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ABSTRACT

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 after a few years of negative rates do affected banks (relative to non-affected banks) decrease their supply and increase their rates, especially when lowly capitalized and lending to risky firms. This suggests that the adverse effects of the negative interest rates on banks' intermediation capacity only show up after a protracted period of ultra-low rates.

Keywords: negative interest rates; negative for long; lending policies; banks capital ratio; risk taking.

JEL Classification: G21, E52, E58.

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 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, respectively, pushing the DFR down to -0.50% where it remains until today.

Policy rate cuts into negative territory are unlikely to work in the same fashion as rate cuts occurring when rates remain positive because of the banks' reluctance to charge negative interest rates on their retail deposits due to the existence of cash as an alternative store of value (Schelling and Towbin, 2018; Eggertsson et al., 2019; Heider et al., 2019). In fact, Eggertsson et al. (2019) document effectively a zero lower bound for deposits in all the jurisdictions that have introduced negative interest rates. Therefore, negative rates may especially harm the net interest income of banks with a high deposit share. Based on these ideas, Heider et al. (2019) find that after the ECB's policy rate entered into negative territory banks with more deposits provide less syndicated loan credit and to riskier borrowers. Eggertsson et al. (2019) also find that Swedish banks that relied more heavily on deposit financing had lower loan growth in the post-zero period, although their lack of firm-level data makes it difficult to disentangle shifts in credit supply from credit demand. While negative interest rates also have positive effects on banks' profitability (for example through a revaluation of bond portfolios, lower credit provisions, and/or higher credit demand)[2], it becomes evident that the bank lending channel may operate differently under negative rates than under positive rates, especially for banks that rely heavily on deposit funding.

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; Bottero et al., 2019; Demiralp et al., 2019; Eisenschmidt and Smets, 2019). This portfolio-rebalancing channel may imply higher risk-taking, as risk-free excess liquidity is converted into bank lending. However, prudential bank capital regulations may prevent greater risk taking in response to negative rates, especially by banks with low capital ratios (Bongiovanni et al., 2019;

[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. Nevertheless, such an analysis is not the focus of our paper.

Brunnermeier and Koby, 2019; Imbierowicz et al., 2019). The argument is simple: a binding capital constraint limits banks' ability to grant loans and take on new risk[3].

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 behavior (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. The analysis of the impact of negative interest rates on banks' credit supply and risk-taking in a "negative-for-long" scenario is the main contribution of the paper because, unlike most other studies that only focus on the immediate impact of the introduction of negative rates, we study their persistence. As emphasized by Eggertsson et al. (2019), negative interest rates may have contractionary effects only when retail deposit rates reach the zero lower bound, which was actually not the case in most euro area economies early-on in 2014.

We build 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, based on confidential answers to the BLS. In particular, we assume that a bank is adversely affected if it reports that the ECB's negative DFR contributed to a decline in the bank's net interest income. As previously explained, while negative interest rates may also have positive effects on other components of banks' profits, it seems clear that negative interest rates squeeze net interest margins in various ways. Since the literature suggests several channels through which a negative interest rate policy (NIRP) affects banks (i.e., through retail deposits, excess liquidity, short-term interbank positions, liquid assets), the BLS provides us with a summary measure of exposure to negative interest rates.

Banks' self-assessment of the impact on negative interest rates on their balance sheets may pose an identification challenge. In particular, weak banks with problems with

[3] 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). By contrast, the risk-bearing capacity hypothesis (Gambacorta and Mistrulli, 2004; Adrian and Shin, 2010; Kim and Sohn, 2017), suggests that higher bank capital allows for more risk taking because of its loss-absorbing capacity.

their business models may have incentives to strategically misreport their evaluation of the policy in order to "blame" the NIRP for their poor performance. In addition, survey respondents may misunderstand the question, not being able to distinguish between the effects of the negative interest rates and those arising from other monetary policy tools. To cope with this misreporting and/or misunderstanding, we verify that banks' answers are consistent with hard data in order to rule out any remaining concerns about banks' self-assessment of the impact on negative interest rates on their balance sheets. Specifically, we find that banks with more deposits, a higher share of short-term loans and more liquid balance sheets have a higher probability of 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 conduct several robustness analyses that confirm our results, for instance, by classifying banks as adversely affected by the negative interest rates according to their deposit ratios or their fraction of credit at floating rates.

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 more than non-affected banks. Thus, we contribute to the stream of the literature that analyzes the capital channel of monetary policy (Van den Heuvel, 2006; Gambacorta and Shin 2018).

Importantly, we allow for different effects in different periods by interacting our key regressor with time dummies, so that we can analyze the dynamic impact of negative interest rates over the period 2014-2019. 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 TLTROs and the successive expansions of the 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, which was announced in January 2015.

Our results indicate that banks adversely affected by the negative interest rates curtailed 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 earlier periods. This finding corroborates the argument that, during a protracted period of negative interest rates, banks may end up decreasing their intermediation activity because of the lack of profitable lending opportunities. We also find that the effect of negative interest rates on banks' credit supply is heterogeneous and depends on the level of banks' capitalization. In particular, we observe that affected banks with low capital ratios contract their lending supply to firms relative to non-affected banks. However, they only do so during the last period 2018-2019. This result may be explained by different factors. First, policy rates in the euro area have been lowered several times since 2014, thus moving further into negative territory as time progressed. Second, 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 zero lower bound. This is consistent with Eggertsson et al. (2019), who document for the Swedish case that further cuts into negative territory do not lead to a pass-through to lending rates once the zero lower bound for deposits was reached. Third, Brunnermeier and Koby (2019) show that the reversal rate, which is the rate at which accommodative monetary policy "reverses" its intended effect and becomes contractionary for lending, "creeps up" over time[4]: given a fixed policy rate, in a "low-for-long" scenario banks may end up curtailing lending. Our findings also show that the reversal rate is bank-specific because it depends on banks' capitalization levels.

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 the policy. Crucially, this adverse effect was stronger for banks that were more dependent on retail deposits and were less well capitalized. Bongiovanni et al. (2019) also document an overall reduction in banks' holdings of risky assets in countries where negative rates have been introduced. Importantly, bank responses to monetary policy are heterogeneous according to their level of capitalization. For undercapitalized (overcapitalized) banks, the introduction of the NIRP implied a reduction (increase) in risk taking.

We also split our sample into safe and risky firms and find that affected low-capitalized banks reduced their credit supply to risky firms in the last two sample periods,

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

2016-2018 and 2018-2019, although the effect is much stronger in the latter period, which is again in line with the "low-for-long" hypothesis. By contrast, there is only a marginally significant effect on safe firms in the last period, and its size is significantly smaller than that for risky firms[5]. Therefore, our findings indicate that affected low-capitalized banks contracted their credit supply to risky firms prior to restricting it to safe firms and by a greater magnitude, presumably because loans to the former consume more regulatory capital than exposures to the latter. This evidence corroborates the relevance of a risk-bearing capacity channel, which implies that undercapitalized banks take less risk because of the lack of capital buffers to bear losses and the need to meet capital requirements. Thus, bank capital may hinder the expansion of credit supply by affected banks, especially in the current European banking landscape in which bank capital is scarce and expensive and retained earnings are low. In a similar vein, Cozzi et al. (2020) find that banks' capital buffers are best augmented during times of affluence, when banks can issue new equity and looser monetary policy can mitigate the negative effects of increasing capital requirements on lending. In sum, our results should not be interpreted based solely on the risk-taking channel of monetary policy but on the interaction between monetary and macroprudential policies.

