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

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Abstract

We show that *loan origination time* is key for bank lending standards, cycles, defaults and failures. We exploit the credit register from Spain, with the time of a loan application and its granting. When VIX is lower (booms), banks shorten loan origination time, especially to riskier firms. Bank incentives (capital and competition), capacity constraints, and borrower-lender information asymmetries are key mechanisms driving results. Moreover, shorter (*loan-level*) origination time is associated with higher ex-post defaults, also using variation from holidays. Finally, shorter pre-crisis origination time —more than other lending conditions— is associated with more *bank-level* failures in crises, consistent with lower screening.

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

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1. Introduction

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

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 (Gourinchas and Obstfeld, 2012; Schularick and Taylor, 2012; Jordà, Schularick and Taylor, 2013). 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, our results suggest:

(1) When VIX is lower (booms), banks shorten loan origination time, especially to ex-ante riskier firms. Effects are stronger in areas with more bank competition and for less-capitalized banks (proxying for bank moral hazard incentives), as well as for banks with more applications per branch (proxying for bank capacity constraints). Further consistent with bank incentives, only for highly capitalized banks, pro-cyclical effects are weaker for less specialized banks in a local area or for (relatively) unknown firms to the lender, proxying both for less *bank-firm* information, and hence with winner's curse problems in lending due to information asymmetry.

(2) Shorter (*loan-level*) origination time is associated with higher ex-post defaults, especially controlling for firm fundamentals, as safer borrowers have shorter average origination time, and also using variation from periods with many social events and holidays. Effects are stronger if the loan is granted when VIX is lower, or for ex-ante riskier firms (even more for weakly capitalized banks, in areas with more bank competition, or for banks with more loan

applications per branch), thereby (again) consistent with bank moral hazard incentives and capacity constraints.

(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), with stronger, or at least similar, economic and statistical effects than the other standards analyzed in the literature —credit (volume) growth, even in real estate, spreads, collateral and maturity—, thereby suggesting that origination time proxies for screening.

Our main contribution to the literature is to analyze loan origination time: (i) throughout a full credit cycle; (ii) depending on borrower risk, lender proxies for bank capacity constraints, and for bank moral hazard incentives, including capital and competition, and borrower-lender proxies of information asymmetry; 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 we also find it is shorter (especially to ex-ante riskier firms) when VIX is lower (also controlling for many unobservables), in part due to (proxies of) bank moral hazard incentives. Moreover, shorter ex-ante loan origination time is associated with more ex-post loan-level defaults and even with more bank failures, consistent with theories of too soft lending standards in booms (that we refer to in the previous page and also in the literature review). 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, and that the importance of this credit condition is 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 potential 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 Registry), including a measure of ex-ante risk score.

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.

In Section 3 we explain the empirical strategy. We first study the determinants of loan origination time at the *loan application-level*, 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 granted-level* with ex-post loan defaults and at the *bank level* for bank failures.

Regarding the first question, we use the exogenously-driven VIX (Rey, 2013) to measure the cycle; we use the European VIX index called VSTOXX, though we use the name of (European) VIX throughout the paper. We analyze how the cycle affects loan origination time, also related to measures of ex-ante borrower and lender risk and balance-sheet strength. A key identification problem is that safer, less opaque borrowers may be easier to screen and hence they may have mechanically lower loan origination time unrelated to less screening effort. Therefore, we isolate (in some regressions) our proxy of bank screening via loan origination time by controlling progressively for borrower fundamentals (such as industry, geography or firm fixed effects, also even interacted with time fixed effects). To further separate it from bank balance-sheet strength or banks' different technologies for screening, we also control for different observed and unobserved bank fundamentals (e.g. bank fixed effects); in addition, to analyze even how the same bank in the same period responds differently to firms with different risk, in some regressions, we control for bank-year:month fixed effects.

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 also control for other key determinants as e.g. other lending conditions (e.g. collateral); or (iii) exploit variation from the Christmas holidays period (21st of December to January 7th, after the Three Wise Men or Epiphany day), in which we find shorter origination time (not explained by different applications or granted loans) in a period in which there are substantially more holidays and many more social events (and hence, consistent with the data, faster decisions). 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 similar strong bank distress episodes.

In Section 4 we explain the results. First, exploiting loan applications, we find that—when VIX is lower—banks shorten loan origination time. In particular, a reduction of one standard deviation of VIX shortens loan origination time by 3.7%. Moreover, the shortening of loan origination time (when VIX is lower) is even stronger for ex-ante riskier firms (either proxied by an ex-ante overall credit risk scoring, or by typical specific measures of borrower risk such as high leverage ratio or previously paid high loan-rates). In particular, a reduction of one standard deviation of VIX with an increase of one standard deviation of ex-ante borrower risk shortens origination time by 4.9%.[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 Herfindahl-Hirschman Index (HHI)) and for banks with less capital – both measures proxying bank moral hazard incentives (Freixas and Rochet, 2008). For instance, one standard deviation reduction of these variables (when VIX decreases by another standard deviation) decreases the average origination time by 4.0% and 4.9%, respectively. Moreover, average loan origination time decreases in boom times (VIX lower) for ex-ante riskier loans, especially in areas with more banking competition, but only for less capitalized banks, with a decrease in average origination time by 5.5%.[2] In addition, the pro-cyclical effects of VIX on riskier firms are stronger for banks with more loan applications per branch, proxying bank capacity constraints (5.3% decrease for one standard deviation change of these variables),[3] and hence with similar economic effects as proxies of bank moral hazard incentives.[4]

Further consistent with bank incentives, and only for higher capitalized banks, the pro-cyclical effects (along the cycle proxied by changes in VIX) are weaker for less specialized banks in a geographical area (-2.6%) or for unknown firms to a bank (-1.8%). Both variables (less bank specialization in firms in a local area and unknown firms for the bank, without previous

[1] In addition, we also find that, across the board, ex-ante riskier borrowers have on average higher loan origination time (though, less so in booms).

[2] Figure 2 and 3 show total loan origination time over the cycle without any control. In Figure 3, we find that, comparing boom vs. bust periods for riskier borrowers and weaker capitalized banks, loan origination time increases from 46 to 60 days. These 14 days are over a 30% increase in average loan origination time. Effects are smaller for safer firms and highly capitalized banks.

[3] Despite these variables proxy for higher bank capacity constraints, constrained banks reduce even more loan origination time when VIX is lower and the corporate borrower is riskier.

[4] 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).

information over the last year from lending from a bank to that borrower) proxy for (less) *bank-firm* information, and hence for winner's curse problems in lending (Freixas and Rochet, 2008).[5]

Second, exploiting all *granted* applications, 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 stronger when controlling for firm fundamentals, as safer borrowers have shorter average origination time. Effects are also robust to controlling for bank and other loan conditions (e.g. collateral). Furthermore, results are robust to using variation stemming from the Christmas period that has many social events and several holidays (including full time school holidays), from the last days of December (21st onwards) to the beginning of January (until 7th), as the Christmas period in Spain lasts until January 7th (just after Epiphany day). We find that during this period loan origination time is lower (see Figure 4), also if we control for bank or firm fundamentals, including number of loan applications and granted loans. The instrument does not suffer from weak IV problems, and the estimated effects in the second stage are very similar to OLS ones. Results in the second stage are robust to varying borrower and lender controls as well as particular days chosen for the Christmas period. For example, the estimated coefficients without versus with firm fixed effects (proxying for firm unobservables) are identical in both specifications, or firm observables in this period as compared to other periods are not different. Therefore, the overall results suggest that shorter origination time implies higher loan defaults, consistent with less screening effort.

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 when VIX is lower (6.0% for one standard deviation reduction of VIX) or for ex-ante riskier firms (in this latter case by 6.9% and comparing a firm in the third versus first quartile of distribution of ex-ante risk).[6] For ex-ante weakly capitalized banks, the impact of lower origination time for ex-ante riskier firms on higher ex-post loan defaults is even stronger in areas with more banking competition, proxied by lower HHI (8.0%), or for banks with more applications per branches (9.7%, comparing a firm in the third versus first quartile of distribution). Results are again consistent with bank moral hazard incentives and capacity constraints.

[5] Expansion in a new location or lending to a new borrower (for the bank) have strong information asymmetric problems for the bank as the borrower may have been rejected by (other) lenders with better information, see e.g. Dell'Ariccia and Marquez (2006), Broecker (1990) and Shaffer (1998). See also Gorton and Winton (2003).

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

To push further on the screening 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, or a recapitalization after a stress test exercise carried out by the bank supervisor; and zero otherwise. Results are robust to different definitions, in particular to the strongest case of bank distress (failure), which is direct public (state) intervention of the bank or public bailout with state funding.

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. In particular, the loan origination time effect is robust across all specifications, differently from other loan conditions: e.g. the maturity effect is not statistically significant; the loan spread effect is weaker both statistically and economically; collateral effect is not robust (though when it is significant, its coefficient is larger than origination time, but not statistically different from origination time). Credit volume growth has very similar impact on the likelihood of a bank failure (or a similar related bank distress event) than loan origination time (though somewhat less robust).

Consistent with less screening, 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.

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 related to the credit cycle, with theoretical testable predictions of less bank screening and less generation of information in booms (see e.g. Ruckes, 2004; Dell'Ariccia and Marquez, 2006; Dang, Gorton, Holmström and Ordoñez, 2017; Asriyan, Laeven and Martin, 2020).[7] We contribute to this literature by proxying screening effort by the

[7] 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). 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, in the sense of the question and results; 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.

time difference between a loan application is submitted and the granting time, and by finding the following results.[8] Exploiting loan applications, we show that loan origination time is shorter in booms, especially for ex-ante riskier borrowers, and results suggest that key drivers are bank moral hazard incentives (capital and competition), capacity constraints and borrower-lender information asymmetry. Further consistent with bank incentives, for higher capitalized banks, the pro-cyclical effects are weaker for less specialized banks in a local area or for unknown firms to the bank, proxying both for less borrower-lender information, and winner's curse problems in lending due to asymmetric information. Moreover, exploiting all granted applications, we show that a shorter loan origination time is associated with more (at the granted loan-level) ex-post defaults (especially for loans granted in boom times, and on riskier firms, particularly from less capitalized banks in areas with more banking competition or from banks with more applications per branch). Finally, a shorter 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 theory.

