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Screening and loan origination time: lending standards, loan defaults and bank failures

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Screening and Loan Origination Time: Lending Standards, Loan Defaults and Bank Failures

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Abstract

We show that *loan origination time* is crucial for bank lending standards over the credit cycle, as well as for ex-post loan-level defaults and bank-level failures. We use the credit register in Spain for the business loans over the 2002-15 period focusing on the time of a loan application and its granting. When VIX is low (proxying for good times) banks shorten the time to originate a loan, particularly to less-capitalized (riskier) firms. Bank moral hazard incentives are a key mechanism. Shorter loan origination time to ex-ante riskier firms in good times is especially stronger for: (i) banks with less capital (proxying for moral hazard problems between bank owners and taxpayers/debtholders); (ii) non-listed banks (proxying for moral hazard problems between bank management and shareholders); (iii) loans to firms in geographical areas which do not form the bank's main market and experience a real estate bubble (proxying for moral hazard problems between local loan officers and the bank headquarter), mainly if those areas have more bank competition; or, relatedly, stronger effects on loans granted to firms operating in industries which the bank is not most specialized at, proxying for moral hazard problems between different parts within the bank. Moreover, shorter origination time is associated with higher ex-post defaults at the *loan-level,* and aggregated at the *bank-level*, with higher likelihood of bank failure or other strong bank distress events, overall consistent with lower screening (time).

JEL Codes: G01; G21; G28; E44; E51.

Keywords: loan origination time; credit standards; credit cycle; defaults; banks; screening; moral hazard.

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1. Introduction

Credit cycles—with too soft lending standards during credit booms and tight standards during crises—are crucial for macro-finance and financial crises (e.g. Bernanke and Lown, 1992; Rajan, 1994; Kiyotaki and Moore, 1997; Gorton and Ping, 2008; Lorenzoni, 2008; Gertler and Kiyotaki, 2010; Bergman and Benmelech, 2012; Coimbra and Rey, 2020). A key theoretical channel is banks excessively softening their lending standards during booms through reducing their screening, with lower generation of borrower information (e.g. Ruckes, 2004; Dell'Ariccia and Marquez, 2006; Freixas and Rochet, 2008; Dang, Gorton, Holmström and Ordoñez, 2017; Asriyan, Martín and Laeven, forthcoming).

However, screening is largely unobserved and there are credit conditions easy to measure. Using large historical data, the best predictor for a financial crisis is strong credit volume growth (Schularick and Taylor, 2012; Gourinchas and Obstfeld, 2012). Using bank-level data, high credit growth is associated with subsequent underperformance in bank stock returns, profits and defaults (Fahlenbrach, Prilmeier and Stulz, 2018). Not only is volume crucial as a credit standard (Maddaloni and Peydró, 2011) but also loan spreads (Stein, 2012), collateral (Geanakoplos, 2010; Gorton and Ordoñez, 2014), and maturity (Diamond, 1991) are.

In this paper we study the time to originate a loan over the credit cycle. For measurement, we exploit the credit register from Spain over the 2002-2015 period (a full credit cycle), which includes the time of a loan application and its granting. In brief, we find that when VIX is low (proxying for good times) banks shorten the time to originate a loan, especially to less-capitalized (riskier) firms. Results suggest that bank moral hazard incentives are an important mechanism for shorter loan origination time. Shorter loan origination time to ex-ante riskier firms in good times is especially stronger for: (i) banks with less capital (proxying for moral hazard problems between bank owners and taxpayers/debtholders); (ii) non-listed banks (proxying for moral hazard problems between bank management and shareholders); (iii) loans to firms in geographical areas which do not form the bank's main market and experience a real estate bubble (proxying for moral hazard problems between local loan officers and the bank headquarter), mainly if those areas have more bank competition; or, relatedly, stronger on loans granted to firms operating in industries which the bank is not most specialized at (proxying for moral hazard problems between different parts within the bank). Moreover, a shorter *loan-level* origination time is associated with higher ex-post defaults, and aggregated at the *bank-level* it involves more bank failures or other strong distress events (even more than other lending conditions), overall consistent with lower screening time (higher risk-taking).

Our main contribution to the literature is to analyze loan origination time: (i) throughout a full credit cycle; (ii) depending on moral hazard incentives; and (iii) its relationship with loan-level defaults and bank-level failures. Loan origination time also depends on better technology and productivity (Fuster, Lo and Willen, 2017; and Fuster, Plosser, Schnabl, and Vickery, 2019), but our results suggest that loan origination time also relates to banks' moral hazard incentives in which a shorter time to originate a loan increases risk-taking, proxying for lower (time) screening (see Hu, 2021), which is difficult to observe (and hence measure), but crucial for theory (see e.g. Gorton and Winton, 2003; Tirole, 2006; Freixas and Rochet, 2008).[1] Moreover, our results show that loan origination time is important for all the questions we analyze, even for bank failures (where social costs/negative externalities tend not to be fully internalized), and our results suggest that the effects are similar or even stronger than other key credit conditions in explaining bank-level failures.

In the remaining part of this introduction we first provide an in depth preview of the paper and then discuss the related literature in detail and its differences with our paper.

Preview of the paper. In Section 2 we explain the data. We use the administrative, supervisory credit register held by Banco de España (the Spanish central bank) in its role of bank supervisor. The register contains information about all granted loans in Spain at the loan level at a monthly frequency, and since 2002 it includes monthly loan applications from borrowers to banks (which they are non-currently borrowing from). Moreover, we know the time of a loan application and its granting. We work with non-financial firms in Spain for which we have access to their balance-sheets and profit and loss financial statements (that firms are required to report to the Spanish Mercantile Register). Most firms in the credit register are private small and medium enterprises, and hence quite opaque. We also have access to the supervisory bank balance-sheet, income and loss statement and other supervisory information that banks are required to report to Banco de España. Given that we know the identity of the borrowing firm (via a unique tax identifier) and that of the bank, we merge the credit register database with these lender-level and borrower-level data sources. Finally, we also know banks' branches' locations, so we measure bank concentration in each geographical area as well as total lending in the area where the bank is headquartered and in other areas.

[1] Our results are consistent with theoretical literature that we refer to in this Introduction. On related empirical contemporaneous papers, Choi and Kim (2020) and Wei and Zhao (2020) also analyze loan origination time. However, different from us, they do not analyze: (i) the moral hazard mechanism; (ii) loans over a full credit cycle; (iii) loans to firms (mostly small and medium enterprises), which are much more difficult to screen than mortgages; nor (iv) bank failures. Wei and Zhao (2020) also link origination time to defaults but through a different channel, namely a behavioral rather than a moral hazard channel, so both papers are complementary. We provide more information in the subsection on the contribution to the literature.

In Section 3 we explain the empirical strategy. We first study the determinants of loan origination time, including how this measure evolves over the credit cycle; and second, we analyze how this behavior is associated with future implications for banks' performance, both at the loan-level with ex-post loan defaults and at the bank-level for bank failures.

Regarding the first objective, we analyze loan origination time over the credit cycle. To proxy for the credit cycle, i.e., good versus bad times, in a parametric way, we use the externally driven (European) level of VIX (Rey, 2013). We analyze how the VIX affects loan origination time, also related to measures of ex-ante borrower capital (a key measure of borrower risk). In addition, we also analyze the main effects for every time period in a non-parametric way (see Figure 2 and 3). Moreover, as safer borrowers may be easier to screen we control for borrower fundamentals. To further separate loan origination time from bank constraints or banks' different technologies for screening purposes, we also control for different observed and unobserved bank fundamentals, as e.g. number of loan applications per bank branch, size, profits or bank fixed effects.

To test for the moral hazard channel of loan origination time, and hence link it with bank screening (time), we study whether loan origination time to riskier firms in good vs. bad times depends on proxies of higher moral hazard problems. In particular, we account for moral hazard problems between the following agents:

First, banks (owners) and taxpayers/debtholders proxied by banks with less capital. Note that bank capital is a key measure of lender moral hazard problems as it represents the skin in the game, see e.g. Holmstrom and Tirole (1997) and Mehran and Thakor (2011).

Second, bank management and shareholders proxied by non-listed banks. Note that banks are opaque as compared to firms in other industries (see e.g. Morgan, 2002), and hence the information provided by listed banks every quarter, including daily stock prices, can be relevant to monitor and discipline banks as this information cannot be fully extracted from just past, current and expected future profits (see e.g. Holmstrom and Tirole, 1993).

Third, local loan officers and the bank headquarter proxied by loans to firms in geographical areas which do not form the bank's main market (especially if those areas experience a bubble and there is a higher bank competition).[2] Or, relatedly, moral hazard

[2] As this paper is about lending conditions over the credit cycle and risk-taking (screening), Spain offers a boom in credit and in real estate activity as well as two consecutive crises (the Lehman Brothers Global Financial Crisis and the Euro Area Sovereign Debt Crisis, i.e., crises or bad times occur since 2008 until 2014). Note also that in Spain, as well as in most countries in Europe, mortgages are with full recourse and hence loan defaults are higher in corporate loans than in mortgages. Therefore, we exploit areas that experienced a real estate bubble and crashed. We also exploit other variation in geographical areas: bank competition (proxied by bank concentration) as bank competition plays a significant theoretical role in screening depending on the credit cycle (Ruckes, 2004).

problems between different parts within the bank (other than due to different geographic areas) proxied by loans granted to firms operating in industries which the bank is not most specialized at. Note that Stein (2003) shows moral hazard problems within firms (e.g. within a bank), in which the internal capital budgeting process does not get right within-firm allocations of capital. For example, an important dimension within a bank is that different departments within it operate across different geographical areas, and hence there may be potential moral hazard problems between the bank headquarter and local lender officer decisions in other locations (Stein, 2002). Relatedly, banks have different specialization in lending across different industries (Paravisini, Rappoport and Schnabl, 2020), and hence moral hazard problems might arise within the bank when lending to different industries (with higher vs. lower specialization), and similarly, when lending in different locations (local loan officers in the headquarters' area versus in other local areas).

Regarding the second objective, we analyze whether ex-ante loan origination time is associated to ex-post loan-level defaults. We control for borrower fundamentals as safer firms, easier to screen, may have on average lower origination time independently of screening time, or control for other key determinants such as credit conditions, e.g. collateral. Even if the hypothesis we test in this paper relates loan origination time to bank screening (time) and hence it is a bank decision, we exploit a period when loan origination time is the shortest during the year and use it for an instrumental variable strategy. Moreover, we aggregate loan origination time at the bank level (directly or cleaned by firm fundamentals) and, exploiting the Global Financial Crisis that started in 2008, we analyze whether pre-crisis origination time is associated with the likelihood of bank-level failures and other strong bank distress episodes.

In Section 4 we explain the results. First, we find that—when VIX is low—banks shorten the loan origination time. In particular, a reduction (in the interquantile range) of VIX shortens the loan origination time by 3%. Moreover, the shortening of loan origination times (when VIX is low) is even stronger for ex-ante less capitalized firms. Interquantile range reductions of VIX and ex-ante borrower capital ratio shorten the average loan origination time by 3.8%.[3] Moreover, we also find that less capitalized banks further decrease the average loan origination time when VIX is lower.

Figure 2 and 3 show the average loan origination time over the credit cycle for each time period in a non-parametric way without any control. Figure 2 shows the overall cyclical behavior, with lower loan origination times in good times compared to crisis times. In Figure

[3] We find that less capitalized firms have on average higher loan origination time (though less so in good times).

3 we find that comparing good versus bad times for low (versus high) capitalized firms and banks (where low/high is defined as below/above the median), the average loan origination time increases by 30%.

Exploiting heterogeneity in bank competition, the average shortening of loan origination time is stronger in areas with more banking competition proxied by a low Herfindahl-Hirschman Index (HHI) when VIX is lower. Further, average loan origination time decreases for ex-ante less capitalized firms (interquantile range reductions), especially in areas with more banking competition, by 4.2% when VIX is lower. However, we find opposite effects in areas with low bank competition. Despite that bank competition and moral hazard are directly linked in banking (see e.g. Vives, 2016), as the net effect is not clear-cut (see e.g. Martinez-Miera and Repullo, 2010), we also analyze other proxies for moral hazard.

