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

Mikel Bedayo Gabriel Jiménez José-Luis Peydró Raquel Vegas*

Abstract

We show that *loan origination time* is key for bank credit standards, defaults and failures over the cycle. We use the credit register from Spain, with the time of a loan application and its granting. When VIX is lower, banks shorten loan origination time, especially to less-capitalized firms. Bank moral hazard incentives (competition and capital) are crucial drivers. Moreover, shorter (*loan-level*) origination time implies higher ex-post defaults, especially for less-capitalized firms in areas with higher bank competition or when VIX is lower. Finally, shorter pre-crisis origination time involves more *bank-level* failures, even more than other lending conditions, consistent with lower screening.

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

Keywords: loan origination time; lending standards over the cycle; defaults; bank failures; screening.

[*] This draft is from March 2021. Mikel Bedayo is from Banco de España, e-mail: mikel.bedayo@bde.es. Gabriel Jiménez is from Banco de España, e-mail: gabriel.jimenez@bde.es. José-Luis Peydró is from Imperial College London, ICREA-Universitat Pompeu Fabra-CREI-Barcelona GSE, and CEPR, e-mail: jose.peydro@gmail.com. Raquel Vegas is from Banco de España, e-mail: raquel.vegas@bde.es. Corresponding author: José-Luis Peydró. We thank Franklin Allen, Vladimir Asriyan, Martin Brown, Xavier Freixas, Andreas Fuster, Javier Gil Bazo, Christian Julliard, Dmitry Kuvshinov, Mike Mariathasan, Alberto Martín, David Martinez-Miera, Vincenzo Pezone, Philipp Schnabl, Anatoli Segura and Victoria Vanasco, for valuable suggestions and comments. We also thank other insightful comments and suggestions from seminar (Imperial College, UPF, Banco de España) and conference participants (17th International Conference on CREDIT in Venice, the central banking conference CEBRA Annual Meeting, the conference on "The use of credit register data for financial stability purposes and credit risk analysis" at the Danmarks NationalBank, the Ninth International Moscow Finance Conference and the Central Bank of Ireland's "Workshop: Borrower finances, financial stability assessment and macroprudential policies". This paper reflects our views and not necessarily the views of Banco de España or the Eurosystem.

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 observe and measure. Using large historical data, across many countries, the best predictor for a financial crisis is a strong credit (volume) growth (Schularick and Taylor, 2012; Gourinchas and Obstfeld, 2012). Relatedly, using bank-level data, high credit (volume) growth implies subsequent underperformance in (bank) stock returns, profits and defaults (Fahlenbrach, Prilmeier and Stulz, 2018). Not only is credit 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 time to originate a loan over the cycle. For identification, we exploit the credit register from Spain over the 2002-2016 period, which has the time of a loan application and its granting. In brief, we find:

(1) When VIX is lower (or in a boom), banks shorten loan origination time, especially to ex-ante less capitalized firms. Moreover, these effects are stronger in areas with more bank competition (proxied by less bank concentration) and for less-capitalized banks, proxying both for bank moral hazard incentives.

(2) Shorter (*loan-level*) origination time is associated with higher ex-post defaults. Unobservables (or observables) are not driving this result. Moreover, default effects stemming from lower origination time are stronger if the loan is granted when VIX is lower, or for ex-ante less capitalized firms, even more in areas with more bank competition.

(3) Exploiting the global financial crisis that started in 2008, less pre-crisis origination time (*aggregated at the bank level*) is associated with higher likelihood of strong financial distress at the bank level (e.g. bank failure). Moreover, effects are stronger, or at least similar, than the other standards analyzed in the literature —credit (volume) growth, even in real estate, spreads, collateral and maturity—, consistent with lower screening.

Our main contribution to the literature is to analyze loan origination time: (i) throughout a full credit cycle; (ii) depending on borrower and lender proxies for moral hazard incentives; and (iii) its relationship with loan-level defaults and bank failures. Loan origination time also depends on technology/productivity (Fuster et al., 2017 and 2019), but results suggest that loan origination time also relates to a bank moral hazard mechanism (consistent with theory that we refer to in this Introduction). Therefore, our results suggest that time to originate a loan also proxies for screening, which is difficult to observe (and measure), but crucial for theory (see e.g. Gorton and Winton, 2003; Tirole, 2006; Freixas and Rochet, 2008). Moreover, our results show that loan origination time is important for all the questions that we analyze, even for bank failures (where social costs/negative externalities tend not to be fully internalized) and effects are economically and statistically stronger, or at least similar, than the other credit conditions in explaining bank-level failures.

In the remaining part of this introduction, we firstly provide a detailed preview of the paper, and then discuss in detail the related literature and its contrast 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 central bank in Spain) 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 opaque. We also have access to the supervisory bank balance-sheet, income and loss statement and other supervisory information that banks are required to declare to Banco de España. Given that we know the identity of the borrowing firm (via a unique tax identifier) and of the bank, we merge the credit register database with these lender-level and borrower-level data sources. Finally, we also know the locations of bank branches to measure bank concentration in geographical areas.

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 has 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 question, we use the externally-driven (European) VIX (Rey, 2013) to exploit variation in aggregated financial conditions. We analyze how changes in VIX affect loan origination time, also related to measures of ex-ante borrower and lender capital (a key measure of borrower and lender moral hazard problems, see Holmstrom and Tirole, 1997). We also analyze the main effects for every time period in a non-parametric way (see Figure 2 and 3). Moreover, as safer, less opaque borrowers may be easier to screen, they may have mechanically lower loan origination time unrelated to less screening effort, and hence, we control progressively for borrower fundamentals. To further separate it from bank constraints or banks' different technologies for screening, we also control for different observed and unobserved bank fundamentals, as e.g. number of loan applications per bank branch, size, ROA or bank fixed effects. We also analyze whether a proxy for bank competition (bank concentration) has important effects as bank competition plays a key theoretical role in screening depending on the credit cycle (Ruckes, 2004; Dell'Ariccia and Marquez, 2006).

Regarding the second question, to analyze how ex-ante loan origination time affects ex-post loan default, we: (i) directly use origination time for every granted loan; or (ii) control for borrower fundamentals (as safer firms, easier to screen, may have on average lower origination time), or control for other key determinants such as other credit conditions, e.g. collateral; or (iii) use an instrumental variable strategy. We also analyze heterogeneous effects depending on firm capital, VIX and bank moral hazard proxies. Finally, 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 the impact of pre-crisis origination time on the likelihood of bank failure, and other strong bank distress episodes.

In Section 4 we explain the results. First, we find that—when VIX is lower—banks shorten loan origination time. In particular, a reduction (the interquantile range) of VIX shortens loan origination time by 3%. Moreover, the shortening of loan origination time (when VIX is lower) is even stronger for ex-ante less capitalized firms. Interquantile range reductions of VIX and ex-ante borrower capital ratio shorten loan origination time by 3.8%.[1]

Exploiting further heterogeneity, the average shortening of loan origination time when VIX is lower is stronger both in areas with more banking competition (proxied by lower Herfindahl-Hirschman Index (HHI)) and for banks with less capital – both measures proxying for bank moral hazard incentives (Freixas and Rochet, 2008).[2] Moreover, average loan origination time decreases when VIX is lower for ex-ante less capitalized firms (interquantile range reductions) especially: (i) in areas with high banking competition, with a decrease in

[1] We find that less capitalized firms have on average higher loan origination time (though, less so in good times).
[2] A proxy of bank lending capacity constraints (number of applications per branch) is significant in levels but our results suggest that it does not change loan origination time over the cycle.

average origination time by 4.2% compared with only a 0.4% decrease in low competitive areas; or (ii) by less capitalized banks (again an interquantile range), with a decrease in average origination time by 4.6%.[3,4]

Figure 2 and 3 show loan origination time over the cycle without any control. Figure 2 shows the overall cyclical behavior. In Figure 3, we find that, comparing boom versus bust periods for low (versus high) capitalized firms and banks (where low/high is below/above the median), loan origination time increases from 46 to 60 days. These 14 days imply a 30% increase in average loan origination time.