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.[9] 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 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.

[8] Results are robust to controls such as firm or bank fundamentals proxying for firm opaqueness, bank technology for screening, etc. See also the last contribution to the literature at the end of the next page.

[9] 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). See also Mian, Sufi and Verner (2017) for a different sample of years and countries.

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 analyze a full credit cycle, and that we link *ex-ante* loan origination time with *ex-post loan-level* defaults and even *bank-level failures*. Moreover, we also analyze other mechanisms such as bank competition and borrower-lender proxies of information asymmetry.

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 that we have a full credit cycle and our results suggest that bank moral hazard problems, borrower-lender information asymmetry and bank capacity constraints are key drivers.

Moreover, with respect to the aforementioned two papers, in addition to different results or/and mechanisms that we just summarized, we analyze loans to *firms* which tend to be more opaque 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 applications and granted loans, 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 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. For example, 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 also depends on screening effort, as we find that loan origination time (especially to ex-ante riskier firms) is shorter when VIX is lower (also controlling for many unobservables), in part due to (proxies of) bank moral hazard incentives, and moreover 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).[10] We also find that bank capacity constraints (in particular loan applications per branch) matter along the credit cycle, similarly to proxies for bank moral hazard incentives (bank capital and competition). 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,[11] possibly related to analyzing firms (in our case) versus mortgages –households have simpler balance sheets and can be sold easily to even public agencies, while soft information is more important in lending to SMEs.

The paper proceeds as follows. Section 2 describes the data. Section 3 describes the empirical strategy and provides descriptive statistics. Section 4 summarizes the main results. Section 5 offers some 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 about almost every loan granted by a financial institution operating in Spain, including loan applications; (ii) firm-level balance sheet and financial information through the Spanish Mercantile Register, including a measure of firm risk; (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. Apart from identifying the borrower and the financial institution granting the loan, it gathers a substantial

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

[11] Though there are identical median days for banks (40 days) in both papers. Note that fintech lending in Spain to *firms* is very small, also in most countries.

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, 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. 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, by measuring the time elapsed between the lodged application and its potential granting, we construct the loan origination time variable for every loan application. We know the exact time (day) of a loan application and its granting month; however, if the loan is not granted, we do not know the status of the loan, hence we need to impose a maximum delay between a loan application is lodged and its concession.[12] We cap to five months the observed granting time after an application, including banking practices during both booms and busts. Therefore, the loan origination time variable we construct takes six different values: 0, 1, 2, 3, 4 and 5. As a robustness check we also show that the results we get for the five-month window are also valid for the three- and four-month ones. Moreover, when we measure the origination time in days, results are very similar. Figure 1 shows that around 70% of accepted loans are granted within month zero (i.e. granting and application month are the same) and the first month after their request, and more than 85% if we add up the second month. Table 1 shows that origination time has a mean equal to 1.20 (slightly more than one month) and its median is one month (51 and 40 days, respectively). 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 booms and increase (tighten) origination time during the crises (the Global Financial crisis and the Euro Area Sovereign Debt crisis).[13] Moreover, Figures 3 analyzes whether this cyclical pattern depends on the balance sheet strength of borrowers (firms) and lenders (banks). Considering loan applications made by firms to banks above and below the median of their capital ratios,

[12] 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, as well as borrower identifiers so that we can link different applications by the same borrower to different banks, and a full cycle so that we can analyze ex-ante loan application time and ex-post bank failures.

[13] Results are very similar if we control for granted applications or number of applications (not reported). In the regression analysis, we will control for these variables and many others.

the figure shows that loan applications made by firms to banks that are both below their median are more cyclical. Comparing boom versus bust periods for riskier borrowers and weaker capitalized banks, average loan origination time increases from 46 to 60 days, i.e. these 14 days imply a 30% increase in average loan origination time. Effects are smaller for safer firms and highly capitalized 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 are 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 get some exogeneity 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 Registers. By identifying the lender and borrower of any loan, we match bank and firm characteristics with loan characteristics, which allows us to end up with banks' and firms' balance-sheet information at the time a loan application is lodged. For example, firms' credit risk score, capital, interest paid, or banks' capital and size.

Moreover, to analyze the impact of bank competition we use the Herfindahl-Hirschman Index at the level of Spanish municipalities according to the number of loans and, in some specifications, according to the volume of the loans or through the number of banks working in the municipality.

3. Empirical strategy and descriptive statistics

Using the loan application data, we start by investigating how borrower, lender and the economic cycle affect loan origination time. Then, using the sample of granted applications, we study the impact of loan origination time on future default, where we also exploit variation in time due to a period with many social events and holidays. 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 at different levels of data aggregation.

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 and economic cycle and/or on key borrower, lender and local market variables (proxying for 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 the same month in which it was requested) to 5 (if the loan was granted at least 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 108% (Table 1 shows the descriptive statistics of the variables used in the paper and Table A1 in the Appendix reports their definition and units). As robustness test we also work with three and four months, finding similar results, and with the measure in days (see below).

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), but for non-granted loans we do not observe the time when the loan was refused. To tackle this issue in our benchmark regressions we estimate a censored Poisson model, which assumes that there is censoring after 5 months and allows us to work with all loan applications, not only those granted. The Poisson 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), but the drawback of this particular censored approach is that the model only allows for a limited set of fixed effects and standard errors can only be clustered in one dimension. To handle these problems, for the benchmark regressions, we use a Poisson pseudo-maximum-likelihood (PPML) estimator for the whole sample, but using the idea that a loan application that is not granted is equivalent to a loan application granted in the infinity. For the purposes of this paper on loans, we proxy infinity by one hundred months. Results are similar if we consider small numbers such as six or ten months (see section 4.1). Taking this into account, we then show that both estimators (censored Poisson model with 5 months or PPML) give similar results. Moreover, as commented before, as robustness we refine our dependent variable to account for the number of days since the loan application was submitted to the Banco de España until the last day of the month in which the application was granted. We show that both measures give similar results.

Formally, the baseline equation we estimate using PPML estimator is the following:

$$
\begin{aligned}
\textit{Loan origination time}_{ijt} \\
&= \exp\big(\beta_1 VIX_{t-1} + \beta_2 int\ rate\ surprise_{t-1} + firm\ variables_{it-1} + bank\ variables_{jt-1} \\
&+ municipality\ variables_{\mathrm{im}t-1} + \eta_i + \eta_j + s_t\big) + \epsilon_{ijt}, \qquad (1)
\end{aligned}
$$

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 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 exogenous to Spain.[14]

The regressors $firm\ variables_{it-1}$ and $bank\ variables_{j,t-1}$ are vectors of firm and bank time-varying characteristics, respectively. Regarding borrower fundamentals, our main variable of interest is an ex-ante measure of firm risk, based on a scoring function capturing the credit risk of the firm, where higher values of this variable indicate higher risk.[15] For robustness we use other firm balance sheet measures to capture the risk of the firm instead the scoring function, such as firm capital ratio (which averages 31%) or the average loan interest rate on previous debt (with a mean value of 2.7%). Regarding other firms' variables that control for the degree of information asymmetry between the bank and the firm, we include a dummy variable, called *Unknown borrower*, that takes the value one if the firm was not a current borrower of the bank

[14] We get very similar results if we use Spanish GDP change and the change of the overnight interest rate instead of VIX and interest rate surprise. Note that in our regressions, the VIX, the interest rate surprise and the firm risk scoring are standardized, so their summary statistics are not commented.

[15] Instead of using a large set of proxies to capture a firm's ex-ante credit risk we use a scoring function that synthesizes a battery of firm financial and non-financial ratios as a sufficient statistic of a firm's solvency (higher values of these variables are related to more risk). This industry-based scoring follows the spirit of the classic Z-Score model (Altman, 1968) and uses fifteen financial ratios and firm balance sheet characteristics to assign a score to each company. More specifically, the scoring function segments each of the variables used in 9 classes. Each class will have a value between 1 and 9, with 1 being assigned to the lowest risk and 9 to the highest risk. The final score is just the weighted sum of each of the ratings assigned to the firm characteristics analyzed. So, at the end of the process, each company is associated with a continuous measure ranging from 1 to 9, where the higher its value, the higher its likelihood of default. Moreover, we have checked the validity of this variable as an *ex-ante* measure of the credit risk of a firm analyzing whether it is a good predictor of the probability of default for one year ahead of non-defaulted firms for the period considered in this paper. Results show a positive and statistically significant at the 1% coefficient with a F-statistic close to 140.

to which it applies over the last twelve months before the application was made, and zero otherwise (which averages 95%, as the database only considers borrowers that are not currently working with the banks at the time of the application);[16] and an additional dichotomous variable called *Specialized in firm's same province*, capturing the expertise of the bank in the province of the applicant. The percentage of firms that share the province with the lender is 24%. Additionally, given that the firm can ask for the same loan to several banks, we include the number of loan applications made by the firm to different banks (in logs) as a control. Most firms only make one application per month, as its third quartile is one and its average 1.2.[17]

Regarding bank variables and in order to control for and exploit bank fundamentals we consider banks' size as the logarithm of their total assets (which averages 114 billion euros in levels), the capital ratio as a measure of their net worth (defined as the ratio of equity over total assets, which averages 6%), the liquidity ratio (ratio of cash and other liquid assets such as deposits with other credit institutions over total assets, with an average value of 15%), ROA (return on assets, with a mean less than 1% in the sample period), loses over interest margin (the ratio of the bank's loses over its interest margin, which averages 46%), and a ratio indicating the number of loan applications (of non-current firms) a bank has received in the previous month over its total number of branches (as a measure of bank capacity constraints, with a mean value of 10). We also consider the change in the logarithm of total loans within the province it is located at the previous month (its average value is 9.7%).