Shorter loan origination time to ex-ante riskier firms when VIX is low (following interquantile range reductions) is especially stronger for: (i) banks with less capital (a decrease in average origination time by 4.6% following an interquantile range reduction); (ii) non-listed banks (average loan origination time decreases by 5.5%); (iii) loans to firms in geographical areas which do not form the bank's main market, especially if those areas are in the Mediterranean coast where there is a real estate price bubble (prices boomed and crashed), in which average loan origination time decreases by 6.3%, and these effects are even stronger if bank competition is higher (a 7.2% decrease). Effects are also stronger for loans granted to firms operating in industries which the bank is not most specialized at (a decrease of 6.1% in origination time).

In consequence, the results suggest that bank moral hazard incentives are an important mechanism for our main result of loan origination time over the cycle with respect to ex-ante riskier firms. In particular, our evidence points to moral hazard problems between: (i) banks (owners) and taxpayers/debtholders (proxied by banks with less capital); (ii) bank management and shareholders (proxied by non-listed banks); (iii) different departments within the bank (proxied by local loan officers and the bank's headquarter, and also between loan officers providing loans to firms operating in industries which the bank is most specialized at versus loans to firms operating in other industries).

Second, we find that a shorter (*loan-level*) origination time is associated with higher ex-post loan defaults on average (up to 11% increase when loan origination time decreases from three months to the month in which the application is registered). Effects are also robust to controlling for firm observables, bank (observables or/and fixed effects) and other loan conditions (e.g. collateral or amount). Effects are also robust to controlling for firm fixed effects, although not surprisingly the coefficient is halved as loan defaults are mainly a between firm phenomenon. Moreover, results are also robust to the more stringent definition of loan default, which implies the firm's closure after it defaults on its loans. As such, if loan origination time decreases by three months, firm closure increases by 8.4%. Further, results are robust to using an instrumental variable setting. Exploiting the period of the year with the shortest loan origination time (see Figure 4) we find that shorter ex-ante origination time is associated with higher ex-post loan defaults.[4]

There are some heterogeneous effects as well. When origination time decreases from three months to the month in which the application is lodged, shorter origination time on loan defaults is higher for ex-ante less capitalized firms (by 1.4 percentage points, p.p., or 7.0% higher when comparing a firm in the third vs. first quartile of the capital ratio's distribution) or when VIX is lower (by 1.3 p.p. or 6.5% higher for the interquantile range of VIX). Moreover, the relatively higher effect of shorter origination times on higher defaults for less capitalized firms is stronger in areas with high bank competition (2.4 p.p. or 11.7% higher for an interquantile range change). Importantly, note that, e.g. for lower VIX, the effects on defaults stem from two related channels: (i) riskier firms during lower VIX periods have a lower origination time, which in turn implies more defaults; (ii) for a given origination time, lower (compared to higher) VIX periods increase the impact of lower origination time on higher defaults. For most variables under consideration, the first channel is the main one driving the results. Finally, effects are even more pronounced for real estate firms (in which competition and risk are higher). For instance, the average impact on future default increases by 7.5% for this type of firms (when origination time decreases from three months to the month in which the application is lodged) and is stronger for less capitalized real estate firms (9.6%, for an interquartile shock), and even more for these risky firms in areas of higher bank competition (11.6% increase for an interquartile change).

[4] The period with the shortest loan origination time is the Christmas holidays period (21st of December to January 7th, after the Three Wise Men or Epiphany day). This is a period in which there are substantially more holidays and many more social events, and hence, consistent with the data, results suggest that banks take faster decisions. Also in this period there may be end of year effects in which banks may also take faster decisions to increase lending, which is consistent with our mechanism. We also analyze the January period uniquely, and results are very similar. Results are also very similar if we include the other period during the year in which loan origination is the second shortest, which corresponds to August's last two weeks, which is also a period of holidays. Note also that we find that during the shortest loan origination time period the borrowers (firms) that obtain the loans are not different in observable ways, either without firm fixed firms comparing the different firms in this period versus other periods, or within firm fixed effects comparing the same firm obtaining loans during this holidays period vs. other periods. Results are robust across substantial different controls for unobservables and the estimated effects in the second stage are very similar to the OLS ones.

To push further on the screening (risk-taking) mechanism, we aggregate loan origination time at the *bank level* and exploit the global financial crisis that started in 2008. We measure strong bank distress as a dummy variable that takes value one when bank overall financial distress is due to its public intervention, a public (state) bailout, a merging process or an acquisition during the crisis, or a recapitalization after a stress test exercise carried out by the supervisor; and zero otherwise.

We find that a shorter pre-crisis loan origination time at the bank level is associated with a higher likelihood of bank failure or a related strong bank distress event. Consistent with less screening (time), an interquantile range reduction of pre-crisis loan origination time is associated with a 12.4% increase in bank overall likelihood of distress after the start of the global financial crisis. Interestingly, the loan origination time has a similar—or even stronger—economic and statistical effects than other credit conditions and standards analyzed in the literature —credit (volume) growth, even in real estate, loan spreads, loan collateral and loan maturity.

Contribution to the literature. We contribute to several strands of the literature. There is a large theoretical literature on screening, in banking in general (see e.g. Freixas and Rochet, 2008; Gorton and Winton, 2003) and also related to the credit cycle, with theoretical testable predictions of less bank screening, less generation of information, during booms, in part due to moral hazard problems (see e.g. Ruckes, 2004; Dell'Ariccia and Marquez, 2006; Asriyan, Laeven and Martín, forthcoming).[5] We contribute to this literature by proxying screening (time) effort by the time difference between a loan application is submitted and its granting time, and by finding the following results. We show that the loan origination time is shorter when VIX is low (or in a boom), especially for ex-ante less capitalized (riskier) borrowers, and results suggest that a key driver is bank moral hazard incentives. In particular, moral hazard problems between (i) bank owners and their debtholders and taxpayers; (ii) bank

[5] See also Broecker (1990) and Dang, Gorton, Holmström and Ordoñez (2017). Hu (2021) exploits the variation of bank screening time and shows how the variations are related to lending standards and credit cycles. In a different setting, Bouvard and Lee (2020) analyze time pressure and time competition as the main driver of risk management (quality) choices of firms that compete in a given market, with a mechanism consistent with our findings (especially their Proposition 4). For a model of rational inattention during the credit cycle see Mariathasan and Zhuk (2018). There is a relatively large empirical literature on credit cycles and lending standards, see e.g. Dell'Ariccia, Laeven and Deniz (2012), Becker and Ivashina, (2014), and Jiménez et al. (2017). This large literature on credit cycles does not analyze loan origination time. Granja, Leuz and Rajan (2020) analyze distance as a measure of risk-taking, we instead analyze loan origination time as well as the loan-level ex-post defaults and bank failures. There are some empirical papers related to screening, see e.g. Cole, Kanz and Klapper (2015), Agarwal and Ben-David (2018), Becker, Bos and Roszbach (2020), and Brown, Kirschenmann and Spycher (2020). Our results are different due to the question that we analyze (loan origination time); our results are not driven by credit conditions such as volume or collateral (controlling for these loan conditions do not change the results), and corporate (mostly SMEs) loans in Spain were not securitized or sold in secondary markets or to public agencies.

management and shareholders; (iii) local loan officers and bank headquarter, or in general between different parts within the bank (the result of bank specialization). Moreover, we show that a shorter loan origination time is associated with higher ex-post loan-level defaults, and aggregated at the bank level, with bank failures or other strong bank distress events. Therefore, our results suggest that a lower loan origination time also proxies for a lower screening (time) effort (higher risk-taking) and are consistent with a theoretical bank moral hazard mechanism.

Moreover, as highlighted in the first page: (i) there is a large banking and macro-finance theoretical literature on credit cycles, lending standards, and more generally on banking crises and bank failures; (ii) the empirical analyses in this literature have analyzed loan volume, rates, collateral and maturity, in part as these are easier-to-observe variables, especially volume. The path-breaking papers by Schularick and Taylor, 2012, also with Jordà, 2011 and 2013, have shown (with country-level data) that the growth of bank credit volume is the best predictor of financial crises throughout history. Importantly, there are also related key results with micro bank-level data using bank credit growth (see Fahlenbrach, Prilmeier and Stulz, 2018). We contribute to this literature by analyzing loan origination time and relating it to the credit cycle, to ex-ante risk-taking, and to ex-post loan-level defaults and bank-level failures. We find that a shorter origination time is associated with higher ex-post defaults at the *loan level* and with higher likelihood of bank failures at the *bank level*. Compared to other key credit standards studied in the literature, our evidence suggests that average loan origination time produces similar or even stronger effects.

There are two close contemporaneous papers to ours which use US data on mortgages. On the one hand, Choi and Kim (2020) use mortgage application processing time at the loan level and exploit the collapse of the private securitization market. After the collapse, lenders spent significantly more time in processing applications for loans larger than the conforming loan limits than for those below. The processing time-gap widened more for banks with greater involvement in the originate-to-distribute model, lower capital, and larger assets. The main differences with our paper are that we link *ex-ante* loan origination time with *ex-post loan-level* defaults and even *bank-level failures*.

On the other hand, Wei and Zhao (2020) link ex-ante processing time to ex-post defaults but though a *different* mechanism. They provide empirical evidence that among privately securitized mortgage loans originated in 2004-2006 the reduction in processing time is associated to higher default, but due to extrapolative beliefs by mortgage lenders. Our main differences with this paper are threefold. First, we analyze a full credit cycle and our results suggest that bank moral hazard problems are a key driver. Second, we analyze bank-level failures (or related strong bank distress events), which in line with the existing theoretical background it is important as excessive risk-taking (too low screening) and bank failures impose social costs (via negative externalities) that tend not to be fully internalized by bankers.

Third, with respect to the previous two papers and in addition to the different results or/and mechanisms just summarized, we analyze loans to *firms* which tend to be more opaque (especially non-listed firms which constitute the bulk of our dataset) and, based on banking theory and practice, screening is particularly more important (given that soft information plays an important role when dealing with extending loans to SMEs). Note that loans to firms, foremost to SMEs, were not securitized in Spain, so the main channel is different from the aforementioned two papers using US mortgage data –a securitization mechanism– and hence, in our results, loan origination time affects ex-post bank failures (as loans are retained).

There are also two other papers (Fuster et al., 2017 and 2019) using loan origination time for US mortgages. Fuster, Plosser, Schnabl and Vickery (2019), using data since 2010, show that fintech lenders process mortgage applications faster than other lenders, reducing capacity constraints associated with traditional mortgages, without suffering from more aggregate defaults. Therefore, loan origination time also depends on better technology and productivity. Our results suggest that loan origination time varies over the cycle and that bank moral hazard incentives are also a key mechanism, and that consistently, a lower ex-ante origination time is associated with higher ex-post loan-level defaults and even bank-level failures (consistent with theories of too soft lending standards in booms that we refer to before). Further, Fuster, Lo and Willen (2017) find that the price of intermediation, measured as a fraction of the loan amount at origination, is large over the 2008-14 period, and increases associated with QE led to increases in the price of intermediation (thereby attenuating the benefits of QE). They also show that application volumes are related to loan origination times (capacity constraints). Our results also suggest that bank capacity constraints (average number of loan applications per branch) do matter, but not differentially over the credit cycle, in contrast to proxies for bank moral hazard problems.[6] In sum, unlike our paper, these papers do not analyze a full credit cycle and pro-cyclicality in credit standards, nor bank-level failures and distress (their analysis does not cover a full cycle) or a moral hazard mechanism. Therefore, our paper asks different questions (and hence it has different, new findings) which complement these crucial papers.

The paper proceeds as follows. Section 2 and 3 respectively describe the data and the empirical strategy. Section 4 discusses the results while Section 5 briefly concludes the paper.

[6] Sharpe and Sherlund (2016) and Choi et al. (2019) also find evidence of capacity constraints.

2. Databases

Our empirical analysis relies on four administrative matched datasets: (i) the Spanish Credit Register (CIR) owned and managed by Banco de España, which contains in-depth information on virtually every loan granted by a financial institution operating in Spain, including loan applications to non-current borrowers; (ii) firm-level balance sheet and financial information through the Spanish Mercantile Register; (iii) bank-level financial statements available at Banco de España in its role of bank supervisor; and (iv) the location of bank branches at the municipal level.

The CIR reports information on every loan exceeding the threshold of just 6,000 euros, which is tiny for corporate loans. 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 or the existence of collateral. We focus on loans granted by commercial banks, savings banks and credit cooperatives to non-financial limited liability companies, which represent around 95% of the Spanish credit market. Our final sample contains more than 160 banks.

