Loan Underwriting Time:
A New Determinant of Bank Lending Standards

Mikel Bedayo **Gabriel Jiménez** **José-Luis Peydró** **Raquel Vegas**[*]

August 2018

Abstract

In this paper we analyze a unique factor within the process of granting a loan: the underwriting time. We investigate the explanatory factors behind the loan underwriting time and to what extend it reflects the credit policy followed by the bank which determines its future performance. The loan granting time is defined as the time elapsed between the loan application is lodged in the system and the loan is granted. For identification, we use data from the official credit register of the Banco de España, which allows us to monitor all loan applications made by non-financial firms to non-current banks from 2002 to 2016 and to select those granted. We first show that the granting time depends on macroeconomic, firm and bank characteristics. In particular, we find that loan underwriting time is inversely related to the business cycle and to banks' growth, which evidences the procyclicality of banks' underwriting standards. Moreover, we also show that banks' appetite for risk also points toward a reduction of the concession time. Thereby, credit growth policies are taken at the expense of granting quicker applications to first-time and poor credit history borrowers. In this sense, controlling for observed and unobserved firm heterogeneity, our estimations show that loans that were granted in a shorter period of time are riskier in the future. For example, the speed up of the underwriting process increases the average probability of future default up to 6%. Finally, we also find that banks' average granting time of their firms' portfolio reveals aspects of their credit policy that affect their future distress.

JEL Codes: G21; E51.

Keywords: Underwriting time; granting time; bank lending; credit standards; default probability.

Mikel Bedayo, Banco de España, e-mail: mikel.bedayo@bde.es. Gabriel Jiménez, Banco de España, e-mail: gabriel.jimenez@bde.es. José-Luis Peydró, ICREA-Universitat Pompeu Fabra, CREI, Barcelona GSE, Imperial College London, and CEPR, e-mail: jose.peydro@upf.edu. Raquel Vegas, Banco de España, e-mail: raquel.vegas@bde.es. Corresponding author: Gabriel Jiménez. We thank Anatoli Segura and David Martinez-Miera for useful comments. This paper reflects our views and not necessarily the views of Banco de España or the Eurosystem.

"MARK: How many loans do you write each month?
MORTGAGE BROKER: It's about 60
MARK: What was it four years ago?
MORTGAGE BROKER: Ten. Maybe 15. [...] The bonuses sky rocketed few years ago"
The Big Short (2015), Movie script.

1. Introduction

The Great Recession has taught us the importance of a continued monitoring of banks' credit policies (including LTVs, sectorial diversification, funding plans, bonus policies, credit growth, etc…) because they are at the same time part and transmitting chain of the financial shocks to the real economy. Previous to the Great Recession and to the global banking crisis, lending standards were substantially loosened (Jiménez et al., 2014) and banks boomed loans to low-quality borrowers. Consequently, the root of the financial crisis can be found in an excessive growth of credit at the expense of the quality of the borrowers. Thus, it can be said that the Great Recession was largely caused by the pro-cyclicality of banks' lending standards.[1]

One of the ways to speed up the granting of credit is a shoddier evaluation of the borrower, which would result in a shorter granting time, ceteris paribus.[2] The more the time spent on a loan application the less the likelihood the loan officer to wrongly evaluate it, so the less its default probability if it is accepted and granted. In line with this idea, we could expect that banks that are fastest during the screening process, on average, have loans with a higher future default probability, compared to loans granted after their application has been studied and thoroughly reviewed for a longer time.

As far as we know, this paper is the first work to analyze the key drivers of the time between a loan request is lodged until the loan application is approved and granted by the lender (granting time), which includes the study of its cyclical behavior. We first empirically show that the time banks spend assessing an application decreases during booms, or when banks decide to increase their loan portfolio, to sharply increase during

---

[1] For instance, in the USA a loosening of lending standards during the economic boom together with the use of Automated Underwriting Systems (AUS, a computer-generated and based on algorithms system which allows to determine a potential borrower's eligibility almost instantly) led to an acceleration of the growth in the total amount of credit granted in the economies that would be soon after hit by the crises.

[2] Granting and underwriting time are used indistinctly throughout the paper, given that the literature uses both terms.

recessions, or when banks deleverage. Although this could be seen as evidence of the cyclicality of banks' lending standards, the identification is a challenge because disentangling cyclical borrower-demand factors from cyclical bank-supply factors is needed. Moreover, we also find that it is precisely during periods of strong economic growth or when banks increase their credit supply that they reduce granting time more intensively on risky borrowers, i.e. those with a bad credit history or with higher adverse selection problems. All this evidence lead us to explore how the granting time, as a sufficient statistic of banks' credit policies, affects the quality of the borrower that enters into the bank's portfolio. Thus, the present work is also the first one to empirically test whether the time elapsed between the loan application is lodged by the bank in the system and the loan is granted, has some effects on the quality of the screening process, which affects the future performance of the loan granted and in particular its probability of default.

We take advantage of the Credit Register held by the Banco de España and, in specifically, of the loan applications database. While the former contains information about all granted loans in Spain at loan level at a monthly frequency, the second stores monthly loan applications from borrowers to non-current banks, those with which the borrower was not working at the time of the request. We can thus track the status of the application to know whether it was finally approved, accepted by the borrower and granted by the lender, and for those loans granted, we are able to compute the time the whole process took. This is the new indicator we use throughout the paper to capture banks' risk profile. In particular, we work with Spanish non-financial firms given that we also have access to Spanish firms' and banks' financial statements to controls for firm and bank characteristics, respectively. Given that we know the identity of the borrowing firm (unique tax identifier) and of the bank, we are able to merge the granted-loan database with the data sources containing economic and financial information from their balance sheets and income statements.

Our main identification challenge is to separately control for bank supply and for firm demand heterogeneity (Khwaja and Mian, 2008; Jiménez et al., 2012, 2014 and 2017; Amiti and Weisntein, 2017). There is reason to believe that banks dedicate a longer time to analyze dubious firms when they apply for a loan, compared to more creditworthy firms. Therefore, unless firm characteristics are fully controlled for in the estimations, underwriting time's effect on a borrower's default probability will be biased. It is also paramount to fully control for credit supply since banks' underwriting time may not depend uniquely on their balance sheet characteristics but also on their available technology to evaluate loan applications, which most likely changes and improves over time. Hence, along the paper we control for firm and bank unobserved and observed characteristics that may evolve over time. We use several databases to tackle possible identification issues. Moreover, our empirical strategy exploits the fact that banks accept more than one loan application each month, which in our baseline specification, allow us to introduce bank-time fixed effects to control for observed and unobserved time-varying bank heterogeneity. We also capture firm heterogeneity with the inclusion of firm fixed effects and, in some specifications, with firm-time fixed effects.

We follow a three-step-bottom-up strategic approach to study the determinants of the granting time, to investigate how this measure reflects the lending standards of the bank over time, and to analyze how this behavior has future implications for the performance of banks, in particular to their risk of failure. First, an analysis of the key drivers of the grating time is showed to shed some light on this first-time analyzed variable. We find that granting time moves inversely with the economic cycle and with the bank's decision to growth. We also find that the time a bank spends in the screening process is positively related to the complexity and the information asymmetry of the firm and negatively related to its creditworthiness. For instance, our results show that riskier firms (those with a bad credit history or new to the bank) are more deeply analyzed than the others. However, the paper also shows that banks' appetite for risk is greater precisely in periods of strong economic growth or when the bank decides to increase its loan portfolio. During this time, riskier firms are more likely to be quicker analyzed. This first set of results provide strong evidence that a bank's credit standards directly affect the granting time. Second, we test this evidence analyzing the impact of a loan's granting time on its future performance. That is, whether, as expected, for a given point in time and for a given bank, those loan application more deeply assessed are less likely to default. The paper shows that this is the case and highlights the relevance of a continuous monitoring by the banking supervisors of this variable when assessing a bank's risk profile. However, given that the analysis is focused on a particular loan portfolio (it covers non-financial firms), and given that banks can hedge credit risk with guarantees, endorsements, or simply taking other less risky positions in other portfolios, our evidence could have no implications for the bank as a whole. This is the reason why in the third step we go a step further and we study the link between the average granting time of banks to firms before the Great Recession and the likelihood of a risk event of the bank during the recent financial crisis. In fact, we want to find evidences suggesting that the loosening of credit standards, capture through a reduction of the time devotes by the bank the assessment of the new applicant firms, reflects the risk strategy follow by the bank and has future real consequences for both the bank and the real economy. We present econometric evidence in this sense which closes the circle and gives us a total vision of the role played by the credit standards of the banks in their portfolio management and their future distress, which has deeply implications for the real economy and the financial stability of the system.

The paper contributes to the literature of lending standards and loan and bank performance. It is the first work that analyzes the determinants of the time between a loan request is lodged until the loan applications is granted. The main contribution of the paper is to enhance the understanding of the integral procedure of the bank credit policies since the screening process to the impact of these decision on bank's future performance. We focus not only on supply and demand heterogeneity that affects underwriting time but also on cyclical changes that might lead banks to modify their screening strength. In the analysis of the granting time we control for comprehensive set of firms and banks characteristic, including firms' ex-ante credit risk.[3] Moreover, we control for the business cycle to set the importance of macroeconomic variables to delimit lenders' underwriting time. We show that during economic upturns lenders take less time to analyze creditors' requests and to grant loans compared to downturns. We also find evidence suggesting that banks are quicker assessing more creditworthiness firms than riskier or unknown ones. Moreover, our results show that the commented cyclical behavior is at the expense of loosening lending standards and increasing their loan portfolios risk. Consequently, we show that all things equal, loans which granting time was shorter report a higher future default probability. Finally, our results present strong evidence on the link between the granting time, as a proxy of credit standards, and the risk profile of the bank.

Besides, our approach allow us to test whether the concentration, as a proxy of competition, of bank branches at a province or municipality level affects the underwriting time and in what sense. Theoretical literature predicts contradictory effects. On the one

[3] Firms' credit history and the strength of the bank-firm relationship during the year before the loan request.

hand, strong competition in a market could make banks more prone to lend, which ultimately speeds up the selection process and, therefore, reduces concession time. On the other hand, asymmetric information increases as competition in the market becomes strong, since lenders offering credit face uncertainty about firms' creditworthiness to the extent they cannot observe some of the borrowers' characteristics and actions. Lenders get over part of this asymmetrical information over time, acquiring some informational power about their clients. Therefore, the less concentrated the supply of credit the higher the uncertainty about clients' creditworthiness and therefore the higher the granting time (see (Utrero-González, 2007) and (Crawford, Pavanini , & Schivardi, 2015)). Our paper shows that the asymmetry information effect prevails over the competition effect, and thus the higher the number of lenders the higher the underwriting time.

The paper proceeds is the following way. Section 2 reports the literature review. Section 3 describes the data sources and reports descriptive statistics. Section 4 provides the empirical methodology for the three different approaches that we follow. Section 5 presents the results and Section 6 concludes.

2. Literature review

It is usually noted that the higher a lender's access to the borrower's private information the better the bank's assessment about the borrower's creditworthiness. A high amount of information about a good quality borrower might lead the lender to offer better credit terms or to relax its requirements, given the lower uncertainty about the nature of the borrower and her ability of paying back the loan.

It is both theoretically and empirically well documented, that banks soften their lending standards during times of strong economic growth or expansionary monetary policy to tighten them during busts or monetary contraction periods (Saurina & Jiménez, (2006) Maddaloni & Peydró, (2011); Greenwood & Hanson, (2013); Becker & Ivashina, (2014); (Jiménez, Ongena, Peydró, & Saurina, (2014); Dell'Ariccia , Laeven , & Suarez, (2007)). Moreover, banks' lending standards change due to firms' ex-ante credit worthiness, which can modify the source of funds across firms and the composition of banks' portfolios (Rodano, Serrano-Velarde, & Enmanuele, (2015); Jiménez, Moral-Benito, & Vegas, (2017); (Loutskina & Strahan, (2009); Rodano, Serrano-Velarde , & Tarantino , (2017)).

There is a myriad of theoretical papers about the way banks' lending standards and screening intensity are set and how it influences banks' profits and overall system risk. In this sense, it is worth mentioning that (Dell'Ariccia & Marquez, 2006) theoretically show that when banks tighten their screening processes to gather more information about their borrowers, credit requirements become less stringent. This leads to a worse equilibrium where banks' profits decrease and financial stability trembles, especially when economic conditions begin to worsen because banks increase their risk portfolio. Similarly, (Mariathasan & Zhuk, 2018) theoretically analyze banks' tradeoff between loosely screening many loan applications received and screening fewer applications with a higher precision of their underwriting process, given banks' capacity constraints. They show that as economic conditions improve, approved loans are riskier ex-ante and generate lower expected returns. As such, (Mariathasan & Zhuk, 2018) is closely related to the present study, given that the theoretical model present in their article explains the deterioration of credit quality during market booms and tighter standards during recessions, which are results we empirically find here.

