Bank Lending Standards over the Cycle: The Role of Firms' Productivity and Credit Risk

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Abstract

We show that bank lending standards are influenced by macroeconomic conditions. We use monthly data from the official credit register of the Bank of Spain, which allow us to monitor all loan applications made by non-financial firms to non-current banks from 2002 to 2015. To test the procyclicality of the appetite for risk of banks, we analyze the likelihood of granting a loan putting the focus on two firm characteristics (ex-ante credit risk and productivity) and interacting them with two macroeconomic indicators (business cycle and the monetary policy stance), while controlling for unobserved heterogeneity by means of firm and bank-time fixed effects. We find that banks soften their credit standards during booms or when monetary is loose to harden them during busts or when sort-term interest rates increases. This is especially relevant in the case of firms' productivity, which might partly explain the dismal evolution of aggregate productivity in Spain during the pre-crisis period. Finally, we also find that these results are more pronounced among less capitalized, less liquid and more profitable banks.

JEL Codes: G21; E51, D24, O47

Keywords: Productivity; credit risk; bank supply; lending standards.

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1. Introduction

The recent financial crisis lived by the Western economies in general and by Spain in particular, has once again put the focus of attention on the behaviour of banks during lending booms, given that it is well rooted that banks soften their lending standards during times of strong economic growth or expansionary monetary policy periods, to tighten them during busts. While the importance of short-term interest rates on banks risk-taking has been widely studied in the empirical literature in recent years (Jiménez at al. 2014; Dell'arriccia, Laeven and Suarez, 2107; Becker and Ivashina, 2015; Chodorow-Reich, 2014; Di Maggio and Kacperczyk, 2017) the literature on the link between economic cycle and the appetite for risk of banks is scarce ((Rodano, Andre , & Serrano-Velarde, 2015)). Our study investigates how bank lending standards are affected by firms' ex-ante creditworthiness, proxied by ex-ante credit risk and productivity, and how this pattern depends not only on the monetary policy stance and the economic cycle, but also on the balance-sheet strength of banks. In this sense, the importance of the firm balance- sheet channel in terms of ex-ante credit risk is well documented in the literature (see, for instance, (Rodano, Serrano-Velarde, & Emanuele, 2017) and (Jimenez, Ongena, Peydró, & Saurina, 2014)) but we know little about the role of productivity differences across firms in the allocation of credit. Moreover, although there is a strong correlation between bank credit and aggregate productivity in Spain (see Figure 1), the link between bank lending standards and productivity, however, is not well understood yet. Our findings indicate that banks soften their lending standards during expansionary times, in terms of firms' productivity and ex-ante credit risk, and especially among lowly capitalized, less liquid and more profitable banks. This pattern might partly explain the misallocation of resources towards low-productivity and risky firms that is at the root of the dismal evolution of aggregate productivity during the Spanish boom (García-Santana, Moral-Benito, Pijoan-Mas, & Ramos, 2016).

There is a vast strand of literature that highlights the importance of lending standards to understand the economic fluctuations and the dynamics of credit over the business cycle (Greenwood & Hanson, 2013) (Lopez-Salido & Zakrajsek, 2015) (Covas & Den Haan, 2011) (Jermann & Quadrini, 2012) (Becker & Ivashina, 2014) (Gilchrist, Yankov, & Zakrajsek, 2009), and there are different theories that provide a rationale for the mechanisms that make creditors vary their lending standards and their perception of credit risk over the cycle: agency problems (Williamson, 1963), herd behavior(Rajan, 1994), institutional memory hypothesis(Berger & Udell, 2004) and disaster myopia (Guttentag & Herring,

1986). Furthermore on the empirical front, there is evidence in the literature that contractive monetary policies and bad economic conditions affect lending standards and reduce banks' credit supply (Jiménez, Ongena, Peydró, & Saurina, 2012) (Dell' Ariccia, Laeven, & Suarez, 2017) (Dell'Ariccia & Marquez, 2006) (Saurina & Jimenez, 2006) (Ozlem, García Montalvo, García Villar, Peydró, & Maria Raya, 2014). Moreover, banks that are less capitalized, less liquid, and small are also those adjusting more pro cyclically their credit risk portfolio levels (Rodano, Serrano-Velarde, & Emanuele, 2017) (Kashyap & Jeremy, 2000) (Jimenez, Ongena, Peydró, & Saurina, 2014) (Bedayo, Estrada, & Saurina, 2017).

Turning to the demand side (balance-sheet strength of firms), a credit contraction affects firms heterogeneously on the basis of their characteristics implying changes in the allocation of funds across firms and the composition of banks' loans portfolios (Jimenez, Ongena, & Peydró, 2017). Indeed, the ability of banks to discriminate in terms of firms' productivity when granting new loans might wave in the end the allocation of resources and shape productivity, real activity and economic growth. (Benigno, Converse, & Fornaro, 2015). (Borio, Kharroubi , Upper, & Zampolli, 2015) show that lax credit conditions lead to misallocation of resources and productivity losses; while (Rodano, Serrano-Velarde, & Emanuele, 2017) show that substandard firms excluded from access to credit during busts (because banks' cyclical adjustment of lending standards) report lower values of production and capital investment than their peers slightly over the threshold cutoff that classified them into performing firms. More broadly, one can also connect these mechanisms with the recent literature about the productivity effects of financial frictions and misallocation of resources across firms (Hsieh & Klenow, 2009) (Gopinath, Kalemli, Karabarbounis, & Villegas-Sanchez, 2017) (García-Santana, Moral-Benito, Pijoan-Mas, & Ramos, 2016) (Dörr, Raissi, & Weber, 2017).

Our work is related to a number of previous studies. The relationship between monetary policy and bank risk-taking has been explored in (Jimenez, Ongena, Peydró, & Saurina, 2014)), Dell'arriccia, Laeven and Suarez (2107) and Ioannidou, Ongena, and Peydro (2015). However these studies do not analyze the economic cycle nor the effect of bank lending standards on other firm measures different from firm risk such as productivity. Moreover, the way we capture bank risk-taking is through the analysis of two firm characteristics over the cycle in the decision of granting a loan request. In this sense, our paper is related to the work by Dell'arriccia, Laeven and Suarez (2107), who use an ex-ante measure of borrower risk instead of the credit history or ex-post defaults rates. The bank-balance sheet channel

using loan applications is also employed in Jiménez et al. (2012) but the focus of that paper was to analyze the impact on monetary policy on bank credit supply.

Our paper complements the literature about the effects of monetary policy and the business cycle on banks` credit supply. While previous papers cast their conclusions about banks' lending standards focusing on different measures of firms' credit risk, to the best of our knowledge, there is no paper that studies how banks consider firms' productivity during a complete business cycle when they choose their loan portfolio. Therefore, we consider how productivity and ex-ante firms' credit risk affect banks' loan granting, and to what extent banks' lending policies vary over the business cycle depending on the balance-sheet strength of the banks.[1] We thus estimate how the ability of banks to discriminate in terms of firms' productivity depends on macroeconomic conditions, which allows us to relate our findings to the literature of misallocation across firms.