Moreover, the credit register records applications of borrowers to non-current banks since 2002 at a monthly level. This is important as loans from current banks may have misleading origination times due to the information banks already have about their borrowers (and hence they could just provide a loan without a new origination time as their "screening" is made during the monitoring of previous loans), and hence (to have a level playing field) we compare lenders to borrowers without this extra information. See Jiménez et al. (2012, 2014 and 2017) for a detailed description of this dataset.

Since we are interested in the loan origination process and to what extend it is related to banks' credit standards, we construct the loan origination time variable for every granted application by measuring the time elapsed between the lodged application and its granting. We know the day of a loan application and its granting month. Therefore, the loan origination time variable takes six different values: 0, 1, 2, 3, 4 and 5 months. Further, as robustness, we use a dummy variable (below/above the median loan origination time).[7] Figure 1 shows that around 70% of loans are granted within month zero (i.e., granting and application month are

[7] After five months there are some loans granted for some applications, but the probability is very small, close to zero. Therefore, we restrict to 5 months the maximum value of loan origination time. As robustness, in Table A2 we test the consistency of the results restricting the sample to 4 or even 3 months and results are the same. In addition, we also have other unreported tests, e.g. our results are identical if we control for week fixed effects to control for the week in which the loan origination started. Further, as robustness, we also proxy the origination time in days assuming that the loan is granted in the last day of the granting month. Results are very similar if we assume that the loan is granted in the middle of the month.

the same) or after the first month following their application, and more than 85% if we add up the second month. Table 1 shows that origination time has a mean equal to 1.2 (slightly more than one month) and its median is one month (measured in days it is approximately 52 and 40 days for the average and the median, respectively).[8]

We also have banks' and firms' administrative balance sheet information at our disposal. Banks' information is obtained through a database owned by Banco the España as a banking supervisor, and firms' information through the Spanish Mercantile Register. 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. Finally, we also know banks' branches' location to measure bank concentration in geographical areas (the Herfindahl-Hirschman Index at the level of municipalities according to credit volume) as well as to measure lending from the area where the bank is headquartered versus other areas (i.e., loans granted by local loan officers in areas different from where the bank is headquartered).[9]

Figure 2 shows the average loan origination time per semester using two different measures (months and days) for the period covering the first semester of 2002 to the last semester of 2015. The cyclical behavior suggests that banks reduce loan origination time during boom times and increase origination time during crisis periods (the Global Financial Crisis and the Euro Area Sovereign Debt Crisis). The results shown in the Figures are obtained without considering any controlling variable. Results are very similar if we control for loan, borrower and lender characteristics, including granted applications or number of applications. In the regression analysis we control for these variables and many others, as it is duly explained in the next two sections.

Moreover, Figure 3 analyzes whether this cyclical pattern depends on the balance sheet strength of borrowers (firms) and lenders (banks) proxying for moral hazard problems, i.e., based on ex-ante firm and bank capital ratios (see Holmstrom and Tirole, 1997). Considering granted applications to firms by banks above and below the median of their capital ratios, the figure shows that granted applications to firms by banks that are both below their median are substantially more cyclical. Comparing boom versus bust periods for less capitalized borrowers and less capitalized banks, average loan origination time increases from

[8] Compared to e.g. Fuster et al. (2019), despite different data, countries and credit markets, we find similar number of days in loan origination time for the summary statistics, even if in our sample there are 4 more days in loan granting on average (though there are identical median days for banks: 40 days in both papers). Note that we analyze firms with more complicated balance sheets and soft information than mortgages.

[9] During our sample period, the effective headquarter of the bank is located in the area where the bank lends most.

approximately 46 to 60 days, i.e., these 14 days imply approximately a 30% increase in average loan origination times. Cyclical effects are substantially smaller for highly capitalized firms and banks.

Finally, Figure 4 suggests that the average loan origination time has a seasonal effect at the end of the year and at the beginning of the next year (school holidays in Spain start after the third week of December and last until 7th of January, the day after Epiphany). The last two weeks of August is the period with the second shortest loan origination time, and it is also a period of holidays. As we will explain in detail in the next sections, given this seasonal monthly effect in our estimations, we control for monthly effects by including monthly seasonal fixed effects or even year:month fixed effects. Further, we exploit this calendar effect to study the impact of ex-ante loan origination time on the probability of ex-post loan defaults.

3. Empirical strategy and descriptive statistics

We start by investigating how borrower, lender and the credit cycle affect loan origination time. Then, we study whether loan origination time is associated with future loan default at the loan-level, and by aggregating at the bank level, we test whether pre-crisis origination time is associated with bank failures or other strong bank distress events, exploiting the period after the Lehman Brothers collapse in September 2008.

3.1. Determinants of loan origination time

In the first part of the paper we want to analyze whether the loan origination time depends on the financial cycle as well as on measures that proxy for moral hazard problems.

The dependent variable is *Loan origination time*, which measures how many months a bank has taken to originate a loan after its application had been lodged. As aforementioned, this is a discrete variable that takes 6 different values, ranging from 0 (if the loan was granted in the same month in which it was requested) to 5 (if the loan was granted five months after the application was made). The average value of *loan origination time* equals 1.2 months with a great heterogeneity of its values, since its coefficient of variation is 106% (Table 1 shows the descriptive statistics of the main variables used in the paper and Table A1 in the Appendix reports their definition and units). As robustness test we also work with the loan origination time measured in days (an approximation) or using a dummy variable reporting below/above the median loan origination time values.

For estimation purposes, as the outcome variable takes different discrete values (from 0 to 5), the Poisson model stands as the preferred one, as this model has the advantage over the OLS estimation that the latter would lead to inconsistent point estimates under heteroscedasticity (see Santos Silva and Tenreyro, 2006); however, as a robustness we also estimate an OLS model for the log of (one plus) loan origination time.[10] The baseline equation we estimate using Poisson pseudo-maximum-likelihood estimator is the following:

$$\begin{aligned} &\text{Loan origination time}_{ijt} \\ &\quad = \exp\big(\beta_1 VIX_{t-1} + \beta_2 int\ rate\ surprise_{t-1} + firm\ variables_{it-1} + bank\ variables_{jt-1} \\ &\quad + local\ competition\ variable_{\mathrm{im}t-1} + \ fixed\ effects + s_t\big) + \epsilon_{ijt}, \end{aligned} \tag{1}$$

where the sub-indexes *i, j, m* and *t* refer to firm, bank, municipality and time, respectively. All variables are lagged one moth. To proxy for the credit cycle, we use the level of VIX. As Europe suffered two crises, we proxy it for the European VIX, in particular the variable $VIX_{t-1}$is a volatility index based on EURO STOXX 50 option prices.[11] We also control for monetary policy rates, in particular $int\ rate\ surprise_{t-1}$ is the European 3-month interest rate surprise computed following Jarociński and Karadi (2020). Note that Figure 2 and 3 show the results considering no control period by period, i.e., in a non-parametric way.

The regressors $firm\ variables_{it-1}$ and $bank\ variables_{j,t-1}$ are vectors of firm and bank time-varying characteristics, respectively. Regarding borrower fundamentals, our main variable of interest proxies firm risk by firm capital ratio, which is also a measure of moral hazard problems (following Holmstrom and Tirole, 1997). Firm capital ratio averages 29%. We control for other key firm, as well as bank variables, as e.g. size, different measures of risk and liquidity.[12] A key bank variable is bank capital, which proxies for bank moral hazard problems (Holmstrom and Tirole, 1997) and has an average value of 6%. Further, we capture the banking structure at the municipality level with the $local\ competition\ variable_{imt-1}$, the Herfindahl-Hirschman Index (HHI) in terms of credit volume, which averages 6.7%.

We also control for different fixed effects. Unobservable bank-specific time-invariant shocks are controlled for with the use of bank fixed effect. These effects may affect loans'

[10] As another robustness check we also analyze non-granted loans, for which we do not observe the time when the loan was refused. To tackle this issue, we estimate a censored Poisson model to 5 months (see Table A2). On the other hand, an advantage of our dataset is that we can compute the time to originate a loan for firms, mostly non-listed SMEs, in which soft information is important, and hence screening (time). Moreover, we do have loan defaults for every single loan, and we have a full cycle so that we can analyze ex-ante loan application time and ex-post loan-level defaults and bank-level failures.

[11] Effects would be very similar if we used credit volume growth or GDP growth instead.

[12] As other firm controls, we consider its size, age, liquidity ratio, ROA, bank indebtedness, productivity, average cost of debt, fixed employee ratio, debt term structure, percentage of collateralized loans, firm's credit history, if the firm had been a bank's customer in the past, the number of loan applications made by the firm in that month and if the firm and the bank share the same industry/region. As other bank controls, we consider the size, the liquidity ratio, the ROA, its losses and its lagged growth in the province of the firm.

average origination time because they could be capturing, for instance, the technology available to a bank to assess firms' creditworthiness. We also control for the average number of loan applications per branch as a measure of bank capacity constraints, and in some robustness checks we use bank*time fixed effects as additional controls. Unobserved firm characteristics are controlled by province and industry (NACE at two digits) dummies that control for time-invariant observable and unobservable firm factors within the province or industry. As further robustness we also consider bank*industry and bank*province effects that allow to control for specialization. As the purpose of this paper is to analyze loan origination time as a proxy for screening (time) for riskier vs. safer borrowers (a between firm phenomena), we do not include (borrower) firm fixed effects.[13] Seasonal time fixed effects are captured by month fixed effects or by year:month fixed effects, and ϵ_{fjt} is the idiosyncratic error term. Our level of clustering is conservative (following e.g. Abadie, Athey, Imbens and Wooldridge, 2017), where we triple-cluster at the bank, firm and time level. Our strategy is to progressively saturate the baseline model to analyze the impact of aggregate (macroeconomic), firm, bank and local market characteristics on the loan origination time.

Our main test is whether loan origination time in good times (proxied by low VIX) is shorter for ex-ante riskier firms (proxied by lower firm capital ratio). That is, we are interested in testing whether the shortening of loan origination time when VIX is low is stronger for ex-ante less capitalized firms.[14] Moreover, by introducing in the baseline specification triple interactions of VIX*firm capital with proxies of bank moral hazard problems, we test for the moral hazard channel of loan origination time, and hence link it with bank screening (time). We study whether loan origination time to riskier firms in good vs. bad times depends on proxies of bank moral hazard problems (see Freixas and Rochet, 2008).

First, we focus on moral hazard problems between banks (owners/shareholders) and taxpayers/banks' debtholders proxied by the bank capital ratio, in which a lower bank capital ratio stands for more moral hazard problems. Note that bank capital is a key measure of lender moral hazard problems as it represents the skin in the game, see e.g. Holmstrom and Tirole (1997) and Mehran and Thakor (2011) for the theoretical justification.

Second, we focus on moral hazard problems between bank management and shareholders proxied by the dummy non-listed banks variable, where non-listed as compared to listed banks

[13] In Table 2, the association between firm capital ratio and loan origination time disappears if we control for firm fixed effects as most variation in firm capital ratios are between firms, not within firms.

[14] We also analyse other heterogeneous effects related to VIX. For instance, local market concentration, bank capital or the number of applications per bank branch.

proxies for bank moral hazard problems. Note that banks are opaque as compared to firms in other industries (see evidence from e.g. Morgan, 2002), and hence the information provided by listed banks every quarter, including daily stock prices, can be relevant to monitor and discipline banks as this information cannot be fully extracted from just past, current and expected future profits (see e.g. Holmstrom and Tirole, 1993, for the theoretical justification).

Third, we focus on moral hazard problems between local loan officers and the bank headquarter proxied by loans to firms in geographical areas which do not form the bank's main market (especially if those areas experience a higher lending activity and competition).[15] Or, relatedly, moral hazard problems between different parts within the bank (other than due to different geographic areas) proxied by loans granted to firms operating in industries which the bank is not most specialized at. For the theoretical justification, note that Stein (2003) shows moral hazard problems within firms (e.g. within a bank), in which the internal capital budgeting process does not get right within-firm allocations of capital. An important dimension within a bank is that different departments within it operate across different geographical areas, and hence there may be potential moral hazard problems between the bank headquarter and local lender officer decisions in other locations (Stein, 2002). Relatedly, banks have different specialization in lending across different industries (Paravisini, Rappoport and Schnabl, 2020), and hence moral hazard problems might arise within the bank when lending to different industries (with higher vs. lower specialization), similarly as the moral hazard problems associated with location (headquarter vs. local loan officers).