In addition, affected banks with low capital charged higher interest rates to firms than non-affected banks during the period 2018-2019[6]. In fact, bank lending rates in some cases increased rather than decreased in response to policy rate cuts. This evidence fits well the previous finding, namely that affected banks reduced their credit supply relative to non-affected, with the corresponding positive impact on their loans rates. The presence of significant switching costs for some firms in the Spanish credit market, documented by López-Espinosa et al. (2017) could have amplified the latter effect.

Finally, we aggregate our dataset at the firm level to investigate whether the companies operating with affected banks experience 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. 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-capitalized banks has been offset by the higher lending supply by non-affected banks, with capacity for taking additional risks. Therefore, while the

[5] Similarly, Boungou (2020) finds that risk-taking has been lower among banks operating in countries where negative rates have been implemented.

[6] There is no available information on interest rates at the loan level before 2018.

reversal rate may be reached by some affected undercapitalized banks, there seems to be no aggregate effect on the supply of lending to non-financial corporations.

We contribute to the literature along four lines. First, we analyze the impact of negative interest rates on banks' credit supply and risk taking in a "negative-for-long" scenario. In particular, while most studies only focus on the introduction of negative interest rates in 2014 (euro area) or 2015 (Switzerland), we study their dynamic effects over a prolonged time (2014-2019). Second, we explore whether the transmission of negative interest rates to banks' credit supply is heterogeneous and depends on the level of banks' capitalization, while most of the evidence on the subject (e.g., Jiménez et al., 2012) pertains to pre-crisis times and conventional monetary policy. We also investigate the pass-through of negative interest rates to banks' lending rates according to their capital ratios, while previous studies (e.g., Eggertsson et al., 2019) have analyzed how this pass-through depends on the reliance on deposit financing[7]. 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 us with a summary measure of exposure to negative interest rates. Reassuringly, these survey data are corroborated with hard data: banks with higher deposit ratios, a higher share of short-term loans and more liquid assets have a higher probability of being adversely affected by the negative rates. In fact, we obtain similar results if we consider banks as adversely affected by the negative interest rates according to their deposit ratios or their fraction of credit at floating rates. 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 take less risk because of the lack of capital buffers to absorb losses and the need to meet capital requirements. Therefore, our results on banks' risk-taking behavior and capital highlight the interaction between monetary and macroprudential policies.

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

[7] In particular, Eggertsson et al. (2019) find that Swedish banks that relied more heavily on deposit financing were less likely to reduce their lending rates once the policy rate went negative.

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. We aggregate the outstanding amount of credit of each firm in each bank on a monthly basis to obtain total credit (both drawn and undrawn in the case of credit lines)[8]. In addition, the dataset contains the 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, saving banks and credit cooperatives in Spain (banks, hereafter). This set of banks does not include specialized lending institutions, whose main activities are leasing, factoring and consumer credit. 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 1th 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, which is even negative for some banks. The average ratio of non-performing loans over total credit (NPL ratio) is relatively high because of the effects associated to the Great Recession in Spain[9], 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 suggests that not all of them can take risks to the same extent. Regarding banks' business models, they are focused on the traditional de-

[8] We include undrawn credit facilities 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.

[9] 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 non-financial private sector fell by more than 18%.

posit-based intermediation activity. The banks with the largest loan-to-deposit ratio and the lowest deposit ratio (i.e., deposits over total assets) are credit establishments. 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 share of almost 30%). For reasons of confidentiality, we cannot provide summary statistics on the TLTRO uptakes over eligible credit. Panel B of Table 1 reports descriptive statistics for the variation of credit at the firm-bank level for both affected and non-affected banks. On average, affected banks have decreased their supply of credit to Spanish firms to a higher extent than non-affected banks.

Table 1: Descriptive statistics

Panel A					
	Mean	**Median**	**SD**	**P1**	**P99**
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
Credit / Deposits	1.1	1.0	0.9	0.5	6.2
Deposit / TA (%)	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 NIR (%)	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
Panel B					
	Mean	Median	SD	P1	P99
Δlog(Credit_AffectedBanks)	-0.06	-0.08	0.85	-2.54	2.61
Δlog(Credit_NonAffectedBanks)	-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 in percentages except for total assets (TA), which are in billions of euros. Panel B reports descriptive statistics for the log change of credit at the bank firm level the four periods considered in our sample period.

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 filed at the mercantile registries 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 respondents are micro-firms and SMEs, which account for the vast majority of Spanish companies. 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 are 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 Table A3 of the Online Appendix[10].

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 Bank Lending Survey (BLS) for a subsample of banks participating in the BLS. The BLS is a quarterly survey through which euro area banks are asked about developments in their respective credit markets since 2003[11]. 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-fi-

[10] The firm variables and the bank-firm log change of credit are winsorized at the 1% and 99% levels.

[11] For more detailed information about the survey see Köhler-Ulbrich, Hempell and Scopel (2016). Visit also https://www.ecb.europa.eu/stats/ecb_surveys/bank_lending_survey/html/index.en.html.

nancial sector in the euro area[12]. Spain contributes to the sample with 10 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 restrict the sample to the period spanning from 2014Q2 to 2018Q1. The resulting sample contains 1,528 observations corresponding to 123 banks from 13 countries (see Table A1 of the Online Appendix).

Our methodology consists of estimating the probability that a bank is 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 the bank's net interest income (NII) in the past six months and 0 otherwise. The variable is constructed using a semiannual 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?" In our sample, NDFR equals 1 in 73% of the observations[13]. 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 Schelling and Towbin (2018) and Heider et al. (2019), we use the deposit ratio, the ratio between the deposits by households and firms over total assets. We also include a liquidity ratio, which is the sum of cash, holdings of government securities and Eurosystem deposits over total assets[14]. 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 matu-

[12] There are six countries that do not share the confidential, non-anonymized replies to the BLS, so they are excluded from the iBLS. Germany participates in the iBLS with a subsample of banks that have agreed to transmit their non-anonymized replies to the ECB.

[13] These figures are representative of the share of outstanding credit associated with banks with NDFR=1. For instance, in June 2014 this share was equal to 80%.

[14] We do not include excess liquidity (as in Basten and Mariathasan, 2018, or Demiralp et al., 2019), in our regressions due to the fact that 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.

rity 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 above regressors, as shown in the following equation (1):

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

where X'_{it} denotes a vector of control variables that capture banks' solvency (capital and reserves over total assets), profitability (ROE), size (log of total assets) and Eurosystem borrowing (total borrowing from the Eurosystem over total assets). Descriptive statistics of these variables are presented in Table A2 of the Online Appendix. Needless to say, equation (1) does not have a causal interpretation, but 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 ten 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 rates on their NII. By 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 terms of loss-absorbing capacity, higher need of Eurosystem funding and lower profitability, are more likely to report a negative impact of negative 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 coefficients 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). We then use the estimates from (1) to predict the probability of NDFR=1 (henceforth, score) in 2014Q2 for our sample of 23 Spanish banks. The median score for the Spanish banks is 0.75. Therefore, banks with a score above 0.75 are the group of affected banks (*Affected*), while banks with a score below 0.75 are the group of non-affected banks.

