column (2), in which we exclude the period 2014–2016, so that we compare the variation of credit between 2016 and 2018 and between 2018 and 2019 with that between 2012 and 2014, and classify low- and high-capital banks depending on their CET1 capital ratio as of December 2015.

We also exploit firm-level heterogeneity by estimating Equation (3) for different groups of firms. In particular, we split our sample into safe and risky firms according to their leverage ratio (ratio of financial debt to total assets) in order to analyse the effects of the negative interest rates on banks' risk taking (Table 8). In particular, firms are classified as risky if their leverage ratio is above the median of the distribution of the leverage ratio of the firms in our sample, while safe firms are those whose leverage ratio is below the median of that distribution. The main reason is that the former are more likely to default than the latter because of their lower loss-absorbing capacity. Accordingly, it is widely used in the literature on the prediction of corporate bankruptcy and financial distress. For instance, it is one of the components of several indicators such as the Altman's Z-Score (Altman, 1968)[31] or those of Shumway (2001), Chava and Jarrow (2004) and Campbell et al. (2008), amongst others. In addition, according to the literature, firms with higher leverage ratios are more prone to risk-shifting (also called 'gambling for resurrection' or asset-substitution), so that they undertake projects with a

31 In particular, the ratio of the firm's equity to total liabilities. The formula uses the market value of equity or its book value depending on whether the company is listed or not.

Table 8. Variation in the supply of credit to safe and risky firms by affected banks depending on their capital ratio

	(1) All	(2) Safe	(3) Risky
Affected bank × Low capital × *Post.14-16*	−0.087	−0.075	−0.104
	[0.061]	[0.054]	[0.080]
Affected bank × Low capital × *Post.16-18*	−0.092	−0.059	−0.127*
	[0.082]	[0.078]	[0.075]
Affected bank × Low capital × *Post.18-19*	−0.150**	−0.111*	−0.188**
	[0.076]	[0.065]	[0.093]
Affected bank × High capital × *Post.14-16*	0.029	−0.005	0.065
	[0.071]	[0.063]	[0.089]
Affected bank × High capital × *Post.16-18*	0.011	0.001	0.010
	[0.080]	[0.072]	[0.098]
Affected bank × High capital × *Post.18-19*	−0.089	−0.105	−0.064
	[0.078]	[0.075]	[0.094]
Observations	728,398	335,501	340,422
R^2	0.388	0.383	0.389
Firm–Time FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes

This table reports the results obtained from a variation of Table 5 in which we consider two subsamples of firms: safe and risky firms. Column (1) reports the results obtained for the whole sample of firms and is equivalent to column (1) of Table 5. Results in columns (2) and (3) are obtained from subsamples of safe and risky firms, respectively. A firm is assumed to be safe when its leverage ratio is below the median of the distribution of the leverage ratios of the firms in our sample, while risky firms are those whose leverage ratio is above the median of that distribution. Note that the sum of the number of observations for safe firms and risky firms is somewhat lower than the number of observations for all firms. The reason behind is that the whole sample includes all the firms in the Central Credit Register, but we do not have information on the financials of some of those firms. The set of control variables and fixed effects used in this estimation is that used in Table 3. Standard errors are reported in brackets and are clustered at bank-time level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

higher probability to fail (e.g. Ben-Zion and Shalit, 1975; Jensen and Meckling, 1976; Carling et al., 2007).[32]

In this exercise, we find that low-capital affected banks reduced their credit supply to risky firms (relative to non-affected banks) in the last two periods, 2016–2018 and 2018–2019, although the effect is substantially larger and more statistically significant in the latter period. In contrast, there is only a marginally significant negative effect in the subsample of safe firms in the last period (2018–2019) and the size of the effect is considerably lower than that for risky firms.[33] This evidence is consistent with the risk-bearing capacity hypothesis (Gambacorta and Mistrulli, 2004; Adrian and Shin, 2010; Kim and

32 We obtain very similar results (available upon request) when using the interest coverage ratio (ICR) as an alternative measure of default risk. The ICR is the ratio of a company's EBITDA to its interest expense. We classify a firm as safe if its ICR is greater than or equal to 1, while we classify a firm as risky its ICR is lower than 1. The condition that the ICR is lower than 1 is usually called cash-flow insolvency: a company is cash flow insolvent if it is unable to pay its debts as they fall due.