Finally, we also analyze bank competition for the moral hazard mechanism as the level of bank competition is directly linked to moral hazard in banking (see e.g. Vives, 2016 and Allen and Gale, 2003). However, theoretical effects are not crystal-clear in the sense that higher bank competition may increase or decrease bank risk-taking due to moral hazard problems (for the theoretical reasoning, see e.g. Martinez-Miera and Repullo, 2010).[16]

3.2. Loan origination time and loan defaults and bank failures

We also study whether loan origination time is associated with loan's *Future Default* at the loan-level, which is a dummy variable that takes value one if a loan becomes delinquent

[15] We also exploit bank competition (proxied by bank concentration) as bank competition plays a significant theoretical role in screening depending on the credit cycle (Ruckes, 2004). There is also potentially more risk-taking and competition in areas subject to the real estate bubble and crash, which in Spain are the sea areas in the Mediterranean coast. As this paper is about lending conditions over the credit cycle and risk-taking (screening), Spain offers a boom in credit and in real estate activity as well as two consecutive crises, in addition to data on loan origination time for corporate loans. Note also that in Spain, as well as in most countries in Europe, mortgages are with full recourse and hence loan defaults are higher in corporate loans than in mortgages.

[16] See also Boyd and De Nicoló (2005), Ruckes (2004), Keeley (1990) and Hellmann, Murdock and Stiglitz (2000).

at some point in the future (until 2016:03). The definition of default follows the policy and academic literature, i.e., at least 90 days overdue. Nevertheless, we also analyze firm closure after loan defaults. Average loan default value equals 20% (given the strong crisis periods during the sample period) and it has a standard deviation of 0.4 points. Our specification focuses on the same applications previously analyzed. We estimate using OLS the following baseline linear probability equation:

$$Future\ Default_{ijlt} = \gamma Loan\ origination\ time_{ijt} + firm\ variables_{it-1} + bank\ variables_{jt-} + loan\ variables_{lt} + local\ market\ variables_{mt-1} + fixed\ effects + \epsilon_{ijlt}, \quad (2)$$

where the sub-indexes i, j, l, m and t refer to firm, bank, loan, local market and time, respectively, $Loan\ origination\ time_{ijlt}$ denotes the loan origination time variable defined in Subsection 3.1; $firm\ variables_{it-1}$ and $bank\ variables_{it-1}$ are the same firm and bank characteristics aforementioned (key capital ratio measures and also different controls); loan controls include the logarithm of the loans' amount, measured in thousands of euros, 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, and zero otherwise; the local market proxy (HHI) of bank competition, and ϵ_{fjlt} is the idiosyncratic error-term. As before, standard errors are multi-clustered at bank, firm and time level. We also control for different fixed effects. When bank*time fixed effects are not included bank variables are added as controls and some of them are included as interactions terms in some specifications. We also include province and industry fixed effects to control for firm unobservable fundamentals and in some specifications we also control for firm fixed effects. These latter effects have the advantage to further isolate bank decisions from firm characteristics (as safer firms have mechanically faster origination time irrespective of screening), but they also absorb most of the variability of the dependent variable as loan defaults are mostly a phenomenon between firms. Additionally, we analyze our risk variable to consider not only future loan defaults but also firm closures after loan default.

We also analyze heterogeneous effects. The VIX variable, absorbed by the time fixed effects, is included in some estimations as an interaction term when we study heterogeneous effects. That is, we also include several interactions between our key variables of interest in the same vein as in the previous subsection 3.1 (e.g. VIX, firm and bank capital, and bank competition). It is important to highlight that if there were effects for e.g. lower VIX, the effects on loan defaults would stem from two related channels. First, loans to riskier firms during lower VIX periods would imply a lower origination time, in turn implying more loan defaults. Second, for a given origination time, during lower (compared to higher) VIX periods would increase the impact of lower origination time on higher defaults. As it will be explained in the results section, for most variables, the first channel is driving the results. Moreover, for risk-taking/screening, this period of time in Spain cannot be analyzed without taking into account the housing bubble, and hence we also test whether the effects are more pronounced for real estate firms.

We also use an instrumental variable strategy. In particular, we analyze whether results on defaults are robust to using an instrumental variable setting by exploiting the period of the year with the shortest loan origination time (see Figure 4). The period with the shortest loan origination time is the Christmas holidays period (21st of December to January 7th, after the Three Wise Men or Epiphany day). This is a period in which there are substantially more holidays and many more social events, and hence, consistent with the data, results suggest that banks take faster decisions. Also, in this period, and consistent with our mechanism, there may be end of year effects in which banks may also take faster decisions to increase lending. In addition, (i) we also analyze the January period uniquely, and test whether results are similar, and (ii) we also test whether results are similar if we consider the second shortest loan origination period during the year, namely August's last two weeks, which is also a period of holidays (see Figure 4). We also analyze whether during the shortest loan origination time period, the borrowers (firms) that obtain loans are different in observable ways, either without firm fixed firms comparing different firms in this period versus other periods, or within firm fixed effects comparing the same firm obtaining loans in this holidays period versus other periods. Similarly, we also analyze whether the estimated effect in the second stage is similar or not to the effect obtained through OLS.

If loan origination times proxies for screening, then not only should it be associated at the loan level with future loan defaults, but there could be bank-level effects as well. However, this potential loan-level risk-taking may not imply a bank failure as the loan-level risk-taking might be compensated by hedges, collateral or via rates, to keep a viable level of overall risk in banks' balance sheets. Hence, we undertake a *bank-level* analysis exploiting the Global Financial Crisis after the Lehman Brothers failure in September 2008 as well as the Euro Area Sovereign Debt crisis.

We estimate a model where we explain banks' strong distress events over the 2008-2015 period on aggregated pre-crisis loan-level variables, including the average loan origination time as an additional regressor, fixed at 2006 (before the crisis), and also controlling for pre-crisis bank characteristics based on a CAMEL model.[17] The period of time considered for the analysis offers a good opportunity to challenge the strength of the average loan origination time as an early warning indicator since 37 banks in Spain experienced severe distress. We end up working with 57 banks following the sample used by Banco de España in its Forward Looking Exercise on Spanish Bank (FLESB) in which we have information on the bank distress events due to supervisory test exercises (we do not have such a granular level of information for the other non-used banks). We define a bank's large distress event in the extended version when banks' financial distress resulted in: (i) public (state) intervention of the bank (by Banco de España); (ii) a public bailout (with state funding); (iii) a merging process or an acquisition (with another banking group or within its banking group); or (iv) a recapitalization (after a supervisory stress test exercise). We define the distress event in the narrow version when only the first two conditions apply.

We analyze these events through a Probit model based on average pre-crisis lending conditions (including loan origination time) and banks' ex-ante overall performance, captured by a CAMEL rating. As a benchmark we use a Probit model instead of a linear probability model given the low number of observations, the large average value of the dependent variable and that the model does not include fixed effects nor interactions terms (we obtain similar results when using the linear model). Specifically, we estimate the probability of bank distress though a Probit model with robust standard errors:

$$Pr(Large\ Distress\ Event_j = 1/x_{j2007}) = F(\alpha\ average\ loan\ origination\ time_{j2006} + bank\ CAMEL_{j2007}) \qquad (3)$$

where *Large Distress Event$_j$* is a binary variable that takes value one if a bank j suffered a distress event after the start of the Global Financial Crisis in 2008, and zero otherwise. This variable has an average value of 75% for the extended definition and of 65% for the narrow one, which shows the great impact of the financial crisis on the Spanish banking system. *Average loan origination time$_{j2006}$* is a bank's average origination time of all its outstanding loans at 2006. Results are similar if we define this variable considering the highest credit increase during the boom (2004-06). Note that the economy in Spain was strong until the

[17] We get similar results if loan origination time is computed in 2007 instead of as an average of 2006 (though in Europe, interbank problems started in the summer of 2007). CAMEL models receive their name from the set of indicators assessed to rank overall banks' condition and financial strength, that are related to Capital adequacy; Assets; Management capability; Earnings/profits and Liquidity. This rating is based on 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 and the liquidity ratio.

second part of 2008 and the first bank falling into severe risk in Spain was in March 2009; nevertheless, there were some interbank problems in Europe in the summer of 2007, and hence we set the main pre-crisis variables in December 2006 before the interbank European problems. *Bank variables*$_{j2007}$ is the vector of the CAMEL rating (as of 2007) plus some additional measures of bank lending conditions used in the literature, such as credit growth, percentage of real estate assets, average maturity, collateral or loan interest rates.

4. Results

Tables 2 to 4 show the estimated coefficients for different specifications of Equation (1), Tables 5 to 7 do so for different specifications of Equation (2), while Table 8 shows the results of the estimation of Equation (3).

4.1. Determinants of loan origination time

Table 2 reports seven different specifications. While columns (1) to (5) show the estimation results for loan origination time in months, column (6) displays the results of time in days, and finally column (7) shows the results with a dummy over and below the median value of loan origination time. We estimate the first six models with Poisson (PPML) and the latter one with OLS given that the dependent variable is a dummy (see Section 3 where the empirical strategy is described). Regarding controls, column (1) only includes seasonal dummies. Column (2) adds firm and bank controls (e.g. size, risk, liquidity, profitability, etc.). Column (3), our benchmark specification, adds province, industry and bank fixed effects and seasonal dummies. Column (4) includes time (year:month) fixed effects that absorb the seasonal dummies, while column (5) additionally includes bank*time fixed effects. Columns (6) and (7) replicates column (3) but for different dependent variables.

Table 2 indicates that loans' origination time is counter-cyclical, i.e., a favorable financial environment proxied by a low VIX is followed by a shorter loan origination time (see also Figure 2 for the non-parametric results, period by period, without controls, for boom versus bust periods). According to column (3), comparing the first versus third quartile of the VIX distribution, the average loan origination time decreases by around 3%. Regarding a one standard deviation reduction of VIX, loan origination time decreases by 2.2%. Differently, the monetary interest rate (surprise) is not as robust statistically speaking and the economic effects are substantially smaller. Regarding column (6) measuring the origination time in days, results for VIX suggest that an interquartile range reduction of VIX decreases the loan origination time by 2.3%, while for the dummy below the median, results for VIX are also significant (and economically of similar magnitude, i.e., implying a 2.9% reduction).

Table 2 also shows that the loan origination time increases with the ex-ante risk of the firm, in particular with ex-ante less capitalized firms, proxying for higher moral hazard problems. For instance, an interquartile range decrease in firm capital ratio increases the average loan origination time by around 1.4% for all the first five specifications; results are similar to the other two different outcome variables (columns (6) and (7)). Furthermore, column (3) shows that more bank competition proxied by bank concentration (an interquartile range decrease in the Herfindahl-Hirschman Index in the municipality) is associated with a decrease in the loan origination time by 1.4%. In addition, Table 2 also documents that banks with less capital present lower origination times. Column (3) shows that an interquartile range decrease in bank capital implies a loan origination time decrease of 8.1%. Finally, origination time per loan decreases with the average number of loan applications received per bank branch (6.8% for an interquartile range increase). Results for firm capital, bank capital and applications per branch and the proxy of bank competition are robust to different left hand side variables (column (6) in days and column (7) as above/below the median).

Table A2 in the Appendix displays five further robustness checks for the baseline estimation of Equation (1) that includes bank, seasonal, province and industry fixed effects. Column (1) shows the estimation results for an OLS model where the dependent variable is the log of (one plus) the loan origination time. Results are qualitatively the same. Columns (2) and (3) perform a robustness check to ensure that the results in Table 2 are not biased by the upper limit of 5 months. In column (2) we reduce the upper limit for the granting time to at most 3 months instead of 5 months, while in column (3) we set the limit to 4 months. Both estimations show that our results are not driven by the choice of this limit. Column (4) saturates the specification with the inclusion of bank*industry and bank*province dummies to control for bank specialization, following Paravisini, Rappoport and Schnabl (2020). These results are robust to considering industry*province*time fixed effects (not reported). Finally, in column (5) we estimate a censored Poisson model for all the applications made, and results are robust.

4.1.1. Heterogeneity in the determinants of loan origination time

Table 3 documents the heterogeneity of the results by introducing interactions in the specification of column (3) of Table (2), i.e., the baseline regression of Table 2. Throughout the paper, when interaction terms are included, all variables are demeaned, so that the coefficients of the variables in levels estimate the average effect; and lower level interactions are always included, even if for the sake of space are not shown in all regressions. Table 3 reports coefficient estimates for the double interactions of VIX with: (i) firm capital ratio; (ii) bank capital ratio and average number of applications per branch; (iii) and the market's competition characteristics (Herfindal-Hirschman Index). The estimated coefficients capture heterogeneous changes in loan origination time over the cycle depending on ex-ante differences across borrowers, lenders and geographical areas. All models in Table 3 but column (5) and (6) consider the loan origination time measured in months as the dependent variable, while column (5) uses a measure in days as a robustness check and column (6) the dummy variable above/below the median (similar to Table 2).