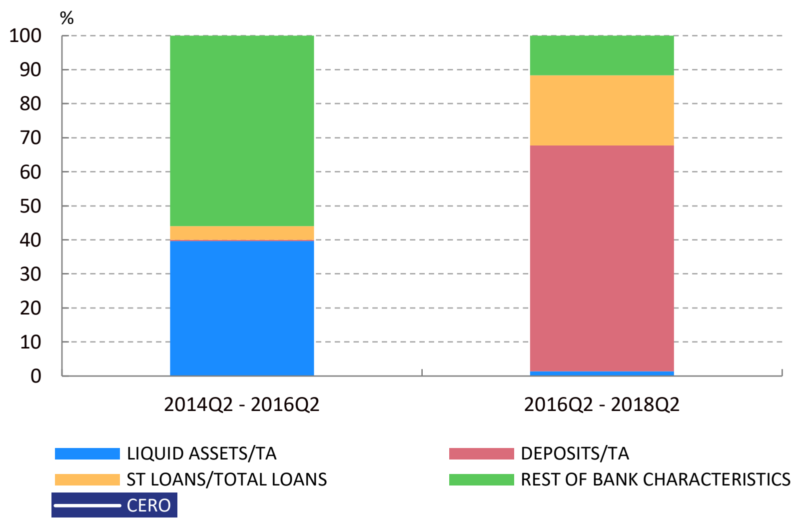
Table 2: Bank characteristics correlated with the probability that its net interest income are adversely affected by negative interest rates

	(1)	(2)
Liquidity ratio	0.007***	0.007***
	(0.002)	(0.002)
Deposit ratio	0.001**	0.001***
	(0.001)	(0.000)
Weight loan overdrafts	0.200	0.071
	(0.136)	(0.116)
Weight loans up 1y	-0.155	-0.116
	(0.113)	(0.097)
Capital ratio	-0.009***	
	(0.002)	
ROE	-0.002*	
	(0.001)	
Eurosystem borrowing	0.020***	
	(0.005)	
Size	0.009	
	(0.009)	
Observations	**1,528**	**1,528**
Number of banks	**123**	**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 zero otherwise. Column (2) shows a variation of equation (1) in which we exclude some control variables. The regressors are bank characteristics. The sample spans from 2014q2 to 2018q1. Robust standard errors are reported in brackets. ***, **, and * denote significance at the 1, 5 and 10% levels.

Finally, Figure 1 contains the percentage of the R-squared, which is obtained from the estimation of equation (1) by OLS, explained by the characteristics that define the banks adversely affected by the negative interest rates: deposit ratio, liquidity ratio and share of short-term loans (overdraft loans and loans that mature in one year). We consider an additional category that comprises the control variables of equation (1) that were previously explained: bank characteristics such as size (log of total assets), profitability (ROE), solvency (capital ratio) and Eurosystem borrowing (total borrowing from the Eurosystem over total assets). The first bar summarizes the percentage of the R-squared explained by each of these bank characteristics based on a sample period that spans from June 2014 to June 2016. During that period, the group of control variables accounts for the highest proportion of the R-squared, followed by the liquidity ratio. This evidence is consistent with Basten and Mariathasan (2018) and Demiralp et al. (2019), who characterize exposed banks as those that hold significant amounts of non-exempted central bank reserves and excess liquidity, respectively[15].

Figure 1: Percentage of R-squared explained by each group of variables



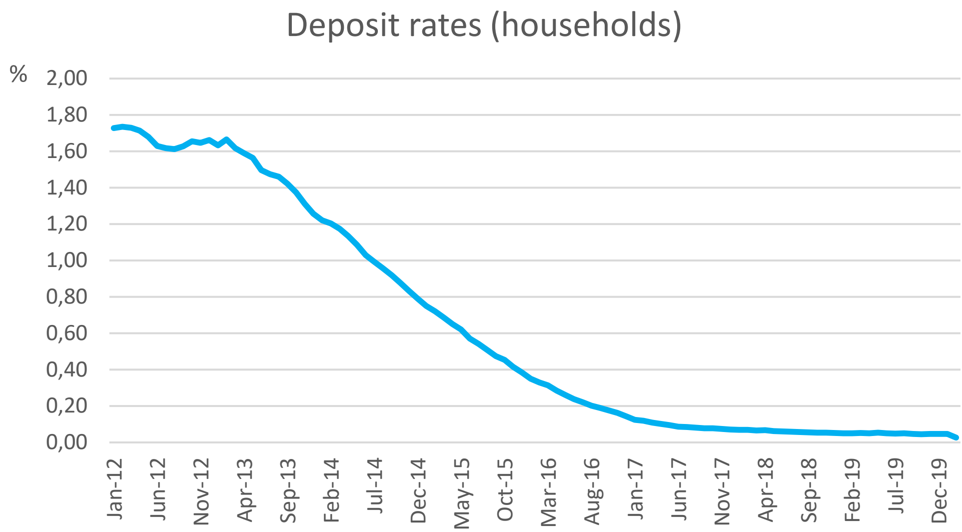
This figure contains the percentage of the R-squared explained by the characteristics that define the banks adversely affected by the negative interest rates: deposit ratio (ratio between the deposits by households and firms over total assets), liquidity ratio (sum of cash, holdings of government securities and Eurosystem deposits over total assets) and the share of short-term loans (both overdraft loans and loans that mature in one 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 (capital and reserves over total assets), and borrowing from the Eurosystem (total borrowing from the Eurosystem over total assets). The results

[15] In our sample, the correlation between Liquidity ratio and Excess liquidity is 0.54.

are obtained from the estimation of equation (1) by OLS. The first bar summarizes the percentage of the R-squared explained by each of these bank characteristics in the period between June 2014 and June 2016. The second bar corresponds to the period between June 2016 and June 2018.

The second bar corresponds to the sample period between June 2016 and June 2018. During this period, the interest rates of deposits by Spanish households and firms (aggregate deposit rates) gradually approached zero and even reached the zero lower bound (the 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 the highest percentage of the R-squared is the deposit ratio, which corroborates the findings of Schelling and Towbin (2018), Eggertsson et al. (2019) and Heider et al. (2019) for other jurisdictions. 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".

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.

Therefore, the variable *Affected* 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 also examine each channel separately.

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

Our identification strategy relies on three pillars. First, as explained in the previous section, a bank is assumed to be adversely affected by the negative interest rates when the estimated probability that its net interest income decreases because of the negative DFR is higher than 75%. It is important to notice 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, which denotes banks adversely affected by negative interest rates, with time dummies, so that we analyze the dynamic impact of negative interest rates over a protracted period (2014-2019). Third, we control for 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 time period. While the long time period examined leaves more room for other confounding shocks, the use of firm-time fixed effects mitigates this confounding events problem to a large extent.

Our first empirical model is a type of difference-in-differences with multiple periods:

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

The dependent variable is the growth in the outstanding credit of firm *i* with bank *b* at time *t*. We consider credit growth between four different periods. Thus, 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.