We use more than one million loan applications matched at the bank-firm level[2] from the Credit Register of Spain (CIR). Banco de España collects this information in a monthly basis for those firms that are not working with the bank at the time of the loan request. Additionally, we match the CIR with banks' monthly balance sheet information (collected by Banco de España in its role as bank supervisor) and with firms' balance sheet data from the Spanish Mercantile Register collected by the Central Balance Sheet Office in the Bank of Spain. Using this information, we compute firms' total factor productivity (TFP) following (Levinsohn & Petrin, 2003) and firms ex ante credit-risk following a Z-score procedure. Both variables summarize the information that banks evaluate for granting a loan to a company. Other firm controls include the number of banking relationships and a set of firm fixed effects, which controls for unobserved firm heterogeneity (including demand factors). Finally, our data allow us, in some specifications, to use bank*time fixed effects to exhaustively control for time varying observable and unobservable bank supply (including the bank balance-sheet channel).

Our main findings are as follows: higher firms' productivity or lower credit risk increase the probability that a loan application is granted. This finding suggests that banks

[1] In the spirit of Markowitz' theory (Markowitz, 1952) our specifications rely on the idea that banks choose their loan portfolio composition considering firms' ex- ante credit risk and productivity (that in the end are presumably correlated with banks' loan portfolio credit- risk and returns). That is, banks would grant a loan to those firms with a specific mix of ex ante credit risk and productivity that would lead them to a loan portfolio composition with a targeted credit risk and returns mix.
[2] 1,027,436 loan applications and 201,741 firms.

discriminate in terms of both productivity and ex-ante credit risk so that bank lending policies might play a role in the allocation of resources towards more/less productive firms. Moreover firm's credit risk and productivity are substitutes in terms of their effects on bank's screening process. Regarding macroeconomic fluctuations, we find that banks soften their lending standards during expansions: he economic cycle and the monetary policy affects lending standards both in terms of firms' credit risk and productivity, i.e., when the economy is growing or in a loosen monetary policy environment, banks react taking on more risk. In other words, their screening process reduces the relative importance of productivity or ex-ante credit risk, to the point of not taking them into account. Finally, our estimates indicate that these patterns are more marked in the case of less capitalized, less liquid and more profitable (higher risk profile) banks.

The remainder of the paper is organized as follows. Section 2A introduces the different datasets employed in the paper. Section 2B describes in detail the variables we use in the regressions. Section 2C presents the empirical specifications considered in the paper. Section 3 discusses our estimates of how bank lending standards depend on macroeconomic conditions as well as bank balance-sheet strength with special emphasis on the role of firms' productivity. Finally, Section 4 concludes.

2. Data and Empirical Strategy

In this section we firstly discuss the data we employ in our analysis. Then, we provide the definition of the dependent and the independent variables and describe our empirical strategy.

A. Database

We use confidential loan level data for Spanish non-financial companies at monthly frequency over the period 2002 to 2015 from the Spanish Credit Register (CIR), which is collected by the Banco de España acting as the national banker supervisor and regulatory authority[3]. We work with commercial and industrial (C&I) loans granted by commercial banks, savings banks and credit cooperatives (what embodies almost the entire Spanish

[3] The CIR was first employed by Jiménez and Saurina (2004) and Jiménez, Salas and Saurina (2006)

banking system) to non-financial publicly limited and limited liability companies (almost the 95% of all non-financial firms).

The CIR contains very detailed loan level data since 1984 on all loan commitments above € 6,000 granted by any bank operating in Spain. It means that more than 600,000 firms and 200 banks are active in the database at any moment in time. The CIR provides some information about borrower, lender and detailed information about loan characteristics, such as the type of instrument, currency, maturity, degree of collateralization, default status, as well as the amount drawn by the firm.

The information about the total current credit exposures, loan characteristics, and (possible) defaults is updated at a monthly frequency basis. All banks receive this information automatically, but only regarding their current borrowers. Therefore, they only file information requests following loan applications from firms that are currently not borrowing from them. Banks are legitimated to demand this data with the consent of their potential borrowers (Jiménez, Ongena, Peydró, & Saurina, 2012) (Jimenez, Ongena, Peydró, & Saurina, 2014), what is considered a signal that they are seriously approaching to the bank to get a credit. We observe all loan applications from 2002:02 to 2015:12 (before 2002 this information was not stored). Requests can be made at any time but they are collected monthly. Each request links uniquely a bank with (a potential) borrower, what permits us to infer which loans are granted by matching the loan application database with the CIR database. We match logged requests by firm i to bank b with new loans coded in the CIR database. For all requests lodged we observe whether the bank accepted and granted the loan (or rejected it) if the new loan is coded (or it is not coded) in CIR within three months after the information request was submitted by the bank.

Although the CIR and loan application databases provides comprehensive data on loans, they don't provide any additional information on borrowers but its identity, the amount drawn by the firm, province and sector of activity and its credits records (if any). We can also obtain from the CIR information about legal status, total credit amount and the number of banking relationships of the firm as well as the non-performing loan ratio. However, additional data on firms' and banks' balance sheets is crucial to build some key variables for our analysis, such as firms' total factor productivity (TFP) and firms' ex-ante credit risk (scoring). This information allows us to disentangle supply from demand factors: loan demand for each bank is given and observed, so each bank has to decide its lending policy

in light of the balance sheet strength of its potential borrowers. Therefore, we match CIR and the loan requests dataset with additional information about firms and banks balance sheets.

We get firm characteristics at a yearly frequency from Central Balance Sheet Data (CBI, *Central de Balances Integrada* in Spanish)[4]. This dataset is only available for researchers undertaking projects for the Banco de España and comprises information from the Spanish Mercantile Register (an administrative database that contains available information from firms financial statements required to be submitted by law to the commercial registry and also on their income corporate tax returns) collected by Central Balance Sheet Office, that is the unit in charge of collecting and cleaning these datasets within Bank of Spain.

Additionally, we get banks' information at a monthly frequency basis from banks' balance-sheet data owned by Banco de España in its role as banking supervisor. To capture macroeconomic conditions, we include a set of variables such as the overnight interest rate change and the GDP growth rate. All firm variables are set at the last December before the loan request is made, as a way to reduce endogeneity. In the same vein, banks and macro characteristics refers to the previous month of the loan application.

B. Variables

We use data about loan applications together with information about bank characteristics (to measure banks' balance sheet strength) as well as firm characteristics. Therefore, we can disentangle supply from demand factors by exploiting within bank variation in credit availability as a function of firm characteristics during upturns and downturns.

Table 1 shows the descriptive statistics of the variables used in the paper for the whole period 2002:02-2015:12.

Dependent variable: Loan application is accepted and the loan is granted

The dependent variable is an indicator dummy, LOAN APPLICATION IS GRANTED, which equals one if the bank b grants a loan requested by firm i at time t within the period t

[4] Central Balance Sheet Database has been filed with Mercantile Registries since 1995. Its size has grown progressively since then. Over 100,000 annual account of non-financial corporation were processed in the first years, while more than 400,000 annual accounts of non-financial corporations are processed each year since 2004 and more than 600,000 since 2011). In the last update, in 2015 9,086 corporations were processed from CBA and 667,585 corporations from CBB.

to t+3 and equals zero otherwise. The average value of loan granting for the period considered is around 35 percent. We focus on loans granted by commercial banks, savings banks and credit cooperatives to nonfinancial limited liability companies.

Independent variables

As independent variables, we include two macroeconomic variables, namely, *ANNUAL CHANGE OF OVERNIGHT INTEREST RATE* (ΔIR_{t-1}) as a measure of the monetary policy stance, and annual *GDP GROWTH RATE* (ΔGDP_{t-1}) as a proxy for the business cycle. In some specifications we substitute these macroeconomic indicators by a set of time dummies.