33 Notice that the sum of the number of observations for safe firms (column (2)) and risky firms (column (3)) is somewhat lower than the number of observations for all firms (column 1). The reason behind is that the whole sample includes all the firms in the Central Credit Register, but we do not have information on the balance sheets or the profit and loss accounts of some of those firms.

Sohn, 2017), which states that undercapitalized banks take less risks because of the lack of capital buffers to absorb losses and the need to meet capital requirements. In this context, undercapitalized banks might improve their regulatory capital ratios by decreasing their risk-weighted assets via a reduction of credit to households and firms and by investing in safe assets such as government bonds, which carry a zero risk-weight (Bongiovanni et al., 2021). Our results also indicate that affected low-capital banks curtailed their credit supply to risky firms before restricting it to safe firms and in a greater magnitude, arguably because loans to the former consumed more regulatory capital than credit to the latter. Moreover, during the post crisis period low net worth banks were under particularly intense regulatory scrutiny about their lending policies and risk taking behaviour. Thus, our results should not be interpreted based solely on the risk taking channel of monetary policy but also on the interaction between monetary and macroprudential policies.

4.2. Pass-through of negative interest rates to lending rates of affected and poorly capitalized banks

We next investigate the pass-through of the negative interest rates to banks' lending rates on loans to firms.[34] We consider banks' interest rates in two dates: June 2018 and June 2019, which correspond to the last period used in the previous analyses and during which low-capital affected banks reduced their credit supply to firms. There is no available information on banks' interest rates at the loan level before June 2018. Therefore, this analysis is conducted on two dates in which the DFR was already negative, based on the following specification:

$$ir_{ibt} = \alpha_{im} + \alpha_{lct} + \beta_1 Affected_b \times Low\ \ Capital_b + \beta_2 Affected_b \times High\ \ Capital_b + \gamma X'_{bt-1} + \varepsilon_{it} \tag{5}$$

where α_{im} are firm-maturity fixed effects, where the variable maturity is split into 10 buckets according to its deciles, and α_{lct} are loan-characteristics fixed effects, which correspond to the interaction between dummy variables denoting several loan characteristics (type of guarantee, type of credit contract, interest rate of reference) and time fixed effects.[35] Regarding the type of guarantee, we consider several categories such as no

34 Those interest rates do not include fees.

35 For floating rate loans, controls such as the type of guarantee, the interest rate of reference and the type of credit contract influence the *spread* to the reference rate (a spread that is usually set at origination). Since the dependent variable in Equation (5) is the *level* of the loan interest rate, these controls could have a different effect on that level depending on the time period if the reference rate changes over time. In that case, the relevant controls should be dummies interacted with time effects rather than just dummies. However, the reference rate, the Euribor 3 months, barely changed between June 2018 (−0.32%) and June 2019 (−0.33%), rendering the two strategies very similar.

guarantee, collateral or personal guarantee. Mosk (2018) shows that decisions regarding guarantees are taken prior to both interest and non-interest rate decisions in loan contracts, implying that our guarantee variable is a predetermined control. The type of credit contract refers to financial credit, commercial credit, leasing, factoring, etc. For the interest rate of reference, we consider fixed rates and several types of floating rates. This identification scheme allows us to compare the interest rates charged on two similar loans granted to the same firm by a low-capital affected bank and by a non-affected bank. The estimation of Equation (5) will tell us whether low-capital affected banks and high-capital affected banks increased/reduced their lending rates to firms relative to non-affected banks between 2018 and 2019.