Additional sources of lending standards' variability could come from market structure. Although the relationship between competition and banks' risk (financial stability) is complex, traditional literature claims that competition increases the pressure for loan growth and commercial funding (margin effect), and that it leads banks to take more risk easing their credit standards to generate profits (Keeley, (1990); Matutes & Vives, (2000)).

More recent literature about market structure and its effects on banks' risk taking conversely argues that more competition leads to more stable financial institutions. These papers state that competition reduces the loan granting rates, which in turn decreases loans' probability of default and therefore the risk of banking failure (Boyd & De Nicolo, (2005)), and the risk-shifting effect. Moreover, when loan default probabilities are not perfectly correlated more competition reduces interest payments also for performing loans, which provides a buffer against loan losses (Mieira & Repullo, 2010). They find that in very concentrated markets, the risk-shifting effect dominates the margin effect (entry reduces the probability of bank failure) whereas in very competitive markets the opposite occurs (further entry increases the probability of failure), so a U-shaped relationship between competition and the risk of bank failure exists.

Allen & Gale, (2003) consider several theoretical models of competition to better understand the trade-off between them. Similarly, Beck, Demirguç-Kunt, & Levine, (2006) focus on bank concentration and regulation to empirically estimate the likelihood of a systemic banking crisis, concluding that a more concentrated banking system decreases the likelihood of a systemic crisis. They argue that bank competitiveness cannot simply be measured with bank concentration. Ruckes, (2004) claims that credit standards and bank competition vary with the economic cycle: banks do not devote many resources to assess a potential borrower during expansions because the probability of identifying a "bad" applicant is lower than in recessions. Nevertheless, by loosening credit standards, price competition becomes fiercer and credit is extended to borrowers with worse credit records. Thus, lower credit standards during expansionary periods entail higher loses during recessions given a higher default probabilities of loans originated during expansions.

Moreover, the strength of banks' lending standards and their screening intensity are highly correlated with bank-firm credit relationships and the overall credit supply. There exists a trade-off between the drawbacks and benefits of single vs multiple bank-firm credit relationship. On the one hand, keeping a single bank relationship –a strong one-may reduce agency costs, allows the lenders to have exclusive access to the firm's soft information, and thus it would increase firm's access to credit or to better funding terms (Agarwal & Elston, (2001)). On the other hand, lenders may exploit its monopsony power and tighten its credit terms. Besides, in the event the lenders might be hit by a financial shock, firms' funding could be at a higher risk of being cut by its unique credit supplier (Santos & Farinha, (2002); Ogawa, Sterken, & Tokutsu, (2007)).

However, less empirical research is available about the linkages between banks' intensity in the screening process and credit supply, mainly because it is difficult to observe and accurately measure how intensively banks monitor their prospective lenders.

Dell'Ariccia, Laeven, & Deniz, (2012) focus on loans performance, loan denials and loan to income ratios as measures of the accuracy and quality of lenders' screening process. They claim that the lowering of lending standards was one of the reasons which triggered the last financial crisis, and empirically show that in US areas with a high demand for mortgages, the lending standards preceding the last 2007 financial crisis were lighter compared to other areas with a minor credit expansion, and that it led to higher delinquency rates.

Demyanyk & Van Hemert, (2011) measure a loan quality by its performance, adjusted for differences in borrower characteristics (credit score, a level of indebtedness, an ability to provide documentation), loan characteristics (product type, a loan amount, and mortgage terms), and macroeconomic conditions (price appreciation, neighborhood income and change in unemployment).

It is undeniable that correctly classifying the repayment ability of a creditor is essential to reduce non-performance loans and that it somehow influences banks' balance sheet strength. Lenders' scoring quality strongly depends on the information they receive from the borrowers and other additional sources. Garmaise, (2015), using data from one US financial institution about around 8,000 residential mortgages between 2004 and 2008, show that borrowers overstating their level of assets are likelier to miss a loan repayment. Jappelli & Pagano , (2002), empirically document that countries where lenders share credit information about their borrowers have a lower overall credit risk (proxied by default rates).

Regarding the screening intensity, Rajan, Seru, & Vig, (2015) show that lenders set loans' terms (specifically interest rates) according to borrowers' hard information (borrower's characteristics that they make public to their lenders and that is easily verifiable) and their level of securitization. As long as securitization increases, lenders tend to disregard soft information, and therefore they might overestimate borrowers' creditworthiness. By observing loan defaults, the authors argue that a default model does not perform well when borrowers' soft information is valuable and not considered by the model, pointing out that most models focus on borrowers' historical data. In the same vein (Jiménez & Saurina, 2004) conclude that collateralized loans are likelier to default given that the lender may decrease its screening process at the time she grants the loan. Besides, they state that saving banks are riskier than commercial banks.

Dell'Ariccia, Laeven, & Deniz, (2012), proxy bank intensity in the screening process through denial rates and loan to income ratio.

Our paper complements the literature about the strength of banks' screening process and the variation of the lending standards. Specifically we measure banks' monitoring intensity using a variable that to the best of our knowledge has received litte attention so far: the underwriting time. [4] We evaluate how the speed in the loan processing process varies with borrowers' characteristics, market structure, macroeconomic conditions and bank characteristics. Additionally, we analyze how loans' delinquency rates vary for different underwriting times, once we control both for observable firm and bank characteristics and also macroeconomic factors. As far as we know we are the first to consider underwriting time to measure banks' screening intensity and to try to identify how it could affect variability on the banks' lending standards over the cycle.

3. Data and descriptive statistics

Our empirical analysis relies on five datasets: i) we employ the Spanish Credit Register (CIR) owned and managed by the Banco de España, which contains in-depth information about almost every loan granted by a financial institution operating in Spain; ii) we use the loan application dataset that records loan request of borrowers to non-current banks; iii) a dataset on firms' financial information through the Spanish Mercantile Registers; iv) a dataset containing banks' financial statements available at the Banco de España in its role of bank supervisor; and v) a database containing the location of bank branches at the municipal level.

The CIR contains financial and non-financial information about every loan exceeding the threshold of 6,000 euros. Apart from identifying the borrower and the financial institution granting the loan, it gathers a substantial amount of relevant information about the loan, such as its amount, maturity time or the existence of collateral. We focus on loans granted by commercial banks, savings banks and credit cooperatives to nonfinancial limited liability companies, which gather around 95% of the Spanish credit market. Our final sample contains more than 160 banks.

The Banco de España sends information to every financial institution located in Spain about their actual clients' aggregate credit exposures with any bank in Spain at a monthly basis. Nevertheless, a financial institutions might request this data about any

[4] Alessandri and Bottero (2017) study the impact of uncertainty on credit supply using monthly data on loan applications received by Italian banks between 2003 and 2012. They focus on how uncertainty affects credit supply and the time firms have to wait for their loans to be granted by a bank. Unlike us, they do not distinguish the time duration since a firm applies for a credit till it is granted by a bank. They only analyze if uncertainty increases the likelihood that loans asked within a month are granted within the same month, losing the main point of our analysis.

potential borrower who has lodged an application for a loan but is not a client of the bank yet, at any time at no monetary cost. Thus, by observing banks' information request about any prospective client at any point in time, and observing whether in the short term these firms has been granted a loan by the same bank, we can conclude that the loan was approved and granted to the firm they had asked information about. See Jiménez et al. (2012, 2014 and 2017) for a detailed description of these datasets.

Since we are interested in the explanatory factors behind the loan underwriting process and to what extend it is related to the credit standards of the bank, by measuring the time elapsed between the lodged request and its concession, we construct the *Underwriting Time* (UT) variable for every new firm-bank relationship.

In this paper we impose the maximum time delay between a loan request is lodged and its concession to be four months. As a robustness check we also show that the results that we get for the four-month window are also valid for the three- and five-month ones. Furthermore, in Figure 1 it can be observed that around 70% of accepted loans are granted within the first month after their request. The corresponding median equals one month, while granting time's mean equals 1.18 months. Figure 2 shows the average granting time since the first semester of 2002 to the last semester of 2015. The cyclical behavior seems to suggest that banks' lending standards are reduced during booms to harden in the recessive phases. Thereby, we observe that upon the start of the last financial crisis loans' underwriting time had been shrinking. Once the financial crisis hit hard, it seems that banks were more wary to concede credit to new customers and increased their average underwriting time.

We observe every bank's loan application for information about any possible future borrower since 2002:02 until 2015:12. This amounts to 4,605,053 loan applications, out of which 1,977,662 were eventually accepted and the loan was granted. After cleaning the data the total number of observations we work with for our baseline regressions sum up to 473,973. The number of observations at our disposal in the most restrictive sample we use throughout the article adds up to 32,657. This reduction is due to the merge with firms' financial information and to the inclusion of firm, bank and time fixed effects to control for observed and unobserved demand factors. The descriptive statistics of the variables used are presented in Table 1.

A loan's underwriting time might last up to four months, so the underwriting time variable we construct takes five different values: 0, 1, 2, 3 and 4. As it can be seen in Table 1, its mean equals 1.18 (slightly more than one month) and its median is one month. Following with a brief summary of Table 1, the average probability of default is 0.20, that is, on average, one out of five borrowers are expected to default on a loan. Besides, banks' average doubtful loans ratio is around 5%, the average granted loan sums up to around 55,000 €, and less than 10% of loans are collateralized. Firms in our sample have been operating on average for around 10 years, and 10% of them have defaulted at least once by the time they start a new relationship with a lender. Around 85% of these firms had used the bank they start a new relationship with in the past twelve months, and around 30% of them are using at least one bank when they obtain credit. Thus, our sample is mainly composed of young firms obtaining small amounts of non-collateralized credit payable in the short term, from usually a unique bank which they have had a relationship in the past with.

We also have at our disposal banks' and firms' balance sheet information. Banks' information is obtained through a database owned by Banco the España as a banking supervisor, and firms' information through the Spanish Mercantile Registers. By identifying the lender and borrower of any loan, we match bank and firm characteristics with loan characteristics, which allows us to end up with banks' and firms' balance-sheet information at the time a loan application is lodged.

Besides, in order to analyze the impact of bank competition or information asymmetry we also have a dataset containing historical data on the location of bank branches at the Spanish zip code level. We use the postal code reported by each bank in the aforementioned dataset to identify the municipality to which it belongs, and sum up the number of every different bank in each municipality. Further, we also consider the number of branches every different bank has in each municipality and sum up the total number of branches. By doing so, we consider that branches of a same bank compete between each other as well as with branches of competing banks. We do not restrict to banks' competition at the postal code level since sometimes the same street has different zip codes on each side, so it is not realistic to consider that banks do not compete with other banks which might be a few meters away just because they are located at different postal codes. Moreover, given Spain's low population density, firms might search for credit in a different city from which they are located, so we generalize the bank concentration measure to a municipal and provincial level.[5] Summing up, we use the Spanish postal code guide to classify banks into their corresponding municipality and province according to their postal code. This allows us to calculate bank concentration indices across Spain. This way, we allow banks within the same province to compete between each other. In our inclusive dataset we work with 3,596 municipalities and 52 provinces.

4. Empirical methodology

To analyze the loan underwriting time, we start by investigating how creditors' characteristics, economic cycle and banks heterogeneity affect the granting time. Then, we study whether the time devoted by a bank to measure the credit risk of a loan, ceteris paribus, is related to its credit standards in the sense that banks decide to soften them, and reduce the granting time, or to toughen them, and increase the underwriting time. The hypothesis is clear; as banks lower their credit standards, the screening time of new operations is lower, which would translate into a higher percentage of risky loans in their portfolios, with the negative consequences that this has in terms of future default. Finally, we also test whether the increase in non-performing loans as a consequence of a lower time devoted to the screening process has a real effect on the future performance of the bank. For this, we analyze the future failure of the banks after the Great Recession taking into account the situation of the bank prior to the crisis, including the average granting time of the bank. We therefore perform the analyses in three steps, by the estimation of three different equations with three different dependent variables.