In addition, we capture the banking structure at the municipality level with the vector $municipality\ variables_{imt-1}$, which includes the Herfindahl-Hirschman Index (HHI) in terms of the number of loans (with an average of 13%) or, in some specifications, the Herfindahl-Hirschman Index in terms of the volume of credit (which averages 6.7%) or the log of the number of banks in the municipality where the firm is located (with an average of 100 and a median of 95 for the variable in levels).

Unobservable bank-specific time-invariant shocks are controlled for with the use of bank fixed effect (η_j). Moreover, as robustness, we use *bank*time* fixed as an additional control in some models. These factors may influence loans' average origination time because they could

[16] This average decreases if we consider longer periods, and results are similar.

[17] As a robustness, in the Appendix we decompose the scoring variable into a battery of firm characteristics and financial ratios that control for the size (logarithm of their total assets) and age (logarithm of their age plus one) of the firm, and that include firms' capital ratio (ratio of own funds over total assets), net liquidity ratio (ratio of the difference between liquid assets and liabilities over total assets), ROA (return on assets), net profit over number of employees (as a measure of firms' productivity), the ratio of fixed employees over total employees, the number of banking relationships (in logs) and the average cost of bank debt and the credit history. Further, we also control for firms' ratio of short-, medium- and long-term credit relative to their total outstanding credit, as well as firms' ratio of their collateralized debt relative to their total debt.

be capturing, for instance, the technology available to a bank to assess the firm's creditworthiness. 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 (η_i). In some specifications we also add *firm* or *firm*time* fixed effects as robustness, but this has the drawback of drastically reducing the sample. Seasonal time fixed effects (s_t) are captured by month fixed effects or by year:month fixed effects, and ϵ_{fjt} is the idiosyncratic error term. When we use the PPML estimate, we can cluster standard errors at the bank, firm and time (year:month) level.[18] Our strategy is to progressively saturate the baseline model to analyze the impact of macro, firm, firm-bank, bank and market characteristics on loan origination time and test its robustness to the inclusion of observables and fixed effects.

We also analyze the heterogeneity of the results to test whether the effect of the financial cycle proxied by VIX and monetary rate surprises on loan origination time differs with the credit risk of the firm, with the degree of asymmetric information between the lender and the borrower at the time of the loan application, with the strength of bank balance sheets or proxies of bank competition. We do this by introducing in the baseline specification double and triple interactions and splitting the sample based on the median value of the banks' capital ratio distribution.

3.2. Loan origination time and lending standards

We also study whether the loan origination time affects the loan's *Future Default*, a dichotomous variable that states whether a loan ever becomes delinquent at some point in the future (until 2016:03).[19] Its average value equals 20% and it has a standard deviation of 0.4 points. Our specification focuses on the same application-level data used in the first part but working only with *granted* loans.[20] We estimate, using OLS, the following baseline linear probability equation:

$$\textit{Future Default}_{ijlt} = \gamma Loan\ origination\ time_{ijt} + firm\ variables_{it-1} + bank\ variables_{jt-1} + loan\ variables_{lt} + \epsilon_{ijlt}, \quad (2)$$

[18] The estimation of the censored Poisson model only allows to cluster at one level. We show the results of clustering at the bank level although results are also statistically significant if instead of bank we cluster at time level or firm level.

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

[20] We have also performed an analysis taking into account selection bias with a two-step approach following Jiménez et al. (2014) which shows similar results.

where the sub-indexes i, j, l and t refer to firm, bank, loan and time, respectively, $Loan\ origination\ time_{ijlt}$ denotes the loan origination time variable defined in section 3.1; $firm\ variables_{it-1}$ is the same set of firm characteristics aforementioned; 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; and ϵ_{fjlt} is the idiosyncratic error-term. As before, standard errors are multi-clustered at bank, firm and time (year: month) level. In additional columns, we add firm fixed effects, and as robustness test, we saturate the model with *firm*year* and *firm*time* (year:month) fixed effects. When bank-time fixed effects are not included, bank variables, the same as in the previous specification, ($bank\ variables_{jt-1}$) are added as controls and some of them included as interactions in some specifications. The VIX variable, absorbed by the time fixed effects, is included in some estimations as an interaction term. As for Equation (1), we use different set of controls, including and excluding bank and firm fixed effects, as well as time fixed effects, and even interacting these effects with time in some regressions.

To push further for identification, we also use more exogenous time variation stemming from the Christmas period that has many social events and holidays (also for school holidays), 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 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. Finally, we also include several interactions between our key variables of interest in the same vein that we follow in the previous subsection 3.1 (e.g. VIX, borrower risk scoring, bank capital and competition).

3.3. Loan origination time and bank failures

If loan origination times proxies for screening, then not only will it be associated at the loan level with future loan defaults, but there will be bank-level effects as well. However, this potential 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 static model where we explain strong distress events of banks over the period 2008-2015 with pre-crisis bank characteristics (using a CAMEL model),[21] and aggregated loan level variables, including the average loan origination time as an additional regressor, fixed as of December 2007 (just before the crisis). 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 banks in Spain experienced strong 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 public (state) intervention of the bank (by Banco de España), 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 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 use the extended definition for the baseline specification and we replace it for the narrow one as robustness. We analyze these events through a Probit model,[22] based on average pre-crisis lending conditions (including loan origination time) and banks' ex-ante overall performance, captured by a CAMEL rating. 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. Specifically, we estimate the probability of bank distress though a Probit model with robust standard errors:

$$Pr(Large\ Distress\ Event_j=1/x_{j2007})=F(\alpha Average\ loan\ origination\ time_{j2007}+bank\ variables_{j2007}), \quad (3)$$

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*$_{j2007}$ is a bank's average origination time of all its outstanding

[21] 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.

[22] Given the low number of observations, the large average value of the dependent variable (close to 80%) and that the model does not include neither large set of 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.

loans at the end of 2007; and *bank variables*$_{j2007}$ is the vector of the CAMEL rating and the bank characteristics employed in the previous equations plus some additional measures of bank lending conditions used in the literature (such as credit growth, percentage of real estate assets, average maturity, collateral or loan interest rates) as of December 2007.[23]

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 (3) show the estimation results of the censored Poisson, columns (4) to (7) display the Poisson pseudo-maximum-likelihood (PPML) estimators. Our purpose is to show the results for the censored model with two specifications: one without time dummies and other with them. Moreover, we want to show that the PPML approach is equivalent to the censored specification replicating columns (2) and (3) with this approach. Then, we show the consistency of the results progressively saturating this latter specification with different fixed effects, something impossible with the censored model. In the appendix, we also show robustness of the results using OLS and Tobit.

Column (1) only includes macro variables. Column (2) adds firms, province, industry and bank variables, bank fixed effects and seasonal dummies. Column (3) includes time (year: month) fixed effects that absorbed the seasonal dummies and the macro variables. Column (4) and (5) replicate the last two previous specifications but with the PPML estimator. Column (4) is our baseline regression and Table 2 in the Appendix reports robustness checks for this specification. Column (6) adds *bank*time* fixed effects to Column (5). Finally, Column (7) adds firm fixed effects to Column (6) instead of province and industry dummies, with the consequent reduction in the number of observations.

Table 2 indicates that loans' origination time is counter-cyclical, i.e. a favorable financial and macroeconomic environment (boom) proxied by lower VIX is negatively associated with the loan origination time. According to column (4), a one standard deviation reduction of VIX decreases loan origination time by 3.7%. Regarding the first versus third quartile of the VIX distribution, column (4) shows that the average loan origination time decreases by around 5.1%. Differently, the monetary interest rate (surprise) is not statistically significant in general.

[23] The first bank falling into severe risk in Spain was in March 2009.

Table 2 also shows that loan origination time increases with the ex-ante risk of the firm, i.e., when the borrower exhibits a high credit risk captured by the credit scoring (higher scoring implies riskier firms). For instance, a one standard deviation increase in the scoring of the firm (more risk) increases the average loan origination time by around 2% for all specifications, but in column (7), it doubles this value to 5.4%. Moreover, the higher the proxies for asymmetric information between the borrower and the lender, the longer the origination time, as the estimated coefficients on *Unknown borrower* (for the bank) or (whether the bank is) *Specialized in firm's same province* reflects.[24] For example, regarding processing a loan application of a borrower that has not worked with the bank in the last 12 months, it increases the loan origination time around 27% for almost all models but the one that includes firm fixed effects (column 7), which shows an increase of 13%. In this line, if the bank is not specialized in the province of the firm, the average granting time increases by around 8%.

Furthermore, from column (4) higher bank competition, which is proxied with lower bank concentration (the Herfindahl-Hirschman Index in the municipality of the loan application), is associated to a decrease in loan origination time by 2.7% (for a one standard deviation decrease in HHI).

In terms of banks characteristics, column (4) of Table 2 also documents that banks that have increased their lending (in the previous month) in the same province where the loan request is done show a shorter loan origination time. In terms of its economic impact, banks that grow by 27% (third versus first quartile of the distribution) decrease the average loan origination time by 3.4%. With regard to other banks characteristics, larger banks, with less capital and more profitable ones are quicker. Finally, loan origination time decreases with the number of loan applications per bank branch (-7.0% for third versus first quartile of the distribution). It is worth noting that the economic impact of bank variables on loan origination time diminishes when time dummies are controlled for (columns (3) and (5)).

Results are moreover largely similar comparing column (2) with (4) or column (3) with (5). Hence the PPML approach provides similar results to the censored Poisson. Tables 1 and 2 of the Appendix show some further robustness tests. Table 1 in the Appendix breaks the borrower risk scoring into a set of firm characteristics. As expected, the higher the creditworthiness of the firm, the lower the loan origination time (see e.g. the estimated

[24] Note that the average value of the variable *unknown borrower* is very high (see Table 1) as the set of loan applications are to non-current borrowers and *unknown* is considered to be unknown by the bank if the non-current borrower has not been a bank's borrower over a relatively short period of time (less than 1 year ago). Results are robust to longer periods of time.

coefficients on firm capital ratio, average previous cost of debt, ROA or bad credit history). The positive coefficient on firm size can be capturing the complexity of the borrower. The last column includes *firm*time* fixed effects on top of *bank*time* dummies. The variables measuring whether a firm is in the province where the bank is specialized or to be a new customer to the bank (i.e. both proxies of lender-borrower information) are still statistically and economically significant even in this specification with a huge set of controls.