In order to disentangle the role of demand and supply factors, we include a set of firm and bank observable characteristics described below. Crucially, we also include a set of firm- and bank-specific fixed effects to control for demand and supply time invariant heterogeneity. Later, to fully account for time-varying heterogeneity in the supply side we saturate the specifications including a set of bank-time fixed effects.

Regarding firm characteristics, our regressors of interest are the two variables that summarize the information about the firms' quality as borrowers: firm's total factor productivity and ex-ante credit risk. These variables are calculated using information from CIR and CBI data.

We use (Wooldridge, 2009) GMM approach to implement (Olley & Pakes, 1996) and (Levinsohn & Petrin, 2003) identification strategy to compute firms' TFP as the residual in a logged production function with three inputs (labor, capital and intermediate materials) and industry-specific technology parameters[5]. For that purpose we use information about firm's revenue, total wage bill, employment, book value of capital stock (both physical and intangible), expenses in intermediate goods, and sector of activity at the NACE 4-digit level. A cut-off of a minimum of 25 observations per sector and year is required for the input variables to estimate sector-specific parameters of the production function. Sectors that do not meet the minimum cut-off criterion are flagged (agriculture and mining, petroleum industry companies) and firm-specific TFP figures are computed using the estimated production function parameters at the corresponding macro-sector level. A full set of year

[5] For robustness, we computed 5 alternative TFP measures: nominal TFP GMM estimation, TFP OLS estimation (we get two measures using alternatively real variables and nominal variables in an OLS regression), and real and nominal TFP estimation using industry-specific US labor shares in total production (constant returns to scale assumed in this case). Main results keep qualitatively the same using all the 5 alternative measures of TFP.

dummies is included to control for sector-specific trends. ECB (2016) contains a detailed description of the methodology used here to estimate TFP at the firm level.

We also consider a numerical score (*SCORING*) to measure ex-ante credit risk for each firm. This variable proxies the firm's likelihood to not fulfill its commitments with any bank based on lagged balance sheet information. To compute this variable we estimate a probability model for the whole sample where the dependent variable is an indicator equal to one when the firm defaulted in any of the 36 following months after a loan was granted and zero otherwise. [6] The variable scoring is a firm's credit risk measure calculated from a probability model. Specifically, each firms score is the total summation of the product between the regressors and their respective coefficients. We use fifteen variables as controls based on firms' balance sheet characteristics -financial ratios, financial indebtedness, solvency, liquidity, profitability, and expertise, structure, credit history and provincial and sectorial dummies - plus their quadratic, cubic and fourth power to assign a score to each company. The higher the scoring the riskier the company and therefore the likelihood to default.

Additionally, we include as another control the logarithm of the number of banks with which a company is indebted each period plus one, $ln(NUMBER\ OF\ BANKS\ RELATIONSHIPS+1)_{bit-1}$, which provides relevant information about the strength of the firm-bank relationship and also, ceteris paribus, about the credit quality of the firm. Notice we are focusing on new loans, so our estimations aren't affected by loan evergreening. Finally, to also control for unobserved firm heterogeneity constant over time, firm fixed effects are included in all estimations. This implies that we are only working with firms that has more than one loan application during the time analyzed (which represents the 96% of total observations).

Turning to bank characteristics to capture supply side developments, we include a set of six bank's balance sheet variables lagged one period (one month), to avoid endogeneity concerns, as we presuppose that banks optimally take decisions about loan granting and capital and liquidity holdings in response to macroeconomic and monetary policy conditions. We include the log of the total assets of the bank, $ln(TOTAL\ ASSETS_{bt-1})$; ROA_{bt-1}, the bank's return on assets; $LIQUIDITY_{bt-1}$ ratio, the ratio of liquid assets (cash and balance with central banks, and loans and advances to governments and credit institutions) held by the

[6] Using alternative time horizons for firm's underperformance (one and two years ahead) to construct our scoring variable, results remain qualitatively the same.

bank over the total assets of the bank; BANK CAPITAL RATIO$_{bt-1}$, the logged ratio of bank equity over total assets of the bank, as a measure of bank's net worth; and the DOUBTFUL LOAN RATIO$_{bt-1.}$ Additionally we include a measure of bank supply constructed following a methodology similar to the one proposed by (Amiti & Weinstein, 2017))[7]. Finally, it is worth mentioning that a set of bank-time fixed effects is included in our most stringent specifications to fully account for supply side factors beyond the ability to discriminate in terms of firms' productivity and credit risk.

Table 1 presents the summary statistics of the variables used in the estimations. The average probability of granting a loan during the period considered is around 36%, with a standard deviation of 0.48. It reaches values between 50% in 2002 to 40% in 2007:08. From then onwards it decreases, being its average value 33.6% in 2015. Average total factor productivity is around to -0.1 with a standard deviation of 0.55. Its value remains stable from 2002-2008 around -0.1 and then suddenly increases (see Figure 1). The average value for scoring is -1.32 with a standard deviation of 0.75, what implies an average predicted default probability of 0.09 for the whole period. It provides a likelihood to default in the future for each borrower, thus the higher its value the higher the credit risk of the firm. As can be seen in Figure 2 yearly average predicted default probability reached its local maximum in 2008 and from then onwards it monotonically decreased.

C. Empirical Strategy

The aim of the paper can be summarized by the following three questions: (1) Does higher firms' productivity or lower firm's ex-ante credit risk increase the likelihood of a loan being granted? Are lending standards cyclical? (2) Does banks' assessment about firms' quality as a debtor (measured in terms of productivity and ex-ante credit risk) vary over the business cycle? That is to say, is there a risk-taking effect? (3) Does bank-balance sheet channel matters for the lending policy? That is to say, does the strength of bank balance-sheet affect the way firms' productivity and ex-ante credit risk vary over the cycle?

[7] We performed a weighted linear regressions where the dependent variable is the bank credit growth from period t to period t-1, over total credit granted by each bank in both periods, with firms and banks fixed effects. The last ones are included to identify the bank supply.

We thus consider three alternative specifications to explore the answers to the three questions above. In all cases we estimate linear probability models[8] at the bank-firm-month (loan-month) level by matching data on the loan application outcome with the relevant macroeconomic, bank and firm balance-sheet characteristics.

The baseline specification tries to answer the first set of questions and it includes firm controls ex-ante credit risk and productivity- together with the business cycle and interest rate. To be more concrete we consider the following equation:

$$Loan\ application\ is\ granted_{bit} = \beta_1 TFP_{it-1} + \beta_2 SCORING_{it-1} + \beta_3 TFP_{it-1} \times SCORING_{it-1} + \beta_F OTHER\ FIRM\ CHARACTERISTICS_{\ bit-1} + \beta_B BANK\ CHARACTERISTICS_{bt-1} + \beta_5 \Delta GDP_{t-1} + \beta_6 \Delta IR_{t-1} + \vartheta_b + f_i + \varepsilon_{bit} \quad (1)$$

where *b* refers to banks, *i* refers to firms, and *t* refers to months. Moreover, firm fixed effects, f_i, and bank fixed effects, ϑ_b, are included to capture time-invariant demand and supply factors. Our main interest relies on the coefficients for productivity (*TFP*) and credit risk (*SCORING*) to understand whether banks' lending standards and credit allocation depend on these two factors. Finally, the interaction between credit risk and productivity informs about the degree of substitutability in banks' assessments between these two firm characteristics. The coefficients on TFP and SCORING comprise the answer to the first set of questions. The expected signs are $\beta_1>0$ and $\beta_2<0$ if banks take into account firm creditworthiness during the granting process of a loan request. The complementarity or substitutability between both variables is captured with its multiplicative. If the estimated coefficient is positive we will conclude that are substitutes, and complementary in the other situation the bank effect which is expected. On the other hand, it is expected to have a positive coefficient, $\beta_5>0$, for ΔGDP and a negative one, $\beta_6<0$, for ΔIR (see Jiménez et al. 2012), which would highlights the cyclical behavior in the credit standards of banks.