Second, we find that shorter (*loan-level*) origination time is associated with higher ex-post loan defaults on average (a 4.5% increase if the loan origination time decreases by 3 months). Moreover, effects are somewhat stronger when controlling for firm fundamentals, as safer borrowers have shorter average origination time (e.g. firm observables or even firm fixed effects). Effects are also robust to controlling for bank (observables or/and fixed effects) and other loan conditions (e.g. collateral or amount). With all these controls, the R-squared increases by 62 percentage points (700% higher), but nevertheless the estimated coefficient does not decrease in absolute value, thereby suggesting that omitted variable problems (further unobservables) are not driving the (significant) results, following Oster (2019) and Altonji et al. (2005). Therefore, results suggest that shorter origination time implies higher loan defaults.

Results are also robust to using an instrumental variable regression. For the Christmas holidays period (21st of December to January 7th, after the Three Wise Men or Epiphany day), we find shorter origination time (see Figure 4), in 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. Moreover, we find that during this 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 in this holidays period versus other periods). Further, the estimated effects of this holidays period on faster loan origination time are very similar across substantial different controls for unobservables (including or not firm,

[3] For models in banking where bank capital matters for moral hazard incentives, see e.g. Holmstrom and Tirole (1997) and Mehran and Thakor (2011). For models on bank competition and moral hazard, see e.g. Allen and Gale (2003), Ruckes (2004), Boyd and De Nicoló (2005), Martinez-Miera and Repullo (2010). For models on bank competition, capital and moral hazard, see e.g. Keeley (1990), and Hellmann, Murdock and Stiglitz (2000). For a model of rational inattention during the credit cycle, see Mariathasan and Zhuk (2018).
[4] 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).

bank or bank-year:month fixed effects). The instrument does not suffer from weak IV problems, and the estimated effect in the second stage, when we control for fixed effects, is very similar to the OLS one. Results in the second stage are robust to particular days chosen for the Christmas period as well as varying borrower and lender controls (e.g. borrower or lender or time or lender-year:month fixed effects).

We also find some heterogeneous effects. The impact of shorter origination time (when origination time decreases from 3 months to the same application month) on ex-post loan defaults is higher for ex-ante less capitalized firms (by 1.4 percentage points or 7.0% higher when comparing a firm in the third versus first quartile of distribution of firm capital ratio) or when VIX is lower (by 1.3 percentage points or 6.5% higher for the interquantile range of VIX). Moreover, the higher effect of shorter origination time on higher ex-post defaults for less capitalized borrowers is stronger in areas with high bank competition (2.4 percentage points or 11.7% higher for an interquantile range change).

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 find that less pre-crisis loan origination time at the bank level is associated with higher likelihood of a bank failure or a related strong bank distress event. We measure strong bank distress as an indicator variable that takes the value of one when bank-level overall financial distress is due to public intervention of the bank, a public (state) bailout, a merging process or an acquisition in the crisis, or a recapitalization after a stress test exercise carried out by the supervisor; and zero otherwise. Results are robust to different definitions, e.g. to the strongest case of bank distress, which is direct public (state) intervention of the bank or public bailout with state funding.

Consistent with less screening, 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, and a 13.5% increase of the likelihood of bank failure (strongest) events. Interestingly, loan origination time has at least similar—or even stronger—economic and statistical effects than the other 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 and less generation of information in booms, in part due to moral hazard problems (see e.g. Ruckes, 2004; Dell'Ariccia and Marquez, 2006; Dang, Gorton, Holmström and Ordoñez, 2017; Asriyan, Laeven and Martin, forthcoming).[5] We contribute to this literature by proxying screening effort by the time difference between a loan application is submitted and the granting time, and by finding the following results. We show that loan origination time is shorter when VIX is lower (or in a boom), especially for ex-ante less capitalized borrowers, and results suggest that key drivers are bank moral hazard incentives (capital and competition). Moreover, we show that a shorter loan origination time implies (at the loan-level) higher ex-post defaults, especially for loans granted when VIX is lower, and on less capitalized firms, particularly in areas with more banking competition. Importantly, a shorter pre-crisis loan origination time, aggregated at the bank level, is associated with higher likelihood of bank failure or other strong bank distress events. Therefore, results suggest that loan origination time proxies for screening effort and are consistent with a theoretical bank moral hazard mechanism.

Moreover, as highlighted in the first page: (i) there is a large theoretical banking and macro-finance literature on credit cycles, lending standards, and more generally on banking crises and bank-level failures; (ii) the empirical analyses in this literature have analyzed loan volume, rates, collateral and maturity, as these are (more easily) observable variables, especially volume. For example, 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.[6] 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 cycle, to ex-ante risk-taking, and to ex-post loan-level defaults and bank-level failures. We find that shorter origination time is associated with higher ex-post defaults at the *loan level* and even with higher likelihood of bank failures at the *bank level*. Compared to other standards studied in the literature, our evidence suggests that average loan origination time produces similar or even stronger economical and statistical effects.

[5] See also Broecker (1990). 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 (see one very recent exception in the next pages). Granja, Leuz and Rajan (2020) analyze distance as a measure of risk-taking, we analyze instead loan origination time and we study loan-level ex-post defaults and bank failures. There are some empirical papers related to screening, e.g. Keys, Mukherjee, Seru and Vig (2010), 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; e.g. our results are not driven by credit conditions such as volume or collateral, and corporate (mostly SMEs) loans in Spain were not securitized or sold in secondary markets or to public agencies.

[6] The evidence comes from 17 to 20 countries over the last 140 years. See Schularick and Taylor (2012) and Jordà, Schularick and Taylor (2011, 2013).

There are two close papers to ours using US data on mortgages. Choi and Kim (2020) use mortgage application processing time at the loan level and exploit the collapse of the private securitization market as a shock. Following the collapse, lenders spent significantly more time in processing applications for loans larger than the conforming loan limits than those below. The processing time gap widened more for banks with lower capital, greater involvement in the originate-to-distribute model, 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*.

In addition, in a posterior paper to ours, Wei and Zhao (2020) link ex-ante processing time to ex-post defaults but via a *different* channel. 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 first that we have a full credit cycle and our results suggest that bank moral hazard problems are key drivers. Second, we analyze bank-level failures (or related strong bank distress events), which is important as theory argues about excessive risk-taking (too low screening) and bank failures impose social costs (via negative externalities) that tend not to be fully internalized by bankers.

Moreover, with respect to the two previous papers, in addition to different results or/and mechanisms that we just summarized, we analyze loans to *firms* which tend to be more opaque (especially non-listed firms which are most of the firms in our dataset) and, based on banking theory and practice, screening is more important (soft information plays an important role in loans to SMEs). Moreover, not only do we analyze loan-level results, but also *bank-level* outcomes, in particular bank failures. Note that loans to firms, even more to SMEs, were not securitized in Spain, so the main channel is different than in 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 recent papers (Fuster et al., 2017 and 2019) using loan origination time for the US mortgage market. Different from us, these papers do not analyze a (full) credit cycle and pro-cyclicality in lending standards, nor bank-level failures and distress (e.g. their analysis does not cover a full cycle). Therefore, our paper asks different questions (and hence we have different results), but we complement these important papers. Fuster, Plosser, Schnabl and Vickery (2019), using data since 2010, show that fintech lenders process mortgage applications faster than other lenders, alleviating capacity constraints associated with traditional mortgage lending (and without more aggregate defaults). Therefore, loan origination time also depends on technology/productivity. Our results suggest that loan origination time varies over the cycle and results suggest that bank moral hazard incentives are a crucial mechanism, and consistently lower ex-ante loan origination time is associated with higher ex-post loan-level defaults and even with bank-level failures (consistent with theories of too soft lending standards in booms that we refer to in the previous pages). Moreover, 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 quantitative easing (QE) leading to substantial 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).[7] Our results also suggest that bank capacity constraints (average number of loan applications per branch) matter but not differentially over the credit cycle, differently to proxies for bank moral hazard incentives (capital and competition).[8]

The paper proceeds as follows. Section 2 describes the data. Section 3 describes the empirical strategy and summary statistics. Section 4 summarizes the main results. Section 5 offers some brief concluding remarks.