Table 2 in the Appendix displays nine further robustness checks for the baseline estimation of Equation (1), that includes bank, time, province and industry fixed effects (column (4) of Table 2). In column (1) we assume that a loan application that is not granted is equivalent to a loan application granted in month 10. Results are almost the same. Figure A1 in the Appendix shows the estimated coefficients on VIX for many different months assigned to non-granted loans. The high stability of the estimates ensures the robustness of the result in the benchmark regression. In column (2), loan origination time is measured in days instead of in months. Results are qualitatively and quantitatively the same. In column (3) a Poisson model is estimated for only granted loans, where we measure perfectly the loan origination time. Moreover, column (4) shows the estimation results for an OLS model under the same sample. In both cases, the magnitude and statistical significance of the coefficients are quite similar. In column (5) a Tobit specification for the log of granting time is estimated. Again, main results remain unchanged. Columns (6) and (7) perform a robustness check to ensure that the results in Table 2 are not biased by the upper limit of 5 months imposed to identify a granted loan. In column (6) we reduce the upper limit for the granting time to at most 4 months instead of 5 months, while in column (7) we set the limit to 3 months. Both estimations ensure that our results are not driven by the choice of this limit. Column (8) saturates the specification with the inclusion of *bank*industry* and *bank*province* dummies to control for bank specialization (Paravisini, Rappoport and Schnabl, 2020). We show that results are similar.

Finally, columns (9) and (10) include two alternative measures of market structure to control for the effect of market competition in the loan origination time. In previous specifications, we proxy the degree of competition in the municipality using the Herfindahl-Hirschman Index using the number of new loans. In column (9) we substitute this measure with the Herfindahl-Hirschman Index that considers the market share for each bank within the municipality in terms of the new credit volume granted in that municipality. In addition, in column (10) we use a simpler indicator, namely the logarithm of the number of banks in the municipality. In line with the previous results, the coefficient on the Herfindahl-Hirschman

Index at the municipality level is positive and significant whereas the log of the number of banks is negative and significance. Therefore, results suggest that an increase in bank competition (more banks or less concentration) decrease loan origination time. All in all, results remain similar in all the robustness checks considered.

4.1.1. Heterogeneity in the determinants of loan origination time

Table 3 documents the heterogeneity of the results.[25] This table reports coefficient estimates for the double and triple interactions of VIX with: (i) firm characteristics (scoring, average cost of debt, firm capital ratio); (ii) firm-bank variables (unknown firm for the lender over the last previous year, bank specialization in the area where the firm is headquartered); (iii) bank characteristics (capital, size, average number of applications per branch) and market's competition characteristics (Herfindal-Hirschman Index). The estimated coefficients capture heterogeneous changes in loan origination time over the cycle depending on ex-ante differences across borrowers, borrower-lender, lenders and geographical areas. In Table 3 we only show the relevant results although all single and double interactions are included in the regression (e.g. when we show a triple interaction, all double interactions and level variables are also estimated depending on the fixed effects, but we do not report all coefficients for the sake of space).

All models in Table 3 but column (7) use as dependent variable the loan origination time measured in months, while column (7) uses a measure in days as a robustness check. We start with column (1) including the interaction terms between VIX and firm risk scoring in the analogous specification of column (5) of Table (2), i.e. the benchmark regression of Table 2 (column (4)) with time fixed effects. Column (2) adds more interaction effects. From column (3) onwards, we include *bank*year:month* fixed effects. Column (4) shows triple interactions of the VIX, firms' scoring and bank characteristics. Column (5) (and (6)) replicate column (4) but for the sample of low (high) capitalized banks, where low capital is below the median. Column (7) uses as dependent variable the loan origination time measured in days. Last, column (8) breaks up firms' scoring into two key risk variables and shows double interactions between VIX and firms' capital ratio and ex-ante cost of debt.

Table 3, column 1, shows that during a positive financial and macro environment (boom) loan origination time is sharply reduced for risky borrowers. This effect is captured by the double interaction between VIX and firms' scoring, which is positive and statistically

[25] In the paper, when interaction terms are included, all variables are demeaned so that the coefficients of the variables in levels estimate the average effect.

significant in every specification. Specifically, loan origination time decreases by 4.9% when VIX decreases in one standard deviation and firm scoring increases in the same proportion. 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.

Columns (2) and (3) further document that, during low VIX periods, banks in more competitive regions (proxied by lower HHI) take less origination time, thereby suggesting that bank competition enhances banks' cyclical behavior with respect to loan origination time. One standard deviation decrease in both VIX and HHI reduce loan origination time by 4.0%. Moreover, we also observe heterogeneity among lenders. Results suggest that the pro-cyclical effects are stronger for less capitalized banks. One standard deviation decrease in both VIX and bank capital reduce loan origination time by 4.9%. Moreover, based on column (5), for less capitalized banks, loan origination time is reduced by 5.2% when VIX is lower, firm risk scoring higher and HHI lower (1 standard deviation in these variables).

However, results suggest that the cyclical pattern driven by VIX on loan origination time diminishes when the information asymmetry between the borrower and the bank is larger, proxied by whether the firm is relatively unknown (it has not worked over the last year with the bank) or when the bank is not specialized in the province of the firm. Results are robust to different definitions of these proxies as e.g. the bank has never lent to that firm or continuous measure of bank specialization (not reported). In both bank specialization and (relatively) unknown borrower, effects are driven only for banks with high capital (see column (6) versus (5)). In particular, for banks with high capital, when VIX is lower by one standard deviation, loan origination time increases by 1.8% for unknown borrowers (for the lender) or decreases by 2.6% in local areas where the bank is specialized. Moreover, when VIX is lower, there is a decrease of 5.3% in loan origination time to ex-ante riskier firms with higher effects for banks' specialized in the local area for lowly capitalized banks.

Furthermore, column (4) and (7) show that the cyclicality driven by VIX of loan origination time for ex-ante riskier firms is more pronounced for banks that receive more applications relatively to its number of branches. Despite these variables proxy for higher bank capacity constraints, constrained banks reduce even more loan origination time when VIX is lower and the corporate borrower is riskier. A reduction in 1 standard deviation of VIX when borrower risk and applications per branch increase by 1 standard deviation reduces loan origination time by 5.3%. Columns (5) and (6) show no differential effects across banks with higher versus lower capital with respect to the latter result.

Finally, analyzing other key firms' risk measures separately instead of using a unique joint measure such as the credit scoring, we observe that during low VIX periods, banks decrease the loan origination time when dealing with lowly ex-ante capitalized firms and with firms with a higher ex-ante cost of debt (column (8)).

All in all, based on Tables 2 and 3, we find that in booms (proxied by lower Euro VIX), banks shorten loan origination time, especially to ex-ante riskier firms. Effects are stronger in areas with more bank competition and for less-capitalized banks (proxying both for bank moral hazard incentives), as well as for banks with more applications per branch (proxying for bank capacity constraints). Further consistent with bank incentives, for highly capitalized banks, pro-cyclical effects are weaker for less specialized banks in a local area or for (relatively) unknown firms to the bank, proxying both for less *bank-firm* information, and hence with winner's curse problems in lending due to information asymmetry.

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. Through 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.

Each column shows a more restrictive model than the predecessor one to fill up the initial specification with different controlling variables. As such, 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 and Appendix), 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 higher in absolute value and statistically significant at 1%. Given that the average default probability is 0.20, a one standard deviation reduction in loan origination time implies an increase of a borrower's average probability of default of around 2%. Moreover, if the loan origination time changes from 3 to 0 months, the future probability of default increases by 4.5%.

We progressively saturate the model with different controls. Column (3) adds loan characteristics to column (2); 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

[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.

*bank*year:month* fixed effects to control for monthly variation within the same bank.[27] Moreover, column (6) includes *firm*year* fixed effects to control for unobserved yearly-variant firm characteristics, instead of using merely firm fixed effects. This restriction entails a loss of observations given that few firms have more than one loan granted in a given year. Column (7) is the most restrictive specification we consider since it restricts the sample to firms which have obtained more than one loan the same year and month.[28] We lose many observations, a decrease by 93% from column (5), but the coefficient is again negative (stronger in absolute value) and statistically significant at 1%.

Column (8) and (9) are two robustness checks of column (5).[29] In column (8) we analyze loan origination time measured by the logarithm of days instead of months on borrowers' future default probability. Results suggest that a 1% decrease on the number of days a bank takes to grant a loan leads the borrower's future default probability to increase by 0.4%. In column (9) we include the time variable measured in months as a categorical variable, where the omitted reference dummy is zero month, i.e., the loan is granted the same month in which it is applied for. Results suggest that the longer a bank takes to grant the loan the higher its impact on reducing the borrower's future default probability. Indeed, the highest economic effect is when the bank grants the credit 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, suggesting concavity). 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).

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 have less time because of many social events and several holidays during this period (including full time school holidays), which would potentially lead them to speed up the process. Columns (10) to (13) indeed show this result in the first stage of loan origination time

[27] To favor comparison across different specifications (columns (1) to (5)), we keep the number of observations constant and equal to the model used in column (5).
[28] This specification also restricts to banks which have granted more than one loan in the same year and month, but this is not a binding restriction.
[29] We have repeated all regressions included in Table 5 without considering loan controls, and the results obtained are qualitatively and quantitatively equivalent to those obtained when including them.

on this Christmas period dummy, where the F-test of the first stages goes from 9.9 to 14.9 depending on different controls.[30]

Moreover, the second stage shows very similar economic effects as the OLS. Columns (11) to (13) as compared to column (10) show results for a variety of specifications with less fixed effects for either firm, bank or other controls. Importantly, neither of these fixed effects or observable controls are 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)). Moreover, the applying firm observables that get a credit in this period as compared to other periods are not different in firm observables (non-reported), e.g. firm risk scoring, size, age, capital ratio, liquidity ratio, ROA, paid loan rates or credit history.

In Table 5 we analyze the heterogeneous results. We consider the baseline regression of column (5) in Table 4 to run different interactions of loans' origination time with firm, macro and bank characteristics.