Concerning the explanatory variables, *Affected* is a dummy variable denoting banks adversely affected by the negative interest rates, as explained in the previous section[16]. 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 (to control for firm-level unobserved heterogeneity in each period (including firms' demand for credit, firms' balance sheet conditions, etc.), bank fixed effects (a_b) to deal with banks' time-invariant unobserved heterogeneity and lagged bank controls (X'_{bt-1}) to avoid a simultaneity bias[17]. Bank controls are proxies for bank size (log of total assets), solvency (equity over total assets), profitability (ROA), risk (NPL ratio), liquidity (loan-to-deposit ratio) and business model (deposits over total assets ratio). We also take into account other confounding events that occurred during our sample period, such as the TLTROs and the APP, by including relevant controls in our regressions. 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 using 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[18]. The regressors of interest are the three interaction terms between *Affected* and the period

[16] 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 non-affected 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 non-affected banks and estimate equation (3). Results are reported in Table A4 and support the robustness of our results.

[17] The time-invariant variable Affected is subsumed into the bank fixed effects and the three dummy variables Post 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.

[18] 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.

dummies *Post.14-16*, *Post.16-18* and *Post.18-19*. The estimation of equation (2) will tells us whether affected banks increase/reduce their credit supply to a given firm (relative to non-affected banks) during each period[19].

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 very economically significant, as the average credit growth in the sample is -6% for affected banks and -5% for non-affected banks. By contrast, there is no effect during the previous periods. This finding is robust to excluding banks whose probability of being adversely affected by the negative interest rates is close to the threshold (i.e., 75%), as displayed in column (2). In particular, we exclude four banks whose probability of being affected 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. All this evidence is consistent with the view that, in a prolonged period of low/negative interest rates, banks may eventually reduce their intermediation activity (Brei et al., 2019), as the persistent negative effect on net interest margins outweighs the potential increase in credit demand. Thus, while most of the cuts of the DFR into negative territory took place in previous periods (between June 2014 and March 2016)[20], they only were transmitted to banks' credit supply later on, between June 2018 and June 2019. In addition, Eggertsson et al. (2019) and Heider et al. (2019) find that negative interest rates only become contractionary for lending once the deposit rates reach the zero lower bound. However, retail 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 zero lower bound. According to Figure 2, interest rates on deposits by Spanish households were at 1% in June 2014 and reached the zero lower bound at the end of 2017. We focus on households' deposits because Altavilla et al. (2019) document that the interest rates on corporate deposits may go negative in the euro area, i.e., there is no zero lower bound for corporate deposits. Therefore, the contraction of lending supply by affected banks in the last sample period 2018-2019 is concurrent with the arrival of zero interest rates on households' deposits.

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[19] Standard errors are clustered at the bank-time level. Alternatively, standard errors could be clustered at the bank level to deal with serial correlation in credit growth within banks over time. However, as the asymptotic justification of cluster-robust standard errors assumes that the numbers of clusters goes to infinity, with a small number of clusters (in our empirical application, 22 banks) the 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.

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

However, interest rates on retail deposits were already very low since 2016, which implies that affected banks curtailed their credit supply to firms as a consequence of a protracted period of low deposit rates, which ended up eroding their profits by squeezing their net interest margins. This result is also in line with the findings of Ampudia and Van den Heuvel (2019), who show a decline in bank equity values and net interest margins of high-deposit banks in Europe in reaction to the ECB rate cuts into negative territory.

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

	(1)	(2)
Affected BLS x Post.14-16	-0.037	0.022
	[0.062]	[0.064]
Affected BLS x Post.16-18	-0.046	0.015
	[0.074]	[0.070]
Affected BLS x Post.18-19	-0.128*	-0.138*
	[0.073]	[0.083]
Observations	728,398	583,243
R-squared	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 (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 its net interest income decreases 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 correspond to proxies for bank size (log of total assets), solvency (equity over total assets), profitability (ROA), risk (NPL ratio), liquidity (loan-to-deposit ratio) and business model (deposits over total assets ratio). 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. Standard errors are reported in brackets and are clustered at bank-time level. ***, **, and * denote significance at the 1, 5 and 10% levels.

4.1.2. CREDIT SUPPLY OF AFFECTED AND POORLY CAPITALIZED BANKS IN A "NEGATIVE-FOR-LONG" SCENARIO

Following previous arguments about the relationship between capital, credit growth and risk taking, we now differentiate between high-capital and low-capital banks: those above/below the median capital ratio in December 2013, i.e., before the DFR turned negative. Therefore, in most of the following analyses our key regressor is the interaction between the dummy *Affected* and the dummy *Low Capital.* Thus, we propose the following empirical model, which is an extension of equation (2), to analyze the amplifying effect of low capital on the credit supply of affected banks relative to non-affected banks in different periods:

$$
\begin{aligned}
\Delta\, ln(Credit)_{ibt} = \alpha_{it} + \alpha_b + \beta_1\, Affected_b \times Low\ Capital_b \times Post.\ 14\text{-}16_t \\
+\beta_2\, Affected_b \times Low\ Capital_b \times Post.\ 16\text{-}18_t \\
+\beta\__3\, Affected_b \times Low\ Capital_b \times Post.\ 18\text{-}19_t \\
+\beta\_4\, Affected_b \times High\ Capital_b \times Post.\ 14\text{-}16_t \\
+\beta\_5\, Affected_b \times High\ Capital_b \times Post.\ 16\text{-}18_t \\
+\beta\_6\, Affected_b \times High\ Capital_b \times Post.\ 18\text{-}19_t + \gamma X'_{bt\text{-}1} + \varepsilon_{ibt} \quad (3)
\end{aligned}
$$

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 increase/reduce their credit supply to a given firm (relative to non-affected banks) during each period.

The corresponding results are presented in Table 4, 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 median in December 2013) exhibit 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 to firms (relative to non-affected banks) by around 15 pp during the last period (2018-2019). 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. By 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 probability of being adversely affected by the negative interest rates 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 period 2018-2019 (-0.15 vs. -0.14, as reported in column (2) in 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 corroborates the theoretical prediction of Brunnermeier and Koby (2019) on the reversal rate. In particular, following a rate cut, if the capital gains from reevaluation of banks' assets are too low to compensate the loss in net interest margins, 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. Our results also suggest that the reversal rate is bank-specific and depends on banks' initial capitalization levels. The fact that the effect is only significant for the last period (2018-2019) is also 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.

Table 4: Variation in the supply of credit to firms by affected banks depending on their capital ratio

	(1)	(2)
Affected Bank x Low Capital x Post.14-16	-0.087	-0.029
	[0.061]	[0.064]
Affected Bank x Low Capital x Post.16-18	-0.092	-0.022
	[0.082]	[0.081]
Affected Bank x Low Capital x Post.18-19	-0.150**	-0.153*
	[0.076]	[0.091]

Affected Bank x High Capital x Post.14-16	0.029	0.098
	[0.071]	[0.066]
Affected Bank x High Capital x Post.16-18	0.011	0.070
	[0.080]	[0.068]
Affected Bank x High Capital x Post.18-19	-0.089	-0.100
	[0.078]	[0.092]
Observations	728,398	583,243
R-squared	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.

Table 5 is a variation of Table 4, 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 4, 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 2012-2014, 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 analyze the impact of the negative DFR from 2016 onwards. The reason for this alternative exercise is that, in the baseline analyzes, 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, as robustness analysis, we classify banks according to their capital ratios as of December 2015. 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 macroprudential requirements, as a more precise measure of capital constraints. In particular, 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 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[21]. Nevertheless, the results are robust to these alternative specifications: according to columns (2) and (3) of Table 5, affected low-capital banks reduced their credit supply to firms (relative to non-affected banks) between 11 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 analyzed[22].