Column (1) includes the interaction terms between VIX and firm capital and bank competition. Column (2) adds more interaction effects, in particular the bank-level ones, both bank capital and applications per branch, each one interacted with VIX. In Column (3) and (4) we analyze the VIX interactions with firm- and bank-level variables but conditioning on low (high) versus high (low) concentration (competition).

While in Table 2 we obtain that a reduction of VIX shortens the loan origination time, column (1) of Table 3 shows that the shortening of loan origination time (when VIX is lower) is even stronger for ex-ante less capitalized firms. In particular, a reduction of an interquartile range of VIX with a reduction of one standard deviation of ex-ante borrower capital ratio shortens origination time by 3.8%. That is, it takes less time to grant a loan to a risky firm during good times (a period of low volatility and uncertainty). This key result is robust across all specifications (columns), with different controls or different ways to measure the outcome variable. See also Figure 3, where we show that this result is driven by the boom period preceding the Lehman crisis.

Exploiting further heterogeneity (column (2) of Table 3), the average shortening of loan origination time is stronger both in areas with more banking competition and for banks with less capital when the VIX is low. Moreover, column (3) and (4) show that the average loan origination time decreases in boom times (VIX low) for ex-ante less capitalized firms, especially in areas with high banking competition, with a decrease in average origination time by 4.2%, whereas results are completely different for low-competitive areas. Finally, the last two columns of Table 3 show that results are robust to the use of different measures of loan origination time, either in days or measured in binary form.

All in all, based on Tables 2 and 3, we find that when there is a low VIX (or in the boom), banks shorten the loan origination time, especially to ex-ante less capitalized firms. These effects are moreover stronger in areas with more bank competition, proxying for bank moral hazard incentives (Vives, 2016). However, as explained in e.g. Martinez-Miera and Repullo (2010), effects are not clear-cut in the sense that higher bank competition may increase or decrease bank risk-taking due to moral hazard problems. Therefore, we analyze other proxies for bank moral hazard as well as ex-post loan defaults associated to short loan origination times.

4.1.2. Moral hazard

In Table 4 we investigate the mechanism that drives the effect of VIX*firm capital on loan origination time by including triple interactions proxies for different bank moral hazard problems. Table 4 has 7 columns, with the triple interaction of VIX, firm capital and different variables depending on the specification (column) analyzed: in column (1) bank capital ratio is used; column (2) uses publicly-listed banks; column (3) considers the largest banks (which includes two commercial banks and two savings banks); column (4) considers the main industry specialization of the bank; and column (5) uses the main geographical specialization of the bank, depending on whether the geographical area is in the Mediterranean coast, which was subject to real estate price boom and bust, while columns (6) and (7) test if bank competition exacerbates the geographical (column (5)) effects.

We find that a shorter loan origination time to ex-ante riskier firms when VIX is low (following interquantile range reductions) is especially stronger for: (i) banks with less capital (a decrease in average origination time by 4.6% following an interquantile range reduction); (ii) non-listed banks (average loan origination time decreases by 5.5%); (iii) loans granted to firms operating in industries which the bank is not most specialized at (a decrease of 6.1% in origination time); (iv) loans to firms in geographical areas which do not form the bank's main market, especially if those areas are in the Mediterranean coast where there is a real estate price bubble (prices boomed and crashed), in which average loan origination time decreases by 6.3%. These latter effects are even stronger if bank competition is higher (a 7.2% decrease).[18]

These results therefore suggest that bank moral hazard incentives are an important mechanism for our main result of loan origination time over the cycle with respect to ex-ante riskier firms. Our evidence suggests moral hazard problems between: (i) banks (owners) and taxpayers/debtholders (proxied with banks with less capital); (ii) bank management and

[18] We find that the shorter loan origination time to ex-ante riskier firms when VIX is low is similar across the largest vs. other banks.

shareholders (proxied with non-listed banks); (iii) different parts within the bank (proxied with local loan officers and the bank headquarter, and also between loan officers providing loans to firms operating in industries in which the bank is most specialized at versus loans to firms operating in other industries).

4.2. Loan origination time and ex-post loan-level defaults

In Table 5 we present the effects of loan origination time on ex-post loan default probability. Throughout the 18 different specifications that we present in the table, we find that a shorter ex-ante loan origination time is associated with a higher borrower's future default rate.

From column (1) to (6), each column shows a more restrictive model than the predecessor one to saturate the initial specification with different controlling variables. Columns (7) and (8) use the other two measures of origination time that we used before in Table 2 and 3 (days and the dummy below/above the median). Column (9) shows the effects for each month testing for a potential non-linearity. In column (10) we analyze firm closure after a loan default, while in column (11) we introduce firm fixed effects. Finally, columns (12) to (18) show the results using an instrumental variable approach.

As safer firms have shorter origination times (see Table 2), in column (1) of Table 5 we control for firm's fundamentals by introducing time-varying firm observables. Additionally, in this specification we include time dummies and bank observable characteristics. The coefficient on loan origination time is statistically significant at a 1% level with a negative sign. Column (2) controls for loan characteristics such as loan volume maturity and collateral (in unreported regressions we also control for other variables as e.g. real estate exposures). Column (3) includes bank fixed effects. Column (4) controls for province and industry fixed effects. To account for any unobserved time-variant bank characteristics, column (5) and (6) further adds bank*year or bank*year:month fixed effects. The coefficient on loan origination time is always negative and statistically significant at a 1% level. Given that the average default probability is 0.20, an interquartile range reduction in loan origination time is associated with an increase of a borrower's average probability of default of around 6%. Moreover, if the loan origination time changes from three months to the same month where it was lodged, the future average probability of default increases by 8.9%.

Column (7) and (8) are two robustness checks of column (6). In column (7) we analyze loan origination time measured by the logarithm of days instead of months on borrowers' future default probability. Results are also significant. In column (8) we include a dummy whether loan origination time is higher than the median, as in previous tables. It is statistically significant at a 1% level, implying that if the loan origination is below the median time, then the probability of default increases by 6.5%.

Column (9) shows non-linearity effects. Results suggest that the longer a bank takes to grant the loan the higher its impact on reducing the borrower's future default probability. The highest economic effect is when the bank grants the loan three and four months after it was requested. Granting the loan three versus one month after it was requested reduces the future default probability by almost threefold. Moreover, the estimated coefficient for months 3 to 5 are not statistically or economically different (i.e., there are non-linear effects and, on the margin, larger origination time over four or five months is not associated to higher defaults). A borrower has on average around 11% lower probability of future default with the bank if the bank grants the loan three months after the borrower has requested it, compared to a loan granted within the month it was applied for (i.e., the omitted dummy).

In column (10) we consider a firm closure after its defaults on at least a loan as the dependent variable. Results are again statistically significant and in line with the one obtained before: less origination time is associated with future firm closure after a loan default. For instance, if loan origination time decreases by three months then the probability of firm closure increases by up to 8.4%. In column (11) we include firm fixed effects as a way to better control for unobservable firm fundamentals. The coefficient on loan origination time halves as most defaults are across firms, not within firms.

Finally, columns (12) to (18) show the results using an IV strategy. We show that results are robust to using an instrumental variable setting. We exploit the period of the year with the shortest loan origination time (see Figure 4) and find that a shorter ex-ante origination time is associated with a higher ex-post loan defaults. The period with the shortest loan origination time is the Christmas holidays period (21st of December to January 7th, after the Three Wise Men or Epiphany day). This is a period in which there are substantially more holidays and many more social events, and hence, consistent with the data, results suggest that banks take faster decisions in terms of loan granting. Results are shown in column (12). Also, in this period, there may be end of year effects in which banks may also take faster decisions to increase lending (see column (13)), which is also consistent with our mechanism.

We also analyze only the January period, and results are very similar (column (14)). Results are also very similar if we include the other period during the year in which loan origination is the second shortest, corresponding to August's last two weeks, which is also a period of holidays (column (15)). Note also that we find that during the shortest loan origination time period, the borrowers (firms) that obtain loans are not different in observable ways, either without firm fixed firms comparing the different firms in this period versus other periods, or within firm fixed effects comparing the same firm obtaining loans in this holidays period vs. other periods (see Table A3). Finally, as columns (16) to (18) show, results are robust across substantial different controls for unobservables and the estimated effect in the second stage is very similar to the OLS one.

Figure 5 plots the time-varying estimated coefficient on loan origination time of column (11). As it can be seen, there is a pro-cyclical pattern suggesting that the association between ex-ante loan origination time and ex-post loan defaults is highest in the most pronounced period of the boom. In Table 6, we also find other heterogeneous effects. In columns (1) to (3), we progressively interact loan origination time by firm/bank capital and VIX. We find a shorter origination time (when origination time decreases from three months to the same month it was lodged) on loans that eventually default for ex-ante less capitalized firms (by 7.0% when comparing a firm in the third versus first quartile of distribution of firm capital ratio) or when VIX is lower (by 6.5% for an interquartile range deviation reduction of VIX, corresponding to 1.3 percentage points). It is important to note that the effects on defaults stem from two related channels: (i) riskier firms during lower VIX periods benefit from lower origination time, which in turn implies more defaults; (ii) for a given origination time, during lower (versus higher) VIX periods increase the impact of lower origination time on higher defaults. For most variables under consideration, the first channel is the main one driving the results. Moreover, in columns (4) and (5) we split the sample depending on the bank concentration of the area where the firm obtains the loan. From these columns, results suggest that the effect of a shorter origination time on ex-post defaults for less capitalized borrowers is stronger in areas with higher bank competition (2.4 p.p. or 11.7% higher for an interquantile range change).

As credit booms associated with real estate are linked with worse financial crises (based on the Jordà-Schularick-Taylor papers) and the Spanish boom was also based on the housing bubble, in Table 7 we analyze the effect on real estate firms. As showed in column (1) of Table 7, loan origination is even a more important determinant for real estate firms' probability of default. We show that if loan origination time decreases by three months the probability of future default increases by 7.5%. Column (2) shows that the result that lower loan origination time on ex-post defaults is higher for less capitalized firms is even stronger for real estate firms (9.6%, for an interquartile shock). Finally, column (3) and (4) suggest that this latter effect takes place in areas with a high banking competition (11.6% increase for an interquartile shock).

4.3. Loan origination time and bank failures

Table 8 shows the results of loan origination time on strong bank distress after the start of the Global Financial Crisis in September 2008. The main dependent variable in all models (extended bank distress definition) but the one in column (10) is a binary variable that takes value one if the bank experienced some of the following distress events after December 2007: public (state) intervention, a public bailout with state funding, a merging process or an acquisition, or a recapitalization after a stress test exercise carried out by the bank supervisor; and zero otherwise. Instead, the dependent variable in column (10) only takes value one for public (state) interventions or bailouts with state funding; and zero otherwise (standing for a narrower definition of bank distress).

As safer firms have mechanically lower loan origination times (Table 2) and we want to analyze loan origination time proxying for bank-level screening time (risk-taking), in columns (1) to (8) and (10) we include the average loan origination time cleaned from borrower fundamentals as a regressor (computed before the crisis, during the year 2006). Model (9) includes the average loan origination time in months for 2006 (without cleaning it from borrower fundamentals) as robustness. To construct our main variable cleaned from borrower fundamentals we measure the bank fixed effects from a linear estimation where the dependent variable is loan origination time and firm fixed effects are included to control for borrower fundamentals; we have also used industry*location fixed effects instead and results are similar (unreported). Model (8) computes the average loan origination time for the period 2004-2006, as a robustness check, as those three years were the most intense during the Spanish credit boom. To facilitate the comparison (through a horserace) of the estimated coefficients across all variables and models, we standardize all variables.

Column (1) only includes a CAMEL rating of the bank using a set of bank characteristics, where higher values imply higher risk. The rest of the models horserace the loan origination time variable at the bank level with other bank level factors that have been widely used in the literature of bank lending standards, such as the credit volume growth, the weight of the construction and real estate sector in the bank portfolio, new loans' average interest rate, loans' average maturity or the average collateralized loans.