Table 5 shows that loan origination time is negatively associated with borrowers' future default probability and that this effect is more pronounced for ex-ante riskier firms (proxied by higher credit scoring). Regarding economic effects, e.g. in column (1), a reduction of (one standard deviation of) loan origination time increases the probability of future loan default by 3.0% for less creditworthy firms (those in the third quartile compared with those in the first one). If the origination time changes from 3 months to 0 (application and granting in the same month), the increase in default probability for ex-ante riskier firms is 6.9%. Effects are similar across all specifications.

Column (2) shows that loan origination time is negatively associated with future default more intensively when VIX is lower. A decrease of loan origination time increases the future default during booming periods (first versus third quartile of the distribution of VIX) by 6.5% if the bank spends zero months instead of three to grant the loan (where zero implies that the granting and application occur in the same month).

Column (3) shows that banks that have more loan applications per branch are the ones in which the impact of loan origination time for riskier firms is stronger. Results are robust across the different specifications and economically strong (an increase of 8.3% of the future default probability if the origination time changes from 3 months to 0 and the other variables change in their interquartile range). That is, banks with more capacity constraints reduce the average

[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.

loan applications when VIX is lower (booms) for ex-ante riskier borrowers, and this is associated with substantial ex-post loan defaults.

Column (4) and (5) restrict the sample to firms applying to low (high) capitalized banks (distributed according to the median value of the distribution). Results suggest that for lowly capitalized banks, the impact of loan origination time for riskier firms is enhanced in more competitive markets or for smaller banks (an increase of 8.0% and 10.0%, respectively, of the future default probability if the origination time changes from 3 months to 0 and the other variables change in their interquartile range).

Column (6) of Table 5 shows that the negative effect on future default probability of the granting time is more relevant for lowly capitalized firms and for those with a high cost of capital, in line with the results on credit risk scoring. We observe an increase of 7.2% on the future default probability for lowly capitalized firms (comparing firms in the first vs. third quartile) if banks reduce loan origination time from 3 months to granting the loan in the same month of the application. Moreover, regarding debts' financing cost, the effect of loan origination time reduction for firms with an ex-ante high cost of credit increases their probability of default (comparing firms in the third vs. first quartile) by 6.4% if loan originated time is reduced by three months.

In sum, results suggest that shorter (*loan-level*) origination time is associated with higher ex-post defaults, with stronger effects controlling for firm fundamentals as safer borrowers have shorter average origination time, and also using variation from periods with many social events and holidays. Effects are stronger when the loan is granted when VIX is lower, or for ex-ante riskier firms (even more for weakly capitalized banks, in areas with more bank competition, or for banks with more loan applications per branch). Therefore, as in the loan granting, results suggest that bank moral hazard incentives and bank capacity constraints are key mechanisms explaining the findings.

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. 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.

Column (1) only includes a CAMEL rating of the bank using a set of bank characteristics (size, fraction of construction and real estate loans over total assets, own fund ratio, ROA, NPL ratio, personnel expenses/operating expenses and a liquidity ratio). 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, loan spreads, loan collateral and loan 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. All in all, results suggest that less pre-crisis origination time increases bank failures or other strong distress bank events, with stronger or at least similar (economic and statistical) effects than the other standards analyzed in the literature, thereby overall results suggest that less loan origination time is consistent with less screening.

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. Our results suggest the following:

First, in booms (proxied by lower Euro VIX), banks shorten loan origination time, especially to ex-ante riskier firms. Effects are stronger in areas with more bank competition and for less-capitalized banks (proxying for bank moral hazard incentives), as well as for banks with more applications per branch (proxying for bank capacity constraints). Further consistent with bank incentives, only for highly capitalized banks, pro-cyclical effects are weaker for less specialized banks in a local area or for (relatively) unknown firms to the lender, proxying both variables for less *bank-firm* information, and hence with winner's curse problems in lending due to information asymmetry.

Second, exploiting granted loans, shorter (*loan-level*) origination time is associated with higher ex-post defaults –especially controlling for firm fundamentals as safer borrowers have shorter average origination time, and also using variation from periods with many social events and holidays. Effects are stronger when the loan is granted when VIX is lower, or for ex-ante riskier firms (even more for weakly capitalized banks, in areas with more bank competition, or for banks with more loan applications per branch), again consistent with bank moral hazard incentives and capacity constraints. Furthermore, exploiting bank-level data as well as the global financial crisis that started in 2008, we find that less pre-crisis origination time (aggregated at the bank level) is associated with a higher likelihood of strong financial distress at the bank level (e.g. bank failure), with stronger, or at least similar, economic and statistical effects than the other lending standards analyzed in the literature —credit (volume) growth, weight of real estate portfolio, spreads, collateral and maturity—, thereby suggesting that loan origination time proxies for screening.

References

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

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.

Altman, E.I., 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance*, 23, 589-609

Asriyan, V., Laeven, L. and Martin, A., 2020. Collateral Booms and Information Depletion. ECB and CREI Working paper.

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

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

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.

Mian, A., Sufi, A. and Verner, E., 2017. Household Debt and Business Cycles Worldwide. *Quarterly Journal of Economics*, 132(4), 1755-1817.

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.

Shaffer, S., 1998. The Winner's Curse in Banking. *Journal of Financial Intermediation*, 7 (4), 359-392.

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

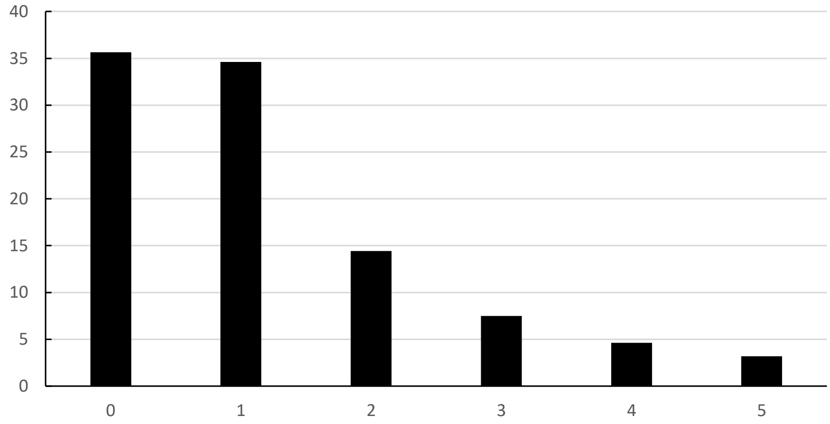
Stein, J. C., 2012. Monetary Policy as Financial-Stability Regulation. *Quarterly Journal of Economics*, 127(1), 57-95.

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

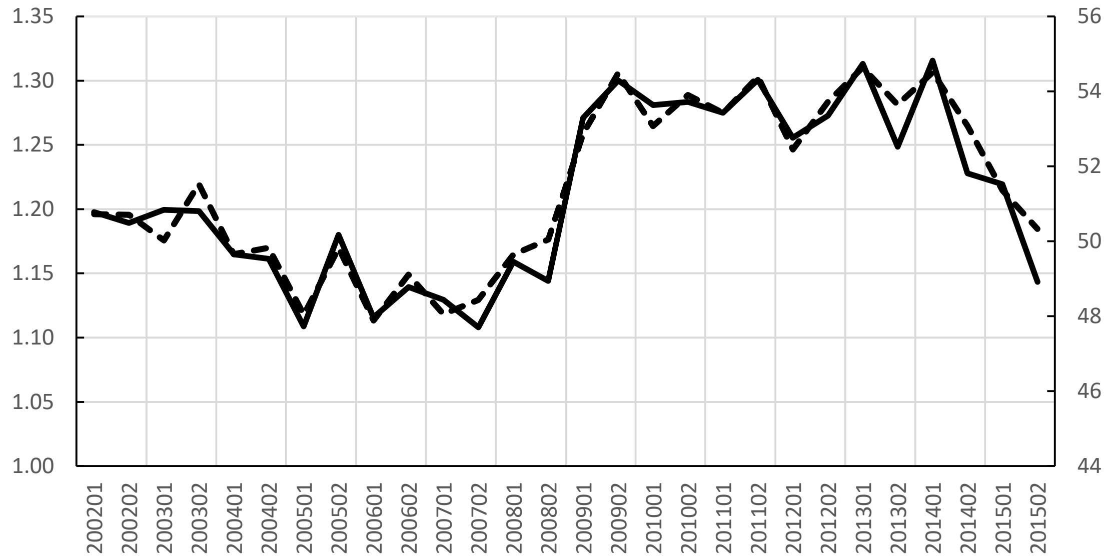
Distribution of the loan origination time, in months (%)



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

FIGURE 2

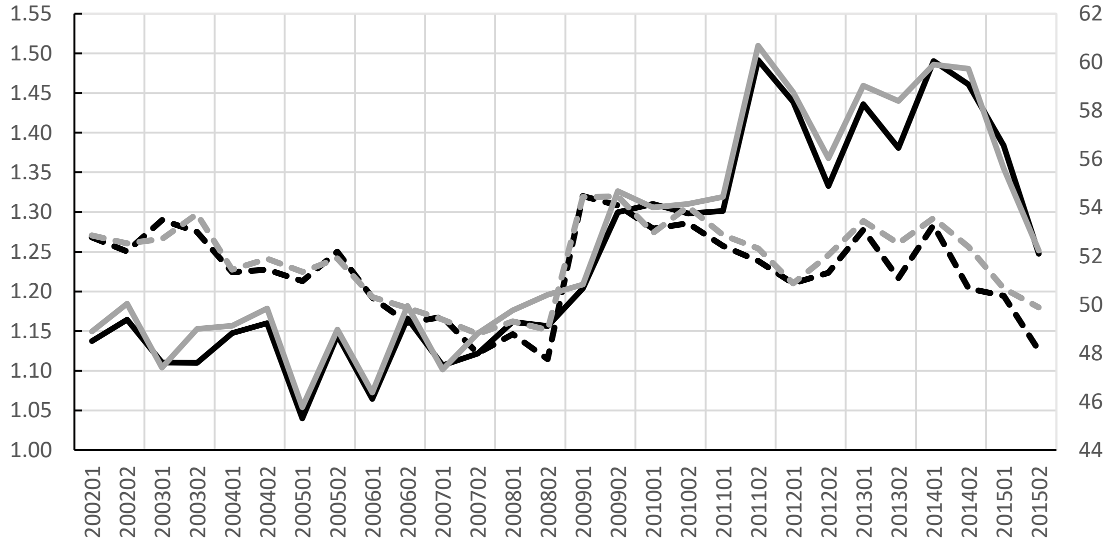
Evolution of the average origination time by semester