Table 5: Variation in the supply of credit to firms by affected banks depending on their capital ratio. Alternative measures of banks' capital position

	(1)	(2)	(3)
	CET1	**CET1**	**Capital Buffer**
Affected Bank x Low Capital x Post.14-16	-0.087		
	[0.061]		

[21] 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 undermine the identification strategy.

[22] 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.

Affected Bank x Low Capital x Post.16-18	-0.092	-0.024	0.014
	[0.082]	[0.062]	[0.057]
Affected Bank x Low Capital x Post.18-19	-0.150**	-0.113*	-0.137**
	[0.076]	[0.067]	[0.068]
Affected Bank x High Capital x Post.14-16	0.029		
	[0.071]		
Affected Bank x High Capital x Post.16-18	0.011	0.001	-0.025
	[0.080]	[0.049]	[0.055]
Affected Bank x High Capital x Post.18-19	-0.089	-0.071	-0.060
	[0.078]	[0.052]	[0.056]
Observations	728,398	726,117	671,436
R-squared	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 2012-2014, 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.

In addition, 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). In particular, 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 low-capital affected banks in the last sample period

2018-2019. Our analyses are based on the results depicted in Figure 1 that shows the percentage of the R-squared, obtained from the estimation of equation (1) by OLS, which is explained by the characteristics that define the banks adversely affected by the negative interest rates (deposit ratio, liquidity ratio and share of short-term loans) and other controls (total assets, ROE, capital ratio and borrowing from the Eurosystem). The first bar summarizes the percentage of the R-squared explained by each of these bank characteristics between June 2014 and June 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-squared is the deposit ratio, followed by the share of short-term loans. In sum, during the last years of our sample, 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. Therefore, we focus the following analysis on these two dimensions.

The estimation results are presented in Table 6. Column (1) replicates our previous analysis, in which a bank is assumed to be adversely affected by the negative interest rates when the estimated probability that its net interest income decreases because of the negative DFR is higher than 75%. In column (2), following the arguments of Schelling and Towbin (2018), Brunnermeier and Koby (2019), Eggertsson et al. (2019) and Heider et al. (2019), banks are considered to be adversely affected by the negative interest rates when their share of deposits over total assets 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. The zero lower bound for retail deposits implies that 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 rate following a reduction in the policy interest rate, which squeezes banks' net interest margins and erodes their net interest income. In the three cases, the coefficient of interest, which is the one of the triple interaction between *Affected, Low Capital* and *Post.18-19,* is negative and statistically significant. In particular, low-capital affected banks reduced their credit supply to firms (relative to non-affected banks) between 14 and 22 pp during the last period (2018-2019). Therefore, regardless of the measure of exposure, affected banks with low capital levels eventually restrict their credit supply when interest rates stay in negative territory during a protracted period.

Table 6: Variation in the supply of credit to firms by affected banks depending on their capital ratio. Alternative measures of exposure to negative interest rates

	(1)	(2)	(3)
	High prob NII decreases because of the negative DFR	High deposit share	High fraction of credit at floating rates
Affected Bank x Low Capital x Post.14-16	-0.087	-0.093	-0.118
	[0.061]	[0.060]	[0.105]
Affected Bank x Low Capital x Post.16-18	-0.092	-0.099	-0.106
	[0.082]	[0.073]	[0.117]
Affected Bank x Low Capital x Post.18-19	-0.150**	-0.136*	-0.222**
	[0.076]	[0.075]	[0.103]
Affected Bank x High Capital x Post.14-16	0.029	0.029	-0.021
	[0.071]	[0.056]	[0.084]
Affected Bank x High Capital x Post.16-18	0.011	0.052	-0.027
	[0.080]	[0.070]	[0.099]
Affected Bank x High Capital x Post.18-19	-0.089	-0.055	-0.138
	[0.078]	[0.070]	[0.087]
Observations	728,398	728,398	728,398
R-squared	0.388	0.388	0.388
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 3 in which we consider alternative channels through which negative interest rates affect banks' net interest income (NII). Column (1) reports the results obtained when banks are classified as affected if the estimated probability that its NII decreases because of the negative DFR is higher than 75% (see Section 3 for details). In column (2) banks are considered as 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 fraction of their credit is granted at a floating rate. The larger this fraction, the larger the income that is adjusted at lower interest rates. 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. The three groups of affected banks are each split into two, depending on whether their CET1 capital ratio is above or below the median of the CET1 ratios of the banks in our sample as of December 2013 (i.e., before the DFR turned negative), such that the control group in each column consists of non-affected banks according to the corresponding measure. The set of control variables and fixed effects used in this estimation is that used in Table 4. Standard errors are reported in brackets and are clustered at bank-time level. ***, **, and * denote significance at the 1, 5 and 10% levels.

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 (defined as financial debt over total assets) in order to analyze the effects of the negative interest rates on banks' risk taking (Table 7). 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. 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 higher probability to fail (e.g., Ben-Zion and Shalit, 1975; Jensen and Meckling, 1976; Carling et al., 2007). In addition, these firms are more likely to default because of their worse loss-absorbing capacity.

In this case, we find that low-capitalized affected banks reduce 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. By 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[23]. This evidence is consistent with the risk-bearing capacity hypothesis (Gambacorta and Mistrulli, 2004; Adrian and Shin, 2010; Kim and Sohn, 2017), which states that undercapitalized banks take less risks

[23] 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 CCR, but we do not have information on balance sheets or profit and loss accounts for some of those firms.

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., 2019). Our results suggest that affected low-capitalized banks reduce their credit supply to risky firms before than restricting it to safe firms and in a greater magnitude, presumably because loans to the former consume more regulatory capital than exposures 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 behavior. Thus, our results should not be interpreted based solely on the risk-taking channel of monetary policy but on the interaction between monetary and macroprudential policies.

Table 7: Variation in the supply of credit to safe and risky firms by affected banks depending on their capital ratio

	(1)	(2)	(3)
	All	**Safe**	**Risky**
Affected Bank x Low Capital x Post.14-16	-0.087	-0.075	-0.104
	[0.061]	[0.054]	[0.080]
Affected Bank x Low Capital x Post.16-18	-0.092	-0.059	-0.127*
	[0.082]	[0.078]	[0.075]
Affected Bank x Low Capital x Post.18-19	-0.150**	-0.111*	-0.188**
	[0.076]	[0.065]	[0.093]
Affected Bank x High Capital x Post.14-16	0.029	-0.005	0.065
	[0.071]	[0.063]	[0.089]
Affected Bank x High Capital x Post.16-18	0.011	0.001	0.010
	[0.080]	[0.072]	[0.098]
Affected Bank x High Capital x Post.18-19	-0.089	-0.105	-0.064
	[0.078]	[0.075]	[0.094]
Observations	728,398	335,501	340,422
R-squared	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 4 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 4. 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. Notice 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 Credit Register, but we do not have information on the financials for some of those firms. The set of control variables and fixed effects used in this estimation is that used in Table 4. Standard errors are reported in brackets and are clustered at bank-time level. ***, **, and * denote significance at the 1, 5 and 10% levels.