We find that a lower pre-crisis loan origination time at the bank level is associated with a higher likelihood of bank failure or a similar related bank distress. A reduction of one standard deviation of pre-crisis loan origination time is associated with a 12.4% increase in bank overall distress after the start of the global financial crisis, and 13.5% for (the strongest) bank failure events. Results are robust to different definitions, in particular to the strongest case of bank distress (failure), which we define as the direct public (state) intervention in the bank or public bailout with state funding.

Interestingly, loan origination time has similar—or even stronger—economic and statistical effects than other key lending standards analyzed in the literature —credit (volume) growth, even in real estate, spreads, collateral and maturity. In particular, loan origination time is robust across all specifications, different from other loan conditions: e.g. maturity is not statistically significant; loan spread is weaker statistically and economically; collateral is not robust (though when it is statistically significant its coefficient is larger than the one on the origination time, but not statistically different from it). Last, we show that the effect of credit volume growth is very similar to the effect of the loan origination time.

5. Conclusions

In this paper we study the time to originate a loan over a full credit cycle. For identification, we exploit the credit register from Spain over the 2002-2015 period (a full credit cycle), which has the time of a loan application and its granting for business loans.

We find that when VIX is low (proxying for good times) banks shorten the time to originate a loan, especially to less-capitalized (riskier) firms. Our results suggest that bank moral hazard incentives are an important mechanism. A shorter loan origination time to ex-ante riskier firms in good times is especially stronger for: (i) banks with less capital (proxying for moral hazard problems between bank owners and taxpayers/debtholders); (ii) non-listed banks (proxying for moral hazard problems between bank management and shareholders); (iii) loans to firms in geographical areas which do not form the bank's main market and experience a real estate bubble (proxying for moral hazard problems between local loan officers and the bank headquarter), especially if those areas have more bank competition; or, relatedly, stronger effects on loans granted to firms operating in industries which the bank is not most specialized at (proxying for moral hazard problems between different parts with the bank). Moreover, we find that a shorter *loan-level* origination time is associated with a higher ex-post defaults, and a shorter pre-crisis origination time aggregated at the *bank-level* implies more bank failures (even more than other lending conditions), overall consistent with lower screening (time).

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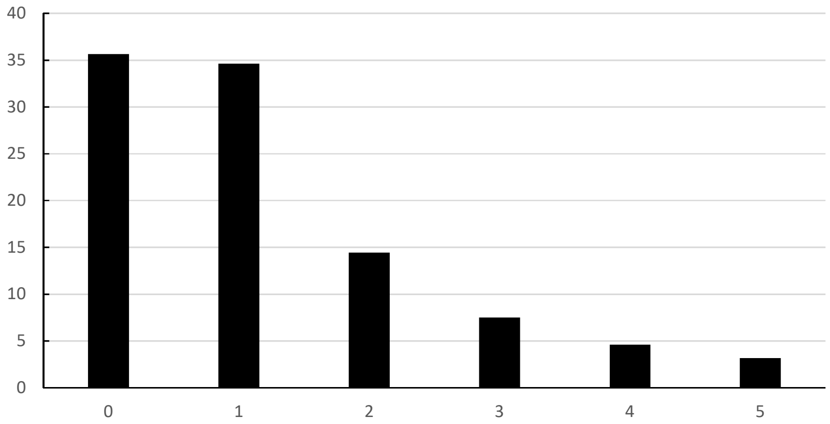
FIGURE 1

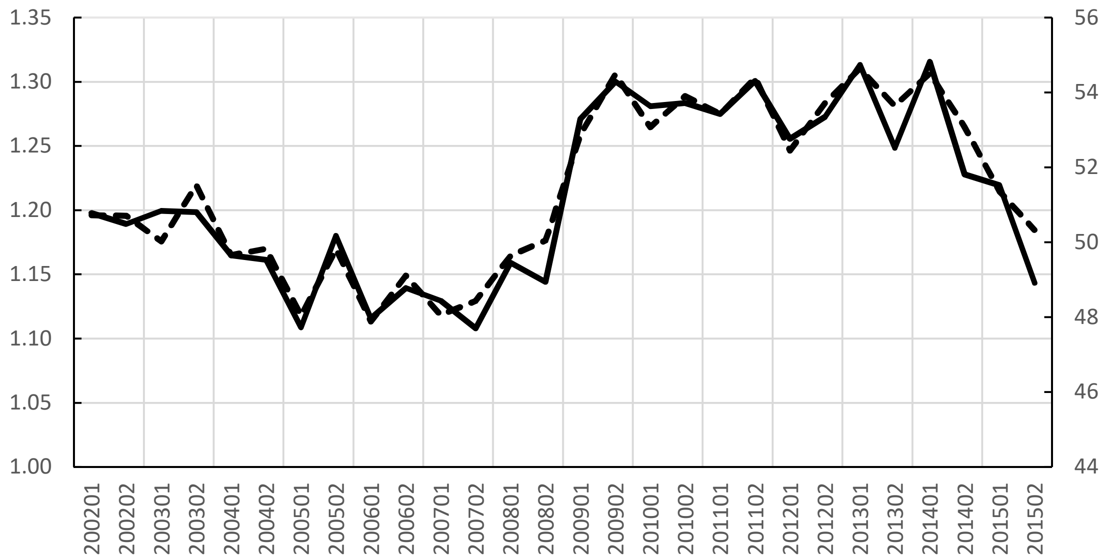
Distribution of loan origination time



Note. This figure shows the distribution of the loan origination time, which measures the number of months a bank takes to grant a loan after an application.

FIGURE 2

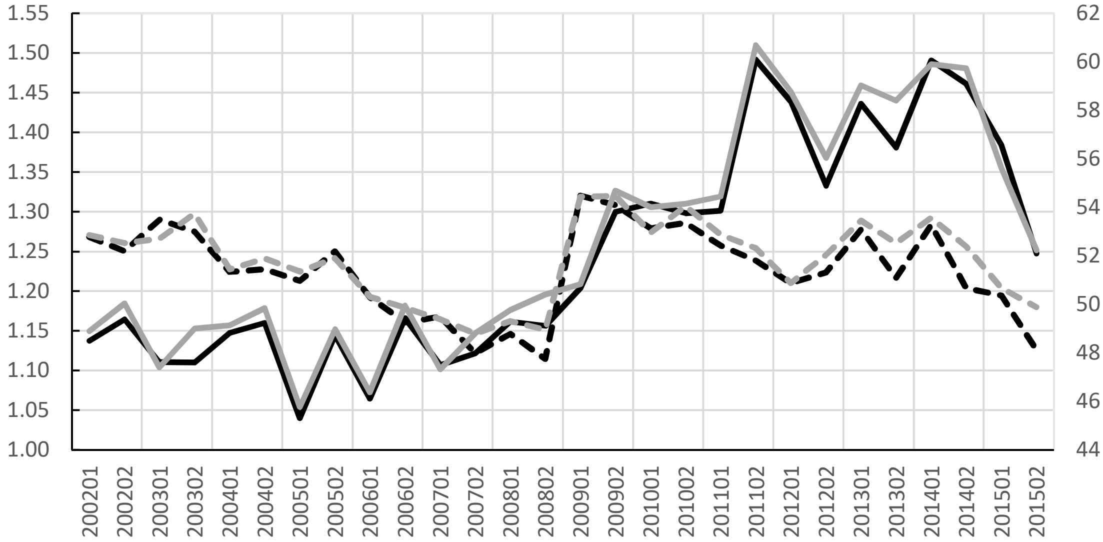
Evolution of the average loan origination time



Note. This figure shows the average loan origination time by semester. In particular, it measures the number of months (solid line, left-hand scale) or days (dashed line, right-hand scale) a bank takes to grant a loan after an application.

FIGURE 3

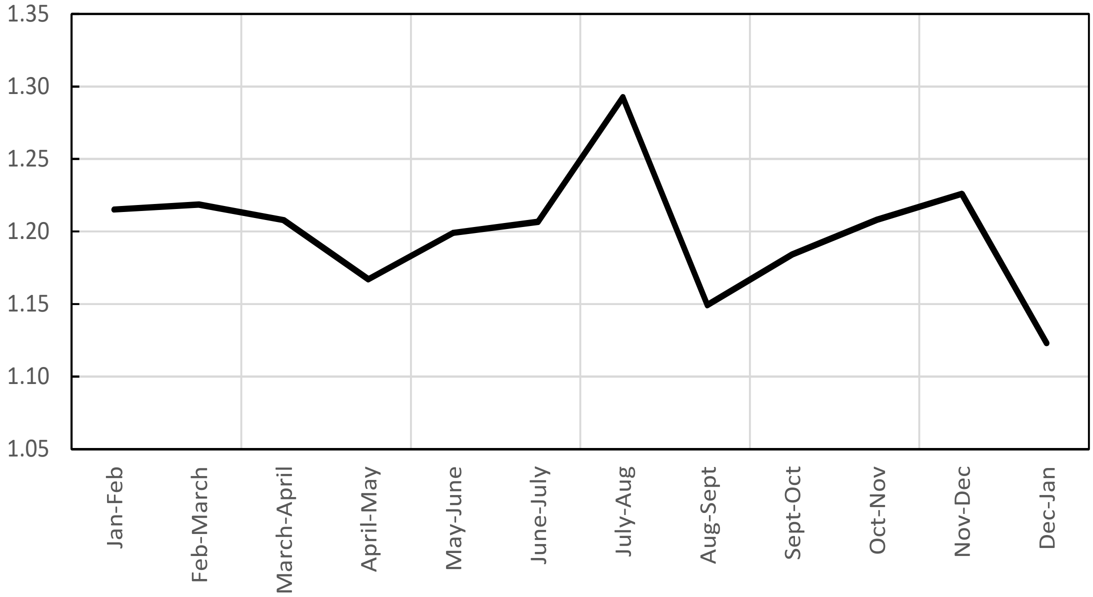
Evolution of the average loan origination time, by firms' and banks' capital ratio



Note. This figure shows the average loan origination time by semester. In particular, it measures the number of months (dark line, left-hand scale) or days (light line, right-hand scale) a bank takes to grant a loan after an application, for banks and firms below the median of their capital ratio (solid line) and above (dashed line).

FIGURE 4

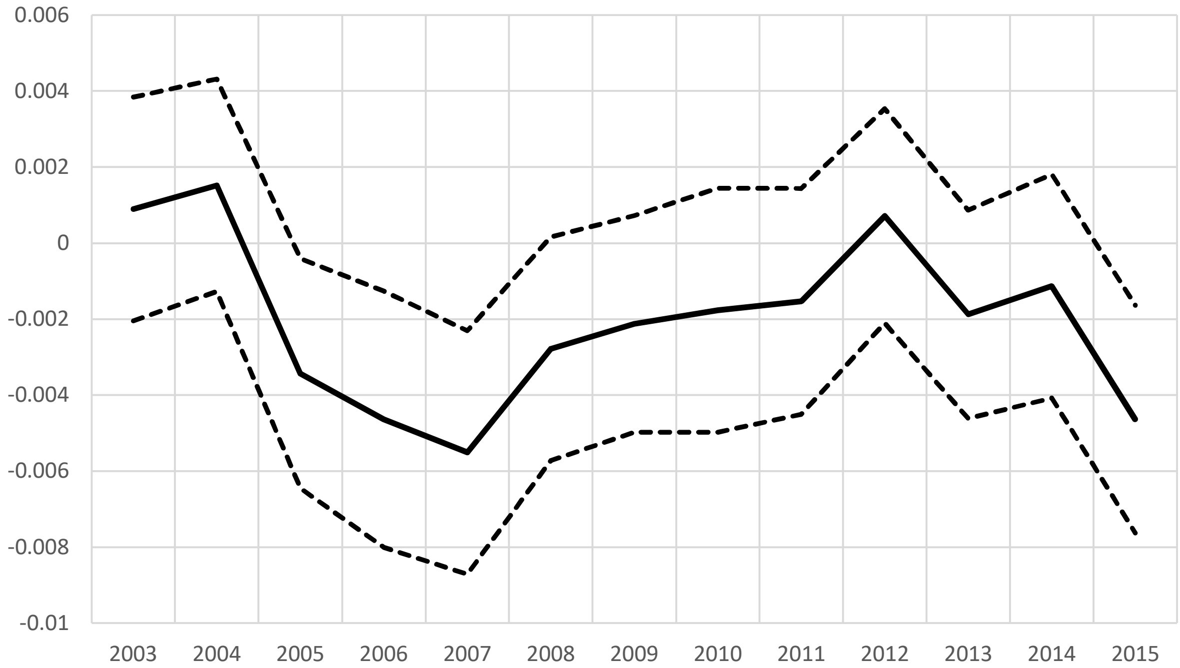
Average loan origination time by date of application



Note. This figure shows the average loan origination time in months by date of application. Each date collects all applications made from the 15th of each month to just before the 15th of the following month.