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 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 contains 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 nonfinancial limited liability companies,

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

[8] Interestingly, despite different data, countries and credit markets, we find similar number of days in loan origination time for the summary statistics (compared to e.g. Fuster, Plosser, Schnabl and Vickery, 2019), though in our sample there are on average 4 more days in loan granting (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 that mortgages (households have simpler balance sheets and can be sold easily to even public agencies). Note that fintech lending in Spain to *firms* is very small, also in most countries.

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 monthly level. This is important as loans from current banks may have different origination time due to their superior information over time (and hence they could just provide a loan without new origination time as their "screening" is their previous monitoring over the past 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 the bank's 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 exact time (day) of a loan application and its granting month.[9] Therefore, the loan origination time variable takes six different values: 0, 1, 2, 3, 4 and 5 months. Further, we also measure the origination time in days, or use a dummy variable (below/above the median); results are similar across the different measures.[10] Figure 1 shows that around 70% of loans are granted within month zero (i.e. granting and application month are 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 (in days, 52 and 40 days, respectively for average and median). Note that, as we write in the Introduction, the median days are very similar to the US mortgage data.

Figure 2 shows the average loan origination time per semester using two different measures (months and days) for the period from 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 (tighten) origination time during crisis periods (the Global Financial crisis and the Euro Area Sovereign Debt crisis). The results in the Figures are without any control. Results are very similar if we control for loan, borrower and lender characteristics, including

[9] If the loan is not granted, we do not know the status of the loan. In robustness (Table A2) we include these loans and hence we need to impose a maximum delay between a loan application is lodged and its potential concession. On the other hand, an advantage of our dataset is that: we have the time to originate a loan for firms in which soft information is important (and hence screening effort); we do have loan level defaults for every single loan, as well as borrower identifiers so that we can link different applications by the same borrower to different banks; and we have a full cycle so that we can analyze ex-ante loan application time and ex-post loan-level default and bank-level failures.

[10] 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.

granted applications or number of applications. In the regression analysis, we will control for these variables and many others.

Moreover, Figures 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 46 to 60 days, i.e. these 14 days imply approximately a 30% increase in average loan origination time. 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 beginning of the year (school holidays in Spain start after the third week of December and go until 7th of January, the day after Epiphany). Probably due to the approaching holidays and many social events, bankers reduce loan origination time. As such, the lowest loan origination time occurs from mid-December to mid-January. 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. Moreover, we will exploit this calendar effect to use an instrumental variable strategy in the analysis of the impact of ex-ante loan origination time on the probability of ex-post default of loans.

We also have at our disposal banks' and firms' balance sheet information. Banks' information is obtained through a database owned by Banco the España as a banking supervisor, and firms' information through the Spanish Mercantile 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. Further, to study the impact of bank competition we use the Herfindahl-Hirschman Index at the level of municipalities according to credit volume.

3. Empirical strategy and descriptive statistics

We start by investigating how borrower, lender and the economic cycle affect loan origination time. Then, we study at the loan-level the impact of loan origination time on future default, as well as some heterogeneous results. Finally, by aggregating up 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. Therefore, we perform the analysis in three steps, by estimating three different equations with different outcomes.

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 proxying for moral hazard problems – borrower and lender capital ratios and a local market HHI variable proxying for bank competition.

The dependent variable is *Loan origination time*, which measures how many months a bank has taken to originate a loan after an application. As commented before, 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 measure in days or using a dummy variable on below/above the median number of days.

We observe the day of the loan application and the month of its granting time, i.e. we know whether it was finally approved, accepted by the borrower and granted by the lender, and hence the loan origination time. For estimation purposes, as the outcome variable takes different values (0, 1 to 5), the preferred model is a Poisson 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 robustness we also estimate an OLS model for the log of (one plus) loan origination time.[11] The baseline equation we estimate using Poisson pseudo-maximum-likelihood estimator is the following:

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

where the sub-indexes *i, j, m* and *t* refer to firm, bank, municipality and time, respectively. All variables are lagged one moth. The variable $VIX_{t-1}$is a volatility index based on EURO

[11] In robustness we also analyze non-granted loans, for which we do not observe the time when the loan was refused. To tackle this issue in we estimate a censored Poisson model to 5 months.

STOXX 50 option prices and it is designed to reflect the market's expectation of its 30-day forward-looking volatility, and $int\ rate\ surprise_{t-1}$ is the European 3-month interest rate surprise computed following Jarociński and Karadi (2020). These variables capture the financial/macroeconomic and monetary conditions over the cycle, respectively, and are externally-driven (exogenous) to Spain.[12]

The regressors $firm\ variables_{it-1}$ and $bank\ variables_{j,t-1}$ are vectors of firm and bank time-varying characteristics, respectively. Regarding borrower and lender fundamentals, our main variables of interest proxy for firm and bank moral hazard problems, and following Holmstrom and Tirole (1997), we use the ex-ante firm and bank capital ratio. Firm capital ratio averages 29% while the bank capital ratio averages 6%. We control for other key firm and bank variables as e.g. size, different measures of risk and liquidity.[13]

In addition, we capture the banking structure at the municipality level with the $local\ competition\ variable_{imt-1}$, which includes the Herfindahl-Hirschman Index (HHI) in terms of the volume of credit (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 influence loans' average origination time because they could be capturing, for instance, the technology available to a bank to assess the firm's creditworthiness. We also control for average number of loan applications per branch as a measure of bank capacity constraints, and in some robustness, we use *bank*time* fixed as an additional control. 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 robustness, we also analyze results with bank*industry and bank*province that allow for specialization. Seasonal time fixed effects are captured by month fixed effects or by year:month fixed effects, and ϵ_{fjt} is the idiosyncratic error term. We cluster standard errors at the bank, firm and time (year:month) level. Our strategy is to progressively saturate the baseline model to analyze the impact of macro, firm, bank and local market characteristics on loan origination time.

[12] We get very similar results if we use Spanish GDP change and the change of the overnight interest rate instead of (European) VIX and interest rate surprise. Note that Figure 3 shows the results without any control period by period, i.e. in a non-parametric way. VIX and interest rate surprise are standardized in the sample.

[13] 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, the credit history of the firm, if the firm was known previously by the bank and the number of loan applications made by the firm in that month. As other bank controls, we consider the size, the liquidity ratio, the ROA, its losses and its previous growth in the province of the firm.

We also analyze the heterogeneity of the results to test whether the effect of the financial cycle proxied by VIX on origination time differs with the ex-ante firm and bank capital, and with the proxy of bank competition. We do this by introducing in the baseline specification double and triple interactions and splitting the sample based on bank competition intensity.[14]

3.2. Loan origination time and lending standards

We also study at the loan-level whether loan origination time affects the loan's *Future Default*, a dichotomous variable that states whether a loan becomes delinquent at some point in the future (until 2016:03).[15] Its average 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 used in the first part. We estimate, using OLS, the following baseline linear probability equation:

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

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 section 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 with at least 50% of the loan's amount, 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. In additional columns, we add firm fixed effects. When bank-time fixed effects are not included, bank variables are added as controls and some of them included as interactions in some specifications.