4.1. Determinants of Underwriting Time

To analyze the determinants of the time elapsed from the time the credit request is registered until it is granted, we rely on information about loan applications to non-current banks granted during a complete business cycle. The use of loan-level information allows us to analyze the role of the business cycle, bank-supply factors and firm-borrowing characteristics independently. The dependent variable is *Underwriting Time*,

[5] Spain's population density in 2017 was around 91 people per squared kilometer. This is lower than many advanced geographically comparable countries. For instance, France, Italy, Germany and UK had a density of around 118, 198, 226 and 268 people per squared kilometer in 2017, respectively. Source: https://www.populationpyramid.net/population-density/2017/.

which measures how many months has a bank taken to approve a loan request and grant the credit to its new customer. As commented before, this is a discrete variable that takes 5 different values, ranging from 0 (if the loan was granted the same month in which it was requested) to 4 (if the loan was granted four months after the requested). As robustness we have also use the log of the time in days since the loan application was submitted to the Banco de España until the last day of the month in which the request was granted.

Formally, the baseline specification we estimate the following equation using OLS:

$$
\begin{aligned}
\text{Underwriting Time}_{fjl,t} &\\
&= \beta_1 \Delta GDP_{t-1} + \beta_2 \Delta int\_rate_{t-1} + bank\ controls_{j,t-1} \\
&+ firm\ controls_{f,t-1} + municipality\ controls_{fm,t-1} \\
&+ loan\ controls_{l,t} + \eta_j + \eta_f + \epsilon_{fjl,t}, \qquad (1)
\end{aligned}
$$

where the sub-indexes *f*, j, m, *l* and t refer to firm, bank, municipality, loan and time, respectively. The variable ΔGDP_{t-1} denotes the annual growth of rate of Spanish GDP, Δint_rate_{t-1} is the annual change of the overnight interest rate, and $bank\ controls_{j,t-1}$ and $firm\ controls_{f,t-1}$ are vectors of bank and firm characteristics, respectively. They include predetermined values from the previous year to when the application is lodged to avoid endogeneity problems. The exhaustive list of all the controls includes a comprehensive set of bank (such as the log of total assets, capital, liquidity and NPL ratios, ROA and the growth of rate of the credit at the province level) and firm controls (those related to financial statements such as log of total assets, capital and liquidity ratios, ROA, productivity, cost of debt, bank indebtedness or the ratio of fixed over total employees; those related to information asymmetry such as the previous knowledge of the bank and the credit history of the firm; an those related to bank debt structure such as the maturity or the collateralization degree of the bank debt). The banking structure at the municipality level is capture with the $municipality\ controls_{fm,t-1}$, which includes the number of bank branches in the municipality where the firm is located or, in some specifications, the number of banks at the province level, and municipality or province fixed effects that absorbs time-invariant municipality characteristics that can be correlated with the number of bank branches. Finally, $loan\ controls_{l,t}$ is a vector of the loan characteristics (capturing the size of the loan through the logarithm of the amount granted, and whether the loan was collateralized and whether it had a maturity greater than 5 years). Observable and unobservable bank-specific time-invariant shocks are controlled for with the use of fixed effect η_j. These factors may influence loans' average granting time because they could be capturing, for instance, the technology available to a bank. Firm fixed effects that control for time-invariant observable and unobservable demand factors are absorbed by η_f, and $\epsilon_{fjl,t}$ is the idiosyncratic error term. Standard errors are clustered at the bank, time, municipality and industry level.

Given that this is the first time the underwriting time is studied, our strategy is to analyze the impact of time, firm and bank characteristics on it. We will also test whether the results are robust to a progressive saturation of the baseline model with fixed effects and we will analyze the heterogeneity of the results obtained. We start with municipality and industry fixed effects to, step by step, include bank, firm and even bank-time fixed effects. Using firm fixed effects Eqn. (1) is estimated for the sub-sample of firms with more than one loan application during the time of the study, which is not very a restrictive requirement.[6] To make all estimations comparable we restrict the sample used to this subsample of firms.

We aim to find evidence of the relationship between the underwriting time and banks' credit standards. Figure 2 gives us some unconditional evidence about this link. This figure shows the average concession time per semester using two different measures of the time elapsed between the time the loan application is received and the moment when it is finally granted. It seems to show that underwriting standards are loosed during boom times and hardened after the beginning of the crisis. However, for the identification of the casual effect it is necessary to disentangle demand from supply. During booms it may be more likely for banks to receive a loan application from a creditworthy firm than it is during recessions. This decreases the bank's marginal benefit of the screening process, but on the other hand, since the number of loan applications is presumably higher during expansive phases of the cycle, it might cause a lengthier underwriting process.

One of our main coefficient of interest is β_1. After the cyclical evidence that emerges from Figure 1, a negative sign is expected ($\beta_1<0$). Thus, we expect, all else equal, a loosening of bank credit standards during expansions followed by a sudden hardening

[6] The volume of committed credit to firms working with more than one bank represents around 80% of the total credit in the system.

of them once the macroeconomic situation deteriorates. Regarding the rest of controls, we expect banks to devote more time to operations with more risk or with more asymmetric information. In this sense, there are two forces moving the sign of the number of bank branches in a municipality in opposite directions. On the one hand, the greater the number of branches the more likely it is an increase of competition between banks and, therefore, the concession time could be reduced. On the other hand, the greater the number of players in the game, the higher the adverse selection that banks face, which could have the effect of increasing the underwriting time to avoid borrowers who were rejected by the rest of the banks in a previous round (winner's curse). We will analyze which of the two effects is the one that prevails.

4.2. Underwriting Time and Lending Standards

To study whether the time devoted by the bank to the screening process reflects its appetite for risk, our second equation analyzes the *Future Default* of the loan, which states whether a firm ever becomes delinquent with the financial institution it obtained credit from at some point in the future (until 2016:03).[7] Our specification focuses, again, on the same loan-level data used in the first part. We estimate using OLS the following baseline linear probability equation:

$$\text{Future Default}_{fjl,t} = \gamma UT_{fjl,t} + loan\ controls_{l,t} + \eta_{jt} + \eta_f + \epsilon_{fjl,t}, \qquad (2)$$

where the sub-indexes *f*, *j*, *l* and *t* refer to firm, bank, loan and time, respectively, $UT_{fjl,t}$ denotes the underwriting time variable defined above, $loan\ controls_{l,t}$ include the same set of factors than in Eqn. (1), η_{jt} denotes time-bank fixed effects, η_f firm fixed effects and $\epsilon_{fjl,t}$ is the idiosyncratic error-term. As before, standard errors are multi-clustered at bank, time, municipality and industry level.

Our hypothesis is that the shorter the underwriting time the less the resources a bank devotes to study the creditworthiness of the borrower. This entails that the bank might end up granting a loan to a new borrower to whom it would not have granted a loan had it assessed the borrower's quality thoroughly. As a consequence, we expect that the shorter the granting time the higher the borrower's future default probability with that financial institution, controlling for the creditworthiness of the firm through unobserved and observed heterogeneity. Therefore, we expect $\gamma<0$ if the speed up of the underwriting

[7] The definition of default follows the policy and academic literature (at least 90 days overdue).

process is made at the expense of the quality of the analysis. The identification is achieved within firm (and firm-time in one specification) variation and within bank-time variation which allows us to disentangle time-invariant demand factors from time-varying supply effects, given that the underwriting time is related to the credit risk of the borrower or to the loan characteristics as well as to bank characteristics, as showed in Eqn. (1). We also include several interactions between our key variable of interest and firm and bank controls to check whether the underwriting time effect is more pronounced for some particular firms or among some particular banks.

As aforementioned, throughout the paper we use several firm, bank and loan controls. Concerning bank and firm controls, we use information of banks' and firms' balance sheet of the year before a loan request is lodged. To control for loans' supply, we consider banks' capital ratios as a measure of their net worth (defined as the ratio of equity over total assets), liquidity ratio (ratio of cash and other liquid assets such as deposits with other credit institutions over total assets), ROA (return on assets), doubtful loans ratio (ratio of doubtful loans over total loans), and the logarithm of their total assets. We also include the change in the logarithm of total loans of the banks within the province it is located at the previous month to analyze the link between credit cycle and credit risk through the underwriting time. Regarding firms' variables to control for firms' demand, we use firms' capital ratio (ratio of own funds over total assets), net liquid assets over total assets (ratio of the difference between liquid assets and liabilities over total assets), ROA (return on assets), liquidity ratio (ratio of liquid assets over total assets), net profit over number of employees (as a measure of firms' productivity), logarithm of their total assets, logarithm of their age plus one, and two dummies indicating whether the firm had ever defaulted before lodging the loan's request (as a measure of a firm's default history), and whether the firm had obtained another loan from the same bank to which it requests the loan twelve months before (as a measure of the existence of a recent bank-firm relationship). Further and in order to account for heterogeneity in firms' balance sheet structure, we include several ratios to measure firms' different outstanding credit's exposure towards banks. Hence, we also control for firms' ratio of short-, medium- and long-term credit relative to their total outstanding credit, as well as firms' ratio of their collateralized debt relative to their total debt.

Regarding loan characteristics, we include the logarithm of the loan's amount, maturity and collateral terms. Loans' amounts are measured in thousands of euros, and we use a dummy to identify whether the loan has a long-term maturity (longer than five years) and another dummy which takes value one if the loan is not collateralized with at least 50% of the loan's amount. We note in Table 1 that the average loan is of around 55,000€, around 90% of these loans are not collateralized and that around 10% of them have a maturity longer than five years.

4.3. Underwriting Time and Financial Stability

In previous sections we have provided the empirical strategy to test the cyclicality of banks' lending standards proxied through loans' granting time, and its effects on firms' future default probability. Our hypothesis is that when banks' soften their lending standards (reducing their underwriting time), they change their portfolio composition of firms towards riskier borrowers. Although this might be a very relevant result we really cannot assert that the aggregate risk of banks increase, which would have an impact in the financial stability of the system. Therefore, from a macroeconomic point of view, the relevant issue is whether the observed underwriting time for firms reflects the overall credit standards of banks and to what extend it affects banks' financial strength and their financial distress probability. It might be the case that banks compensate the risk of the firm portfolio with that of households or that the risk is hedged with collateral, to keep a viable level of overall risk in their balance sheet. It therefore would imply a low level of correlation between average bank's granting time (AGT) and financial distress probability. Conversely, it might be the case that the AGT provides relevant information about banks' overall balance sheet risks. This is what we want to test with this exercise.

To shed some light on this issue, we estimate a static CAMEL[8] model where the risk event of banks over the period 2008-2015 is explained with bank characteristics, where AGT is included as an additional regressor, fixed as of December 2007. The period of time considered for the analysis offers a very good opportunity to challenge the strength of the average granting time as an early warning indicator since more than 40 banks experienced a bailout or a merging process in Spain within those years.

The probability of a bank's *Risk Event* (that includes public intervention, bailouts, recapitalization with public aids or mergers and acquisitions and the need of capital after

[8] CAMEL models receive their name because the set of indicators assessed to rank overall banks' condition and financial strength, that are related to **C**apital adequacy; **A**ssets; **M**anagement Capability; **E**arnings /profits and Asset **L**iability management

stress test analysis) is estimated through a probit model, where banks' capital adequacy, assets, management capability, banks' earnings and asset liability management are measured through the following set of financial performance indicators: banks' capital ratio, logarithm of banks' total assets, banks' return on assets, losses to net interest income ratio, staff costs to banks' operating costs ratio, liquidity ratio, and average granting time[9]. We understand the last one as an indicator that provides information regarding banks' management capabilities that somehow reflects how trends in lending standards evolve.

Specifically, we estimate the probability of bank distress though a probit model:

$$Pr(Risk\ Event_{i,2008\text{-}2015}=1/x_{i2007})=F(\alpha AGT_{i,2007}+bank\ controls_{i,2007}), \qquad (3)$$

where $Risk\ Event_{i,2008\text{-}2015}$ is a binary variable that takes the value one if a bank *i* failed in any moment of the period considered (as defined above) and zero otherwise, and $bank\ controls_{i,2007}$ is a vector of bank characteristics as of December 2007.[10] If the average granting time has an impact on the future financial distress of the bank we would expect α to be positive and significant ($\alpha > 0$).

5. Results

Tables 2-3-4 show the estimated coefficients for different specifications of Equation (1), and Tables 5 to 6 for different specifications of Equation (2). Finally, Table 7 shows the results of the estimation of Equation (3).

5.1. Determinants of Underwriting Time

Table 2 reports six different models. We consider bank fixed effects to control for unobserved time invariant bank characteristics and firm characteristics; The drawback of including firm characteristics to the specification is the loss of observations[11], given that it restrict the sample, as we need to merge the information from the CIR with that from the firm's financial statements. All the specifications also include the variation in the previous period of the logarithm of the total amount of credit in the province at the bank level; and two variables that account for the degree of competition at the municipality

[9] Average granting time is computed quarterly.
[10] We established 2007 since the first bank on risk was as of March 2009 and by then most of the banks become stricter in terms of lending standards due to the burst of the financial crisis.
[11] From 1,449,055 in the whole sample to 479,973 in the restricted sample.

level: the logarithm of the number of banks in the municipality in the previous period and a dummy equal to one when there are no banks in the municipality in the previous period.