FIGURE 5

Time-varying coefficient on loan origination time on defaults



Note. This figure shows the estimated time-varying coefficients on loan origination time of column (11) from Table 5 allowing it to vary over time in a non-parametric way and referred to year 2002. Confidence bands at 90%.

TABLE 1
Descriptive statistics

TABLE 1. SUMMARY STATISTICS

	Mean	Median	SD	P25	P75
Main variables					
Loan origination time$_{ijt}$ (months)	1.224	1.000	1.301	0.000	2.000
Loan origination time$_{ijt}$ (days)	51.824	40.000	39.086	24.000	69.000
Loan origination time$_{ijt}$>median	0.510	1.000	0.500	0.000	1.000
Future default$_{ijt}$	0.201	0.000	0.401	0.000	0.000
Closure after future default$_{ijt}$	0.108	0.000	0.310	0.000	0.000
Bank large distress event$_{j}$					
Extended definition	0.754	1.000	0.434	1.000	1.000
Narrow definition	0.649	1.000	0.481	0.000	1.000
Macro variables (t)					
VIX$_{t-1}$	0.000	-0.229	1.000	-0.761	0.602
MP rates$_{t-1}$	0.000	0.050	1.000	-0.199	0.248
Firm variables (i)					
Capital ratio$_{it-1}$	0.294	0.252	0.307	0.111	0.452
Construction&Real Estate$_{it-1}$	0.199	0.000	0.400	0.000	0.000
Local competition variables					
HHI loans$_{t-1}$	0.067	0.063	0.024	0.047	0.079
Bank variables (j)					
Capital ratio$_{jt-1}$	0.059	0.056	0.018	0.045	0.072
No. of loan applications per branch$_{jt-1}$	10.931	0.733	8.224	3.892	16.647
Firm-Bank variables (ij)					
Industry specialization$_{ijt-1}$	0.125	0.000	0.331	0.000	0.000
Geographical specialization$_{ijt-1}$	0.225	0.000	0.418	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 definitions of the variables are in the Appendix.

TABLE 2
Determinants of loan origination time: overall effects

Dependent variable:	Loan origination time (LOT)$_{ijt}$					LOT (days)$_{ijt}$	LOT$_{ijt}$>median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Macro variables (t)							
VIX$_{t-1}$	0.031***	0.017***	0.022***			0.017***	0.011***
	(0.008)	(0.006)	(0.006)			(0.004)	(0.003)
MP rates$_{t-1}$	0.006	0.004	0.004*			0.005**	0.004**
	(0.004)	(0.003)	(0.003)			(0.002)	(0.002)
Firm variables (i)							
Capital ratio$_{it-1}$		-0.047***	-0.041***	-0.041***	-0.042***	-0.030***	-0.023***
		(0.009)	(0.008)	(0.008)	(0.008)	(0.006)	(0.004)
Local competition variables							
HHI loans$_{it-1}$		1.075***	0.453***	0.062	0.039	0.335***	0.194***
		(0.199)	(0.131)	(0.081)	(0.080)	(0.089)	(0.070)
Bank variables (j)							
Capital ratio$_{jt-1}$		1.030	3.040***	2.468***		2.039***	1.283***
		(0.776)	(0.595)	(0.692)		(0.337)	(0.235)
No. of loan applications per branch$_{jt-1}$		-0.064**	-0.064***	-0.086***		-0.036***	-0.030***
		(0.032)	(0.016)	(0.018)		(0.010)	(0.008)
Other firm and bank controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Seasonal (Month) Fixed Effects	Yes	Yes	Yes	-	-	Yes	Yes
Year:Month Fixed Effects	No	No	No	Yes	-	No	No
Bank Fixed Effects	No	No	Yes	Yes	-	Yes	Yes
Bank*Year:Month Fixed Effects	No	No	No	No	Yes	No	No
No. of Observations	604,099	604,099	604,099	604,099	604,099	604,099	604,099

Note. This table reports estimates from a PPML model for the period 2002:02 to 2015:12 for columns (1) to (6), and for column (7) the estimates of a linear probability model are showed. The dependent variable is the loan origination time, which measures the number of months (for columns (1) to (5)) or days (column (6)), a bank takes to grant a loan after an application is lodged. Column (7) uses as dependent variable a discrete version of the loan origination time which takes value one when the loan origination time is above its median value, and zero otherwise. Coefficients are listed in the first row, robust standard errors that are corrected for (multi-) clustering at the bank, year: month, and firm level are reported in the row below. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that they are not included and "-" that they are spanned by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 3
Determinants of loan origination time: heterogeneous effects

Dependent variable:	Loan origination time $(LOT)_{ijt}$				LOT $(days)_{ijt}$	LOT_{ijt}>median
			Low Concentration	High Concentration		
	(1)	(2)	(3)	(4)	(5)	(6)
VIX_{t-1}	0.018***	0.018***	0.023***	-0.013	0.011*	0.007***
	(0.006)	(0.006)	(0.006)	(0.021)	(0.006)	(0.004)
VIX_{t-1}*Firm capital $ratio_{it-1}$	-0.018**	-0.018**	-0.024***	0.029*	-0.014**	-0.010**
	(0.008)	(0.008)	(0.009)	(0.016)	(0.007)	(0.005)
VIX_{t-1}*HHI $loans_{it-1}$	-0.399***	-0.336***			-0.230***	-0.067
	(0.120)	(0.110)			(0.081)	(0.061)
VIX_{t-1}*Bank capital $ratio_{jt-1}$		-0.416*	-0.312	-0.607	-0.352*	-0.266**
		(0.245)	(0.231)	(0.444)	(0.193)	(0.115)
VIX_{t-1}*No. of loan applications per $branch_{jt-1}$		0.008	0.012	-0.007	0.007	0.003
		(0.017)	(0.016)	(0.026)	(0.011)	(0.006)
Other firm and bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal (Month) Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	604,099	604,099	453,058	151,016	604,099	604,099

Note. This table reports estimates from a PPML model for the period 2002:02 to 2015:12 for columns (1) to (5), and for column (6) the estimates of a linear probability model are showed. The dependent variable is the loan origination time, which measures the number of months (for columns (1) to (4)) or days (column (5)), a bank takes to grant a loan after an application is lodged. Column (6) uses as dependent variable a discrete version of the loan origination time which takes value one when the loan origination time is above its median value, and zero otherwise. In columns (3) and (4) low or high concentration are defined according to its third quartile value (below or above). Coefficients are listed in the first row, robust standard errors that are corrected for (multi-)clustering at the bank, year: month, and firm level are reported in the row below. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that they are not included and "-" that they are spanned by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 4

Determinants of loan origination time: Moral hazard problems

Dependent variable: Loan origination time $(LOT)_{ijt}$						Low Concentration	High Concentration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VIX_{t-1}	0.014*	0.015**	0.014**	0.023***	0.017***	0.022***	0.008
	(0.009)	-0.006	(0.006)	(0.006)	(0.006)	(0.005)	(0.013)
VIX_{t-1}*Firm capital $ratio_{it-1}$	-0.021**	-0.014*	-0.014*	-0.030**	-0.019**	-0.027***	0.021
	(0.009)	(0.008)	(0.008)	(0.014)	-0.008	(0.009)	(0.018)
VIX_{t-1}*Firm capital $ratio_{it-1}$*Bank capital $ratio_{jt-1}$	-0.636*			-0.049*			
	(0.377)			(0.027)			
VIX_{t-1}*Firm capital $ratio_{it-1}$*Listed $banks_j$		-0.035***					
		(0.014)					
VIX_{t-1}*Firm capital $ratio_{it-1}$*Largest $banks_j$			0.002				
			(0.016)				
VIX_{t-1}*Firm capital $ratio_{it-1}$*Industry $specialization_{ij}$				-0.049*			
				(0.027)			
VIX_{t-1}*Firm capital $ratio_{it-1}$*$Coastal_i$*Geographical $specialization_{ij}$					-0.054*	-0.073*	0.008
					(0.032)	(0.038)	(0.079)
Other firm and bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal (Month) Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	604,099	604,099	604,099	604,099	604,099	604,099	604,099

Note. This table reports estimates from a PPML model for the period 2002:02 to 2015:12. The dependent variable is the loan origination time, which measures the number of months a bank takes to grant a loan after an application is lodged. In columns where low or high concentration is used, they are defined according to their third quartile value (below or above). Largest banks is a dummy that equals one for the four largest banks, two commercial banks and two savings banks. Listed banks is a dummy that equals one for the listed banks. Coastal is a dummy that equals one if the firm is located in the Mediterranean coast and zero otherwise. Geographical specialization is a dummy that equals one if the province where the bank is most specialized (in terms of loans to firms, i.e., the main province for the bank) matches with the province where the firm is located, and zero otherwise. Industry specialization is a dummy that equals one if the industry where the bank is most specialized (in terms of loans to firms, i.e., the main industry of the bank) matches with the industry the firm operates in, and zero otherwise. Coefficients are listed in the first row, robust standard errors that are corrected for (multi-)clustering at the bank, year: month, and firm level are reported in the row below. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that they are not included and "-" that they are spanned by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 5

Loan origination time and borrower's future loan-level default probability: overall effects

Dependent variable: Future Default$_{ijt}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
												Instrumental Variable						
										Firm Closure		December & January	December	January	Plus August			
Loan origination time$_{ijt}$	-0.005***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***				-0.003***	-0.003***	-0.004**	-0.003*	-0.005*	-0.004**	-0.005**	-0.006**	-0.006**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)				(0.001)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Log(Loan origination time in days$_{ijt}$)							-0.008***											
							(0.002)											
Loan origination time$_{ijt}$>median								-0.013***										
								(0.003)										
Loan origination time=1									-0.006***									
									(0.001)									
Loan origination time=2									-0.014***									
									(0.003)									
Loan origination time=3									-0.022***									
									(0.004)									
Loan origination time=4									-0.024***									
									(0.005)									
Loan origination time=5									-0.023***									
									(0.004)									
First Stage. Dependent variable: Loan origination time																		
Loan application made between December 21 to January 7												-0.094***	-0.104***	-0.086***	-0.137***	-0.084***	-0.087***	-0.087***
												(0.025)	(0.031)	(0.032)	(0.027)	(0.027)	(0.027)	(0.023)
Year:month Fixed Effects	Yes	Yes	Yes	Yes	Yes	-	-	-	-	-	-	-	-	-	-	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	Yes	-	-	-	-	-	-	-	-	-	-	-	Yes	No	No
Province & Industry Fixed Effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-	-	-	-	-	-	-	Yes
Firm Fixed Effects	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics	Yes	Yes	Yes	Yes	Yes	-	-	-	-	-	-	-	-	-	-	Yes	Yes	Yes
Loan characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*year Fixed Effects	No	No	No	No	Yes	-	-	-	-	-	-	-	-	-	-	No	No	No
Bank*year:month Fixed Effects	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
R^2	0.125	0.127	0.145	0.161	0.169	0.189	0.189	0.189	0.189	0.255	0.725							
F test												13.7	10.9	7.1	43.6	9.9	10.6	14.9
No of Observations	502,994	502,994	502,994	502,994	502,994	502,994	502,994	502,994	502,994	502,994	502,994	502,994	502,994	502,994	502,994	502,994	502,994	502,994

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 on the loan for which the loan origination time is measured, for all columns but (10), where the dependent variable in that case is firm closure after loan default. Columns (12) and (16) to (18) estimate an IV model where the origination time is instrumented using the Christmas holidays, from December 21st to January 7th, for different set of controls, taking into account the lower time to originate a loan for this period from Figure 4. In column (13) only December holidays are used as instrument and in column (14) only January is used. Column (15) estimates an IV but including also the second half of August, again based on the observed evidence from Figure 4. Coefficients are listed in the first row, robust standard errors that are corrected for multi-clustering at the bank, firm and time (year:month) are reported in the row below. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that they are not included and "-" that they are spanned by the included set of fixed effects. Significance level: *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 6