Finally, 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 do heterogeneous effects. That is, we also include several interactions between our key variables of interest in

[14] In some regressions we control for the interactions of industry and location dummies with time fixed effects, or even introduce firm fixed effects, though in this latter case we lose substantially heterogeneity of (between) firm variation, and hence the key variation that we exploit in this first part of the paper.
[15] The definition of default follows the policy and academic literature (at least 90 days overdue).

the same vein that we follow in the previous subsection 3.1 (e.g. VIX, firm and bank capital, and bank competition).

In addition to testing for (further) unobservables (omitted variables) via the Oster (2019) test, we also push for further identification using an instrumental variable strategy exploiting the Christmas period, which has many social events and holidays (also for school holidays), especially from the last days of December (21st onwards) to the beginning of January (until 7th). As Figure 4 shows, we find that in this period loan origination time is lower, also if we control for bank or firm fundamentals, including number of loan applications and granted loans. We also analyze whether firms with granted loans in this period are different in observables from other periods, both across firms or within the same firm obtaining loans in different periods (and we find that there are no significant differences, see Table A3). In addition, we use this time period to instrument loan origination time and analyze its impact on defaults. As the next section shows, results are very similar to the OLS ones. Further, results are very similar if we control for firm and/or bank(-year:month) fixed effects, i.e. further suggesting that unobservables do not play a key role.

3.3. Loan origination time and bank failures

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 level failure result 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 and the Euro Area Sovereign Debt crisis.

We estimate a model where we explain strong distress events of banks over the period 2008-2015 on aggregated pre-crisis loan level variables, including the average loan origination time as an additional regressor, fixed at 2006 (before the crisis),[16] and also controlling for pre-crisis bank characteristics based on a CAMEL model.[17] The period of time considered for the analysis offers a very good opportunity to challenge the strength of the average loan origination time as an early warning indicator since 43 (or 37) banks in Spain

[16] We get similar results if instead of an average in 2006, loan origination time is computed in 2007 (though in Europe, interbank problems started in the summer of 2007).

[17] 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.

experienced strong (severe) distress. For the analysis we work with 57 individual banks, following the sample used by the Banco de España in its Forward Looking Exercise on Spanish Bank (FLESB).

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 (37 banks under severe distress). We analyze these events through a Probit model,[18] based on average pre-crisis lending conditions (including loan origination time) and banks' ex-ante overall performance, captured by a CAMEL rating. 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 the 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 in the strongest part of the boom (2004-06). Note that the economy in Spain was strong until the 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 2006 before the interbank European problems.[19] *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,[20] such as credit growth, percentage of real estate assets, average maturity, collateral or loan interest rates.

[18] 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 use in the benchmark regressions a Probit model instead of a linear probability model. However, we obtain statistically equivalent results when using a linear model.
[19] Loan origination time also starts only increasing in the last part of 2008 (see Figure 2).
[20] 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.

4. Results

Tables 2 and 3 show the estimated coefficients for different specifications of Equation (1), and Tables 4 and 5 do so for different specifications of Equation (2). Finally, Table 6 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 PPML and the latter one with OLS given that the dependent variable is a dummy (see Section 3 for the empirical strategy).[21] 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 lower VIX is followed by shorter loan origination time (see also Figure 2 for the non-parametric results, period by period, without controls, for boom versus bust periods).[22] According to column (3), comparing the first versus third quartile of the VIX distribution, column (3) shows that the average loan origination time decreases by around 3.0%. Regarding a one standard deviation reduction of VIX decreases loan origination time by 2.2%. Differently, the monetary interest rate (surprise) is not as robust statistically speaking and the economic effects are substantially smaller (note that the macro VIX and rate variables are both standardized). Regarding column (6) in origination time in days, results for VIX suggest that an interquartile range reduction of VIX decreases loan origination time by 2.3%, while for the dummy below the average, results for VIX are also significant.

---

[21] In the appendix, we also show the results using a censored Poisson for the whole sample of loan applications.

[22] The analogous result (but with opposite sign) is obtained if VIX is substituted by the Spanish GDP growth rate. In general, we obtain similar results if we use GDP growth or a dummy for boom (before the Lehman crisis or 2008), 0 otherwise. In addition, results are similar if we control for fixed effects on the week of the loan application in addition to seasonal fixed effects (not reported).

Table 2 also shows that loan origination time increases with the ex-ante risk of the firm, in particular less ex-ante capitalized firms, proxying for higher moral hazard problems.[23] For instance, an interquartile range decrease in firm capital ratio increases the average loan origination time by around 1.4% for all five first specifications; results are similar with the other two different outcome variables (columns (5) and (6)). Furthermore, from column (3) higher bank competition proxied with (an interquartile range decrease in) bank concentration (the Herfindahl-Hirschman Index in the municipality) is associated to a decrease in loan origination time by 1.4%; results are nevertheless not robust to time or bank*time fixed effects. In addition, Table 2 also documents that banks with less capital are quicker. Column (3) shows that a decrease in loan origination time by 8.1% for an interquartile range decrease in bank capital. Finally, loan origination time 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 2 in the Appendix displays five further robustness checks for the baseline estimation of Equation (1), that includes bank, seasonal, province and industry fixed effects (as our baseline model). 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 basically 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). We show that results are similar. Results are also robust to industry*province*time fixed effects or to firm fixed effects (not reported). In column (5) a censored Poisson model is estimated for all applications made. All in all, results remain similar in all the robustness checks considered.

[23] Other measures of firm risk have similar effects.

4.1.1. Heterogeneity in the determinants of loan origination time

Table 3 documents the heterogeneity of the results.[24] This table 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 market's competition characteristics (Herfindal-Hirschman Index). We also analyze some triple interactions effects. 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 (6) and (7) use as dependent variable the loan origination time measured in months, while column (6) uses a measure in days as a robustness check and column (7) the dummy variable above/below the median (similar to Table 2).

We start with column (1) including the interaction terms between VIX and firm capital and bank competition in the analogous specification of column (3) of Table (2), i.e. the benchmark regression of Table 2. 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). In column (5) we introduce the triple interaction of VIX with firm and bank capital ratio.

While in Table 2 we obtain that a reduction of VIX shortens 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%. This key result is robust across all specifications (columns), with different controls or different ways to measure the outcome variable. That is, it takes less time to grant a loan to a risky firm during good periods (low volatility and uncertainty). Results are robust across the different specifications in Table 3 and to additional controls such as number of loan applications per firm in a period. See also Figure 3, where it shows that this result is driven by the boom period before the Lehman crisis.

Exploiting further heterogeneity (column (2) of Table 3), the average shortening of loan origination time when VIX is lower is stronger both in areas with more banking competition and for banks with less capital – both measures proxying for bank moral hazard incentives. Moreover, column (3) and (4) show that average loan origination time decreases in boom times (VIX lower) for ex-ante less capitalized firms, especially in areas with high banking

[24] In the whole paper, when interaction terms are included, all variables are demeaned so that the coefficients of the variables in levels estimate the average effect; other controls are also included as interactions terms.

competition, with a decrease in average origination time by 4.2%, compared to only 0.4% in low-competitive areas. In addition, column (5) shows that average loan origination time decreases in boom times (VIX lower) for ex-ante less capitalized firms, especially less capitalized banks, with a decrease in average origination time by 4.6%, for interquartile differences.[25] Finally, the last two columns of Table 3 shows that our 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 lower VIX (or in the boom), banks shorten loan origination time, especially to ex-ante less capitalized firms. These effects are moreover stronger in areas with more bank competition and for less capitalized banks, proxying both for bank moral hazard incentives.