The Models differ by the fixed effects and the covariates that are included with the aim to progressively saturate the specification. Model (1) uniquely includes firms' municipality and industry fixed effects.[12] Model (2) adds bank FE to Model (1), and Model (3) adds Year: Month of Loan Request fixed Effects to Model (2). Model (4) only includes Firm and Bank Fixed Effects[13], while Model (5) adds Firm and Year-Month of Loan Request Fixed Effects and Bank*Year Month of Loan Request Fixed Effects to Model (4). Model (6) aims to fully control for loans' demand side. To do that we saturate Model (5) by additionally including loan terms: loan commitment (amount), collateralization and the loan's repayment terms.

It can be seen that loans' granting time is counter-cyclical.[14] The GDP growth negatively affects the granting time while the interest rate seems to have a marginal significant impact which vanishes when industry and municipality Fixed Effects (FE) are included. According to the most saturated specification with macroeconomic variables, Model (2), a one percentage point change of GDP decreases the granting time by 0.016 months. As the average length of granting time equals 1.18 months (considering a maximum granting time of four months), the estimated GDP growth's semi-elasticity equals 1.36%. The interest rate seems to have an impact when Firm FE are included into the specification. In that case (Model (4)), the coefficient obtained for the variation of the interest rate equals 0.018*, that is[15], a one percentage point change of interest rate increases the granting time by 0.018 months, that is to say, the estimated interest rate growth's semi-elasticity equals -1.53%.

Besides, results are largely homogenous and stable across all specifications. For instance, having worked with the bank to which the firm has applied in the last 12 months

[12] There are 2,711 different combinations of province and industry.
[13] In Table 9 we present a robustness check of this Model (4) considering selection bias, where it can be observed that results remain consistent to a possible selection bias issue.
[14] We have also considered both an ordered logit and a fixed effects ordered logit specifications for robustness, and in both cases results are robust to using a linear model as it is presented here. We do not show their results here because they present some problems. Implementing a plain ordered logit does not allow to consider fixed effects nor clusters, and using a fixed effects ordered logit through a "Blow-Up and Cluster" estimator does not allow for high dimension fixed effects and marginal effects cannot be computed (Brown & Gray, 2017).
[15] Throughout the paper and following standard notation, we use stars to denote regression coefficients' statistical significance. *** stands for significance at 1% statistical level, ** at 5% and * at 10%.

reduces the loan's granting time around 5 days.[16] Having more than one banking relationship increases underwriting time around one day.[17] According to results in Table 2, granting time is not affected by lenders' credit history neither the number of banks within the municipality or the number of loan requested by the firm to different banks within the same month, but credit growth rate in the province has a small (but statistically significant) effect in granting time. 1-log percentage point increase in credit growth in the province decreases granting time by 0.008%.

Other creditors' characteristics such as the volume of total assets increase the granting time. These results are robust to the inclusion of granting terms (Model (6)) such as collateralization, repayment time and amount of the loan borrowed.

Table 3 displays 12 robustness checks for the estimation of equation 1. For consistency purposes, every regression to estimate Equation 1 is run on the most restrictive sample used to estimate Equation 1, where firm fixed effects are considered (Model (5) in Table 2).

Models (1) to Model (5) perform some robustness checks to ensure that the results in Table 2 are not biased by the time measurement or the loan requests that are considered granted. Given our data, we conclude a loan is granted linking information in the loan requests database with the information we extract from CIR. We consider a loan is granted if after at most 4 months since the lender asked for it, the credit is registered in the CIR. Otherwise, we consider it as not granted and therefore it does not enter into the analysis. The first two models in Table 3 verify the robustness of the results in Table 2 regarding the upper limit of 4 months imposed to identify a granted loan. In Model (1) we reduce the upper limit for the time elapsed from the act of requesting until the time of registering a loan to at most 3 months instead of 4 months, while in the Model (2) we increase the upper limit for loan's granting time to at most 5 months. In Model (3) loans' granting time is measured in days instead of in months; and in Model (4) granting time is modeled by a Poisson process instead of by a linear function on firms, banks, and macroeconomic variables.

Model (1) and Model (2) are equivalent to Model (4) in Table 2 with the sole difference that it considers that loan requests might be approved and granted up to three

[16] 0.171 months that is 5.13 days (= 0.171*30).
[17] 1.2 days (= 0.035*30).

(five) months after their request, instead of just after four months. Given that we allow the time window between loans' requests and approvals to narrow (widen), a lower (higher) number of loans are now approved and therefore the number of observations logically decreases in Model 1 (increases in Model 2) compared to the number of observations in Table 2.

In Model (3), we proceed as follows to consider the granting time in days instead of in months: given that our loans' applications data indicates the exact day in which an applicant lodges a loan request, we compute the number of days between the application date and the last day in the month when the loan was granted. We observe when a loan request has been approved and granted by observing the first month in which that operation appears in CIR. Unfortunately, we do not observe the exact day in which the operation is approved. Therefore, we assume that loans are approved at the end of each month to proxy the number of days elapsed between the loan's request and its approval. We include the logarithm of this variable in the regression. In Model (4) we estimate the granting time assuming a Poisson distribution for the number of granted loans, that is, within a time interval, loans granted would be approximately proportional to the length of the interval.

Regardless of the specification considered the results remain stable and in line with those reported in Table 2. A bank takes a longer time to approve a loan when the borrower is unknown and slightly less time when a creditor has multiple lenders. Granting time is not affected by lenders' credit history neither by the number of banks within the municipality or by the number of loan requested by the firm to different banks within the same month. The credit growth rate in the province has a small (but statistically significant) effect on granting time.

Models (5) to Model (10) report additional robustness checks that saturate the specification in Model (4) in Table 2.

Model (5) includes two additional covariates to consider the impact of uncertainty on granting time: the *IBEX-35* growth rate and an *economic policy uncertainty index* (EPU) growth rate for the Spanish economy. The IBEX-35 is the main reference market index for the Spanish stock market constructed by Bolsas y Mercados Españoles (BME) based on the stock market capitalization of the 35 companies with the higher liquidity ratios quoted on Madrid, Barcelona, Bilbao and Valencia. An increase in the IBEX growth rate reflects a rise in the investment mood and an increase on investors' confidence on the Spanish firms that comprise the index. EPU is an index based on newspaper coverage of certain words which captures both short-term concerns and longer term concerns. An increase in EPU reflects an increase in the economic policy uncertainty. Both measures of uncertainty have a null statistical effect on granting time but the results are robust to their inclusion.

Models (6) to Model (8) include some measures of market structure to control for the effect of market competition in granting time. In previous specifications we measure the degree of competition in the municipality using gross measures: (i) the logarithm of the number of banks in the municipality and (ii) a dummy variable to identify those municipalities where there are no banks at all. In Model (6) we alternatively include to control for the effect of market structure, the logarithm of the number of banks in the province, and in Model (7) a "pseudo"-Herfindahl-Hirschman index (pseudo-HHI) that considers the market share for each bank within the municipality[18] as the inverse of the number of branches that the bank have in the municipality. In Model (8) we include the pseudo-HHI calculated at the province level.

It seems that an increase in the number of banks in the municipality increases the average length of granting time around a 0.002% (Models 1, 2, 3, 4, 5, 9, 10, 11 and 12). When the number of banks at the province level is considered instead, the effect of competition doubles: a one percentage increase in the number of banks in the province increases the granting time in 0.002% (Model (6)). Results are coherent when competition is measured by the pseudo-HHI at the province level: more concentration (less banks) implies a reduction of the granting time.

Model (9) saturates the specification with the inclusion of *bank*industry* and *bank*province* dummies to avoid selection bias that could arise between firms and banks, given that banks of different net worth may be approached by specific borrowers in an industry or in a province with different net worth and risk. Model (10) includes seasonal dummies to control for some calendar effects not taken into account before. Model (11) performs the analysis using the whole sample at the expense of not including information about firm observable characteristics. Last, in order to tackle the possibility that selection

[18] We consider the covariate for this robustness check a "pseudo" HHI because it is constructed without considering the total credit each bank have within the municipality but only the number of bank branches in the municipality.

bias may exist in our sample, because granting time can be only observed for those loan requests that were indeed granted, we replicate our estimations considering that likelihood and its effects on the previous results. Hence, as we may face a potential sample selection bias from the granting of loan applications and unobserved heterogeneity, we estimate a panel-data version of the sample selection model of (Heckman, 1979) following (Jiménez, Ongena, Peydró, & Saurina, (2014) and (Kyriazidou, 1997). We observe that results are consistent when controlling for sample selection. This is Model (12).

Results remain qualitatively the same in all the robustness checks considered.

Table 4 reports the coefficient estimates for the double and triple interactions of firm characteristics (*unknown borrower, bad credit history*), with macroeconomic variables (*GDP* and *interest rate growth*), banks' credit supply variable (*total loans in a province growth rate),* and banks' balance sheet characteristics *(capital ratio, liquidity ratio, ROA, doubtful ratio and total assets)*. The coefficients would capture heterogeneous changes in banks' granting time over the cycle and as a function of their balance sheet characteristics which reflect differences in the risk that banks introduce in their loan portfolio. In Table 4 we only show significant results and not every interaction conducted for the sake of clarity.

We expect the interaction terms between macroeconomic variables and firm characteristics, as well as macroeconomic variables and total loans' growth rate in a province to mirror banks' lending standard variation during the cycle. Specifically, we expect according to the aforementioned literature about lending standards that banks grant loans to riskier borrowers during upturns and therefore the interaction between GDP (overnight interest rate) growth and firms characteristics to be negative (positive). In the same vein we expect the interaction term between total loans in a province growth rate growth and firms characteristics to be negative. In boom periods, when lending accelerates, banks introduce in their loan portfolios riskier loans which in our specification it would imply a lower underwriting time for unknown borrowers or who have a bad credit history. During recession periods, when lending decelerate, banks become much more cautious in terms of the quality of the borrowers and it would widen grating time for those that are riskier

All columns include firm, bank, and time fixed effects. First column in Table 4 shows the double iteration of macroeconomic variables with firm characteristics that reflect risk. Second column includes only the double interaction between banks' credit supply variables and firms' characteristics reflecting risk: being an unknown borrower and having a bad credit history. Third column includes simultaneously both the double interaction between risk measures and macroeconomic present in column 1 and the double interaction between risk measures and credit supply variables present in column 2. The fourth column in Table 4 adds all the set of triples interaction coefficients present in column 3 with bank characteristics.

The positive sign of the double iteration between GDP and unknown borrower indicates that banks not only reduce granting time during upturns but also that they relax their lending standard criteria during upturns: it takes less time to grant a loan to an unknown borrower. Specifically, being an unknown borrower when GDP's annual growth rate is 2 points above its average level in the period considered have a 9.5% lower impact in granting time. Similarly, underwriting time diminishes a 0.001% for those firms which underperformed in previous periods (bad credit history) when loans in the province are growing at 1% rate.

Moreover, the negative and statistically significant effect of the triple interaction of Δlog(Total loans in a province$_{jt-1}$)*I(Bad credit history$_{it-1}$)*Doubtful ratio$_{jt-1}$ seems to indicate that are specially those banks with higher doubtful ratios the ones that introduce more risk in their loan portfolio during periods when total credit loans are increasing within a province.

5.2. Underwriting Time and Lending Standards

In Table 5 we present the effect of the underwriting time on a borrower's future default probability with the lender. We find under several specifications that the longer the underwriting time the smaller a borrower's future default rate. In other words, we observe that the longer the time elapsed between the day the bank received a loan application and the day it granted it, the smaller it is the borrower's probability of default with that lender on the future, under different controlling factors.