To answer question number two we enhance the baseline specification with interaction terms between firm controls (credit risk scoring and productivity) and macroeconomic variables (ΔGDP and ΔIR) to show how the cycle drives banks' lending policies and its

[8] We estimate linear models instead of non-linear ones to allow us to multi-cluster the standard errors, to avoid selection problems that arise in such cases and to improve the interpretability of coefficients (Chunrong & Norton, 2003); Norton an, Wang, and Ai (2004)).

compositional effects on banks' loan portfolio through the demand side. In particular, we consider the following model:

$$
\begin{aligned}
&Loan\ application\ is\ granted_{bit} = \\
&= \beta_1 TFP_{it-1} + \beta_2 SCORING_{it-1} + \beta_3 TFP_{it-1} \times SCORING_{it-12} \\
&\qquad + \beta_F OTHER\ FIRM\ CHARACTERISTICS_{it-12} \\
&\qquad + \beta_B BANK\ CHARACTERISTICS_{bt-1} \\
&\qquad + \beta_c MACRO\ CHARACTERISTICS_{\ t-1} \\
&\qquad + \vartheta_b + f_i \\
&\qquad + \beta_7 \begin{pmatrix} TFP_{it-1} \\ SCORING_{it-1} \end{pmatrix} \times MACRO\ CHARACTERISTICS_{\ t-1} \\
&+ \beta_8 TFP_{it-1} \times SCORING_{it-1} \times MACRO\ CHARACTERISTICS_{\ t-1} + \varepsilon_{bit} \qquad (2)
\end{aligned}
$$

The coefficients on the cross-effects give answer to the second question about the compositional effects of the cyclicality of bank lending standards. On the one hand, we expect to have $\beta_7<0$ and $\beta_{10}>0$; while on the other hand $\beta_8>0$ and $\beta_{11}<0$. This would imply that banks increase their appetite for risk, softening their lending standards, when the economy is growing or during times of loose monetary policy.

Turning to the third specification, we add triple interaction terms between firms' variables, macroeconomic variables and banks characteristics, to test whether the cyclicality of the lending policy of the banks depends on the strength of their balance sheets. More specifically, in order to analyze how bank lending standards variation is related with bank characteristics, we enlarge specification (2) and estimate the following specification:

$$
\begin{aligned}
&Loan\ application\ is\ granted_{bit} = \\
&= \beta_1 TFP_{it-12} + \beta_2 SCORING_{it-1} + \beta_3 TFP_{it-1} \\
&\qquad \times SCORING_{it-12} + \beta_4 OTHE\ R\ FIRM\ CHARACTERISTICS_{\ it-1} \\
&+ \beta_B BANK\ CHARACTERISTICS_{\ b,t-1} + \beta_C MACRO\ CHARACTERISTICS_{\ t-1} + \vartheta_b + f_i + \\
&\qquad \beta_7 \begin{pmatrix} TFP_{it-1} \\ SCORING_{it-1} \end{pmatrix} \times MACRO\ CHARACTERISTICS_{\ t-1} \\
&\qquad + \beta_8 TFP_{it-1} \times SCORING_{it-1} \times MACRO\ CHARACTERISTICS_{\ t-1} \\
&\qquad \beta_{Bcg} BANK\ CHARACTERISTICS_{\ b,t-1} \times MACRO\ CHARACTERISTICS_{\ t-1} \\
&+ \beta_{Bc1} BANK\ CHARACTERISTICS_{\ b,t-1} \times \begin{pmatrix} TFP_{it-1} \\ SCORING_{it-1} \end{pmatrix}
\end{aligned}
$$

$$+ \beta_{Bcs} BANK\ CHARACTERISTICS_{\ b,t-1} \times \begin{pmatrix} TFP_{it-1} \\ SCORING_{it-1} \end{pmatrix} \times$$

$$MACRO\ CHARACTERISTICS_{\ t-1} + \varepsilon_{bit} \qquad (3)$$

The coefficients β_{Bc1} and β_{Bc2} provide information about the variation in lending standards associated with banks' balance sheet characteristics to investigate whether the pro-cyclicality in bank lending policies is more marked in certain type of banks.

Finally, it is worth highlighting that in all the three specifications we consider a final version of the models in which we substitute bank variables and bank fixed effects by a set of bank-time fixed effects (ϑ_{bt}) to better identify supply factors beyond banks' lending standards in terms of firms productivity and credit risk.

3. Results

Table 2 reports the estimates of the baseline specification, which aims to answer the question: Does higher firms' productivity or lower firm's ex-ante credit risk increase the likelihood of a loan being granted? Does the likelihood to grant a loan depend on the cycle? We start analyzing these two questions in column (1) of Table 1, where our two main firm variables of interest (TFP and SCORING) are included. Macroeconomic conditions are controlled using the GDP growth and the change in interest rate. In addition, a set of bank controls is also included to account for differences in time-varying fluctuations in the supply side. Unobserved time-invariant firm and bank heterogeneity in the demand and supply side is controlled through the inclusion of firm and bank fixed effects in the demand and supply sides. The estimated model in column (2) includes the interaction term $\mathrm{TFP}_{\mathrm{it}-1} * \mathrm{SCORING}_{\mathrm{it}-1}$, which captures the potential complementarities between productivity and credit risk in the loan granting decision process considered by the banks.[9] Finally, in column (3) we substitute the bank fixed effects, the bank balance-sheet variables and the macroeconomic indicators by a set of bank*time dummies. This saturated specification allows us to identify the coefficients by exploiting variation across firms within the same month and bank in order to isolate the role of firm productivity and ex-ante credit risk while controlling for time-variant supply factors.

[9] All variables are demeaned to keep the economic sense of all the variables in levels.

According to the estimates in Table 2, a one standard deviation increase in firm's total factor productivity rises the probability of loan granting in around 2.3 p.p., while a one standard deviation increase in firm's credit risk scoring reduces the probability of loan granting by 1.4 p.p. These effects are significant not only statistically but also economically. In particular, the TFP effect is around 6.6% of the average loan granting probability (see Table 1) and the corresponding credit risk effect is -4.3%. Both effects are fairly stable across all the three specifications considered in Table 2. We therefore conclude that both dimensions are relevant in the banks' decision of granting a loan.

The interaction coefficient in columns (2) and (3) can be interpreted in terms of substitutability or complementarity between the firms' characteristics considered. Given the estimated coefficients, we conclude that firm's ex-ante credit risk and productivity are substitutes in terms of their effects on the banks' credit granting process. In particular, this result implies, for instance, that the importance of the ex-ante credit risk of the firm in the granting decision is lower among highly productive firms.

Columns (1) to (3) also shows that higher interest rates or lower GDP growth contract credit availability, which reflects the cyclicality of lending standards of banks.