The estimations are presented in Table 9. Columns (1) and (3) exclude the size of the loan, because this characteristic could be jointly determined with the loan's interest rate, which would make it a 'bad control' (Angrist and Pischke, 2009). However, its inclusion in columns (2) and (4) does not substantially change the main results. In columns (1) and (2), we estimate a restricted version of Equation (5), in which the loan's interest rate is regressed on the dummy variable *Affected*, the previous sets of fixed effects and time-varying bank controls. The results are similar in both columns: The coefficient of interest is not statistically different from zero, which implies that affected banks did not charge higher interest rates to firms than non-affected banks. In columns (3) and (4) we estimate Equation (5), splitting affected banks into low-capital and high-capital ones. The results are very alike, as the coefficient of interest is not statistically significant, which means that there were no significant differences in the interest rates charged by low-capital affected banks and those charged by non-affected banks. Similarly, high-capital affected banks did not seem to charge higher interest rates to firms than non-affected banks (there is only a marginally significant coefficient in column (3), where we do not control for loan size).

In sum, both affected banks and low-capital affected banks did not transmit their higher funding costs to their borrowers during the period 2018–2019, arguably because firms borrowing from those banks could substitute away from them (i.e. loan demand was perfectly elastic). We will explore this hypothesis in more depth in the following section.

4.3. Credit supply of affected and poorly capitalized banks in a 'negative-for-long' scenario: a firm-level analysis

Finally, we aggregate our loan-level dataset at the firm level to investigate whether the companies operating with affected banks experienced a contraction in their overall

Table 9. Variation of interest rates charged by affected banks depending on their capital ratio

	(1)	(2)	(3)	(4)
Affected bank	0.131	0.090		
	[0.082]	[0.071]		
Affected bank × Low capital			0.188	0.137
			[0.111]	[0.105]
Affected bank × High capital			0.126*	0.086
			[0.074]	[0.068]
Observations	121,336	121,336	121,336	121,336
R^2	0.819	0.831	0.819	0.831
Firm-maturity FE	Yes	Yes	Yes	Yes
Guarantee type-type of credit-IR reference-time FE	Yes	Yes	Yes	Yes
Loan size	No	Yes	No	Yes
Bank controls	Yes	Yes	Yes	Yes

This table reports the results obtained from the estimation of Equation (5), where the dependent variable is the interest rate of each loan granted by a given bank *b* to firm *i*. We consider banks' interest rates in two months: June 2018 and June 2019. Data on interest rates at the loan level are not available before June 2018. In columns (1) and (2), we estimate a restricted version of Equation (5) in which we do not split the banks depending on their capital ratio, such that the variable of interest (*Affected*) is a dummy variable that equals 1 if the estimated probability that a bank reports that its NII decreased because of the negative DFR is higher than 75% and 0 otherwise (see Section 3 for details). The results in columns (3) and (4) are obtained from the estimation of Equation (5) such that the group of banks adversely affected by the negative rates is split into two, depending on whether their CET1 capital ratio was above or below the median of the CET1 capital ratios of the banks in our sample as of December 2013 (i.e. before the DFR turned negative). In addition, we use firm-maturity fixed effects, where the variable maturity is split into ten buckets according to its deciles, loan-characteristics fixed effects, which correspond to the interaction between dummy variables denoting several loan characteristics (type of guarantee, type of credit contract, interest rate of reference) and time fixed effects, and bank controls as of December 2017. Columns (2) and (4) also include loan size as an additional control. Standard errors are reported in brackets and are clustered at bank-time level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

bank credit or were able to mitigate the effect by borrowing more from non-affected banks. Our empirical model is the following:

$$\begin{aligned}\Delta\ln(Credit)_{it} = {} & \hat{\alpha}_{it} + \alpha_t + \beta_1 MainBankAffected_i + \beta_2 MainBankAffected_i \times Post.14-16_t \\ & + \beta_3 MainBankAffected_i \times Post.16-18_t + \beta_4 MainBankAffected_i \\ & \times Post.18-19_t + X'_{\mathrm{mb}t-1} + \varepsilon_{it}\end{aligned} \tag{6}$$