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[24]. We consider banks' interest rates in two dates: June 2018 and June 2019, which correspond to the last period used in previous analyses and during which low-capital affected banks cut 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:

$$ir_{ibt} = \alpha_{lc} + \alpha_{it} + \beta_1\, Affected_b \times Low\ Capital_b + \beta_2\, Affected_b \times High\ Capital_b + \gamma X'_{bt-1} + \varepsilon_{it} \quad (4)$$

where a_{lc} are loan-characteristics fixed effects, which correspond to the interaction of dummy variables denoting the type of guarantee, the interest rate of reference and the type of credit contract[25]. Regarding the type of guarantee, we consider several categories such as no guarantee, real guarantee or personal guarantee. Mosk (2018) shows that collateral decisions are taken prior to both interest and non-interest rate

[24] Those interest rates do not include fees.

[25] 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 (4) 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.

decisions in loan contracts, implying that our guarantee variable is a predetermined control. For the interest rate of reference, we consider fixed rates and several types of floating rates. Finally, the type of credit contract refers to financial credit, commercial credit, leasing, factoring, etc. This identification scheme, which also includes firm-time fixed effects (a_{it}), 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 (4) will tell us whether low-capital affected banks and high-capital affected banks increase/reduce their lending rates to firms relative to non-affected banks in 2018 and 2019.

The estimations are presented in Table 8. Columns (1) and (3) exclude two loan characteristics, the maturity and the size of the loan, because they could be jointly determined with the loan's interest rate, making them "bad controls" (Angrist and Pischke, 2009). However, their 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 (4), in which the loan's interest rate is regressed on the dummy *Affected,* which denotes banks adversely affected by negative interest rates according to the methodology described in Section 3, and a wide set of fixed effects and bank controls. The results are similar in both columns: an affected bank charges an interest rate around 22 bps higher than a non-affected bank on a loan with similar characteristics. In columns (3) and (4) we estimate equation (4), splitting affected banks into low-capital and high-capital ones. The results are again alike: the interest rate charged on a loan by a low-capital affected bank is quite high, between 45 and 50 bps higher than the interest rate charged on a similar loan by a non-affected bank. By contrast, we do not find significant differences in the interest rates charged by high-capital affected banks and those charged by non-affected banks. Notice that the relevant coefficients in columns (3) and (4) are substantially higher than those in columns (1) and (2): banks' low levels of capital function as an amplification mechanism. In sum, affected banks with low capital charge higher interest rates on loans to firms than non-affected banks during the years 2018 and 2019. This finding, consistent with those of Amzallag et al. (2019) and Eggertsson et al. (2019), indicates a significant breakdown in the pass-through of policy rates to lending rates for this group of banks. The result also suggests that low-capitalized affected banks contracted their credit supply (to risky firms and to a lesser extent to safe firms, as documented in Table 7) because they could not compete on a level playing field with the rest of banks in this segment of the market. Instead, they had to charge higher interest rates, at the expense of losing some customers and market share, and only retained the borrowers that could not easily switch to other banks or replace bank loans with other sources of financing due to asymmetric information problems in the credit market. Therefore, this finding suggests the presence of switching costs for some firms in the Spanish credit market, characterized by relationship lending in the case of SMEs, which are more informationally opaque than large corporations (López-Espinosa et al., 2017).

Table 8: Variation of interest rates charged by affected banks depending on their capital ratio

	(1)	(2)	(3)	(4)
Affected Bank	0.219**	0.209**		
	[0.105]	[0.103]		
Affected Bank x Low Capital			0.496***	0.448***
			[0.166]	[0.153]
Affected Bank x High Capital			0.194	0.187
			[0.121]	[0.116]
Observations	123,806	123,806	123,806	123,806
R-squared	0.825	0.830	0.825	0.831
Firm-Time FE	YES	YES	YES	YES
Guarantee type - Type of Credit-IR Reference FE	YES	YES	YES	YES
Loan Maturity & Loan Size	NO	YES	NO	YES
Bank Controls	YES	YES	YES	YES

This table reports the results obtained from the estimation of equation (4) 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 (4) 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's NII decreases because of the negative DFR is higher than 75% and zero otherwise (see Section 3 for details). The results in columns (3) and (4) are obtained from the estimation of equation (4) 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-time fixed effects, loan-characteristics fixed effects, which correspond to the interaction of dummy variables denoting several loan characteristics (type of guarantee, interest rate of reference and type of credit contract), and bank controls as of December 2017. Columns (2) and (4) also include loan maturity and loan size as additional controls. Standard errors are reported in brackets and are clustered at bank-time level. ***, **, and * denote significance at the 1, 5 and 10% levels.

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 experience a contraction in their overall bank credit or they are able to mitigate the effect by borrowing more from non-affected banks. Our empirical model is:

$$\begin{aligned}\Delta \ln(Credit)_{it} = &\widehat{\alpha_{it}} + \alpha_t + \beta_1 \text{ Main Bank Affected}_i \\ &+ \beta_2 \text{ Main Bank Affected}_i \times \text{Post. 14-16}_t \\ &+ \beta_3 \text{ Main Bank Affected}_i \times \text{Post. 16-18}_t \\ &+ \beta_4 \text{ Main Bank Affected}_i \times \text{Post. 18-19}_t + \varepsilon_{it} \quad (5)\end{aligned}$$

The dependent variable is the growth in the total outstanding credit of firm i at time t. We consider credit growth between 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 adversely affected by the negative interest rates and has a low capital ratio. 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. According to our previous results, this is the only group of banks that reduce credit supply to Spanish firms in a "negative-for-long" scenario. The firm's main bank is that with the highest share of credit for that company. We also include estimates of firm credit demand ($\widehat{\alpha_{it}}$) obtained from equation (3), as in Cingano et al. (2016) and Bonaccorsi di Piatti and Sette (2016). The inclusion of 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 (a_t) to control for aggregate shocks.

According to Table 9, 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 indicates that the lower supply of credit by low-capitalized affected banks has been offset by the higher lending supply by non-affected banks, with capacity for taking additional risks.. In addition, as shown before, the reversal rate is bank-specific and depends on banks' capitalization levels, which means that, while some affected undercapitalized banks may curtail credit supply, there seems to be no aggregate effect on the supply of lending to non-financial corporations. 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 an effect would be absorbed by the firm-time fixed effects and it will not show up in the estimates.

Table 9: Variation in the supply of credit to safe and risky firms by affected banks depending on their capital ratio. Firm level analysis

	(1)	(2)	(3)
	All	**Safe**	**Risky**
Main Bank Affected x Post.14-16	0.016	-0.015	-0.026
	[0.018]	[0.025]	[0.025]
Main Bank Affected x Post.16-18	-0.002	-0.022	-0.043*
	[0.018]	[0.025]	[0.025]
Main Bank Affected x 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-squared	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 (4), 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 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 and time fixed effects. 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. Notice 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 Credit Register, but we do not have information on the financials for 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.

5. CONCLUSIONS

Negative interest rates are a relatively new phenomenon, and only a few Central Banks around the world have implemented them. They are unlikely to work as positive rate cuts because of a particular friction, the zero lower bound on retail deposits. This implies that, while all other bank liabilities reprice in line with negative policy rates, interest rates on retail deposits are stuck at zero. Therefore, while negative interest rates also have positive effects on banks' profitability (revaluation of bond portfolios, lower credit provisions, higher credit demand), they may especially harm the net interest income of banks with a high deposit share. In addition, banks that 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, may also be adversely affected by the negative rates because they squeeze their net interest margins. In that context, it becomes evident that the bank lending channel under negative rates is different than under positive rates, mostly for banks that rely heavily on deposit funding.