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

FIGURE 3

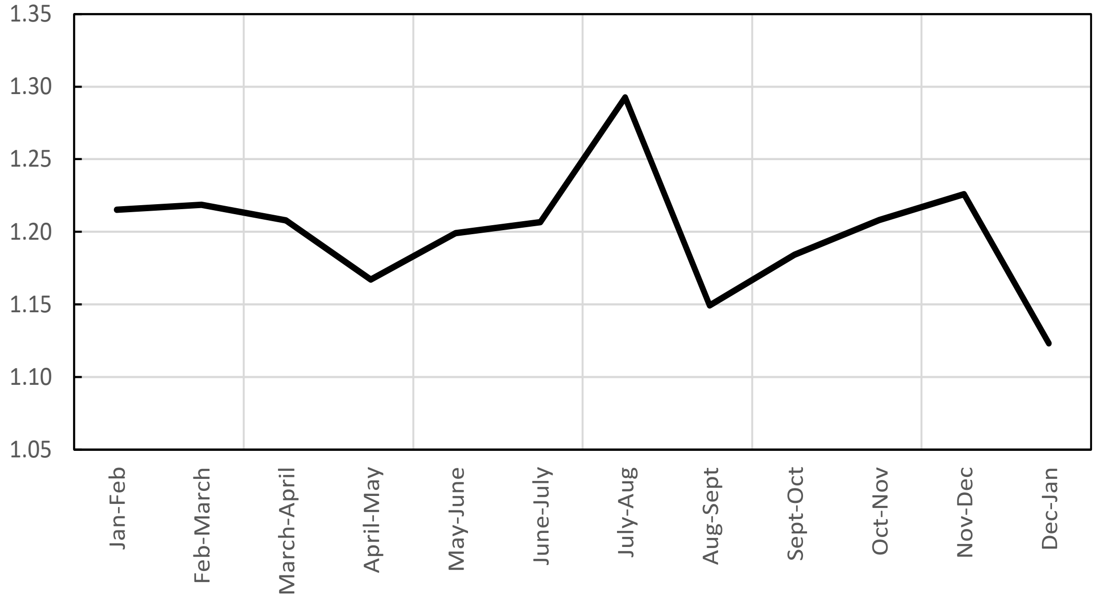
Evolution of the average loan origination time, by semester and by firms' and banks' strength



Note. This figure shows the average loan origination time, which measures the number of months (dark line, left-hand scale) or days (light line, right-hand scale) a bank takes to originate 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 since the 15th of each month until the 15th of the following month.

TABLE 1
Descriptive statistics

	Mean	Median	SD	P25	P75
Main variables					
Loan origination time$_{ijt}$ (months)	1.203	1.000	1.297	0.000	2.000
Loan origination time$_{ijt}$ (days)	51.129	40.000	38.974	23.000	68.000
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	-0.171	1.000	-0.785	0.583
Interest rate surprise$_{t-1}$	0.000	0.049	1.000	-0.206	0.239
Firm variables (i)					
Risk Scoring$_{it-1}$	0.000	-0.086	1.000	-0.836	0.764
Unknown borrower$_{ijt-1}$	0.950	1.000	0.219	1.000	1.000
Bad credit history$_{it-1}$	0.095	0.000	0.293	0.000	0.000
Specialized in firm's same province$_{ijt-1}$	0.237	0.000	0.425	0.000	0.000
log(No. of loan applications made$_{it}$)	0.127	0.000	0.308	0.000	0.000
log(Total assets$_{it-1}$)	6.530	6.656	1.363	5.588	7.698
log(Age$_{it-1}$)	2.294	2.398	0.849	1.792	2.890
Capital ratio$_{it-1}$	0.310	0.260	0.239	0.112	0.473
ROA$_{it-1}$	0.079	0.067	0.091	0.026	0.124
Productivity$_{it-1}$	0.037	0.013	0.097	0.002	0.050
Liquidity ratio$_{it-1}$	0.084	0.037	0.109	0.009	0.115
Cost of debt$_{it-1}$	0.027	0.023	0.023	0.008	0.040
Permanent employees/Total employees$_{it-1}$	0.770	0.881	0.275	0.618	1.000
Short-term bank debt/Total bank debt$_{it-1}$	0.152	0.000	0.298	0.000	0.081
Medium-term bank debt/Total bank debt$_{it-1}$	0.091	0.000	0.222	0.000	0.000
Long-term bank debt/Total bank debt$_{it-1}$	0.087	0.000	0.234	0.000	0.000
Collateralized bank debt/Total bank debt$_{it-1}$	0.079	0.000	0.226	0.000	0.000
Loan variables					
log(Credit volume)	4.020	3.912	1.214	3.178	4.779
Non-collateralized	0.915	1.000	0.279	1.000	1.000
Long-term	0.099	0.000	0.299	0.000	0.000
Local competition variables					
HHI (number of loans)$_{it-1}$	0.131	0.108	0.095	0.080	0.146
log(No. of banks in the province$_{it-1}$)	4.544	4.554	0.387	4.317	4.898
HHI (volume of loans)$_{it-1}$	0.067	0.063	0.033	0.047	0.078
Bank variables (j)					
Δlog(Total loans in a province$_{jt-1}$)	0.097	0.070	0.190	-0.046	0.221
Log(Total Assets$_{jt-1}$)	17.748	17.932	1.562	16.812	18.904
Capital ratio$_{jt-1}$	0.060	0.055	0.024	0.044	0.071
Liquidity ratio$_{jt-1}$	0.148	0.138	0.071	0.100	0.178
ROA$_{jt-1}$	0.006	0.006	0.007	0.004	0.009
Losses/Interest margin$_{jt-1}$	0.462	0.343	0.478	0.208	0.574
No. of loan applications received/No. branches$_{jt-1}$	10.140	0.645	7.954	3.606	15.204

Note. This table reports summary statistics of the variables. The mean, median, standard deviation, first quartile and third quartile are displayed. The definition of the variables can be found in the Appendix.

TABLE 2
Determinants of loan origination time: overall effects

Dependent variable:	Loan origination time$_{ijt}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Macro variables (t)							
VIX$_{t-1}$	0.054***	0.039***		0.037***			
	(0.008)	(0.005)		(0.006)			
Interest rate surprise$_{t-1}$	0.002	0.003**		0.002			
	(0.008)	(0.001)		(0.004)			
Firm variables (i)							
Risk Scoring$_{it-1}$		0.018***	0.020***	0.016***	0.018***	0.019***	0.054***
		(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.003)
Unknown borrower$_{ijt-1}$		0.267***	0.269***	0.265***	0.266***	0.271***	0.130***
		(0.015)	(0.015)	(0.014)	(0.014)	(0.013)	(0.017)
Specialized in firm's same province$_{ijt-1}$		-0.090***	-0.090***	-0.079***	-0.079***	-0.086***	-0.082***
		(0.016)	(0.013)	(0.017)	(0.014)	(0.010)	(0.008)
log(No. of loan applications made$_{it}$)		0.098***	0.093***	0.087***	0.081***	0.082***	0.032***
		(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.006)
Local competition variables							
HHI (number of loans)$_{it-1}$		0.316***	0.284***	0.286***	0.263***	0.258***	0.444***
		(0.056)	(0.052)	(0.044)	(0.041)	(0.040)	(0.050)
Bank variables (j)							
Δlog(Total loans in a province$_{jt-1}$)		-0.140***	-0.048***	-0.127***	-0.039**	-0.009	-0.016
		(0.035)	(0.018)	(0.033)	(0.017)	(0.016)	(0.011)
log(Total assets$_{jt-1}$)		0.190***	-0.145***	0.192***	-0.122***		
		(0.026)	(0.051)	(0.027)	(0.042)		
Capital ratio$_{jt-1}$		1.138***	-0.086	0.935**	-0.044		
		(0.434)	(0.755)	(0.428)	(0.675)		
Liquidity ratio$_{jt-1}$		-0.574***	-0.159	-0.577***	-0.157		
		(0.168)	(0.134)	(0.151)	(0.128)		
ROA$_{jt-1}$		-4.399***	-2.601**	-3.742***	-2.389**		
		(1.312)	(1.191)	(1.118)	(0.976)		
Losses/Interest margin$_{jt-1}$		-0.006	-0.006	-0.008	-0.007		
		(0.014)	(0.016)	(0.012)	(0.013)		
No. of loan applications received/No. branches$_{jt-1}$		-0.079***	-0.083***	-0.072***	-0.075***		
		(0.014)	(0.020)	(0.015)	(0.019)		
Province Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	-
Industry Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	-
Firm Fixed Effects	No	No	No	No	No	No	Yes
Seasonal (Month) Fixed Effects	No	Yes	-	Yes	-	-	-
Year:Month Fixed Effects	No	No	Yes	No	Yes	-	-
Bank Fixed Effects	No	Yes	Yes	Yes	Yes	-	-
Bank*Year:Month Fixed Effects	No	No	No	No	No	Yes	Yes
No. of Observations	1,418,909	1,418,909	1,418,909	1,418,909	1,418,909	1,418,909	1,259,440
No. of uncensored observations	604,950	604,950	604,950				

Note. This table reports estimates from a Poisson model for the period 2002:02 to 2015:12. Columns (1) to (3) estimate the censored version where the upper limit is above 5 months. The dependent variable is loan origination time, which measures the number of months a bank takes to originate a loan after an application. Coefficients are listed in the first row, robust standard errors that are corrected for (multi-)clustering at the bank (columns 1 to 3), year: month, and firm level (columns 4 to 7) 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: heterogeneity effects