Thus, Table 5 shows 9 different specifications of Eq. (2) together with 2 further robustness checks through 11 columns. Each column shows a more restrictive model than the predecessor one to fill up the initial specification with different controlling variables. As such, Model (1) in Table 5 which results are displayed in Column (1) includes time fixed effects. The coefficient on *granting time* is insignificant and positive. As expected, we have an omitted variable problem when bank-supply heterogeneity and firm-demand factors are not controlled for. From the first part of the analysis we know that banks spend more time screening the loan application of risky borrowers and that larger banks seem to have a better technology than small ones. Therefore, to know the unbiased estimation of *grating time* more covariates are needed. Model (2) adds bank characteristics to Model (1). Again, the coefficient is statistically insignificant but it is now negative. When we do not include firm fixed effects, the granting time might be capturing firms' unobservable risk, so we improve the specification by controlling for loans' demand side introducing firm fixed effects. Model (3) includes firm and bank fixed effects in parallel with time-varying firm and bank characteristics. As expected, once we control for firm and bank heterogeneity, the coefficient on granting time becomes statistically significant and negative (-0.003***). Given that the average future default probability stands at 0.20, an increase from zero to three months in the underwriting time implies a reduction of a borrower's average probability of default of around 5%. Model (3) is our baseline regression, which specification is also used in Table 2 in Column 4. Model (4) adds loan characteristics to Model (3) and we observe that results do not vary. Moreover, results are robust across every specification we use. [19]

Model (5) adds bank*year fixed effects to account for any unobserved yearly-variant bank characteristics, and Model (6) further adds bank*year*month fixed effects to control for monthly variation, with the aim of controlling as much as possible for loans' supply side. Model (7) distinguishes from Model (6) because the former includes firm*year fixed effects to control for unobserved yearly-variant firm characteristics, instead of using merely firm fixed effects. This restriction entails a loss of observations given that fewer firms have lodged more than one loan application in a given year. Model (8) is the most restrictive specification we consider since it restricts the sample to banks which have granted more than one loan the same year and month, and to firms which have lodged more than one loan application the same month. As expected, we lose out many observations which do not satisfy this strict requirement.

Last, Model (9) and Model (10) are two robustness checks of Model (6). Model (9) analyzes the effect of the underwriting time measured in the logarithm of days instead of in months on the borrower's future default probability, while Model (10) includes the time variable measured in months as a categorical variable. Given that the granting time

[19] In Table 5 we present a robustness check of Model (4) considering selection bias, where it can be observed that results remain consistent to a possible selection bias issue.

takes values zero, one, two, three and four, we include these values as different dummies. The omitted reference dummy is zero months, i.e., the loan is granted the same month in which is it applied for, so results are interpreted with respect to it.

Model (9) considers the granting time in terms of days instead of months. We proceed as follows: given that our loans' applications data indicates the exact day in which an applicant lodges a loan request, we compute the number of days between this date and the granting month's ending day. We observe when a loan request has been approved and granted by observing the first month in which that operation appears in CIR. Unfortunately, we do not observe the exact day in which the operation is approved. Therefore, we assume that loans are approved at the end of each month. This allows us to calculate the number of days elapsed between the loan's request and its approval. We include its logarithm in the regression. Model (10) discretizes the granting time variable and, finally, Model (11) takes into account the possible bias due to the selection that we face as we only have the granting time for granted loans.

Model (9) tells us that a 10% increase on the number of days a bank takes to grant a loan, the borrower's future default probability is reduced by 0.04%. Finally, Model (10) shows that the longer the bank takes to grant the loan the higher it is its impact on reducing the borrower's future default probability. Indeed, the highest economic and statistically significant result is obtained when the bank grants the credit three and four months after it is requested (coefficient equal -0.011***). We observe that granting the loan three month after it is requested reduces the future default probability almost twice as much as if it is granted two months after it is requested. As aforementioned, a borrower has on average around 5% less probability of future default with the bank if the bank grants the credit three months after the borrower has requested it. Last, replicating Model (4) considering a possible selection bias issue, we show that the underwriting time's effect on a borrower's future default probability is kept constant, and thus, there seems not to be a selection bias issue.

In short, independently of the specification used, the granting time negatively affects the future default probability, and the result always remain statistically significant. That is, the higher a borrower's loan's granting time the lower the borrower's future default probability with the bank it received the loan from. This result implies that when banks reduce their lending standards by means of speeding up the process of loan granting, it is more likely that these borrowers will default with them in the future.

Therefore, we observe that results concerning the effect of the granting time on a borrower's future delinquency rate are not altered with the specification once we control extensively for the supply and demand side.[20]

Concerning Table 6, the baseline regression of Model (4) of Table 5 is considered to run different interactions of loans' granting time with firm, bank and macroeconomic characteristics. Every model displayed includes several interactions of the control variables with the granting time, in order to see whether the effect of the granting time is stronger for borrowers with certain characteristics. We focus on firms' capital ratio as a measure of their financial strength and on their cost of debt as a measure of their vulnerability to market conditions. All regressions include bank*year:month and firm fixed effect other than firm characteristics to control for evolving lender supply's conditions and firms' observed and non-observed characteristics. Model (1) in Table 6 includes as many controls as Model (4) of Table 5, and an interaction between firms' capital ratio and their cost of debt with their loan's granting time. Model (2) includes all firm controls' interactions with the granting time and not uniquely the interaction of our two variables of interest. Model (3) includes interactions between bank controls and granting time as well, and Model (4) mimics Model (3) without the loan controls to show that results are not derived from the inclusion of loan controls.

We clearly observe that a loan's underwriting time negatively affects the borrower's future default probability. The longer the time elapsed between the moment a loan is requested and it is granted the lower the borrower's future default probability with that bank, ceteris paribus. Besides, the granting time's effect on the default probability is watered down for highly capitalized firms and augmented for those with a high cost of capital. The effect of analyzing a loan request for a longer time seems not to have an effect on a borrower's future default probability for highly capitalized banks, given their strong financial situation to make up any loan repayment with own funds and not to depend highly on debt nor its cost. On the other hand, the higher the debt's financing cost the stronger it is the effect of the underwriting time to set the probability of default, such

[20] We have repeated all regressions included in Table 5 without considering loan controls, and the results obtained are qualitatively and quantitatively equivalent to those obtained when including them, so we do not show them in the paper.

that the effect of the granting time for firms with a high cost of credit more than doubles the probability of default of firms which enjoy a lower cost of debt.

Thus, according to the results, the granting time's effect on a borrower's future default probability is strongly significant and robust.

5.3. Granting Time and Financial Stability

Results of Eqn. (3) are show in Table 7. The dependent variable in Columns (1), (3), (5) and (7) is a binary variable that takes the value of one if the bank experienced some of next risk events after December 2007: public intervention, bailout, recapitalization with public aids or mergers and acquisitions and the need of capital after stress test analysis; whereas the dependent variable in columns (2), (4), (6) and (8) only takes value equal one for public interventions and recapitalizations with public aids, and zero otherwise. Specifications (1) to (4) include Average Granting Time (AGT) as a regressor; Specifications (5) to (8) instead include Average Granting Time cleaned from demand (AGT-CD) as regressor. AGT-CD is the bank*year fixed effect from a linear regression where the dependent variable is Granting Time, and firm*year fixed effects and the bank*year fixed effect are included as regressors. That is, AGT-CD is the average granting time orthogonal to demand factors because if two banks face a different pool of borrowers, the average granting time would differ for causes other than supply factors.

As it can be seen, the longer the granting time the lower banks' bankruptcy probability. Specifically, the marginal effect for the AGT when the other performance indicators take their mean values, varies from -0.104** in Column (1) to -0.063** in Column (8). Results show that average granting time is a statistically significant variable to predict banks' distress probability. These results indicate that the variable AGT might deserve greater attention as a possible warning indicator of future systemic risk. As such, the coefficient -0.104** present in Colum (1) denotes that increasing the AGT by one month, banks' future default decreases by 0.104 which implies a decrease on banks' average default probability of about 16%, given that banks' average future probability of default in this specification is 66.18%.

7. Conclusions

We have analyzed loans' underwriting time, which is the time elapsed between a potential borrower registers a loan application and the application is approved and the loan granted. As far as we know, this is the first paper analyzing the economic determinants that affect the underwriting time and its impact on the portfolio composition of banks. Our results suggest that banks dedicate a longer time to assess applications from less creditworthy firms. We also show that underwriting standards are soften during booms (or when interest rates decrease) and when banks endogenously decide to grow. This is done at the expense of attracting riskier borrowers, which seems to point towards banks' riskier strategies during economic upwards. The paper shows that this behavior led to fatal consequences.

In particular, we study the link between the underwriting time and the reduction of lending standards analyzing the probability of future default of granted loans depending, ceteris paribus, on the underwriting time. Therefore, one of the challenges of the paper is to fully control for observed and unobserved firm heterogeneity is one of the challenges of the paper. Moreover, it is also key to control for credit supply since banks' underwriting time may not depend uniquely on their balance sheet characteristics but also on their available technology to evaluate loan applications, which most likely changes and improves over time. This is our second challenge: disentangling firm-supply from bank-supply factor. Our contribution to the literature also lies in meeting these two identification challenges. To separately control for bank supply and firm demand heterogeneity, we exploit the Spanish Credit Register and the Spanish firms' and banks' balance sheets to control for credit demand and supply determinants of the underwriting time. Hence, along the paper we control for firm and bank unobserved and observed characteristics that may evolve over time and we use several databases to tackle possible identification issues.

We find that banks take more time to roughly analyze riskier loan requests, and that underwriting time increases as a consequence of the presence of asymmetric information in the market. Banks that have some private information about their clients' credit-worthiness are able to better distinguish "good" borrowers from "bad" borrowers that are new or unknown to them. We show that the granting time is shorter for those borrowers which had a previous relationship with the bank they apply for a loan to. On the contrary, maintaining different bank relationships increases a new loan's underwriting time, since these firms are riskier and there is more asymmetric information, ceteris paribus.

Our second result is that the market structure also influences underwriting time. Specifically, an increase in the level of competition between banks increases underwriting time. We show that the higher the competition among banks the higher the adverse selection problems that arise under asymmetric information.

Thirdly, we finally show that the lending standards that we capture through the underwriting time have an impact on the future performance of the bank, which highlights the importance of the results, given its impact on the financial stability and, therefore, on the real economy.

It is difficult to disentangle whether a shorter acceptation period might be due to an increase in the efficiency of the underwriting process that might be caused for instance by a technological improvement or due to a lighter intensity when analyzing a possible borrower's creditworthiness. If the latter effect there may be negative consequences for financial stability since it could lead to wrong measurements of borrowers' risks. Given the importance of this question, we go a step further and analyze if ex-post credit risk is related with underwriting time. More precisely, we question whether a loan's underwriting time affects a borrower's future probability of default with the financial institution it had obtained a loan from. We find that a loan's underwriting time is negatively related to the borrower's future probability of default, implying that a speed-up in the evaluation process of a potential borrower ends up with higher default rates on average. Considering that the average default probability is 0.20%, if the granting time were to increase from zero to three months, the borrower's default probability on average would be reduced by around 5%.

We have shown that increasing loans' granting time, the borrowers' future default rates are substantially reduced, controlling for borrower, lender and macroeconomic characteristics. This finding enhances the well-sounded idea that a more in-deep (time-consuming) analysis of possible borrowers' credit standards reduces their future default probabilities, and highlights the importance of thinking about new macroeconomic prudential tools that take into account these results.

References

Agarwal, R., & Elston, J. ((2001). Bank–firm relationships, financing and firm performance in Germany. *Economics Letters, 72*(2), 225-232.

Allen , F., & Gale, D. ((2003). Competition and Financial Stability. *Journal of Money, Credit and Banking, 36*(3).

Baker, S., Bloom, N., & Davis , S. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics, 131*(4), 1593.

Beck, T., Demirguç-Kunt, A., & Levine, R. ((2006). Bank concentration, competition, and crisis: first results. *Journal of Banking & Finance, 30* , 1581–1603.

Becker, B., & Ivashina, V. ((2014). Cyclicality of credit supply: Firm level evidence . *Journal of Monetary Economics, 62*, 76-93.

Boyd, J., & De Nicolo, G. ((2005). The theory of Bank of Risk Taking and Competition Revisited. *Journal of Financce*, 1329-43.

Brown, S., & Gray, D. (2017). Household finances and well-being in Australia: an empirical analysis of comparison effects. *Journal of Economic Psychology, 53*, 17-36.

Crawford, G., Pavanini , N., & Schivardi, F. (2015). Asymmetric Information and Imperfect Competition. *Working Paper Series, University of Zurich*.

Dell'Ariccia , G., Laeven , L., & Suarez, G. ((2007). 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. (2006). Lending Booms and Lending Standards. *The Journal of Finance, LXI*(5), 2511-2546.

Dell'Ariccia, G., Laeven, L., & Deniz, I. ((2012). Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market. *The Journal of Money, Credit and Banking, 44*(2-3), 367-384.

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

Demyanyk, Y., & Van Hemert, O. ((2011). Understanding the Subprime Mortgage Crisis. *RFS, 24*(6), 1848-1880.

Garmaise, M. ((2015). Borrower Misreporting and Loan Performance. *Journal of Finance, LXX, NO. 1*(1).

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

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

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica, 47*(1), 153-161.

Jappelli, T., & Pagano , M. ((2002). Information sharing, lending and defaults: Cross-country evidence. *Journal of Banking and Finance, 26*, 2017–2045.