Therefore, banks characterized by high deposit rates and a high share of floating-rate loans or short-term loans, may contract their credit supply. However, some banks with excess liquidity holdings, on which they earn a negative return, could increase their lending to the non-financial private sector in a bid to reduce their holdings of costly central bank reserves. This portfolio-rebalancing channel implies higher risk-taking, as risk-free excess liquidity is converted into bank loans.

Against this backdrop, we use survey data from the ECB's Bank Lending Survey, coupled with detailed balance sheet information on a large sample of euro area banks, to construct a summary measure of exposure to the negative interest rates, which incorporates the three aforementioned channels (retail deposits, floating rate or short-term loans, liquid assets).

We contribute to the existing literature by studying 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. Unlike most studies that only focus on the introduction of the NIRP in 2014 (euro area) or 2015 (Switzerland), we study the dynamic effects of negative interest rates over a protracted period. In particular, 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 is no effect during the previous periods. This evidence is consistent with the view that, in a prolonged period of negative interest rates, banks may eventually reduce their intermediation activity because of the lack of profitable lending opportunities.

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. In this context, undercapitalized banks might improve capital ratios by reducing risk-weighted exposures such as credit to some firms and households and by investing in safe assets such as government bonds, which carry a zero risk-weight. Consistent with this hypothesis, our results indicate that banks adversely affected by the negative interest rates and with low capital ratios contract their lending supply to firms relative to non-affected banks, which means that the reversal rate is bank-specific and depends on banks' capitalization levels. However, they only do so during our last sample period 2018-2019, i.e., after a prolonged period of negative rates, probably because at that time deposit rates reached the zero lower bound in Spain. We also document that affected low-capitalized banks reduce 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. By 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. This evidence suggests that those banks take less risk because of the lack of capital buffers to absorb losses and the need to meet capital requirements.

Moreover, affected banks with low capital charged higher interest rates to firms than non-affected banks during the period 2018-2019. This finding implies a significant breakdown in the pass-through of policy rates to lending rates once deposit rates reach the zero lower bound, as policy rate cuts to negative levels were not transmitted to the main funding source of most Spanish banks. It may also suggest that affected low-capitalized banks contracted their credit supply because they could not compete on price with the other banks in this segment of the market. Instead, they had to charge higher interest rates to risky firms and to a lesser extent to safe firms, at the expense of losing some customers and only keeping firms with high switching costs due to information asymmetries in the Spanish credit market, which is characterized by relationship lending in the case of SMEs, which are more informationally opaque than large corporations.

Finally, we find that the companies whose main credit institution is an affected low-capitalized bank did not experience a contraction in their total bank credit, which suggests that the lower loan supply by those banks was offset by the higher supply of credit by non-affected banks, which have capacity for taking further risks. Thus, while the reversal rate might be reached by some affected undercapitalized banks, our analysis provides suggestive evidence that the negative interest rates had no aggregate effect on the lending supply to non-financial corporations.

The results of our study highlight the interaction between monetary and macroprudential policies. It is well-known that the build-up of capital buffers, while essential for the resilience of the banking system, it has short-run costs in terms of credit supply and output. Accommodative monetary policy may mitigate those costs when policy rates are above zero, but further cuts into negative territory may instead exacerbate them when capital requirements are binding and deposit rates are at the zero lower bound, especially in a “negative- for-long” scenario such as the one analyzed in this paper.

REFERENCES

Adrian, T. and Shin, H. S. (2010) "Financial intermediaries and monetary economics" in *Handbook of Monetary Economics*, volume 3, pages 601-650.

Altavilla, C., Burlon, L., Giannetti, M. and Holton, S. (2019): "Is there a zero lower bound? The effects of negative policy rates on banks and firms," Working Paper Series 2289, European Central Bank.

Ampudia, M. and S. J. Van den Heuvel, (2019): "Monetary policy and bank equity values in a time of low and negative interest rates," Finance and Economics Discussion Series 2019-064, Board of Governors of the Federal Reserve System (U.S.).

Amzallag, A., Calza, A., Georgarakos, D. and Sousa, J. (2019): "Monetary policy transmission to mortgages in a negative interest rate environment," Working Paper Series 2243, European Central Bank.

Angrist, J., and Pischke, J. (2009): *Mostly Harmless Econometrics. An Empiricist's Companion.* Princeton University Press.

Ben-Zion, U. and S. S. Shalit (1975): "Size, Leverage, and Dividend Record As Determinants of Equity Risk," *The Journal of Finance,* 30 (4), pp. 1015–1026.

Basten, C., and M. Mariathasan (2018): "How banks respond to negative interest rates: Evidence from the Swiss exception threshold," CESifo Working Paper No. 6901.

Bertrand, M., Dufflo, E. and S. Mullainathan (2004): "How much should we trust differences-in-differences estimates?" *Quarterly Journal of Economics*, 119, pp. 249–275.

Bonaccorsi di Patti, E., and E. Sette (2016): "Did the securitization market freeze affect bank lending during the financial crisis? Evidence from a credit register," *Journal of Financial Intermediation*, vol. 25, issue C, pages 54-76.

Bongiovanni, A., Reghezza, A., Santamaria, R. and Williams, J. (2019): "Do negative interest rates affect bank risk-taking?" Bangor Business School Working Paper No. 19012.

Bottero, M., Minoiu, C., Peydro, J.L., Polo, A., Presbitero, A. F., and Sette, E.

(2019): "Negative monetary policy rates and portfolio rebalancing: Evidence from the credit register data," IMF Working Paper 19/44.

Boungou, W. (2020): "Negative interest rates policy and banks' risk-taking: Empirical evidence," *Economic Letters* 186.

Brei, M., Gambacorta, L., and Borio, C. (2019): "Bank Intermediation Activity in a Low Interest Rate Environment," BIS Working Paper No. 807.

Brunnermeier, M. K., and Koby, Y. (2019): "The "reversal interest rate": an effective lower bound on monetary policy," mimeo, Princeton University.

Carling, K., Jacobson, Lindé, T. J. and K. Roszbach (2007): "Corporate Credit Risk Modeling and the Macroeconomy," *Journal of Banking and Finance* 31(3), pp. 845–868.

Cingano, F., Manaresi, F., and Sette, E. (2016): "Does Credit Crunch Investment Down? New Evidence on the Real Effects of the Bank-Lending Channel," *The Review of Financial Studies*, Volume 29, Issue 10, pp. 2737–2773

Cozzi, G., Darracq-Paries, M., Karadi, P., Körner, J., Kok, C., Mazelis, F., Nikolov, K., Rancoita, E., Van der Ghote, A., and Weber, J. (2020): "Macroprudential policy measures: macroeconomic impact and interactions with monetary policy," ECB Working Paper No. 2376.

Demiralp, S., Eisenschmidt, J., and Vlassopoulos, T. (2019): "Negative interest rates, excess liquidity and retail deposits: banks' reaction to unconventional monetary policy in the euro area," Working Paper Series 2283, European Central Bank.

Eggertsson, G., Juelsrud, R., Summers, L., and Wold, E. (2019): "Negative nominal interest rates and the bank lending channel", NBER Working Paper No. 25416.