Dependent variable: Loan origination time$_{ijt}$	Months	Months	Months	Months	Months Low Capitalized banks	Months High Capitalized banks	Days	Months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VIX_{t-1}*Risk Scoring$_{it-1}$	0.012***	0.012***	0.013***	0.007***	0.009***	0.008**	0.007***	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	
VIX_{t-1}*HHI (number of loans)$_{it-1}$		-0.036***	-0.033***	-0.031***	0.006	-0.074*	-0.031***	-0.036***
		(0.011)	(0.011)	(0.011)	(0.046)	(0.046)	(0.011)	(0.012)
VIX_{t-1}*Unknown borrower$_{it-1}$		-0.015**	-0.012*	-0.012*	-0.008	-0.019*	-0.012*	
		(0.008)	(0.006)	(0.007)	(0.007)	(0.011)	(0.007)	
VIX_{t-1}*Specialized in firm's same province$_{it-1}$		0.008	0.006	0.006	0.003	0.011**	0.006	
		(0.005)	(0.004)	(0.004)	(0.007)	(0.004)	(0.004)	
VIX_{t-1}*log(Total assets$_{jt-1}$)		-0.001						
		(0.003)						
VIX_{t-1}*Bank capital ratio$_{jt-1}$		-0.486***						
		(0.181)						
VIX_{t-1}*No. of loan applications received/No. branches$_{jt-1}$		-0.004						
		(0.011)						
VIX_{t-1}*Risk Scoring$_{it-1}$*HHI (number of loans)$_{it-1}$				-0.010	-0.059*	-0.009	-0.010	
				(0.014)	(0.033)	(0.028)	(0.014)	
VIX_{t-1}*Risk Scoring$_{it-1}$*Unknown borrower$_{ijt}$				0.001	0.005	0.002	0.001	
				(0.005)	(0.007)	(0.016)	(0.005)	
VIX_{t-1}*Risk Scoring$_{it-1}$*Specialized in firm's same province$_{it-1}$				0.003	0.004*	-0.001	0.003	
				(0.002)	(0.002)	(0.007)	(0.002)	
VIX_{t-1}*Risk Scoring$_{it-1}$*No. of loan applications received/No. branches$_{jt-1}$				0.006***	0.000	-0.002	0.006***	
				(0.002)	(0.003)	(0.003)	(0.002)	
VIX_{t-1}*Firm capital ratio$_{it-1}$								-0.031***
								(0.006)
VIX_{t-1}*Cost of Debt$_{it-1}$								0.278***
								(0.068)
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year:Month Fixed Effects	Yes	Yes	-	-	-	-	-	-
Bank Fixed Effects	Yes	Yes	-	-	-	-	-	-
Bank*Year:Month Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	1,418,909	1,418,909	1,418,909	1,418,909	708,972	708,322	1,418,909	1,418,909

Note. This table reports estimates from a Poisson model for the period 2002:02 to 2015:12. The dependent variable is loan origination time, which measures the number of days or months a bank takes to originate a loan application. 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. In columns (5) and (6) low- or high-capitalized banks are defined according to its median value (below or above). When double or triple interactions are included, the estimation also controls for all terms of lower order. "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	-0.002*	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***	-0.007***			-0.004**	-0.005**	-0.006**	-0.006**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)			(0.002)	(0.002)	(0.002)	(0.003)
ln(Loan origination time in days)								-0.004***					
								(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)
Bank FE	Yes	Yes	Yes	-	-	-	-	-	-	-	Yes	No	No
Province & Industry Fixed Effects	Yes	-	-	-	-	-	-	-	-	-	-	-	Yes
Firm FE	No	Yes	Yes	Yes	Yes	-	-	Yes	Yes	Yes	Yes	Yes	No
Firm characteristics	No	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
Year:month FE	Yes	Yes	Yes	Yes	-	-	-	-	-	-	Yes	Yes	Yes
Firm*Year FE	No	No	No	No	No	Yes	-	No	No	No	No	No	No
Firm*Year:month FE	No	No	No	No	No	No	Yes	No	No	No	No	No	No
Bank*year FE	No	No	No	Yes	-	-	-	-	-	-	No	No	No
Bank*year:month FE	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	0.845	0.843	0.725	0.725				
F test										13.7	9.9	10.6	14.9
No of Observations	502,994	502,994	502,994	502,994	502,994	271,799	35,152	502,994	502,994	502,994	502,994	502,994	502,994

Note. This table reports estimates from a linear probability model using ordinary least square for the period 2002:02 to 2015:12. The dependent variable is future default which measures whether a firm defaulted the loan granted by the bank for which loan origination time is measured. Columns (10) to (13) 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: heterogeneity effects

Dependent variable: Future Default$_{ijt}$				Low Capitalized banks	High Capitalized banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Loan origination time$_{ijt}$ (LOT$_{ijt}$)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
LOT$_{ijt}$*Risk Scoring$_{it-1}$	-0.001***	-0.001***	-0.001***	-0.001	-0.002***	
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	
LOT$_{ijt}$*VIX$_{t-1}$		0.001***	0.001***	0.000	0.001	0.001***
		(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
LOT$_{ijt}$*Risk Scoring$_{it-1}$*Herfindahl Index$_{it-1}$			0.002	0.008**	0.000	
			(0.002)	(0.004)	(0.004)	
LOT$_{ijt}$*Risk Scoring$_{it-1}$*Unknown borrower$_{it-1}$			0.001	-0.000	0.001	
			(0.001)	(0.001)	(0.001)	
LOT$_{ijt}$*Risk Scoring$_{it-1}$*Specialized in firm's same province$_{it-1}$			-0.001	-0.000	-0.000	
			(0.001)	(0.001)	(0.001)	
LOT$_{ijt}$*Risk Scoring$_{it-1}$*log(Total assets$_{jt-1}$)			0.000	0.001**	0.000	
			(0.000)	(0.000)	(0.000)	
LOT$_{ijt}$*Risk Scoring$_{it-1}$*Bank capital ratio$_{jt-1}$			-0.028			
			(0.017)			
LOT$_{ijt}$*Risk Scoring$_{it-1}$*No. of loan applications received/No. branches$_{jt-1}$			-0.001*	-0.002**	0.001**	
			(0.000)	(0.001)	(0.000)	
LOT$_{ijt}$*VIX$_{t-1}$*Herfindahl Index$_{it-1}$			-0.001	-0.006	0.006	
			(0.003)	(0.004)	(0.004)	
LOT$_{ijt}$*VIX$_{t-1}$*Unknown borrower$_{it-1}$			0.000	0.000	-0.000	
			(0.001)	(0.001)	(0.001)	
LOT$_{ijt}$*VIX$_{t-1}$*Specialized in firm's same province$_{it-1}$			0.000	-0.000	0.000	
			(0.001)	(0.001)	(0.001)	
LOT$_{ijt}$*VIX$_{it-1}$*log(Total assets$_{jt-1}$)			-0.000	0.000	-0.000	
			(0.000)	(0.001)	(0.000)	
LOT$_{ijt}$*VIX$_{t-1}$*Bank capital ratio$_{jt-1}$			0.003			
			(0.019)			
LOT$_{ijt}$*VIX$_{t-1}$*No. of loan applications received/No. branches$_{jt-1}$			0.000	0.002	-0.002	
			(0.001)	(0.001)	(0.001)	
LOT$_{ijt}$*Firm capital ratio$_{it-1}$						0.005***
						(0.002)
LOT$_{ijt}$*Cost of Debt$_{it-1}$						-0.041***
						(0.016)
Bank*year:month FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm 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	0.724	0.724	0.765	0.776	0.724
No. of Observations	502,994	502,994	502,994	211,723	208,343	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. 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. In columns (4) and (5) lowly or highly capitalized banks are defined according to its median value (below or above). 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

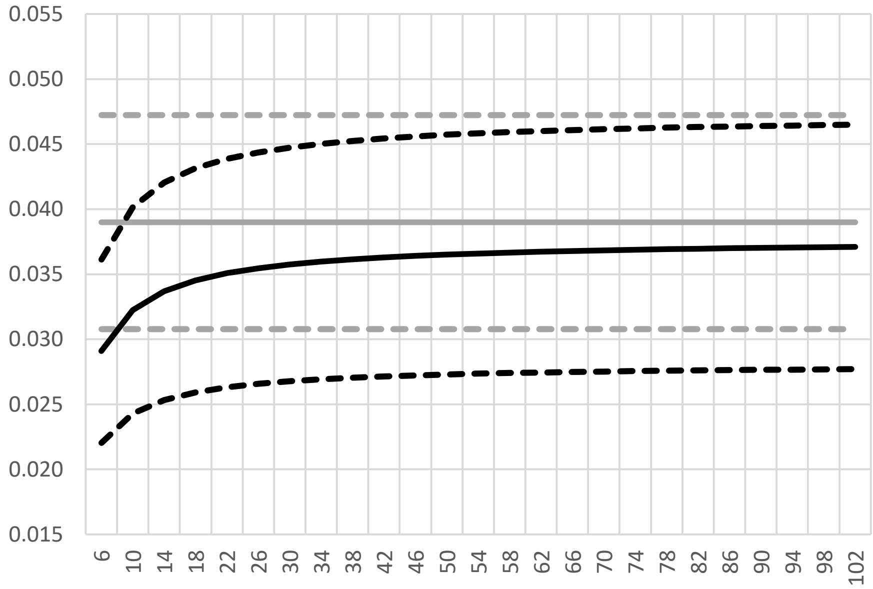
Loan origination time on future bank-level distress probability

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)
Averate 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 model where banks' default probability is estimated through a Probit model (as there are no fixed effects and interactions). 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:quarter fixed effect derived from a regression where the dependent variable is the loan origination time and as additional controls firm*Year:quarter and bank characteristics are included. All variables are standardized to facilitate the comparison of the estimated coefficients. 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

FIGURE A1
Estimated coefficients on VIX of censored Poisson vs. PPML for different months assigned to non-granted loans



Note. This figure shows the estimated coefficients on VIX of censored Poisson from column (2) of Table 2 (light line) vs. PPMML analogous to column (4) of Table 2 (dark line) for different months assigned to non-granted loans. Confidence bands at 90%.