where the dependent variable is the growth of the total outstanding credit of firm *i* at time *t*. We consider credit growth during the same four periods as in Equation (2). With respect to the explanatory variables, *Main Bank Affected* is a dummy variable that equals 1 if the firm's main bank is affected by the negative interest rates and has a low capital ratio, and 0 otherwise. To put it differently, we assume that a firm is affected by the negative interest rates if its main bank is affected by them and has a low capital ratio, since this is the only group of banks that reduced their credit supply to firms, as shown in previous analyses. The firm's main bank is that with the highest share of credit in the company. We also include estimates of firm credit demand ($\hat{\alpha}_{it}$) obtained from Equation (3), as in Cingano et al. (2016) and Bonaccorsi di Patti and Sette (2016). The inclusion of

Table 10. Variation in the supply of credit to safe and risky firms by affected banks depending on their capital ratio. Firm level analysis

	(1) All	(2) Safe	(3) Risky
Main bank affected × *Post.14-16*	0.016	−0.015	−0.026
	[0.018]	[0.025]	[0.025]
Main bank affected × *Post.16-18*	−0.002	−0.022	−0.043*
	[0.018]	[0.025]	[0.025]
Main bank affected × *Post.18-19*	0.002	−0.033	−0.023
	[0.017]	[0.024]	[0.025]
Main bank affected	−0.023	0.031	0.008
	[0.017]	[0.024]	[0.024]
Observations	256,568	111,867	117,514
R^2	0.915	0.915	0.916
Firm demand controls	Yes	Yes	Yes
Main bank controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

This table reports the results obtained from the estimation of Equation (6), where the dependent variable is the growth of the outstanding credit of a given firm i at time t. We consider credit growth during four periods: June 2012–June 2014, June 2014–June 2016, June 2016–June 2018 and June 2018–June 2019. The variables of interest are three interaction terms obtained as the product of a dummy variable denoting firms whose main bank was adversely affected by the negative interest rates and has a capital ratio below the median (*Main Bank Affected*) and a series of dummy variables referred to the three time periods after June 2014 used to define credit growth (*Post.14-16, Post.16-18* and *Post.18-19*). In addition, we use the firm-time fixed effects estimated in Equation (3) as credit demand controls, time fixed effects and lagged main bank controls. Main bank controls are the log of total assets, the ratio of equity to total assets, ROA, NPL ratio, loan-to-deposit ratio, deposit ratio, banks' TLTRO-I and TLTRO-II uptakes over the eligible credit and the ratio of sovereign bonds to total assets. Results in column (1) are estimated using the whole sample of firms whereas those in columns (2) and (3) are obtained from a subsample of safe and risky firms, respectively. A firm is assumed to be safe when its leverage ratio is below the median of the distribution of the leverage ratios of the firms in our sample, while risky firms are those whose leverage ratio is above the median of that distribution. Note that the sum of the number of observations for safe firms and risky firms is somewhat lower than the number of observations for all firms. The reason behind is that the whole sample includes all the firms in the Central Credit Register, but we do not have information on the financials of some of those firms. Standard errors are reported in brackets and are clustered at bank-time level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

the estimated firm-time fixed effects allows us to control explicitly for potential changes in the credit demand of the firms exposed to low-capital affected banks. In addition, we use time dummies (α_t) to control for aggregate shocks and the same lagged controls for the main bank (X'_{mbt-1}) as in Equation (2).

According to Table 10, we find no significant effects on either safe firms or risky firms, except for a marginally significant negative effect on lending to risky firms between 2016 and 2018. This evidence suggests that the lower supply of credit by low-capital affected banks was offset by the higher lending supply by non-affected banks, with capacity for taking additional risks thanks to their higher capital buffers. Hence, there seems to be no aggregate effect on the credit supply to companies. However, this last conclusion must be drawn with caution, because of the diff-in-diff nature of our analyses and the use of firm-time fixed effects. In particular, if there is an effect of the negative interest rates that is common across all banks, such effect would be absorbed by the firm-time fixed effects and it will not show up in the estimates.