Turning to the next question (Does banks' assessment about firms' quality as a debtor vary over the business cycle?), we gradually saturate the baseline specification by adding interaction terms to see how banks frame their lending policies over the cycle in response to loans applicants' productivity and ex-ante credit risk. Table 3 reports the estimated coefficients for the specification in Model 2. In column (1) we only add an interaction term between firms' productivity and macroeconomic variables. In column (2) we only consider an interaction between firms' ex-ante credit risk and the macroeconomic variables. In column (3) we include both firms' TFP and SCORING interacted with macroeconomic variables. The specification in column (4) also includes two triple interactions between TFP, SCORING and the two macroeconomic indicators to test whether the substitutability pattern identified above varies with aggregate macroeconomic conditions. All specifications from columns (1) to (4) include firm and bank fixed effects. As a robustness check, in column (5) we include a set of time fixed effect while in column (6) a set of bank*time fixed effects is included instead of the macro and bank variables. In both columns (5) and (6), the results remain virtually

unaltered with respect to those of column (4) where macroeconomic and bank variables are included as controls instead of time and bank*time fixed effects.

The main conclusion from the estimates reported in Table 3 is that bank lending standards vary with macroeconomic conditions. This is so because the interaction terms of firm characteristics with macroeconomic variables are statistically significant in most cases. In particular, we estimate a negative (positive) coefficient for the interaction of TFP with GDP growth rate (ΔIR), and a positive (negative) coefficient for the interaction of *SCORING* with GDP growth rate (ΔIR). These findings indicate that during the expansionary phases of the cycle banks soften their lending standards implicitly increasing the risk in banks' loan portfolios, while they tighten lending standards during downturns so that the implicit credit risk assumed by banks is reduced. When TFP is interacted with annual overnight interest growth rate its coefficient is statistically significant what can be interpreted as evidence of cyclical impact of monetary policy in the loan portfolio composition in terms of productivity[10]. Summing up, both economic cycle and monetary policy appear to have a compositional effect on banks' loan portfolios. The former would affect loan portfolios both in terms of credit risk and productivity of the borrowers, while the latter would only change the loan portfolio composition in terms of firms' credit risk.

Turning to the economic significance of the estimated effects in column (4) of Table 3, a one percentage point increase in the GDP growth rate reduces the positive effect of firms' productivity on the probability of being granted a loan in 33% (from 0.022 to 0.016). On the other hand, a one percentage point increase in the GDP growth rate would reduce the negative effect of ex-ante credit risk on the loan granting probability in 35% (from -0.013 to -0.008). It is worth highlighting that the positive effect of firms' TFP on loan granting probability vanishes when annual GDP growth is above 3.2%, the 75th percentile in the sample. These effects remain very similar when we control for time or bank*time fixed effects in columns (5) and (6). Finally, the lack of statistical significance of the triple interaction terms (*TFP*SCORING*GDP* and *TFP*SCORING*INTERESTRATE*) suggests that the substitutability between credit risk and productivity discussed above does not vary with macroeconomic conditions.

[10] Only when firm fixed effects and bank-time fixed effects are included the coefficient for the interaction of TFP and annual overnight interest growth rate is marginally significant (p-value of 0.12), although its economic impact is almost unaltered.

Finally, we are also interested in how banks' lending policies vary with macroeconomic conditions depending on their balance sheet strength. In particular, we aim to answer the question: Do different banks account for firms' productivity and credit risk differently over the business cycle?

Table 4 reports the coefficient estimates for the triple interaction terms of firm characteristics (TFP and SCORING) with bank characteristics (*ROA, LIQUIDITY, BANK CAPITAL RATIO*…) and macroeconomic variables (*GDP* and *INTEREST RATE*), which correspond to the parameters $\beta_{Bc1s}, \beta_{Bc2s}, \beta_{Bc1p}, \beta_{Bc1p}$ in specification (3) above[11]. These coefficients would capture heterogeneous changes in banks' lending standards over the cycle as a function of banks' balance sheet characteristics. To be more concrete, we focus on three variables that reflect banks' balance sheet strength, bank's liquidity, banks net worth, and banks' return on assets. The last variable can be understood as a proxy of banks' internal efficiency and as a measure of their risk appetite, in the sense that higher risk portfolios usually led to higher returns on assets. Column (1) includes firm, bank, and time fixed effects while column (2) includes bank*time fixed effect and firms' fixed effects instead of bank and time fixed effects separately. In a few words, the estimated results indicate that less capitalized, less liquid and the more profitable banks are those that soften the more their credit standards during upturns, especially in the case of firms' ex-ante credit risk. These results are robust to the inclusion of the different specification for the bank and time-fixed effects, and highlight the need to design regulatory frameworks which lead banks to adequate capitalization and liquidity management, easing the evolution of the banking business to an environment where the basis for banks profitability to be an adequate creditor risk assessment, regardless the business cycle.

4. Conclusions

We identify the impact of the cycle on the composition of the supply of credit. In particular, in this paper we analyze whether bank lending policies are influenced by the economic cycle or the monetary policy, and to what extent these factors has a compositional effect on banks' credit supply. To perform the analysis and to capture firm fundamentals while

[11] Other bank balance sheet variables are also included as controls in the regressions reported in Table 4 together with all the remaining controls considered in equation (3).

controlling for unobserved heterogeneity with firm fixed effects, we construct two variables, that summarize banks' loan portfolio characteristics and that can be understood as a proxy of firms' quality as debtors: firms' ex ante credit risk and firms' total factor productivity. While the former measures company's' loan default probability the latter measures firms' allocative efficiency in production. We construct these variables using information from the Credit Register managed by the Banco de España, and from Central Balance Sheet Data.

From our knowledge, this is the first paper that analyzes explicitly the importance that firms' efficiency in the production process has for banks when they assess firms applying for a loan. Here, we study not only the degree of substitutability between credit risk and efficiency when firms are assessed but also we test whether banks soften their credit standards during booms to tighten them during busts, raising or decreasing the weight given to this firms' characteristics. Moreover we show how economic cycle and monetary policy change the appetite for risk of banks. During upturns banks soften their lending standards and firms both with higher credit risk and less efficient production process have a higher probability of being granted a loan. Monetary policy also change banks risk appetite and this effect is more pronounced among less capitalized, less liquid and more profitable banks.

In this sense the changes in capital, liquidity and systemic banks' regulation introduced by Basel III with the aim of reinforcing the financial stability, improve bank management and strengthen banks' transparency would, accordingly with our results, also smooth banks' lending-standards-cyclicality. Thus, leading to capital allocation of resources better aligned with firms' productivity and credit risk.

References

Amiti, M., & Weinstein, D. (2017). How much do Idiosyncratic Bank Shocks Affect Investment? Evidence form Matched Bank-Firm Loan Data. *Journal of Political Economy*, forthcoming.

Becker, B., & Ivashina, V. (2014). Cyclicality of Credit Supply: Firm Level Evidence. *Journal of Monetary Economics, 62*, 76-93.

Bedayo, M., Estrada, A., & Saurina, J. (2017). Bank capital, lending booms, and busts. Evidence from Spain in the last 150 years. *mimeo*.

Benarke, B., & Gertler, M. (1989). Agency Cost, Net Worth, and Business Fluctuations. *American Economic Review, 79*, 14–31.

Benigno, G., Converse, N., & Fornaro, L. (2015). Large Capital Inflows, Sectoral Allocation, and Economic Performance. *Journal of International Money and Finance, 55*, 60-87.

Berger, A. N., & Udell, G. F. (2004). The institutional memory hypothesis and the procyclicality of bank lending behavior. *Journal of Financial Intermediation, 13*, 458–495.

Borio, C., Kharroubi , E., Upper, C., & Zampolli, F. (2015). *Labour reallocation and productivity dynamics: financial causes real consequences.* Bank of International Settlements, Monetary and Economics Department. .