Jiménez, G., & Saurina, J. (2004). Collateral, type of lender and relationship banking as determinants of credit risk. *Journal of Banking & Finance, 28*(9), 2191-2212.

Jiménez, G., Moral-Benito, E., & Vegas, R. ((2017). The Role of Bank Lending Standards over the Cycle: Productivity versus Risks. *Documento de Trabajo de Banco de España*.

Jiménez, G., Ongena, S., & Peydró, J.-L. (2017). Do Demand or Supply Factors Drive Bank Credit, In Good and Crisis Times? Obtenido de https://ssrn.com/abstract=2959509

Jiménez, 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.

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

Keeley, M. C. ((1990). Deposit Insurance, Risk and Market Power in Banking. *American Economic Review, 80*(5), 1183-1200.

Kyriazidou, E. (1997). Estimation of a Panel Data Sample Selection Model. *Econometrica, 65*(6), 1335-1364.

Loutskina, E., & Strahan, P. ((2009). Securitization and the Declining Impact of Bank Finance on Loan Supply: Evidence from Mortgage Originations. *Journal of Finance, LXIV*(2), 861-889.

Maddaloni , A., & Peydró, J. ((2011). Bank Risk-taking, Securitization, Supervision, and Low Interest Rates: Evidence from the Euro-area and the U.S. Lending Standards. *The Review of Financial Studies, 6*, 2121-2165.

Mariathasan, M., & Zhuk, S. (2018). Rational Inattention and Counter-Cyclical Lending Standards. *Mimeo*.

Matutes, C., & Vives, X. ((2000). Imperfect Competition, Risk and Regulation in Banking. *European Economic Review, 40*, 1-34.

Mieira, D., & Repullo, R. (2010). Does Competition Reduce the Risk of Bank Failure? *Review of Financial Studies, 23*, 3638-3664.

Ogawa, K., Sterken, E., & Tokutsu, I. ((2007). Why do Japanese firms prefer multiple bank relationship? Some evidence from firm-level data. *Economic Systems, 31*(1), 49-70.

Rajan, U., Seru, A., & Vig, V. ((2015). The failure of models that predict failure: Distance, incentives, and defaults. *Journal of Financial Economics, 115*, 237-260.

Rodano, G., Serrano-Velarde , N. A., & Tarantino , E. ((2017). Lending Standards Over the Credit Cycle (October 30, 2015). Obtenido de Available at SSRN: https://ssrn.com/abstract=2699553

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

Ruckes, M. ((2004). Bank Competition and Credit Standards. *The Review of Financial Studies, 17*(4), 1073-1102.

Santos, J. A., & Farinha, L. A. ((2002). Switching from Single to Multiple Bank Lending Relationships: Determinants and Implications. *Journal of Financial Intermediation, 11*(2), 124–151.

Saurina, J., & Jiménez, G. ((2006). Credit Cycles, Credit Risk, and Prudential Regulation. *International Journal of Central Banking*, 65-98.

Utrero-González, N. (2007). Banking regulation, institutional framework and capital structure: International evidence from industry data. *The Quarterly Review of Economics and Finance*, 481-506.

FIGURE 1

Distribution of the variable granting time, which measures the number of months between the loan application is made and the loan is granted

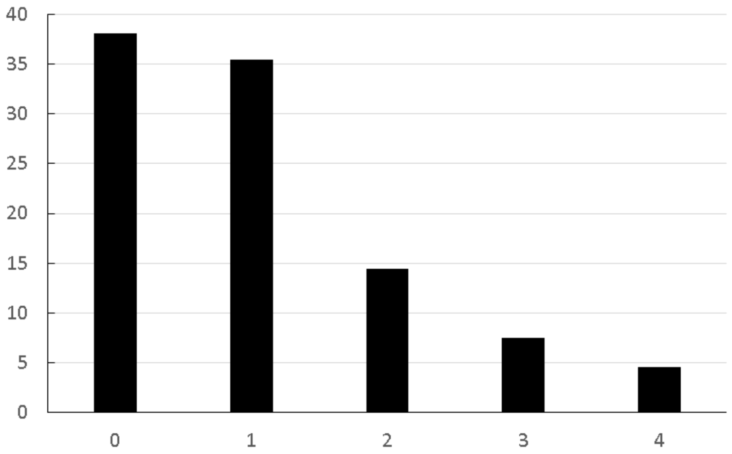
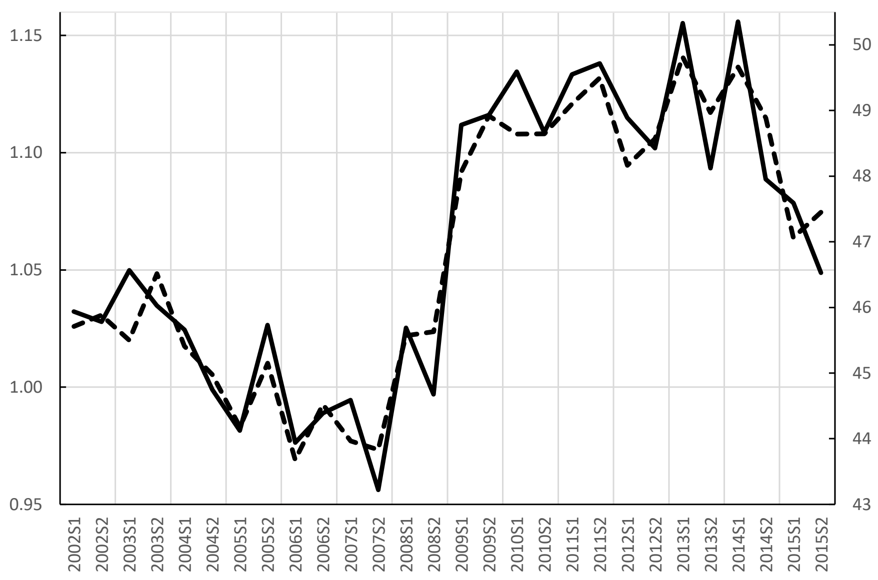


FIGURE 2

Evolution of the average grating time, by semester



Note. This figure shows the average granting time in months (solid line, left-hand scale) and in days (dashed line, right-hand scale).

TABLE 1

Descriptive statistics

	Mean	Median	SD	P25	P75
Dependent variables					
Future Default$_{ijt}$	0.203	0.000	0.402	0.000	0.000
Underwriting time$_{ijt}$ (months)	1.176	1.000	1.148	0.000	2.000
Log(Underwritting time$_{ijt}$ (days))	3.689	3.738	0.780	3.258	4.248
Macro variables (t)					
ΔGDP$_{t-1}$	1.099	1.852	2.578	-1.233	3.358
ΔInterest rate$_{t-1}$	-0.230	-0.028	1.015	-0.490	0.258
ΔIBEX$_{t-1}$	0.037	0.101	0.219	-0.098	0.206
Uncertainty in Spain$_{t-1}$	103.313	95.498	51.197	70.410	129.953
Firm variables (i)					
I(Unknown borrower$_{ijt-1}$)	0.159	0.000	0.366	0.000	0.000
I(Bad credit history$_{it-1}$)	0.099	0.000	0.298	0.000	0.000
I(More than one banking relatioship$_{it-1}$)	0.713	1.000	0.452	0.000	1.000
log(No. Of loan Request$_{it}$)	0.128	0.000	0.304	0.000	0.000
log(Total assets$_{it-1}$)	6.741	6.718	1.528	5.731	7.686
log(Age$_{it-1}$)	2.308	2.485	0.843	1.792	2.890
Capital ratio$_{it-1}$	0.294	0.250	0.216	0.118	0.432
ROA$_{it-1}$	0.086	0.074	0.087	0.036	0.128
Productivity$_{it-1}$	0.035	0.014	0.073	0.003	0.046
Liquidity ratio$_{it-1}$	0.079	0.036	0.104	0.009	0.103
Bank indebtedness$_{it-1}$	0.290	0.283	0.206	0.102	0.480
Cost of debt$_{it-1}$	0.029	0.025	0.023	0.011	0.042
Fixed employees/Total employees$_{it-1}$	0.758	0.860	0.277	0.600	1.000
Short-term bank debt/Total bank debt$_{it-1}$	0.447	0.450	0.357	0.036	0.762
Medium-term bank debt/Total bank debt$_{it-1}$	0.233	0.124	0.287	0.000	0.348
Long-term bank debt/Total bank debt$_{it-1}$	0.192	0.000	0.295	0.000	0.314
Collateralized bank debt/Total bank debt$_{it-1}$	0.171	0.000	0.289	0.000	0.254
Province variables					
I(There are banks in the municipality$_{it}$)	0.003	0.000	0.052	0.000	0.000
log(No. of banks in the province$_{it-1}$)	4.221	4.025	0.734	3.664	4.844
log(No. of banks in the municipality$_{it-1}$)	4.023	4.025	0.702	3.638	4.369
Herfindhal of banks in province$_{t-1}$	0.114	0.105	0.035	0.087	0.135
Herfindhal of banks in municipality$_{t-1}$	0.068	0.064	0.035	0.048	0.080
Bank variables (j)					
Δlog(Total loans in a province$_{jt-1}$)	0.096	0.063	0.187	-0.045	0.216
Log(Total Assets$_{jt-1}$)	17.816	17.939	1.525	16.936	18.917
Capital ratio$_{jt-1}$	0.059	0.055	0.020	0.045	0.071
Liquidity ratio$_{jt-1}$	0.149	0.139	0.069	0.105	0.177
ROA$_{jt-1}$	0.006	0.006	0.007	0.004	0.009
Doubtful ratio$_{jt-1}$	0.052	0.036	0.054	0.008	0.074
Loan variables					
log(Amount of the loan$_{ijt}$)	4.020	3.912	1.205	3.178	4.771
I(No-collateralized loan$_{ijt}$)	0.916	1.000	0.277	1.000	1.000
I(Long-term loan$_{ijt}$)	0.098	0.000	0.298	0.000	0.000

Note. This table reports summary statistics of the variables. The mean, median, standard deviation, first quartile and third quartile are displayed. The number of firms is 142,548 and the number of observations 479,973. The definition of the variables can be found in the Appendix.

TABLE 2

Regression results, the analysis of the determinants of the loan underwriting time

Dependent variable: Underwriting time$_{ijt}$	(1)	(2)	(3)	(4)	(5)	(6)
Macro variables (t)						
ΔGDP$_{t-1}$	-0.015 ***	-0.016 ***	-0.016 ***	-0.023 ***	-	-
	(0.005)	(0.006)	(0.005)	(0.006)		
ΔInterest rate$_{t-1}$	0.004	0.004	0.004	0.018 *	-	-
	(0.006)	(0.008)	(0.007)	(0.011)		
Firm variables (i)						
I(Unknown borrower$_{ijt-1}$)	0.183 ***	0.171 ***	0.172 ***	0.175 ***	0.173 ***	0.172 ***
	(0.012)	(0.012)	(0.012)	(0.019)	(0.018)	(0.021)
I(Bad credit history$_{it-1}$)	0.017 **	0.017 **	0.017 **	0.006	0.010	-0.001
	(0.008)	(0.008)	(0.008)	(0.019)	(0.025)	(0.023)
log(Total assets$_{it-1}$)	0.118 ***	0.111 ***	0.111 ***	0.039 ***	0.037	0.043 ***
	(0.007)	(0.007)	(0.007)	(0.012)	(0.092)	(0.011)
log(Age$_{it-1}$)	-0.020 ***	-0.020 ***	-0.020 ***	0.018	0.022 **	0.017
	(0.006)	(0.006)	(0.006)	(0.017)	(0.011)	(0.019)
Capital ratio$_{it-1}$	-0.084 ***	-0.087 ***	-0.087 ***	-0.018	-0.013	-0.003
	(0.014)	(0.014)	(0.013)	(0.037)	(0.035)	(0.032)
Cost of debt$_{it-1}$	0.083	0.084	0.083	0.107	0.065	0.013
	(0.110)	(0.119)	(0.119)	(0.208)	(0.205)	(0.202)
Municipality variables						
log(No. of banks in the municipality$_{it-1}$)	0.038	0.052	0.043	0.183 *	0.016	0.018
	(0.067)	(0.077)	(0.074)	(0.101)	(10.372)	(0.030)
Without banks in the municipality$_{it-1}$	0.151	0.182	0.151	0.638	0.102	0.104
	(0.224)	(0.252)	(0.243)	(0.343)	(2.549)	(0.143)
Bank variables (j)						
Δlog(Total loans in a province$_{jt-1}$)	-0.110 ***	-0.099 ***	-0.100 ***	-0.085 ***	-0.043 *	-0.043 *
	(0.036)	(0.021)	(0.020)	(0.025)	(0.024)	(0.023)
Other bank characteristics	Yes	Yes	Yes	Yes	-	-
Bank Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	Yes	Yes	Yes
Municipality Fixed Effects	Yes	Yes	Yes	-	-	-
Industry Fixed Effects	Yes	Yes	Yes	No	No	No
Year: Month of Loan Request Fixed Effects	No	No	No	No	-	-
Bank*Year Month of Loan Request Fixed Effects	No	No	No	No	Yes	Yes
Loan Controls	No	No	No	No	No	Yes
R^2	0.04	0.05	0.05	0.33	0.36	0.36
No. of Firms	142,584	142,584	142,584	142,584	142,584	142,584
No. of Observations	479,973	479,973	479,973	479,973	479,973	479,973