Loan origination time and future loan-level defaults: heterogeneous effects

Dependent variable: Future Default$_{ijt}$				Low Concentration	High Concentration
	(1)	(2)	(3)	(4)	(5)
Loan origination time$_{ijt}$ (LOT$_{ijt}$)	-0.003***	-0.003***	-0.003***	-0.004***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
LOT$_{ijt}$*Firm capital ratio$_{it-1}$	0.005***	0.005***	0.005***	0.007***	0.003*
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
LOT$_{ijt}$*Bank capital ratio$_{jt-1}$		0.002	0.005	-0.013	0.015
		(0.022)	(0.023)	(0.033)	(0.030)
LOT$_{ijt}$*HHI loans$_{it-1}$			-0.009		
			(0.008)		
LOT$_{ijt}$*VIX$_{t-1}$			0.001***	0.001*	0.001*
			(0.000)	(0.000)	(0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes
Bank*year:month FE	Yes	Yes	Yes	Yes	Yes
Firm and bank characteristics	Yes	Yes	Yes	Yes	Yes
Loan characteristics	Yes	Yes	Yes	Yes	Yes
R^2	0.724	0.725	0.725	0.729	0.758
No. of Observations	502,994	502,994	502,994	232,556	230,124

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 on the loan for which the loan origination time is measured. In columns (4) and (5) low or high concentration are defined according to its median value (below or above). Coefficients are listed in the first row, robust standard errors that are corrected for multi-clustering at the bank, firm and time (year:month) are reported in the row below. When double or triple interactions are included, the estimation also controls for all terms of lower order. "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

Loan origination time and future loan-level defaults: construction and real estate firms

Dependent variable: Future Default$_{ijt}$			Low Concentration	High Concentration
	(1)	(2)	(3)	(4)
Loan origination time$_{ijt}$ (LOT$_{ijt}$)	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.001)	(0.000)
LOT$_{ijt}$*Construction&Real Estate$_{it}$	-0.002**	-0.002**	-0.003*	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)
LOT$_{ijt}$*Firm capital ratio$_{it-1}$		0.005***	0.007***	0.003*
		(0.002)	(0.003)	(0.002)
LOT$_{ijt}$*Construction&Real Estate$_{it}$*Firm capital ratio$_{it-1}$		0.005*	0.007*	0.001
		(0.003)	(0.004)	(0.005)
Firm FE	Yes	Yes	Yes	Yes
Bank*year:month FE	Yes	Yes	Yes	Yes
Firm and bank characteristics	Yes	Yes	Yes	Yes
Loan characteristics	Yes	Yes	Yes	Yes
R^2	0.725	0.725	0.731	0.758
No. of Observations	502,994	502,994	502,994	232,556

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 on the loan for which the loan origination time is measured. In columns (3) and (4) low or high concentration are defined according to its median value (below or above). Coefficients are listed in the first row, robust standard errors that are corrected for multi-clustering at the bank, firm and time (year:month) are reported in the row below. When double or triple interactions are included, the estimation also controls for all terms of lower order. "Yes" ("No") indicates that the set of characteristics or fixed effects is (not) included. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 8

Pre-crisis average loan origination time and post-Lehman bank-level distress probability

Bank event risk:	*Extended definition*									*Narrow definition*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Bank CAMEL	0.989***	1.399***	1.512***	1.690***	1.959***	2.035**	2.137**	2.310**	1.244***	1.388***
	(0.211)	(0.315)	(0.321)	(0.528)	(0.715)	(0.836)	(0.832)	(0.939)	(0.306)	(0.336)
Average loan origination time$_{it-1}$		-0.700***	-0.732**	-0.670*	-0.638**	-0.705**	-0.746**		-0.395*	-0.481**
		(0.267)	(0.310)	(0.342)	(0.294)	(0.330)	(0.316)		(0.239)	(0.241)
Average loan origination time$_{i,2004\text{-}2006}$								-0.845***		
								(0.324)		
Rate of change of total loans$_{it-1}$			0.365**	0.624***	0.758***	0.780***	0.847***	0.889***	0.666***	0.305
			(0.180)	(0.198)	(0.226)	(0.255)	(0.273)	(0.290)	(0.250)	(0.209)
% Loans to construction and real estate firms/Total loans$_{it-1}$				0.708***	0.700**	0.751**	0.807**	0.847**	0.887***	0.344
				(0.251)	(0.272)	(0.329)	(0.333)	(0.367)	(0.274)	(0.217)
Average interest rate of loans$_{it-1}$					-0.358	-0.055	-0.428	-0.374	-0.464	-0.594*
					(0.318)	(0.452)	(0.520)	(0.546)	(0.350)	(0.340)
% Real collateralized loans$_{it-1}$						-0.344	-0.961	-1.089*	-0.696	-1.071*
						(0.444)	(0.619)	(0.649)	(0.617)	(0.551)
% Long term loans (More than 5 years)$_{it-1}$							-0.949	-1.013	-0.694	-0.569
							(0.709)	(0.699)	(0.782)	(0.655)
Observations	57	57	57	57	57	57	57	57	57	57
Pseudo R-squared	0.303	0.433	0.468	0.556	0.569	0.578	0.599	0.617	0.534	0.491

Note. This table reports the estimates from a cross-section model where banks' default probability is estimated through a Probit model (as there are no fixed effects and interactions). The dependent variable in columns (1) to (9) is an indicator variable that takes value one when banks' financial distress results in the public (state) intervention of the bank, a public bailout with state funding, a merging process or an acquisition (with another banking group or within its banking group), or a recapitalization after a stress test exercise carried out by the bank supervisor (and zero otherwise). The dependent variable in column (10) is an indicator that takes value one when banks' financial distress results in the state intervention of the bank or a public bailout with state funding (and zero otherwise). Average loan origination time cleaned from firm fundamentals (used in all columns but in Column (9)) comes from a bank*year fixed effect derived from a regression where the dependent variable is the loan origination time and firm*year fixed effects are included as additional controls. All variables are standardized to facilitate the comparison of the estimated coefficients; t-1 refers to end of 2006, and bank CAMEL ratings are from 2007. 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. *** Significant at 1%, ** significant at 5%, * significant at 10%.

APPENDIX

TABLE A1
Definition of the variables

	Unit	Definition
Main variables		
Loan origination time$_{ijt}$	months	The number of months a bank *j* takes to originate a loan from firm *i* after an application made at *t*
Loan origination time in days$_{ijt}$	days	The number of days a bank *j* takes to originate a loan from firm *i* after an application made at *t*
Loan origination time$_{ijt}$>median	0/1	A dummy variable which equals one when the loan origintaion days is longer than 40 days
Future default$_{ijt}$	0/1	A dummy variable which equals one when the loan is doubtful or more than ninety days overdue, and zero otherwise
Closure after future default$_{it}$	0/1	A dummy variable which equals one when the firm closes after a loan default, and zero otherwise
Bank large distress event$_{j}$	0/1	A dummy variable which equals one after December 2007 when banks' financial distress results in the intervention of the bank, a bailout, a merging process or a recapitalization (extended definition) or just when banks' financial distress results in the intervention of the bank or a bailout (narrow definition), and zero otherwise
Macro variables (t)		
VIX$_{t-1}$	standardized	European volatility index that is designed to measure the market's expectation of future volatility implied by options prices at *t-1*
MP rates$_{t-1}$	standardized	European (3-month interest rate) surprises following Jarociński and Paradi (2018) at *t-1*
Firm variables (i)		
Capital ratio$_{it-1}$	0.0x%	Own funds over total assets of firm *i* at *t-1*
Construction&Real Estate$_{it-1}$	0/1	A dummy variable which equals one for construction and real estate firms, and zero otherwise
Coastal$_{it-1}$	0/1	A dummy variable which equals one if the firm is located in the Mediterranean coast, and 0 otherwise
Local competition variables		
HHI loans$_{it-1}$		The Herfindahl Index in terms of the volume of loans
Bank variables (j)		
Capital ratio$_{jt-1}$	0.0x%	The ratio of bank equity over total assets of bank *j* at *t-1*
No. of loan applications per branch$_{jt-1}$	0.0x	The number of loan applications a bank *j* receives divided by its number of branches at *t-1*
Listed banks$_{jt-1}$	0/1	A dummy variable which equals one if the bank is publicly listed, and zero otherwise
Largest banks$_{jt-1}$	0/1	A dummy variable which equals one if the bank belongs to the four largest banks, and zero otherwise
Firm-Bank variables (ij)		
Industry specialization$_{ijt-1}$	0/1	A dummy variable which equals one if the industry of the firm and the main industry of the bank (in terms of loans) matches, and zero otherwise
Geographical specialization$_{ijt-1}$	0/1	A dummy variable which equals one if the province of the firm and the main province of the bank (in terms of loans) matches, and zero otherwise

TABLE A2
Determinants of loan origination time: robustness results

Dependent variable	$Log(1+LOT_{ijt})$	LOT_{ijt}	LOT_{ijt}	LOT_{ijt}	LOT_{ijt}
	(1)	(2)	(3)	(4)	(5)
		$LOT_{ijt} \leq 3$	$LOT_{ijt} \leq 4$	Bank*Indus Bank*Prov	Selection
Macro variables (t)					
VIX_{t-1}	0.012***	0.022***	0.018***	0.022***	0.037***
	(0.003)	(0.005)	(0.001)	(0.006)	(0.005)
Interest rate $surprise_{t-1}$	0.003*	0.004**	-0.000	0.004	0.002
	(0.001)	(0.002)	(0.001)	(0.003)	(0.004)
Firm variables (i)					
Firm capital $ratio_{it-1}$	-0.026***	-0.037***	-0.046***	-0.041***	-0.025***
	(0.004)	(0.007)	(0.006)	(0.008)	(0.005)
Local competition variables					
HHI $loans_{it-1}$	0.234***	0.392***	1.060***	0.411***	0.058
	(0.078)	(0.134)	(0.057)	(0.132)	(0.082)
Bank variables (j)					
Capital $ratio_{jt-1}$	1.533***	2.800***	0.935***	3.151***	1.217**
	(0.282)	(0.624)	(0.077)	(0.607)	(0.601)
No. of loan applications per $branch_{jt-1}$	-0.037***	-0.073***	-0.065***	-0.065***	-0.078***
	(0.009)	(0.017)	(0.003)	(0.016)	(0.013)
Other firm and bank controls	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Seasonal (Month) Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bank*Province & Bank*Industry Fixed Effects	No	No	No	Yes	No
No. of Observations	604,099	555,970	584,533	604,099	1,419,053

Note. This table reports estimates from a PPML model for the period 2002:02 to 2015:12 for columns (2) to (5) and for column (1) the estimates of a linear probability model are showed. The dependent variable is the loan origination time, which measures the number of months a bank takes to grant a loan after an application is lodged. Column (1) uses as dependent variable the log of the loan origination time plus one and column (5) includes also non-granted applications with a censored Poisson model. Coefficients are listed in the first row, robust standard errors that are corrected for (multi-)clustering at the bank, year:month, and firm level are reported in the row below. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that they are not included and "-" that they are spanned by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE A3
Firm observable differences for the IV strategy

	(1)	(2)
Capital ratio	0.000	0.001
	(0.004)	(0.002)
Ln(Total assets)	-0.000	0.000
	(0.001)	(0.001)
Ln(Age+1)	-0.002	-0.003***
	(0.002)	(0.001)
Liquidity ratio	-0.000	-0.000
	(0.000)	(0.000)
ROA	-0.000	-0.000
	(0.000)	(0.000)
Productivity	0.006	0.006
	(0.008)	(0.006)
Bank debt/Total assets	-0.001	-0.002
	(0.004)	(0.002)
Cost of debt	-0.012	0.011
	(0.031)	(0.016)
Fixed employees ratio	0.001	-0.001
	(0.003)	(0.002)
Bad credit history	-0.003	0.001
	(0.002)	(0.001)
Firm Fixed Effects	Yes	No
Zip code*Industry Fixed Effects	-	Yes
Bank*Time Fixed Effects	Yes	Yes
R-squared	0.598	0.374
Observations	269.502	298.808

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 a dummy variable that takes value one if the firm has a granted a loan during the Christmas holidays, namely from December 21st to January 7th, and zero otherwise. Productivity is defined as the ratio of sales over the number of employees. Bad credit history is a dummy that takes value one if the firm had non-performing outstanding loans, and equals zero otherwise. Coefficients are listed in the first row, robust standard errors that are corrected for multi-clustering at the bank, firm and year are reported in the row below. All estimates include bank*zip code and bank*industry fixed effects to control for possible selection issues. "Yes" ("No") indicates that the set of characteristics or fixed effects is (not) included. *** Significant at 1%, ** significant at 5%, * significant at 10%.