Chunrong, A., & Norton, E. C. (2003). Interaction Terms in Logit and Probit Models. *Economics Letters, 80*(1), 123-29.

Covas, F., & Den Haan, W. (2011). The Cyclical Behaviour of Debt and Equity Finance. *American Economic Review, 101*(2), 877-899.

Cuadrado, P., & Moral-Benito, E. (2016). Potential growth of the Spanish economy. *Ocassional Paper Banco de España*.

Dell' Ariccia, G., Laeven, L., & Suarez, G. (April de 2017). Bank Leverage and Monetary Policy's Risk-Taking Channel: Evidence from the United States. *The Journal of Finance*, 613-654.

Dell'Ariccia, G., & Marquez, R. (October de 2006). Lending Booms and Lending Standards. *The Journal of Finance, LXI*(5), 2511-2546.

Dörr, S., Raissi, M., & Weber, A. (2017). Credit-Supply Shocks and Firm Productivity in Italy. *IMF Working Paper WP 17/67*.

García-Santana, M., Moral-Benito, E., Pijoan-Mas, J., & Ramos, R. (2016). Growing Like Spain: 1995-2007. *Banco de Espana Working Paper No. 1609*.

Gilchrist, S., Yankov, V., & Zakrajsek. (2009). Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bonds and Stock Markets. *Journal of Monetary Economics, 56*, 471-493.

Gopinath, G., Kalemli, S., Karabarbounis, L., & Villegas-Sanchez, C. (July de 2017). Capital Allocation and Productivity in South Europe. *The Quarterly Journal of Economics*.

Greenwood, R., & Hanson, S. G. (2013). Issuer Quality and Corporate Bonds Returns. *Review of Financial Studies, 26*(6), 1483-1525.

Guttentag, J., & Herring, R. (1986). Disaster Myopia in International Banking. *Essays in International Finance*(164), 332-342.

Hsieh, C.-T., & Klenow, P. (2009). Misalocattion adn Manufacturing TPF in China and India. *The Quaterly Journal of Economics*, 1403-1448.

Jermann, U., & Quadrini, V. (2012). Macroeconomic Effects of Financial Shocks. *American Economic Review, 102*(1), 238-271.

Jimenez, G., Ongena, S., & Peydró, J.-L. (2017). Do Demand or Supply Factors Drive Bank Credit, In Good and Crisis Times? *European Banking Center Discussion Paper*.

Jiménez, G., Ongena, S., Peydró, J.-L., & Saurina, J. (2012). Credit Supply and Monetary Policy: Identifying the Bank Balance-Sheet Channel with Loan Applications. *American Economic Review*, 2301-2326.

Jimenez, G., Ongena, S., Peydró, J.-L., & Saurina, J. (2014). Hazardous Times for Monetary Policy: what do twenty-three million bank loanssay about the effect of monetary policy on credit risk-taking. *Econometrica, 82*(2), 463-505.

Kashyap, A., & Jeremy, C. (June de 2000). What do a Million Observations on Banks Say About the Transmission of Monetary Policy. *The American Economic Review, 90*(3).

Levinsohn, J., & Petrin, A. (2003). Estimating Production Functions Using Inputs as Controls for Unobservables. *The Review of Economic Studies*, 317-342.

Lopez-Salido, D., & Zakrajsek, E. (2015). Credit Market Sentiment and the Business Cycle. Unpublished Manuscript.

Olley, S., & Pakes, A. (1996). The dynamic of Productivity in the Telecommunications Equipment Industry. *Econometrica*, 1263-1297.

Ozlem, A., García Montalvo, J., García Villar, J., Peydró, J.-L., & Maria Raya, J. (2014). The real estate and credit bubble: evidence from Spain. *SERIES, 5*, 223-243.

Rajan, R. (1994). Why Bank Credit Policies Fluctuate: A Theory and Some Evidence. *The Quarterly Journal of Economics*, *109*(2), 399-441.

Rodano, G., Andre , N., & Serrano-Velarde, B. (October de 2015). Lending Standards Over the Credit Cycle. *Available at SSRN: https://ssrn.com/abstract=2699553*.

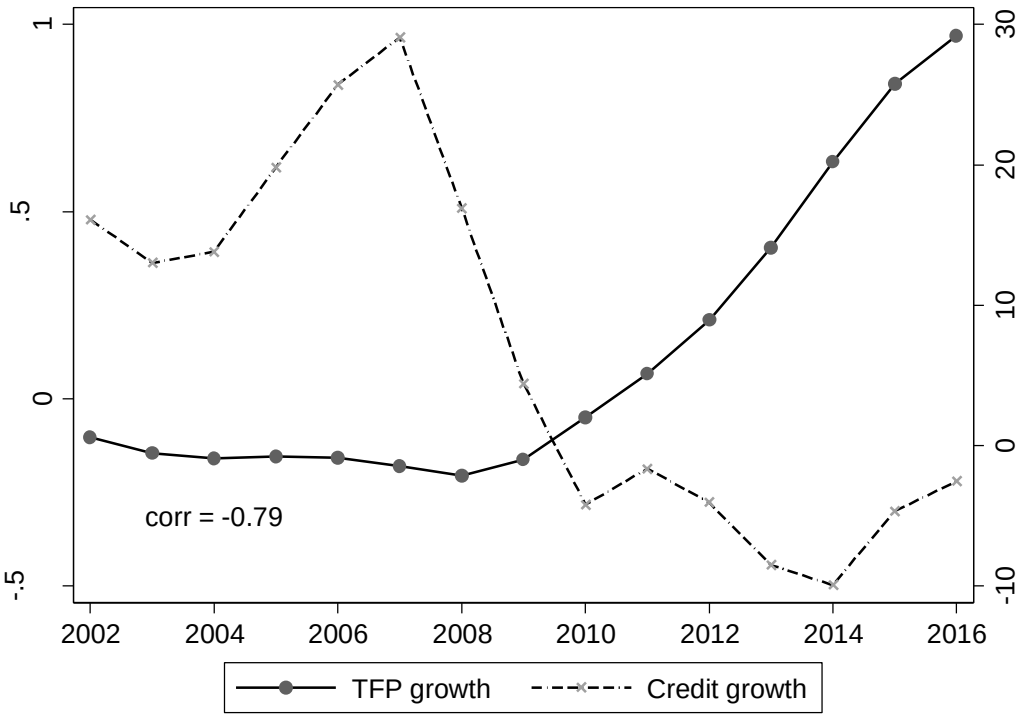
Rodano, G., Serrano-Velarde, N., & Emanuele, T. (2017). Lending Standards Over the Credit Cycle. *Unpublished working paper*.

Saurina, J., & Jimenez, G. (2006). Credit Cycles, Credit Risk, and Prudential Regulation. *International Journal of Central Banking*, 66-98.

Williamson, O. (1963). Managerial Discretion and Business Behaviour. *American Economic Review*, 1032-57.