Note. This table reports estimates from a linear probability model using ordinary least square for the period 2002:02 to 2015:12.The dependent variable is granting time, which measures the number of months a bank takes to approve a loan application and to grant the loan since the request is made. Coefficients are listed in the first row, robust standard errors that are corrected for multi-clustering at the bank, year: month, province and industry level are reported in the row below, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 3

Regression results, the analysis of the determinants of the loan underwriting time controlling for firm fixed effects

Dependent variable: Underwriting time$_{ijt}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	UT≤3 months	UT≤5 months	Log(UT in days)	Poisson	Uncertainty	Market: Province	Market: Municipality	Market : HHI Prov	Bank* Ind Bank*Mun	Seasonal Dummies	Whole Sample	Selection bias correction
Macro variables (t)												
ΔGDP$_{t-1}$	-0.015 ***	-0.032 ***	-0.014 ***	-0.019 ***	-0.024 ***	-0.021 ***	-0.023 ***	-0.022 ***	-0.026 ***	-0.023 ***	-0.022 ***	-0.023 ***
	(0.005)	(0.007)	(0.004)	(0.002)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
ΔInterest rate$_{t-1}$	0.010	0.025 *	0.009	0.01 ***	0.018	0.017 *	0.016	0.015 *	0.021 *	0.018 *	0.017 *	0.015
	(0.008)	(0.013)	(0.007)	(0.004)	(0.011)	(0.009)	(0.010)	(0.008)	(0.013)	(0.010)	(0.010)	(0.010)
Firm variables (i)												
I(Unknown borrower$_{ijt-1}$)	-0.169 ***	0.177 ***	0.174 ***	0.157 ***	0.175 ***	0.175 ***	0.176 ***	0.175 ***	0.165 ***	0.174 ***	0.173 ***	0.210 ***
	(0.018)	(0.023)	(0.017)	(0.010)	(0.019)	(0.017)	(0.019)	(0.017)	(0.020)	(0.019)	(0.019)	(0.030)
I(Bad credit history$_{it-1}$)	0.004	-0.010	0.007	0.005	-0.007	-0.006	-0.005	-0.004	-0.008	-0.001	0.018	-0.020
	(0.018)	(0.026)	(0.016)	(0.013)	(0.020)	(0.015)	(0.019)	(0.015)	(0.026)	(0.020)	(0.014)	(0.034)
log(Total assets$_{it-1}$)	0.032 ***	0.038 ***	0.027 ***	0.036 ***	0.039 ***	0.038 ***	0.041 ***	0.041 ***	-0.034 **	0.037 ***	-	0.030 *
	(0.010)	(0.013)	(0.008)	(0.007)	(0.012)	(0.010)	(0.012)	(0.010)	(0.014)	(0.012)		(0.016)
log(Age$_{it-1}$)	0.032 **	0.005	0.019	0.016	0.018	0.015	0.006	0.004	-0.025	0.002	-	0.002
	(0.012)	(0.017)	(0.012)	(0.010)	(0.017)	(0.014)	(0.017)	(0.015)	(0.020)	(0.020)		(0.028)
Capital ratio$_{it-1}$	-0.041	-0.016	-0.028 *	-0.011	-0.018	-0.018	-0.025	-0.023	0.034	-0.022	-	-0.005
	(0.034)	(0.048)	(0.016)	(0.021)	(0.037)	(0.038)	(0.038)	(0.038)	(0.042)	(0.038)		(0.052)
Cost of debt$_{it-1}$	0.188	0.027	0.138	0.097	0.123	0.107	0.132	0.132	-0.087	0.132	-	0.314
	(0.204)	(0.245)	(0.150)	(0.147)	(0.205)	(0.186)	(0.213)	(0.185)	(0.224)	(0.210)		(0.213)
Municipality variables												
log(No. of banks in the municipality$_{it-1}$)	0.169 *	0.196 *	0.118 *	0.157 **	0.181 *	-	-	-	0.228 *	0.157	0.175 *	0.165 **
	(0.090)	(0.114)	(0.063)	(0.070)	(0.100)				(0.115)	(0.098)	(0.100)	(0.071)
HHI $_{it-1}$	-	-	-	-	-	-	-1.249	-	-	-	-	-
							(0.967)					
HHI in the province $_{it-1}$	-	-	-	-	-	-	-	-1.052 *	-	-	-	-
								(0.594)				
log(No. of banks in the province$_{it-1}$)	-	-	-	-	-	0.231 *	-	-	-	-	-	-
						(0.121)						
Without banks in the municipality$_{it-1}$	0.609 **	0.702 *	0.420 **	0.536 **	0.632 *	-	-	-	-	0.554	0.608 *	0.485 **
	(0.301)	(0.388)	(0.207)	(0.226)	(0.341)					(0.330)	(0.338)	(0.203)
Bank variables (j)												
Δlog(Total loans in a province$_{jt-1}$)	-0.083 ***	-0.073 **	-0.077 ***	-0.069 ***	-0.089 ***	-0.083 ***	-0.082 ***	-0.082 ***	-0.076 **	-0.089 ***	-0.087 ***	-0.079 **
	(0.024)	(0.029)	(0.017)	(0.015)	(0.023)	(0.024)	(0.024)	(0.024)	(0.032)	(0.024)	(0.024)	(0.033)
Other bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Industry Fixed Effects	No	No	No	No	No	No	No	No	Yes	No	No	No
Bank*Municipality Fixed Effects	No	No	No	No	No	No	No	No	Yes	No	No	No
Bank*Year:month Fixed Effects	No	No	Yes	No	No	No	No	No	No	No	No	No
R^2	0.33	0.32	0.35	-	0.33	0.33	0.33	0.39	0.38	0.33	0.31	0.31
No. of Firms	136,235	146,804	142,584	146,804	142,584	142,584	142,584	137,593	137,593	142,584	408,190	408,190
No. of Observations	446,771	502,994	479,973	455,320	479,973	479,973	479,973	502,994	459,175	455,320	1,449,055	1,449,055

Note. This table reports estimates from a linear probability model using ordinary least square for the period 2002:02 to 2015:12.The dependent variable is granting time, which measures the number of months a bank takes to approve a loan application and to grant the loan since the request is made. Coefficients are listed in the first row, robust standard errors that are corrected for multi-clustering at the bank, year: month, province and industry level are reported in the row below, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%

TABLE 4

Robustness results, the analysis of the determinants of the loan underwriting time controlling for firm fixed effects

Dependent variable: Underwriting time$_{ijt}$	(1)	(2)	(3)	(4)
Macro variables (t)				
ΔGDP$_{t-1}$	-0.024 ***	-0.023 ***	-0.025 ***	-0.025 ***
	(0.006)	(0.006)	(0.006)	(0.007)
ΔInterest rate$_{t-1}$	0.018 *	0.018 *	0.018 *	0.018
	(0.011)	(0.011)	(0.011)	(0.011)
Firm variables (i)				
I(Unknown borrower$_{ijt-1}$)	0.181 ***	0.176 ***	0.180 ***	0.180 ***
	(0.020)	(0.021)	(0.020)	(0.022)
I(Bad credit history$_{it-1}$)	0.005	0.011	0.008	0.008
	(0.020)	(0.020)	(0.020)	(0.032)
I(More than one banking relatioship$_{it-1}$)	0.029 ***	0.029 ***	0.029 ***	0.029 **
	(0.008)	(0.009)	(0.009)	(0.012)
Log (No. Of loan Request$_{it}$)	0.003	0.003	0.003	0.003
	(0.022)	(0.022)	(0.022)	(0.026)
Bank Variables (j)				
Δlog(Total loans in a province$_{jt-1}$)	-0.085 ***	-0.076 ***	-0.068 ***	-0.068 **
	(0.025)	(0.026)	(0.025)	(0.033)
Interactions				
ΔGDP$_{t-1}$*I(Unknown borrower$_{ijt-1}$)	-0.007 **	-	-0.008 **	0.026
	(0.003)		(0.003)	(0.047)
ΔGDP$_{t-1}$*I(Bad credit history$_{it-1}$)	0.002	-	0.004	0.002
	(0.004)		(0.005)	(0.007)
Δlog(Total loans in a province$_{jt-1}$)*I(Unknown borrower$_{ijt-1}$)	-	-0.014	0.029	-0.032
		(0.042)	(0.043)	(0.057)
Δlog(Total loans in a province$_{jt-1}$)*I(Bad credit history$_{it-1}$)	-	-0.096 *	-0.110 **	-0.463
		(0.052)	(0.054)	(0.464)
Δlog(Total loans in a province$_{jt-1}$)*I(Bad credit history$_{it-1}$)*Doubtful ratio$_{jt-1}$	-	-	-	-1.725 ***
				(0.526)
Bank Fixed Effects	Yes	Yes	Yes	-
Firm Fixed Effects	Yes	Yes	Yes	Yes
Bank*Year:month Fixed Effects	No	No	No	No
Other Macro, Firm & Bank Controls	Yes	Yes	Yes	Yes
R^2	0.33	0.33	0.33	0.36
No. of Firms	142,584	142,584	142,584	142,584
No. of Observations	479,973	479,973	479,973	479,973

Note. This table reports estimates from a linear probability model using ordinary least square for the period 2002:02 to 2015:12.The dependent variable is for all columns but column III granting time, which measures the number of months a bank takes to approve a loan application and to grant the loan since the request is made. For column III the dependent variable is the log of the underwriting time in days. Coefficients are listed in the first row, robust standard errors that are corrected for multi-clustering at the bank, year: month, province and industry level are reported in the row below, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 5

Regression results, impact of the underwriting time on a borrower's future default probability under a different set of fixed effects

Dependent variable: Future Default$_{ijt}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11) - selection
Underwriting Time	0.0003	-0.002	-0.003 ***	-0.003 ***	-0.003 ***	-0.003 ***	-0.003 ***	-0.007 ***	-	-	-0.003 **
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)			(0.001)
ln(Underwriting Time in days)	-	-	-	-	-	-	-	-	-0.004 ***	-	-
									(0.001)		
I(Underwriting Time=1)	-	-	-	-	-	-	-	-	-	-0.004 ***	-
										(0.001)	
I(Underwriting Time=2)	-	-	-	-	-	-	-	-	-	-0.006 ***	-
										(0.002)	
I(Underwriting Time=3)	-	-	-	-	-	-	-	-	-	-0.011 ***	-
										(0.002)	
I(Underwriting Time=4)	-	-	-	-	-	-	-	-	-	-0.011 ***	-
										(0.002)	
Province*Industry FE	No	Yes	-	-	No	No	No	No	No	No	-
Bank FE	No	Yes	Yes	Yes	-	-	-	-	-	-	Yes
Firm FE	No	No	Yes	Yes	Yes	Yes	-	-	Yes	Yes	Yes
Firm characteristics	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Bank characteristics	No	Yes	Yes	Yes	No	No	No	No	No	No	Yes
Loan characteristics	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year:month FE	Yes	Yes	Yes	Yes	No	-	-	-	-	-	Yes
Firm*Year FE	No	No	No	No	No	No	Yes	-	No	No	No
Firm*Year:month FE	No	No	No	No	No	No	No	Yes	No	No	No
Bank*year FE	No	No	No	No	Yes	-	-	-	-	-	No
Bank*year:month FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	No
R^2	0.064	0.108	0.709	0.711	0.714	0.725	0.843	0.845	0.725	0.725	-
No. of Firms	142,584	142,584	142,584	142,584	142,584	142,584	82,765	13,912	142,584	142,584	142,584
No of Observations	479,973	479,973	479,973	479,973	479,973	479,973	251,040	32,657	479,973	479,973	479,973

Note. This table reports estimates from a linear probability model using ordinary least square for the period 2002:02 to 2015:12. The dependent variable is future default which measures whether a firm defaulted the loan granted by the bank for which granting time is measured. Coefficients are listed in the first row, robust standard errors that are corrected for multi-clustering at the bank, firm, firm's industry and year and month in which the loan was asked are reported in the row below, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. Significance level: *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 6