Eisenschmidt, J., and F. Smets (2019): "Negative interest rates: Lessons from the euro area", *Monetary Policy and Financial Stability: Transmission Mechanisms and Policy Implications*, edited by A. Aguirre, M. Brunnermeier and D. Saravia, edition 1, volume 26, chapter 2, pages 013-042, Central Bank of Chile.

Freixas, X. and Rochet, J.C. (2008): *The microeconomics of banking*. Cambridge: MIT Press.

Gambacorta, L. and Mistrulli, P.E. (2004): "Does bank capital affect lending behavior?", *Journal of Financial Intermediation*, Volume 13, Issue 4, pp. 436-457. Why bank capital matters for monetary policy

Gambacorta, L. and Shin, H.S. (2018): "Why bank capital matters for monetary policy," *Journal of Financial Intermediation*, Volume 35, pp. 17-29.

García-Posada, M. and Vegas, R. (2018): "Bankruptcy reforms in the midst of the Great Recession: the Spanish Experience," *International Review of Law & Economics*, Volume 55, September 2018, pp 71–95.

Heider, F., Saidi, F., and Schepens, G. (2019): "Life below zero: bank lending under negative policy rates". *The Review of Financial Studies*, Volume 32, Issue 10, pp. 3728-3761.

Holmstrom, B. and Tirole, J. (1997): "Financial intermediation, loanable funds, and the real sector," *Quarterly Journal of Economics*, 112(3), 663-691.

Imbierowicz, B., Löffler, A., and Vogel, U. (2019): "The transmission of bank capital requirements and monetary policy to bank lending," Deutsche Bundesbank Discussion Paper No. 49.

Jensen, M. and W. Meckling (1976): "Theory of the firm: Managerial behavior, agency costs and ownership structure", *Journal of Financial Economics*, 3, 305-360.

Jimenez, G., Ongena, S., Peydro-Alcalde, J., and Saurina, J. (2012): "Credit Supply and Monetary Policy: Identifying the Bank Balance-Sheet Channel with Loan Applications," *The American Economic Review*, Vol. 102 No. 5, pp. 2301-2326.

Jimenez, G., Ongena, S., Peydro-Alcalde, J., and Saurina, J. (2014): "Hazardous times for monetary policy: what do twenty-three million bank loans say about the effects of monetary policy on credit risk?" *Econometrica*, 82, 2, pp. 463-505.

Khwaja, A. and A. Mian (2008): "Tracing the impact of bank liquidity shocks: Evidence from an emerging market", *American Economic Review*, 98, pp. 1413-42.

Kim, D. and Sohn, W. (2017): "The effect of bank capital on lending: Does liquidity matter?" *Journal of Banking and Finance*, 77, pp. 95-107.

Kirti, D. (2020): "Why do bank-dependent firms bear interest-rate risk?" *Journal of Financial Intermediation,* Volume 41, January.

Köhler-Ulbrich, P., H. Hempell and S. Scopel (2016): "The euro area bank lending survey. Role, development and use in monetary policy preparation", European Central Bank Occasional Paper Series No 179.

López-Espinosa, G., Mayordomo, S. and A. Moreno (2017): "When does relationship lending start to pay?", *Journal of Financial Intermediation,* Volume 31, pp. 16-29.

Molyneux, P., Reghezza, A., Thornton, J. and Xie, R. (2019): "Did negative interest rates impact bank lending?," *Journal of Financial Services Research* 57(2).

Mosk, T. (2018): "Bargaining with a Bank," mimeo Goethe University.

Schelling, T. and Towbin, P. (2018): "Negative interest rates, deposit funding and bank lending". Mimeo, Swiss National Bank.

Van den Heuvel, S. (2006): "The Bank Capital Channel of Monetary Policy," Meeting Papers 512, Society for Economic Dynamics.

ON-LINE APPENDIX

Table A1: Number of banks by country

Country	Freq.	Percent
AT	8	6.5
BE	4	3.3
DE	27	22.0
EE	4	3.3
ES	10	8.1
FR	14	11
IE	7	5.69
IT	22	17.9
LT	4	3.3
LU	5	4.1
NL	8	6.5
PT	5	4
SK	5	4.07
Total	123	100

This table summarizes the number of banks in our sample for each country as of 2018Q1.

Table A2: Descriptive statistics of bank characteristics

Variable	Obs	Mean	Std. Dev.	Min	Max
NDFR (0/1)	1,926	0.73	0.45	0.00	1.00
Size (ln)	1,761	10.69	1.54	2.77	13.88
ROE (%)	1,535	4.86	10.61	-85.67	39.96
Capital ratio (%)	1,757	9.99	5.69	0.25	93.75
Liquidity ratio (%)	1,761	8.32	6.42	0	34.24
Deposit ratio (%)	1,761	41.01	22.48	0	87.00
Eurosystem borrowing (%)	1,761	0.97	2.43	0	17.39
Excess liquidity (%)	1,255	2.49	4.59	0	30.87
Weight loan overdrafts (%)	1,745	15.00	12.00	0	72.00
Weight loans up to 1 year (%)	1,745	23.00	15.00	0	93.00

This table contains the descriptive statistics of the bank characteristics that are used for the regression displayed in Table 2. Sample period: 2014Q2-2018Q1. Size is the natural logarithm of banks' total assets, ROE is net income over total equity, Capital ratio is capital and reserves over total assets, 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, Eurosystem borrowing is the total borrowing from the Eurosystem over total assets, Excess liquidity is deposit facility plus current account minus minimum reserve requirement 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.

Table A3: Firm descriptive statistics

	Mean	Median	SD	P1	P99
Total assets (TA) (€M)	6.64	1.17	24.04	0.07	189.52
Total financial debt / TA (%)	68.87	68.31	66.36	8.77	103.44
Liquid assets / TA (%)	6.56	2.51	10.14	0	50.84
ROA (%)	1.65	1.45	10.04	-41.24	30.12

This table reports the descriptive statistics of the firm characteristics that are used to classify firms as safe or risky in Tables 7 and 9. All the variables are in percentages but total assets, which are expressed in millions of euros.

Table A4: Variation in the supply of credit to firms by affected banks depending on their capital ratio. Dealing with generated regressors

	Baseline	Robustness
Affected Bank x Low Capital x Post.14-16	-0.087	-0.074
	[0.061]	[0.064]
Affected Bank x Low Capital x Post.16-18	-0.092	-0.079
	[0.082]	[0.084]
Affected Bank x Low Capital x Post.18-19	-0.150**	-0.153**
	[0.076]	[0.075]
Affected Bank x High Capital x Post.14-16	0.029	-0.011
	[0.071]	[0.069]
Affected Bank x High Capital x Post.16-18	0.011	-0.023
	[0.080]	[0.076]
Affected Bank x High Capital x Post.18-19	-0.089	-0.113
	[0.078]	[0.075]
Observations	728,398	728,398
R-squared	0.388	0.388
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. Given that the variable denoting affected banks is a particular type of a generated regressor, we perform a robustness test based on resampling techniques in column (2). To conduct this analysis, we first 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. 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 non-affected if the score is below this figure. We use the new classification of affected banks and report the results obtained from an estimation similar to that described above in column (2). Standard errors are reported in brackets and are clustered at bank-time level. ***, **, and * denote significance at the 1, 5 and 10% levels.

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