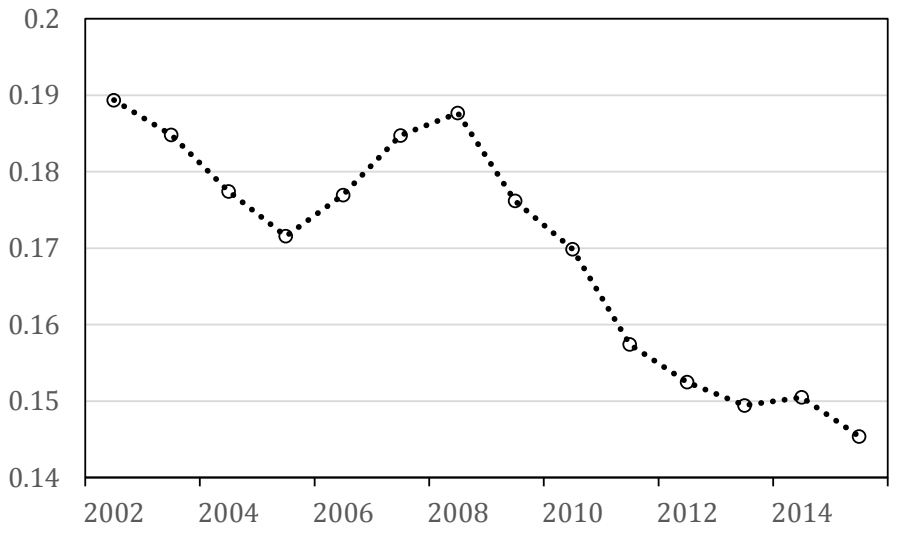
Wooldridge, J. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*(104), 112–114.

Figure 1. Credit, investment and TFP in Spain



Notes. Credit refers to bank credit to non-financial corporations taken from Banco de España and TFP is sourced from (Cuadrado & Moral-Benito, 2016).

Figure 2. Average predicted firm's defaulted probability



Notes. Own calculations, from a linear probability model that provides a score for each borrower. The score is the total summation of the product between the repressors and their respective coefficients.

Table 1. Descriptive statistics

DEPENDENT VARIABLE				
	Mean	Sd	25^{pth}	75^{pth}
LOAN APPLICATION IS GRANTED$_{ibt}$	0.357	0.479	0.000	1.000
INDEPENDENT VARIABLES				
Macroeconomic conditions (t)				
ΔGDP_{t-1}	0.778	2.596	-1.673	3.262
ΔIrt-1	-0.278	1.183	-0.740	0.443
Firm characteristics (i)				
TOTAL FACTOR PRODUCTIVITY $_{i,\ t-1}$	-0.093	0.551	-0.403	0.218
SCORING$_{i,\ t-1}$	-1.312	0.746	-1.575	-0.871
ln(NUMBER OF BANK RELATIONSHIPS $_{ibt-1}$	1.424	0.542	1.099	1.792
Bank characteristics (b)				
ln(TOTAL ASSETS)$_{b,t-1}$	17.801	1.489	16.890	18.883
ln(LIQUIDITY RATIO)$_{b,\ t-1}$	14.754	6.609	10.210	17.810
ROA $_{b,t-1}$	0.573	0.657	0.331	0.871
BANK CAPITAL RATIO $_{b,t-1}$	-2.896	0.435	-3.114	-2.650
DOUBTFUL LOAN RATIO $_{b,t-1}$	5.242	5.147	0.855	7.255
SUPPLY SHOCK$_{bt}$	0.140	0.211	-1.920	1.975

Notes: Table 1 reports means, standard deviations, first and third quartiles of loan applications. For the definition of the variables see Appendix.

Table 2. Baseline specification: Lending Standards over the Credit Cycle

Dependent variable: Loan Granted ibt=1 if the bank b grants a loan requested by firm i at time t within the period t to t+3, and equals zero otherwise

	(1)	(2)	(3)
$PRODUCTIVITY_{it-1}$	0.023***	0.021***	0.021***
	(0.002)	(0.002)	(0.002)
$SCORING_{it-1}$	-0.015***	-0.014***	-0.014***
	(0.002)	(0.002)	(0.002)
ΔGDP_{t-1}	0.021***	0.021***	
	(0.002)	(0.002)	
$\Delta INTEREST\ RATE_{t-1}$	-0.014***	-0.014***	
	(0.004)	(0.004)	
$PRODUCTIVITY_{it-1}*SCORING_{it-1}$		0.022***	0.022***
		(0.002)	(0.002)
Observations	921,637	921,637	921,672
Firms	179,200	179,200	179203
Banks	174	174	174
R-squared	0.289	0.289	0.290
Firm Fixed Effect	YES	YES	YES
Bank Fixed Effect	YES	YES	YES
Time Fixed Effect	NO	NO	NO
Time periods, months	167	167	167

Notes: The table reports estimates from our baseline specification. Column 2 adds the interaction for the firms' quality variables to capture differences in the slope for the probability of loan granting to allocative efficiency for firms with a certain level of risk. Bank covariates ($SUPPLY_{bt}$; $TOTAL\ ASSETS_{bt}$; $LIQUIDITY\ RATIO_{bt}$; ROA_{bt}; $BANK\ CAPITAL\ RATIO_{bt}$; $DOUBTFUL\ LOANS\ RATIO_{bt}$) are also included but their coefficients are not reported. We report standard errors in brackets. The dependent variable we use is a binary indicator that takes the value 1 if loan is granted by bank b to firm i in period t, and zero otherwise. See Table A.1 for the definition of the variables. One star denotes significance at the 10% level, two stars denotes significance at the 5% level and three stars denotes significance at the 1% percent level. For the definition of the variables see Appendix.

Table 3. Analyzing Compositional Effects of the cyclicality of lending standards: Bank-risk Taking

Dependent variable: Loan Granted ibt=1 if the bank b grants a loan requested by firm i at time t within the period t to t+3, and equals zero otherwise						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$PRODUCTIVITY_{it-1}$	0.022***	0.0209***	0.022***	0.022***	0.022***	0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$SCORING_{it-1}$	-0.014***	-0.014***	-0.014***	-0.014***	-0.013***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ΔGDP_{t-1}	0.0217***	0.0216***	0.022***	0.022***		
	(0.002)	(0.002)	(0.002)	(0.002)		
$\Delta INTEREST\ RATE_{t-1}$	-0.014***	-0.014***	-0.014***	-0.014***		
	(0.004)	(0.004)	(0.004)	(0.004)		
$PRODUCTIVITY_{it-1}*SCORING_{it-1}$	0.021***	0.025***	0.024***	0.024***	0.023***	0.023***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$PRODUCTIVITY_{it-1}*\Delta GDP_{t-1}$	-0.007***		-0.007***	-0.007***	-0.006***	-0.008***
	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
$PRODUCTIVITY_{it-1}*\Delta INTEREST\ RATE_{t-1}$	0.003**		0.003*	0.003*	0.003	0.004**
	(0.002)		(0.002)	(0.002)	(0.002)	(0.002)
$SCORINGi_{t-1}*\ln(\Delta GDP)_{t-1}$		0.005***	0.005***	0.005***	0.005***	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$SCORING_{it-1}*\Delta INTEREST\ RATE_{t-1}$		-0.003**	-0.003**	-0.003**	-0.003**	-0.002
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$PRODUCTIVITY_{it-1}*SCORING_{it-1}*\Delta GDP_{t-1}$				-0.001	-0.001	-0.001
				(0.001)	(0.001)	(0.001)
$PRODUCTIVITY_{it-1}*SCORINGi_{t-1}*\Delta INTEREST\ RATE_{t-1}$				0.001	0.001	0.001
				(0.002)	(0.002)	(0.002)
Observations	921,637	921,637	921,637	921,637	921,637	921,287
Firms	179,200	179,200	179,200	179,200	179,200	179145
Banks	174	174	174	174	174	173
R-squared	0.289	0.289	0.289	0.289	0.292	0.313
Firm Fixed Effect	YES	YES	YES	YES	YES	YES
Bank Fixed Effect	YES	YES	YES	YES	YES	NO
Time Fixed Effect	NO	NO	NO	NO	YES	NO
Bank-time fixed effect	NO	NO	NO	NO	NO	YES
Time periods, months	167	167	167	167	167	167