In addition, we carry out a robustness analysis at the firm level using a more stringent definition of being affected by the negative interest rates. In particular, we now assume that a firm is affected by the negative interest rates if the following conditions are satisfied: (i) its main bank is affected by the negative interest rates and has a low capital ratio; (ii) more than 25% of the firm's outstanding credit has been granted by low-capital affected banks. Accordingly, the variable *Affected Firm* is a dummy variable that equals 1 if the two conditions are met and 0 otherwise.[36] Therefore, the new empirical model is the following:

$$\begin{aligned}\Delta\ln(Credit)_{it} = {} & \hat{\alpha_{it}} + \alpha_t + \beta_1 AffectedFirm_i + \beta_2 AffectedFirm_i \times Post.14-16_t \\ & + \beta_3 AffectedFirm_i \times Post.16-18_t + \beta_4 AffectedFirm_i \times Post.18-19_t \\ & + X'_{mbt-1} + \varepsilon_{it}\end{aligned} \tag{7}$$

where, as in the baseline analysis, the dependent variable is the growth of the total outstanding credit of firm i at time t. Similarly, we also include estimates of firm credit demand ($\hat{\alpha_{it}}$), time dummies (α_t) and lagged main bank controls (X'_{mbt-1}).

The estimates of Equation (7) are displayed in Table 11. Again, we find no significant effects on either safe firms or risky firms, except for a marginally significant negative effect on lending to risky firms between 2016 and 2018 and a marginally significant positive effect on lending to safe firms between 2018 and 2019. This robustness analysis provides further evidence that there is no aggregate effect on the credit supply to companies, even when using a more stringent definition of firms affected by the negative interest rates.

In addition, it provides further support to the hypothesis that the lower supply of credit by low-capital affected banks was offset by the higher lending supply by non-affected banks, with capacity for taking additional risks. This differential effect is corroborated by the evolution of the credit granted to non-affected firms.[37] In particular, the annualized credit growth to those firms in the sub-periods June 2014–June 2016, June 2014–June 2018 and June 2014–June 2019 was 3.6%, 2.6% and 6%, respectively. These positive and sizeable growth rates suggest that our identification strategy (i.e. identification through relative exposures) estimate the lower bound of the actual causal effect.

36 To illustrate that this definition is more restrictive let us consider a firm whose main bank is affected and has low capital, its loans only account for 10% of the firm's outstanding credit and other low-capital affected banks have granted loans to the company that represent, in total, 10% of the firm's outstanding credit. As the loans granted by low-capital affected banks to the company only account for 20% of its outstanding credit, the variable *Affected Firm* would equal 0. In contrast, the key variable in the baseline analysis, *Main Bank Affected*, would equal 1.

37 Using the baseline definition, i.e. a firm is affected if its main bank is affected by the negative interest rates and has a low capital ratio. Results (available upon request) are very similar when using the alternative more stringent definition.

Table 11. Variation in the supply of credit to safe and risky firms by affected banks depending on their capital ratio. Firm level analysis. Robustness analysis

	(1) All	(2) Safe	(3) Risky
Affected firm × *Post.14-16*	−0.005	0.033	−0.039
	[0.017]	[0.024]	[0.025]
Affected firm × *Post.16-18*	−0.012	0.037	−0.050*
	[0.018]	[0.024]	[0.027]
Affected firm × *Post.18-19*	0.007	0.045*	−0.013
	[0.017]	[0.024]	[0.025]
Affected firm	−0.028	−0.035	−0.011
	[0.019]	[0.023]	[0.024]
Observations	256,568	111,867	117,514
R^2	0.915	0.914	0.916
Firm demand controls	Yes	Yes	Yes
Main bank controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