Regression results, the heterogeneous impact of a loan's granting time on the future default probability controlling for firm fixed effects

Dependent variable: Future Default$_{ijt}$	(1)	(2)	(3)	(4)
Underwriting Time (UT)	-0.003 ***	-0.003 ***	-0.003 ***	-0.003 ***
	(0.001)	(0.001)	(0.001)	(0.001)
UT*Capital ratio$_{it-1}$	0.005 ***	0.005 **	0.005 **	0.005 **
	(0.002)	(0.002)	(0.002)	(0.002)
UT*cost of debt$_{it-1}$	-0.061 ***	-0.055 ***	-0.054 ***	-0.067 ***
	(0.017)	(0.020)	(0.020)	(0.020)
Bank*Year:month Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Firm Characteristics	Yes	Yes	Yes	Yes
Other firm Characteristics*GT	No	Yes	Yes	Yes
Bank controls*GT	No	No	Yes	Yes
Loan controls	Yes	Yes	Yes	No
R^2	0.725	0.726	0.726	0.724
No. of Firms	142,584	142,584	142,584	142,584
Observations	479,973	479,973	479,973	479,973

Note. This table reports estimates from a linear probability model using ordinary least square for the period 2002:02 to 2015:12.The dependent variable is future default which measures whether a firm defaulted a loan obtained from a bank since it obtained the loan which granting time is measured. Coefficients are listed in the first row, robust standard errors that are corrected for multi-clustering at the bank, firm, firm's industry and month in which the loan was granted are reported in the row below, and the corresponding significance levels are in the adjacent column. "Yes" ("No") indicates that the set of characteristics or fixed effects is (not) included. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 7

Granting Time and Banks' Default Probability

Dependent variable: banks' future default	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Averate Underwriting Time $(UT)_{it-1}$	-0.104 **	-0.077 **	-	-	-0.106 **	-0.107 **	-	-
	(0.042)	(0.036)			(0.050)	(0.051)		
Averate Underwriting Time Cleaned from Demand$(UT\text{-}CD)_{it-1}$	-	-	-0.065 **	-0.058 *	-	-	-0.069 **	-0.063 **
			(0.033)	(0.033)			(0.028)	(0.030)
Pseudo R-squared	0.471	0.503	0.454	0.496	0.513	0.517	0.493	0.503
Observations	56	56	56	56	56	56	56	56

Note. This table reports the estimates from a CAMEL model where banks' default probability is estimated through a probit model. Dependent variable in Columns (1), (3), (5) and (7) is an indicator variable that takes value 1 when banks' financial distress results in a merging process and zero otherwise. Dependent variable in columns (2), (4), (6) and (8) is an indicator that takes value 1 when banks' financial distress results in a merging or an acquisition process and zero otherwise. Specifications (1) to (4) include Average Granting Time (AGT) as a regressor; Specifications (5) to (8) instead include Average Granting Time cleaned from demand (AGT-CD) as regressor. AGT-CD is the bank*year fixed effect from a linear regression where the dependent variable is Granting Time, and firm*year fixed effects and the bank*year fixed effect are included as regressors. Coefficients are listed in the first row, robust standard errors that are corrected for clustering at the bank level are reported in the row below, and the corresponding significance levels are in the adjacent column. . *** Significant at 1%, ** significant at 5%, * significant at 10%.

APPENDIX

Definitions of the variables used in the analysis

	Unit	Definition
Dependent variables		
Underwriting time$_{ijt}$ (months)	months	The number of months a bank *j* takes to approve a loan application from firm *i* and to grant the loan since the request is made in *t*
log(Underwritting time$_{ijt}$ (days))	log(days)	The log of the number of days a bank *j* takes to approve a loan application from firm *i* and to grant the loan since the request is made in *t*
I(Future default probability$_{ijt}$)	0/1	A dummy variable which equals one if the borrower *i* defaults with the bank *j* granting it the loan any time after it gets the loan in *t*, and equals 0 otherwise
Macro variables (t)		
ΔGDP$_{t-1}$	%	Annual growth of rate of Spanish gross domestic product in real terms at *t-1*
ΔInterest rate$_{t-1}$	%	Annual change of overnight interbank interest rate at *t-1*
ΔIBEX$_{t-1}$	%	Montlhy annual variation of Spanish Stock IBEX indicator in *t-1*
Uncertainty in Spain$_{t-1}$	0.0x	Uncertainty measure for the Spanish economy in *t-1*
Firm variables (i)		
I(Unknown borrower$_{ijt-1}$)	0/1	A dummy variable which equals one if the borrower *i* was not its lender *j*'s customer during the previous year to *t*, and zero otherwise
I(More than one banking relatioship$_{it-1}$)	0/1	A dummy variable which equals one if the borrower *i* had more than one banking relationship the previous month to *t*
I(Bad credit history$_{it-1}$)	0/1	A dummy variable which equals one if the borrower *i* has ever had non-performing outstanding loans until *t*, and equals zero otherwise
log(Total assets$_{it-1}$)	log(000 €)	The log of total assets of borrower *i* at *t-1*
log(Age$_{it-1}$)	log(years)	The log of the age of borrower *i* plus one at *t-1*
Capital ratio$_{it-1}$	0.0x%	Own funds over total assets of borrower *i* at *t-1*
ROA$_{it-1}$	0.0x%	Return of Assets of borrower *i* at *t-1*
Productivity$_{it-1}$	0.0x%	The log of sales over the number of employees of borrower *i* at *t-1*
Liquidity ratio$_{it-1}$	0.0x%	The ratio of current assets minus current liabilities over total assets of borrower *i* at *t-1*
Bank indebtedness$_{it-1}$	0.0x%	The ratio of bank debt over total debt of borrower *i* at *t-1*
Cost of debt$_{it-1}$	0.0x%	Average interest rate of all outstanding loans of borrower *i* at *t-1*
Fixed employees/Total employees$_{it-1}$	0.0x%	The ratio of fixed employees over total employees of firm *i* at *t-1*
Short-term bank debt/Total bank debt$_{it-1}$	0.0x%	The ratio of short-term bank debt (<1 year) over total bank debt of borrower *i* at *t-1*
Medium-term bank debt/Total bank debt$_{it-1}$	0.0x%	The ratio of medium-term bank debt (1-5 years) over total bank debt of borrower *i* at *t-1*
Long-term bank debt/Total bank debt$_{it-1}$	0.0x%	The ratio of long-term bank debt (>5 years) over total bank debt of borrower *i* at *t-1*
Collateralized bank debt/Total bank debt$_{it-1}$	0.0x%	The ratio of collateralized bank debt over total bank debt of borrower *i* at *t-1*
Number of loan requests$_{it}$	0.0x	Number of total loan requests made by borrower *i* to different banks at time *t*
Province variables		
I(There are banks in the municipality$_{it}$)	0/1	A dummy variable which equals one if there is at least one bank in the municipality firm *i* is located at at *t*
log(No. of banks in the province$_{it-1}$)	log(banks)	Logarithm of the number of banks in the province firm *i* is located at at *t*
log(No. of banks in the municipality$_{it-1}$)	log(banks)	Logarithm of the number of banks in the municipality firm *i* is located at at *t*
Herfindhal of banks in province$_{t-1}$	0/1	Herfindhal index of bank concentration in the province firm *i* is located at at *t*
Herfindhal of banks in municipality$_{t-1}$	0/1	Herfindhal index of bank concentration in the municipality firm *i* is located at at *t*
Loan variables		
I(Long-term loan$_{ijt}$)	0/1	A dummy variable which equals one if borrower *i* obtained a loan from lender *j* at time *t* with a maturity of more than 5 years, and equals 0 otherwise
ln(Amount of the loan$_{ijt}$)	log(000 €)	Amount of the loan the lender *j* granted to the borrower
I(No-collateralized loan$_{ijt}$)	0/1	A dummy variable which equals one if borrower *i* did not collateralize the loan she obtained from lender *j* at time *t*, and equals 0 otherwise
Bank variables (j)		
Log(Total Assets$_{jt-1}$)	log(000 €)	The logarithm of total assets of lender *j* the previous year to *t*
Capital ratio$_{jt-1}$	0.0x%	The ratio of bank equity over total assets of lender *j* the previous year to *t*
Liquidity ratio$_{jt-1}$	0.0x%	The ratio of liquid assets (cash and balance with central banks, and loans and advances to governments and credit institutions) over the total assets of lender *j* the previous year to *t*
ROA$_{jt-1}$	0.0x%	The total net income over assets of lender *j* the previous year to *t*
Doubtful ratio$_{jt-1}$	0.0x%	The doubtful loan ratio of lender *j* the previous year to *t*
Δlog(Total loans in a province$_{jt-1}$)	0.0x%	The change in the logarithm of total loans of lender *j* in the province of borrower *i* the previous month to t

Full TABLE 7

Granting Time and Banks' Default Probability

Dependent variable: banks' future default	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Averate Granting Time $(AGT)_{it-1}$	-0.104 **	-0.077 **	-	-	-0.106 **	-0.107 **	-	-
	(0.042)	(0.036)			(0.050)	(0.051)		
Averate Granting Time Cleaned from Demand$(AGT\text{-}CD)_{it-1}$	-	-	-0.065 **	-0.058 *	-	-	-0.069 **	-0.063 **
			(0.033)	(0.033)			(0.028)	(0.030)
Log(Total assets$_{it-1}$)	-0.524 **	-0.469 **	-0.452 **	-0.458 **	-0.824 ***	-0.891 ***	-0.734 ***	-0.775 ***
	(0.210)	(0.209)	(0.214)	(0.228)	(0.255)	(0.297)	(0.226)	(0.264)
Capital ratio$_{it-1}$	-34.576 ***	-35.715 ***	-36.966 ***	-39.794 ***	-15.053	-17.565	-19.343	-21.383 *
	(11.080)	(12.369)	(11.532)	(12.367)	(11.279)	(11.032)	(11.862)	(11.606)
ROA$_{it-1}$	-0.149	1.403	0.659	2.027	3.615	3.671	3.411	3.869
	(4.915)	(4.951)	(4.925)	(5.055)	(4.129)	(4.126)	(4.511)	(4.248)
Losses/Net interest income$_{it-1}$	3.058	1.840	2.015	0.929	5.711 **	6.052 ***	4.569 **	4.414 **
	(2.064)	(2.339)	(2.065)	(2.295)	(2.274)	(2.324)	(2.064)	(2.076)
Staff cost$_{it-1}$/Operating Cost$_{it-1}$	6.182	5.235	9.887	7.202	1.929	1.946	5.253	4.618
	(6.034)	(6.739)	(6.366)	(6.887)	(6.844)	(6.490)	(6.910)	(6.802)
Liquidity ratio$_{it-1}$	-13.458 **	-11.048 *	-12.901 **	-11.266 *	-20.239 ***	-20.325 ***	-18.795 ***	-17.260 ***
	(5.859)	(5.684)	(5.709)	(5.766)	(5.737)	(5.852)	(5.633)	(5.589)
Total credit variation 1999-2007$_i$	6.683	3.559	7.743	6.132	1.640	3.984	3.539	5.336
	(9.688)	(9.733)	(10.445)	(10.837)	(7.537)	(8.554)	(8.477)	(9.550)
% Loans to firms/Total Loans$_{it-1}$	-	1.721	-	1.327	-	-1.335	-	-1.029
		(1.601)		(1.641)		(1.572)		(1.833)
%Loans to C&RE firms/Total Loans to firmsit-1	-	3.170 *	-	3.077 *	-	-0.123	-	1.365
		(1.744)		(1.645)		(1.934)		(1.996)
Pseudo R^2	0.471	0.503	0.454	0.496	0.513	0.517	0.493	0.503
Observations	56	56	56	56	56	56	56	56

Note. This table reports the estimates from a CAMEL model where banks' default probability is estimated through a probit model. Robust standard errors are reported in parenthesis. In Columns (1) to (4) dependent variable is an indicator that takes value 1 if the bank has been intervened, has been recapitalized with public aids, has been merged (Caixa Girona, Banesto, Pastor) or has needed capital after the stress tests carried out by the supervisor (Caja3, Ibercaja and Popular) and zero otherwise. In Columns (5) to (8) dependent variable is instead defined as an indicator that takes value 1 if the bank has been intervened, has been recapitalized with public aids and zero otherwise. Columns (1),(2) , (5) and (6) include Average Granting Time (AGT) as a regressor; Columns (3), (4), (7) and (8) instead include Average Granting Time cleaned from demand (AGT-CD) as regressor. AGT-CD is the bank*time fixed effect from a linear regression where the dependent variable is Granting Time, and firm*time fixed effects and the bank*year fixed effect are included as regressors. 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