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

In Table 4 we present the effects of loan origination time on ex-post loan default probability. Throughout the 13 different specifications that we present in the table, we find that the shorter the loan origination time, the higher a borrower's future default rate is.

For column (1) to (5) of our main loan origination time variable, each column shows a more restrictive model than the predecessor one to fill up the initial specification with different controlling variables. Columns (6) and (7) 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 (8) shows the effects for each month testing for a potential non-linearity, while column (9) shows the results weighting each observation by each loan size. Finally, columns (10) to (13) show the results for the instrumental variable.

Column (1) of Table 4 includes basic (time, province and industry) fixed effects and bank controls (fixed effects and time-varying bank characteristics). The coefficient on loan origination time is significant at 10% and negative.[26] As safer firms have less origination time (see Table 2), in column (2) we control for firm's fundamentals by introducing firm fixed effects and time-varying firm observables. The coefficient on loan origination time is again negative, but somewhat higher in absolute value and statistically significant at 1%. Given that the average default probability is 0.20, an interquartile range reduction in loan origination time implies an increase of a borrower's average probability of default of around 3%. Moreover, if

[25] With firm fixed effects, results on the VIX and firm capital interacted with bank capital or VIX interacted with competition variable are significant, though we lose substantial (between) firm heterogeneity (the key variable in the first part of our paper).
[26] As explained in the empirical strategy, 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.

the loan origination time changes from 3 to 0 months, the future probability of default increases by 4.5% (which corresponds to 0.9 percentage points).

We further saturate the model with different controls. Column (3) adds loan characteristics (e.g. loan volume or collateral) to column (2);[27] results do not vary. Column (4) adds *bank*year* fixed effects to account for any unobserved yearly-variant bank characteristics, and column (5) further adds *bank*year:month* fixed effects to control for monthly variation within the same bank.[28] Crucially, comparing column (1) with column (5), the R-squared increases by 60 percentage points (700% higher), but nevertheless the estimated coefficient does not decrease in absolute value, thereby suggesting that omitted variable problems (i.e. further unobservables) are not driving the significant results, following Oster (2019) and Altonji et al. (2005, 2008).[29] Therefore, the overall results suggest that shorter origination time implies higher loan defaults.

Column (6) and (7) are two robustness checks of column (5). In column (6) 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 (7) we include a dummy whether loan origination time is higher than the median, as in previous tables. It is significant at 10%, implying that if the loan origination is below the median time, then the probability of default increases by 3.0%.

Column (8) 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). A borrower has on average around 5.5% lower probability of future default with the bank if the bank grants the loan three months after the borrower has requested it, with respect to a loan granted within the month in which it was applied (i.e. the omitted dummy). In addition, in column (9), we show similar (statistically non-different) results when we weight each observation by each loan size, though the estimated coefficient is somewhat reduced. This suggest that an aggregation at the bank level may imply results for bank failure (see Table 6 and next section).

[27] Other unreported controls are e.g. real estate exposures.
[28] To favor comparison across different specifications (columns (1) to (5)), e.g. for the Oster (2019)'s test, we keep the number of observations constant and equal to the model used in column (5).
[29] We have also repeated all regressions without considering loan controls, and the results obtained are qualitatively and quantitatively equivalent to those obtained when including them.

Finally, columns (10) to (13) show an IV estimation where we instrument the loan origination time variable by a Christmas period dummy (over December 21st to January 7th). Results are very similar to other related days around this period. We exploit the fact that loan officers may have less time because of many social events and several holidays during this period (including full time school holidays), which could potentially lead them to speed up the process. Figure 4 and Columns (10) to (13) of Table 4 indeed show that banks take less loan origination time in this time period. The first stage of loan origination time on this Christmas period dummy shows that the F-test of the first stages go from 9.9 to 14.9 depending on different controls, i.e. the instrument does not suffer from a weak instrument problem.

Moreover, results are robust to unobservables, e.g. different set of borrower and/or lender fixed effects, without changing the estimated coefficient, thereby suggesting that results are robust to further unobservables following Oster (2019) and Altonji et al. (2005, 2008).[30] Moreover, as Table A3 shows in the Appendix, we find that during this period the borrowers (firms) that obtain the loans are not different in observable ways (either without firm fixed effects, comparing the different firms in this period versus other periods, or within firm fixed effects, comparing the same firm obtaining loans in this holydays period versus other periods). For observable characteristics, we include the same set of firm characteristics used in the rest of the paper, which includes for example e.g. firm size, age, capital ratio, liquidity ratio, ROA, productivity, cost of debt, bank debt leverage, fixed employees ratio or credit history.

In addition, the second stage shows very similar economic effects as the OLS (see e.g. the benchmark IV regression, column (10), with the OLS benchmark regression, column (5)). Columns (11) to (13) as compared to column (10) show results for a variety of specifications with less fixed effects for either firm or bank (or bank-year:month). Importantly, neither of these fixed effects (or observable controls) are significantly changing the results. For example, the estimated coefficients are identical with or without firm fixed effects proxying for firm unobservables (see in this case column (13) versus (12)). Or for example, results are very similar if we analyze the different loans granted from the same bank in the same year:month period (i.e. within this holidays period within the same bank as compared to granted loans on earlier days in December or posterior days in January from the same bank).

In Table 5, we also find some heterogeneous effects. In columns (1) to (3), we progressively interact loan origination time by firm/bank capital and VIX. We find that the impact of shorter origination time (when origination time decreases from 3 months to the same

[30] Results are robust to controls such as the number of applications per firm and for each bank, granted loans, seasonal effects, and year:month time dummies.

application month) on ex-post loan defaults is higher 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).[31] 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, we derive that the higher effect of shorter origination time on higher ex-post defaults for less capitalized borrowers is strong in areas with higher bank competition (11.77% or 2.4 percentage points higher). Finally, column (6) analyzes whether the effect of firm capital and loan origination time on future default depends on the level of the bank capital, but as in column (2), bank capitalization does not seem to play a role in ex-post loan defaults.

4.3. Loan origination time and bank failures

Table 6 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 the 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 (a narrow definition of bank distress).

Models in columns (1) to (8) and (10) include average loan origination time cleaned from borrower fundamentals as a regressor and it is computed for 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*year* fixed effects from a linear estimation where the dependent variable is loan origination time and *firm*year* fixed effects are included to control for borrower fundamentals (we have also used instead *industry*location*year* fixed effects, not reported). Model (8) computes the average loan origination time for the years 2004 to 2006, as a robustness check, as those three years were the strongest ones for the Spanish credit boom. To facilitate the comparison (horserace) of the estimated coefficients across all variables and models, we standardize all variables.

[31] For a one standard deviation change on loan origination time, the effects are 3.0% and 2.6%, respectively.

Column (1) only includes a CAMEL rating of the bank using a set of bank characteristics. 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 less pre-crisis loan origination time at the bank level is associated with higher likelihood of a bank failure or a similar related bank distress. Results are robust to different definitions, in particular to the strongest case of bank distress (failure), which is directly public intervention in the bank or public bailout. Interestingly, loan origination time has at least similar—or even stronger—economic and statistical effects than the other 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 origination time, but not statistically different from origination time). Credit volume growth is very similar to loan origination time (though somewhat less robust).

Overall, 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. In sum, results suggest that less pre-crisis origination time (consistent with less bank screening) increases bank failures or other strong distress bank events, with stronger or at least similar effects than the other standards analyzed in the literature.