This table reports the results obtained from the estimation of Equation (7), where the dependent variable is the growth in the outstanding credit of a given firm i at time t. We consider credit growth during four periods: June 2012–June 2014, June 2014–June 2016, June 2016–June 2018 and June 2018—June 2019. The variables of interest are three interaction terms obtained as the product of the variable *Affected Firm* and a series of dummy variables referred to the three time periods after June 2014 used to define credit growth (*Post.14-16, Post.16-18* and *Post.18-19*). *Affected Firm* is a dummy variable that equals 1 if the firm's main bank is affected by the negative interest rates, it has a low capital ratio and more than 25% of the firm's outstanding credit has been granted by low-capital affected banks, and 0 otherwise. In addition, we include the firm-time fixed effects estimated in Equation (3) as credit demand controls, time fixed effects and lagged main bank controls. Main bank controls are the log of total assets, the ratio of equity to total assets, ROA, NPL ratio, loan-to-deposit ratio, deposit ratio, banks' TLTRO-I and TLTRO-II uptakes over the eligible credit and the ratio of sovereign bonds to total assets. Results in column (1) are estimated using the whole sample of firms whereas those in columns (2) and (3) are obtained from a subsample of safe and risky firms, respectively. A firm is assumed to be safe when its leverage ratio is below the median of the distribution of the leverage ratios of the firms in our sample, while risky firms are those whose leverage ratio is above the median of that distribution. Note that the sum of the number of observations for safe firms and risky firms is somewhat lower than the number of observations for all firms. The reason behind is that the whole sample includes all the firms in the Central Credit Register, but we do not have information on the financials of some of those firms. Standard errors are reported in brackets and are clustered at bank-time level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

5. CONCLUSIONS

Negative interest rates have been a relatively new phenomenon. Only a few central banks implemented them following the strong disinflationary forces unchained by the Global Financial Crisis and most of them turned into positive as high inflation stemming from increases in energy prices and bottlenecks in global supply chains has recently required a drastic change in their monetary stance.

In principle, negative rates are unlikely to work as positive rate cuts because of a particular friction, the zero lower bound on retail deposit rates. The existence of such limit implies that, while all other bank liabilities reprice following a policy rate cut into negative territory, interest rates on retail deposits are often stuck at zero, which may especially harm the net interest income of banks with a high deposit share.

Against this backdrop, we analyse the effect of the ECB's negative DFR on the supply of credit by Spanish banks to firms during the period 2014–2019. The analysis of the impact of negative interest rates on banks' credit supply and risk taking in a 'negative-for-long' scenario is a distinctive feature of our paper because it allows us to study the role of the initial conditions, as deposit rates in Spain were well above the ZLB in 2014 but reached it in 2018. Accordingly, we find that affected banks decreased their credit supply to firms (relative to non-affected banks) during the last sample period (2018–2019), but there was no effect during the previous periods.

Moreover, prudential bank capital regulations may prevent greater risk taking in response to negative rates, especially by banks with low capital, because a binding capital constraint limits banks' ability to grant loans and take on risk. Consistent with this hypothesis, our results indicate that banks adversely affected by the negative interest rates and with low-capital ratios contracted their lending supply to firms relative to non-affected banks. However, they only did so during our last sample period 2018–2019, arguably because at that time deposit rates reached the ZLB in Spain. We also document that affected low-capital banks reduced their credit supply to risky firms in the last two sample periods, 2016–2018 and 2018–2019, although the effect is much stronger in the latter period.

We also find that affected low-capital banks did not charge higher interest rates on loans to firms than non-affected banks during the period 2018–2019. This result suggests that low-capital affected banks did not pass on their higher funding costs to their borrowers, arguably because firms borrowing from those banks could substitute away from them. Interestingly, companies whose main credit institution was an affected low-capital bank did not experience a contraction in their total bank credit, which suggests that the contraction of the lending supply by those banks was offset by an expansion of the supply of credit by non-affected banks, with capacity for taking further risks.

Regarding the monetary policy implications of our findings, we offer new evidence about some potential unintended consequences for credit supply of a protracted period of negative interest rates, especially when bank capital is scarce and costly.

SUPPLEMENTARY DATA

Supplementary data are available at *Economic Policy* online.

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