Notes: Table 3 reports estimates that enhance specification in Table 2 by adding interaction terms for the firms' quality and macroeconomic variables to capture differences in the slope for the probability of loan granting over the cycle. Bank covariates ($SUPPLY_{bt}$; TOTAL $ASSETS_{bt}$; LIQUIDITY $RATIO_{bt}$; ROAbt; BANK CAPITAL $RATIO_{bt}$; DOUBTFUL LOANS $RATIO_{bt}$) are also included but their coefficients are not reported here. Standard errors are reported in brackets. The dependent variable we use is a binary indicator that takes the value 1 if loan is granted by bank b to firm i in period t, and zero otherwise. See Table A.1 for the definition of the variables. Scoring is defined as a measure of ex- ante risk that recaps firm's predicted probability of default in any of the 36 following months after a loan granted. Fifteen variables based on firms' financial ratios, balance sheet characteristics (financial indebtedness, solvency, liquidity, profitability, and expertise), structure and credit history plus its quadratic, cubic and fourth power are the set of information to compute the numerical value for the scoring. See Table A.1 for the definition of the variables. One star denotes significance at the 10% level, two stars denotes significance at the 5% level and three stars denotes significance at the 1% percent level. For the definition of the variables see Appendix.

Table 4. Heterogeneous lending standards over the credit cycle by type of bank

Dependent variable: Loan Granted$_{ibt}$=1 if the bank b grants a loan requested by firm i at time t within the period t to t+3, and equals zero otherwise

	(1)	(2)
PRODUCTIVITY$_{it-1}$*ΔGDP$_{t-1}$*LIQUIDITY RATIO$_{bt-1}$	-0.00006	-0.00006
	(0.000)	(0.000)
PRODUCTIVITY$_{it-1}$*ΔGDP$_{t-1}$*ROA$_{bt-1}$	-0.00096	-0.00083
	(0.001)	(0.001)
PRODUCTIVITY$_{it-1}$*ΔGDP$_{t-1}$*BANK CAPITAL RATIO$_{bt-1}$	0.006***	0.006***
	(0.002)	(0.001)
SCORING$_{it-1}$*ΔGDP$_{t-1}$*LIQUIDITY RATIO$_{bt-1}$	-0.0002**	-0.0002*
	(0.000)	(0.000)
SCORING$_{it-1}$*ΔGDP$_{t-1}$*ROA$_{bt-1}$	0.003***	0.003***
	(0.001)	(0.001)
SCORING$_{it-1}$*ΔGDP$_{t-1}$*BANK CAPITAL RATIO$_{bt-1}$	0.001	0.001
	(0.002)	(0.002)
PRODUCTIVITY$_{it-1}$*ΔINTEREST RATE$_{t-1}$*LIQUIDITY RATIO$_{bt-1}$	-0.001**	-0.0004
	(0.000)	(0.000)
PRODUCTIVITY$_{it-1}$*ΔINTEREST RATE$_{t-1}$*ROA$_{bt-1}$	-0.00038	-0.002
	(0.004)	(0.004)
PRODUCTIVITY$_{it-1}$*ΔINTEREST RATE$_{t-1}$*BANK CAPITAL RATIO$_{bt-1}$	-0.00478	-0.007
	(0.004)	(0.004)
SCORING$_{it-1}$*ΔINTEREST RATE$_{t-1}$*LIQUIDITY RATIO$_{bt-1}$	0.0004*	0.0003
	(0.000)	(0.000)
SCORING$_{it-1}$*ΔINTEREST RATE$_{t-1}$*ROA$_{bt-1}$	-0.010***	-0.009***
	(0.004)	(0.003)
SCORING$_{it-1}$*ΔINTEREST RATE$_{t-1}$*BANK CAPITAL RATIO$_{bt-1}$	-0.00133	-0.003
	(0.003)	(0.003)
Observations	921,637	921,252
Firms	179,200	179,142
Banks	174	173
R-squared	0.293	0.313
Firm Fixed Effect	YES	YES
Bank Fixed Effect	YES	NO
Time Fixed Effect	YES	NO
Bank and Time Fixed Effect	NO	YES
Time periods, months	167	167

Notes: The table reports estimates that enhance previous specification in Table 3, by adding interaction terms for the firms' quality variables with banks and macroeconomic variables to capture cyclical fluctuations in the slopes that would reveal a heterogeneous change in banks' lending standards over the cycle. Productivity, Scoring, Bank covariates (SUPPLYbt;TOTAL ASSETSbt; LIQUIDITY RATIObt; ROAbt; BANK CAPITAL RATIObt; DOUBTFUL LOANS RATIObt) and all the double and triple interactions between and macroeconomic variables are included as a controls although not reported here. Standard errors are in brackets. The dependent variable is a binary indicator that takes the value 1 if loan is granted by bank b to firm i in period t, and zero otherwise. Scoring is defined as a measure of ex- ante risk that recaps firm's predicted probability of default in any of the 36 following months after a loan is granted. Fifteen variables (firms' financial ratios, balance sheet characteristics such as financial indebtedness, solvency, liquidity, profitability, and expertise, firms' structure and credit history plus its quadratic, cubic and fourth power are the set of information used to compute the numerical value for the scoring. See Table A.1 for the definition of the variables. One star denotes significance at the 10% level, two stars denotes significance at the 5% level and three stars denotes significance at the 1% percent level. For the definition of the variables see Appendix.

Appendix

Variable Name	Definition
Dependent variables	
I(GRANTING OF LOAN APPLICATIONS $_{tbi}$)	A dummy variable, which equals 1 if the loan application made in month t to bank *b* by firm i is successful and the loan is granted in t to t+3, and equals cero otherwise.
Independent variables	
Firm characteristics	
PRODUCTIVITY$_{it-1}$	Total Factor Productivity (TFP), computed as the residual in a production function, where output is measured as real value added and three inputs are considered (labor, capital and intermediate materials)
SCORING$_{it-1}$	Firm's likelihood to fulfill her commitments with any bank based on lagged balance sheet information: financial ratios, financial indebtedness, solvency, liquidity, profitability, and expertise, structure, credit history and provincial and sectorial dummies,plus their quadratic, cubic and fourth power. Firms' balance sheet information refers to consolidated data regarding December of the previous year.
ln (BANK RELATIONSHIPS+1)$_{it-1}$	Log of the number of loans that a firm holds with a bank each period plus one,
Macroeconomic conditions	
ΔGDP$_{t-1}$	Annual growth rate of Spanish Gross Domestic Product in real terms (%)
ΔINTEREST RATE$_{t-1}$	Annual change of overnight interbank interest rate (%)
Bank characteristics	
ln (Total Assets)$_{t-1}$	Log of the total assets of the bank
ROAt-1	Banks' return on assets: ratio of profit before taxes over banks' average total assets
Liquidity ratio$_{t-1}$	The ratio of liquid assets that the bank holds over total assets of the bank
Bank capital ratio $_{t-1}$	The logged ratio of equity over bank total assets
Doubtful loans ratio$_{t-1}$	Ratio of doubtful loans over total loans
Supply shock$_{t-1}$	Difference in the residuals of two weighted linear regressions where the dependent variable is the bank credit growth from period t and period t=0 (January 2002), over total credit granted by each bank in t=0 and t, where the former includes firms fixed effects and the latter firms and banks fixed effects