5. Conclusions

In this paper we study time to originate a loan over a full credit cycle. For identification, we exploit the credit register from Spain over the 2002-2016 period, which has the time of a loan application and its granting. We find: (1) When VIX is lower (or in a boom), banks shorten loan origination time, especially to ex-ante less capitalized firms. Moreover, these effects are stronger in areas with more bank competition and for less-capitalized banks, proxying for bank moral hazard incentives. (2) Shorter (*loan-level*) origination time imply higher ex-post defaults. These effects are stronger if the loan is granted when VIX is lower, or for ex-ante less capitalized firms, even more in areas with more bank competition. (3) Exploiting the global financial crisis that started in 2008, less pre-crisis origination time (*aggregated at the bank level*) is associated with higher likelihood of strong financial distress at the bank level (e.g. bank failure). Moreover, effects have stronger, or at least similar, economic and statistical effects than the other standards analyzed in the literature —credit growth, even in real estate, spreads, collateral and maturity—, thereby suggesting that origination time proxies for screening. Finally, given the ex-ante findings and the ex-post loan defaults and especially bank failures, results are consistent with excessive risk-taking as bankers do not tend to fully internalize the social costs of bank failures.

References

Abadie, A., Athey, S., Imbens, G. and Wooldridge, J., 2017. When Should You Adjust Standard Errors for Clustering? Working Paper 24003, NBER.

Agarwal, S. and Ben-David, I., 2018. Loan Prospecting and the Loss of Soft Information. *Journal of Financial Economics*, 129(3), 608-628.

Allen, F. and Gale, D., 2003. Competition and Financial Stability. *Journal of Money, Credit and Banking,* 36(3), 453-480.

Altonji, J. G, T. E. Elder, and C. R. Taber, 2005. Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *Journal of Political Economy*, 113-1, 151-184.

Altonji, J. G, T. E. Elder, and C. R. Taber, 2008. Using Selection on Observed Variables to Assess Bias from Unobservables when Evaluating Swan-Ganz Catheterization. *American Economic Review: Papers & Proceedings*, 98, 345-350.

Asriyan, V., Laeven, L. and Martin, A., 2021. Collateral Booms and Information Depletion. *Review of Economic Studies*. Forthcoming.

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

Becker, B., Bos, M. and Roszbach, K., 2020. Bad Times, Good Credit. *Journal of Money, Credit and Banking*. Forthcoming.

Bergman, N. and Benmelech, E., 2012. Credit Traps. *American Economic Review*, 102(6), 3004-3032.

Bernanke, B. S. and Lown, C., 1992. Credit crunch. *Brookings Paper on Economic Activity*. 2, 205-239.

Bouvard, M. and Lee, S., 2020. Risk Management Failures. *The Review of Financial Studies*, 33-6, June 2020.

Boyd, J. and De Nicoló, G., 2005. The Theory of Bank of Risk Taking and Competition Revisited. *Journal of Finance*, 1329-1343.

Broecker, T., 1990. Credit-Worthiness Tests and Interbank Competition. *Econometrica*, 58 (2), 429-452.

Brown, M., Kirschenmann, K. and Spycher, T., 2020. Numeracy and the Quality of On-the-Job Decisions: Evidence from Loan Officers. *Economic Inquiry,* 58, 998-1022.

Choi, D. B., Choi, H.-S. and Kim, J.-E., 2019. Clogged Intermediation: Were Home Buyers Crowded Out? *SSRN WP*.

Choi, D. B. and Kim, J.-E. 2020. Does Securitization Weaken Screening Incentives? *Journal of Financial and Quantitative Analysis*. Forthcoming.

Coimbra, N. and Rey, H., 2020. Financial Cycles with Heterogeneous Intermediaries. London Business School WP.

Cole, S., Kanz, M. and Klapper, L., 2015. Incentivizing Calculated Risk-Taking: Evidence from an Experiment with Commercial Bank Loan Officers. *The Journal of Finance*, 70(2), 537-575.

Dang, T., Gorton, G., Holmström, B. and Ordoñez, G., 2017. Banks as Secret Keepers. *American Economic Review*, 107(4), 1005-1029.

Dell'Ariccia, G. and Marquez, R., 2006. Lending Booms and Lending Standards. *The Journal of Finance*, 70(2), 2511-2546.

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

Diamond, D. W., 1991. Debt Maturity Structure and Liquidity Risk. *The Quarterly Journal of Economics*, 106 (3), 709–737.

Fahlenbrach, R., Prilmeier, R. and Stulz, R. M., 2018. Why Does Fast Loan Growth Predict Poor Performance for Banks? *The Review of Financial Studies*, 31(3), 1014-1063.

Freixas, X. and Rochet, J. C., 2008. *Microeconomics of banking. The MIT Press.*

Fuster, A., Lo, S. H. and Willen, P., 2017. The Time-Varying Price of Financial Intermediation in the Mortgage Market. *Federal Reserve Bank of New York Staff Reports*, Issue 805.

Fuster, A., Plosser, M. C., Schnabl, P. and Vickery, J., 2019. The Role of Technology in Mortgage Lending. *The Review of Financial Studies*, 32(5), 1854-1899.

Geanakoplos, J., 2010. The Leverage Cycle. NBER Macroeconomics Annual.

Gertler, M. and Kiyotaki, N., 2010. Financial Intermediation and Credit Policy in Business Cycle Analysis. *Handbook of Monetary Economics*.

Gorton, G. and Winton, A., 2003. Financial Intermediation. *Handbook of the Economics of Finance*, Elsevier.

Gorton, G. and Ordoñez, G., 2014. Collateral Crises. *American Economic Review*, 104(2), 343-378.

Gorton, G. and Ping, H., 2008. Bank Credit Cycles. *Review of Economic Studies*, 75(4), 1181-1214.

Gourinchas, P. O. and Obstfeld, M., 2012. Stories of the Twentieth Century for the Twenty-First. *American Economic Association: Macroeconomics*, 4(1), 226-265.

Granja, J., Leuz, C. and Rajan, R.G., 2020. Going the Extra Mile: Distant Lending and Credit Cycles. Available at SSRN, working paper.

Hellmann, T., Murdock, K. and Stiglitz, J., 2000. Liberalization, Moral Hazard in Banking, and Prudential Regulation: Are Capital Requirements Enough? *American Economic Review*, 90, 147-165.

Holmstrom, B. and Tirole, J., 1997. Financial Intermediation, Loanable Funds, and the RealSector. *The Quarterly Journal of Economics*, 112 (3), 663-691.

Jarociński, M., and Karadi, P., 2020. Deconstructing Monetary Policy Surprises—The Role of Information Shocks. *American Economic Journal: Macroeconomics*, 12(2), 1-43.

Jiménez, G., Ongena, S., Peydró, J.-L. and Saurina, J., 2012. Credit Supply and Monetary Policy: Identifying the Bank Balance-Sheet Channel with Loan Applications. *American Economic Review*, 102(5), 2301-2326.

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

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J., 2017. Macroprudential Policy, Countercyclical Bank Capital Buffers, and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments. *Journal of Political Economy*, 125(6), 2126-2177.

Jordà, O., Schularick, M. and Taylor, A. M., 2011. Financial Crises, Credit Booms, and External Imbalances: 140 Years of Lessons. *IMF Economic Review*, 59(2), 340-378.

Jordà, O., Schularick, M. and Taylor, A. M., 2013. When Credit Bites Back. *Journal of Money, Credit, and Banking*, 45(2), 3–28.

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

Keys, B., Mukherjee, T., Seru, A. and Vig, V., 2010. Did Securitization Lead to Lax Screening? Evidence from Subprime Loans. *The Quarterly Journal of Economics*, 125(1), 307–362.

Kiyotaki, N. and Moore, J., 1997. Credit Cycles. *Journal of Political Economy*, 105(2), 211-248.

Lorenzoni, G., 2008. Inefficient Credit Booms. *The Review of Economic Studies*. 75(3), 809-833

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

Mariathasan, M. and Zhuk, S., 2018. Attention Allocation and Counter-Cyclical Credit Quality. SSRN WP.

Mehran, H. and Thakor, A., 2011. Bank Capital and Value in the Cross-Section. *The Review of Financial Studies*, 24 (4), 1019–1067.

Martínez-Miera, D. and Repullo, R., 2010. Does Competition Reduce the Risk of Bank Failure? *Review of Financial Studies*, 23, 3638-3664.

Oster, E., 2019. Unobservable Selection and Coefficient Stability: Theory and Evidence. *Journal of Business Economics and Statistics*, 37(2), 187-204.

Paravisini, D., Rappoport, V. and Schnabl, P., 2020. Specialization in Bank Lending: Evidence from Exporting Firms. LSE WP.

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

Rey, H., 2013. Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence. Paper presented at the Federal Reserve Jackson Hole Symposium.

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

Santos Silva, J. M. C. and Tenreyro, S., 2006. The Log of Gravity. *The Review of Economics and Statistics*, 88, 641-658.

Schularick, M. and Taylor, A. M., 2012. Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008. *American Economic Review*, 102(2), 1029-1061.

Sharpe, S. and Sherlund, S., 2016. Crowding Out Effects of Refinancing on New Purchase Mortgages. *Review of Industrial Organization*, 48(2), 209-239.

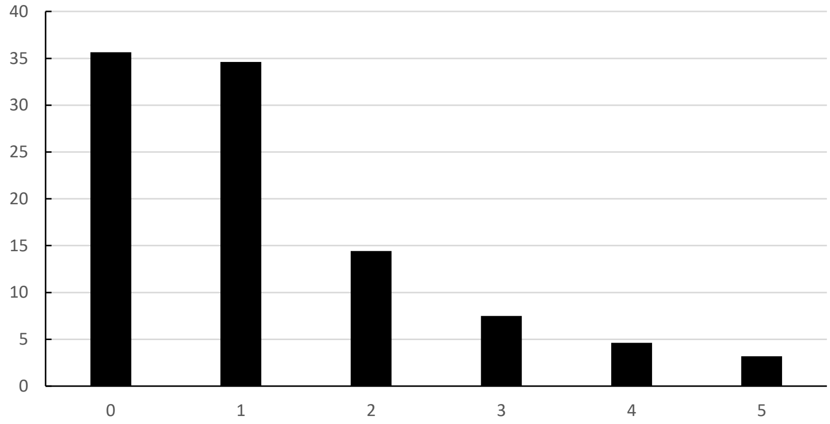
Stein, J. C., 2012. Monetary Policy as Financial-Stability Regulation. *Quarterly Journal of Economics*, 127(1), 57-95.

Tirole, J., 2006. The Theory of Corporate Finance. Princeton University Press.

Wei, B. and Zhao, F., 2020. Processing Time and Lending Standards: The Role of Extrapolative Expectations in Mortgage Loans. Mimeo.

FIGURE 1

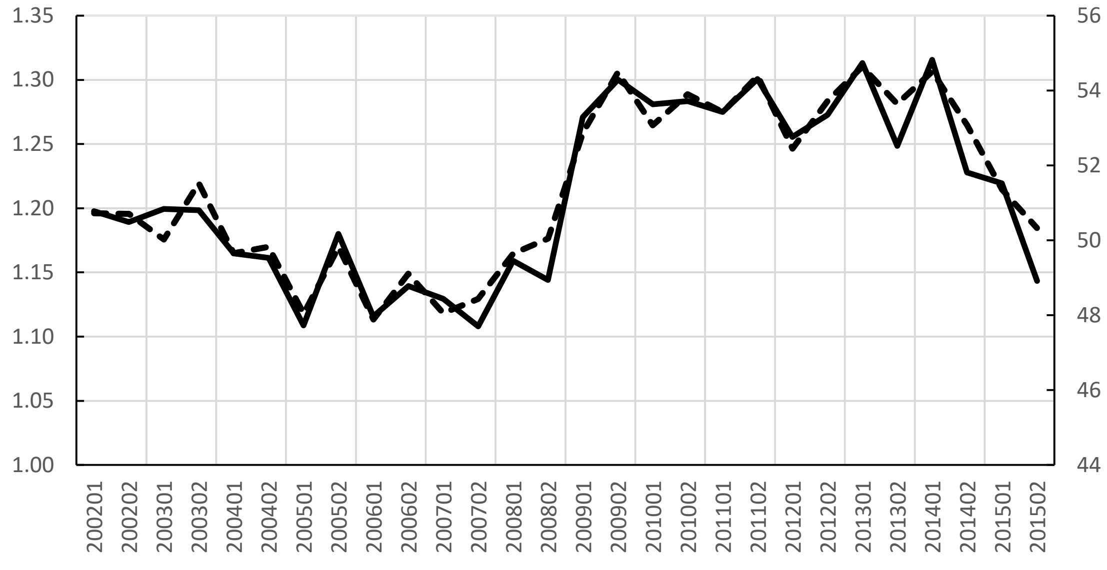
Distribution of loan origination time



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

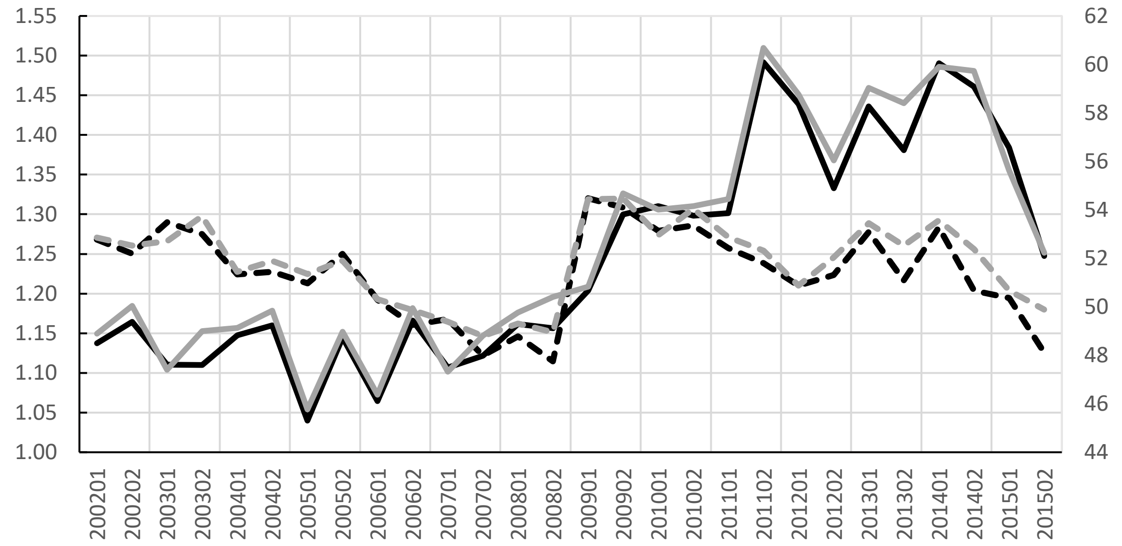
Evolution of the average loan origination time



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

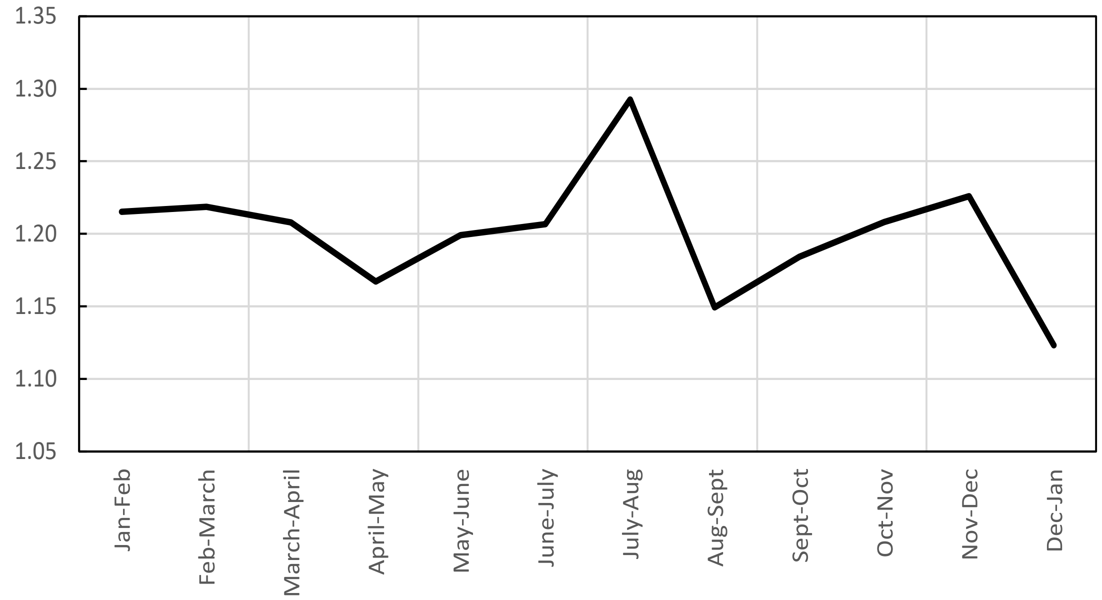
Evolution of the average loan origination time, by firms' and banks' capital ratio



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.

TABLE 1
Descriptive 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
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
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

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. Column (7) uses as dependent variable a discrete version of the loan origination time which takes the value of 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)	(7)
VIX$_{t-1}$	0.018***	0.018***	0.023***	-0.013	0.014*	0.011*	0.007***
	(0.006)	(0.006)	(0.006)	(0.021)	(0.009)	(0.006)	(0.004)
VIX$_{t-1}$*Firm capital ratio$_{it-1}$	-0.018**	-0.018**	-0.024***	0.029*	-0.021**	-0.014**	-0.010**
	(0.008)	(0.008)	(0.009)	(0.016)	(0.009)	(0.007)	(0.005)
VIX$_{t-1}$*HHI loans$_{it-1}$	-0.399***	-0.336***			-0.338***	-0.230***	-0.067
	(0.120)	(0.110)			(0.113)	(0.081)	(0.061)
VIX$_{t-1}$*Bank capital ratio$_{jt-1}$		-0.416*	-0.312	-0.607	-0.421	-0.352*	-0.266**
		(0.245)	(0.231)	(0.444)	(0.268)	(0.193)	(0.115)
VIX$_{t-1}$*No. of loan applications per branch$_{jt-1}$		0.008	0.012	-0.007	0.007	0.007	0.003
		(0.017)	(0.016)	(0.026)	(0.017)	(0.011)	(0.006)
VIX$_{t-1}$*Firm capital ratio$_{it-1}$*Bank capital ratio$_{jt-1}$					-0.636*	-0.435	-0.312*
					(0.377)	(0.279)	(0.172)
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	453,058	151,016	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. Column (7) uses as dependent variable a discrete version of the loan origination time which takes the value of one when the loan origination time is above its median value and zero otherwise. In columns (4) and (5) 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

Impact of loan origination time on a 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)
										Instrumental Variable			
Loan origination time$_{ijt}$	-0.002*	-0.003***	-0.003***	-0.003***	-0.003***				-0.002***	-0.004**	-0.005**	-0.006**	-0.006**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)				(0.000)	(0.002)	(0.002)	(0.002)	(0.003)
Log(Loan origination time in days$_{ijt}$)						-0.004***							
						(0.001)							
Loan origination time$_{ijt}$>median							-0.006***						
							(0.001)						
Loan origination time=1								-0.004***					
								(0.001)					
Loan origination time=2								-0.007***					
								(0.002)					
Loan origination time=3								-0.011***					
								(0.002)					
Loan origination time=4								-0.011***					
								(0.002)					
Loan origination time=5								-0.013***					
								(0.002)					
First Stage. Dependent variable: Loan origination time													
Loan application made between December 21 to January 7										-0.094***	-0.084***	-0.087***	-0.087***
										(0.025)	(0.027)	(0.027)	(0.023)
Year:month Fixed Effects	Yes	Yes	Yes	Yes	-	-	-	-	-	-	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	-	-	-	-	-	-	-	Yes	No	No
Province & Industry Fixed Effects	Yes	-	-	-	-	-	-	-	-	-	-	-	Yes
Firm Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Firm characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics	Yes	Yes	Yes	Yes	-	-	-	-	-	-	Yes	Yes	Yes
Loan characteristics	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*year Fixed Effects	No	No	No	Yes	-	-	-	-	-	-	-	-	-
Bank*year:month Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
R^2	0.109	0.709	0.711	0.715	0.725	0.725	0.725	0.725	0.797				
F test										13.7	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

Note. This table reports estimates from a linear probability model using ordinary least square for the period 2002:02 to 2015:12 12 but for column (9) where weighted least squares using as weights the total amount granted is estimated. The dependent variable is future default which measures whether a firm defaulted the loan granted by the bank for which loan origination time is measured. Columns (9) to (12) 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. 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 5

Impact of loan origination time on future loan-level defaults: heterogeneous effects

Dependent variable: Future Default$_{ijt}$				Low Concentration	High Concentration	
	(1)	(2)	(3)	(4)	(5)	(6)
Loan origination time$_{ijt}$ (LOT$_{ijt}$)	-0.003***	-0.003***	-0.003***	-0.004***	-0.002***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
LOT$_{ijt}$*Firm capital ratio$_{it-1}$	0.005***	0.005***	0.005***	0.007***	0.003*	0.005***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)
LOT$_{ijt}$*Bank capital ratio$_{jt-1}$		0.002	0.005	-0.013	0.015	0.008
		(0.022)	(0.023)	(0.033)	(0.030)	(0.026)
LOT$_{ijt}$*HHI loans$_{it-1}$			-0.009			-0.013
			(0.008)			(0.008)
LOT$_{ijt}$*VIX$_{t-1}$			0.001***	0.001*	0.001*	0.001**
			(0.000)	(0.000)	(0.000)	(0.000)
LOT$_{ijt}$*Firm capital ratio$_{it-1}$*Bank capital ratio$_{jt-1}$						-0.000
						(0.069)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank*year:month FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm and bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.724	0.725	0.725	0.729	0.758	0.723
No. of Observations	502,994	502,994	502,994	232,556	230,124	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 a loan obtained from a bank for which the loan which 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 6

Pre-crisis average loan origination time on 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 1 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 1 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 (using in all columns but Column (9)) comes from a bank*year fixed effect derived from a regression where the dependent variable is the loan origination time and as additional controls firm*year fixed effects are included. 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 probability$_{ijt}$	0/1	A dummy variable which equals one when the loan is doubtful or more than ninety days overdue, 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*
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*

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}≤3	LOT_{ijt}≤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. 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 differences in Christmas holidays

	(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 1 if the firm has a granted loan in Christmas holidays, from December 21st to January 7th, and zero otherwise. Productivity is the ratio of sales over the number of employees of the firm. Bad credit history is a dummy that takes the value of 1 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%.