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*
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*
Interest rate surprise$_{t-1}$	standardized	European (3-month interest rate) surprises following Jarociński and Paradi (2018) at *t-1*
Firm variables (i)		
Risk Scoring$_{it-1}$	standardized	Scoring based on firm characterisctics to summarize into one variable many different observable firm factors capturing the observed risk profile of the firm at *t-1*. More scoring implies more risk
Unknown firm$_{ijt-1}$	0/1	A dummy variable which equals one if firm *i* was not a current customer of bank *j* at *t-1* , and zero otherwise
More than one bank$_{it-1}$	0/1	A dummy variable which equals one if firm *i* had more than one banking relationship at *t-1*
Bad credit history$_{it-1}$	0/1	A dummy variable which equals one if firm *i* had non-performing outstanding loans until *t* , and equals zero otherwise
Specialized in firm's same province$_{ijt-1}$	0/1	A dummy variable which equals one if bank *j* provides most of its credit in the province where firm *i* has its headquarter at *t-1* , and equals 0 otherwise
Number of loan applications made$_{it}$	0.0x	Number of total loan applications made by firm *i* to different banks at time *t*
log(Total assets$_{it-1}$)	log(000 €)	The log of total assets of firm *i* at *t-1*
log(Age$_{it-1}$)	log(years)	The log of the age of firm *i* plus one at *t-1*
Capital ratio$_{it-1}$	0.0x%	Own funds over total assets of firm *i* at *t-1*
ROA$_{it-1}$	0.0x%	Return of Assets of firm *i* at *t-1*
Productivity$_{it-1}$	0.0x%	The log of sales over the number of employees of firm *i* at *t-1*
Liquidity ratio$_{it-1}$	0.0x%	The ratio of current assets minus current liabilities over total assets of firm *i* at *t-1*
Cost of debt$_{it-1}$	0.0x%	Average interest rate of all outstanding loans of firm *i* at *t-1*
Permanent employees/Total employees$_{it-1}$	0.0x%	The ratio of fixed employees over total employees of firm *i* at *t-1*
Short-term bank debt/Total bank debt$_{it-1}$	0.0x%	The ratio of short-term bank debt (<1 year) over total bank debt of firm *i* at *t-1*
Medium-term bank debt/Total bank debt$_{it-1}$	0.0x%	The ratio of medium-term bank debt (1-5 years) over total bank debt of firm *i* at *t-1*
Long-term bank debt/Total bank debt$_{it-1}$	0.0x%	The ratio of long-term bank debt (>5 years) over total bank debt of firm *i* at *t-1*
Collateralized bank debt/Total bank debt$_{it-1}$	0.0x%	The ratio of collateralized bank debt over total bank debt of firm *i* at *t-1*
Loan variables		
log(Credit volume)	log(000 €)	The log of committed credit of the loan
Non-collateralized	0/1	A dummy variable which equals one if the loan is not collateralized, and zero otherwise
Long-term	0/1	A dummy variable which equals one if the maturity of the loan is greater than 5 years, and zero otherwise
Local competition variables		
HHI$_{it-1}$		The Herfindahl Index in terms of the number of loans or in terms of the volume of credit
log(No. of banks in the province$_{it-1}$)	log(banks)	Logarithm of the number of banks in the province firm *i* is located at *t-1*
Bank variables (j)		
Δlog(Total loans in a province$_{it-1}$)	0.0x%	The change in the logarithm of total loans of bank *j* in the province of firm *i* at *t-1*
Log(Total Assets$_{jt-1}$)	log(000 €)	The logarithm of total assets of bank *j* at *t-1*
Capital ratio$_{jt-1}$	0.0x%	The ratio of bank equity over total assets of bank *j* at *t-1*
Liquidity ratio$_{jt-1}$	0.0x%	The ratio of liquid assets (cash and balance with central banks, and loans and advances to governments and credit institutions) over total assets of bank *j* at *t-1*
ROA$_{jt-1}$	0.0x%	The total net income over total assets of bank *j* at *t-1*
Losses/Interest margin$_{jt-1}$	0.0x%	The ratio of losses over interest margin of bank *j* at *t-1*
No. of loan applications received/No. branches$_{jt-}$	0.0x	The number of loan applications a bank *j* receives divided by its number of branches at *t-1*

TABLE A2
Determinants of origination time: firm variables

Dependent variable:	Loan origination time$_{ijt}$				
	(1)	(2)	(3)	(4)	(5)
Macro variables (t)					
VIX$_{t-1}$	0.037***	0.035***			
	(0.005)	(0.005)			
Interest rate surprise$_{t-1}$	0.002**	0.002			
	(0.001)	(0.004)			
Firm variables (i)					
Unknown borrower$_{ijt-1}$	0.263***	0.259***	0.265***	0.133***	0.193***
	(0.015)	(0.014)	(0.014)	(0.017)	(0.019)
Bad credit history$_{it-1}$	0.035***	0.033***	0.035***	0.081***	
	(0.007)	(0.007)	(0.007)	(0.008)	
log(Total assets$_{it-1}$)	0.063***	0.049***	0.047***	0.039***	
	(0.008)	(0.008)	(0.008)	(0.008)	
log(1+Age$_{it-1}$)	0.015***	0.018***	0.015***	0.015	
	(0.004)	(0.004)	(0.005)	(0.011)	
Capital ratio$_{it-1}$	-0.026*	-0.018	-0.022	-0.098***	
	(0.014)	(0.013)	(0.014)	(0.016)	
ROA$_{it-1}$	-0.314***	-0.330***	-0.317***	-0.253***	
	(0.026)	(0.022)	(0.019)	(0.018)	
Liquidity ratio$_{it-1}$	0.032	0.027	0.021	0.109***	
	(0.041)	(0.041)	(0.040)	(0.024)	
Productivity$_{it-1}$	0.066***	0.043***	0.035**	-0.074***	
	(0.016)	(0.014)	(0.015)	(0.014)	
Cost of debt$_{it-1}$	0.231*	0.161	0.146	0.578***	
	(0.136)	(0.149)	(0.143)	(0.114)	
Permanent employees/Total employees$_{it-1}$	0.023***	0.023***	0.021***	0.024***	
	(0.004)	(0.005)	(0.005)	(0.006)	
More than one bank$_{it-1}$	-0.066***	-0.068***	-0.067***	0.110***	
	(0.009)	(0.009)	(0.009)	(0.011)	
Short-term bank debt/Total bank debt$_{it-1}$	-0.022**	-0.031**	-0.028**	0.073***	
	(0.011)	(0.013)	(0.013)	(0.013)	
Medium-term bank debt/Total bank debt$_{it-1}$	0.055***	0.059***	0.059***	0.094***	
	(0.011)	(0.011)	(0.011)	(0.013)	
Long-term bank debt/Total bank debt$_{it-1}$	0.092***	0.089***	0.088***	0.096***	
	(0.011)	(0.010)	(0.010)	(0.018)	
Collateralized bank debt/Total bank debt$_{it-1}$	0.050***	0.046***	0.047***	0.033**	
	(0.007)	(0.006)	(0.006)	(0.013)	
Specialized in firm's same sector$_{ijt-1}$	-0.006	0.002	-0.001	0.008	-0.001
	(0.010)	(0.010)	(0.011)	(0.010)	(0.016)
Specialized in firm's same province$_{ijt-1}$	-0.076***	-0.070***	-0.079***	-0.079***	-0.059***
	(0.016)	(0.016)	(0.011)	(0.008)	(0.014)
log(No. of loan applications made$_{it}$)	0.086***	0.082***	0.078***	0.035***	
	(0.010)	(0.011)	(0.010)	(0.006)	
Local competition variables					
HHI (number of loans)$_{it-1}$	0.321***	0.286***	0.269***	0.442***	
	(0.054)	(0.042)	(0.039)	(0.050)	
Bank variables (j)					
Δlog(Total loans in a province$_{jt-1}$)	-0.128***	-0.111***	-0.011	-0.015	-0.007
	(0.033)	(0.030)	(0.015)	(0.010)	(0.021)
log(Total assets$_{jt-1}$)	0.157***	0.159***			
	(0.024)	(0.026)			
Capital ratio$_{jt-1}$	0.863*	0.644			
	(0.453)	(0.442)			
Liquidity ratio$_{jt-1}$	-0.549***	-0.556***			
	(0.156)	(0.139)			
ROA$_{jt-1}$	-3.710***	-3.054***			
	(1.249)	(1.061)			
Losses/Interest margin$_{jt-1}$	-0.005	-0.007			
	(0.013)	(0.011)			
No. of loan applications received/No. branches$_{jt-1}$	-0.080***	-0.075***			
	(0.012)	(0.012)			
Province Fixed Effects	Yes	Yes	Yes	-	-
Industry Fixed Effects	Yes	Yes	Yes	-	-
Firm Fixed Effects	No	No	No	Yes	-
Firm*Year:Month Fixed Effects	No	No	No	No	Yes
Seasonal (Month) Fixed Effects	Yes	Yes	-	-	-
Bank Fixed Effects	Yes	Yes	-	-	-
Bank*Year:Month Fixed Effects	No	No	Yes	Yes	Yes
No. of Observations	1,418,909	1,418,909	1,418,909	1,259,440	199,723
No. of uncensored observations	604,950				

Note. This table reports estimates from a Poisson model for the period 2002:02 to 2015:12. Column (1) estimates the censored version where the upper limit is above 5 months. The dependent variable is loan origination time, which measures the number of months a bank takes to originate a loan after an application. 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
Determinants of loan origination time: robustness results

Dependent variable: Loan Origination Time (LOT)$_{ijt}$	Months	Days	Months							
				OLS	Tobit					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Only granted			LOT≤4	LOT≤4	Bank*Indus. Bank*Prov.		
Macro variables (t)										
VIX$_{t-1}$	0.032***	0.037***	0.018***	0.013***	0.065***	0.036***	0.034***	0.036***	0.040***	0.043***
	(0.005)	(0.006)	(0.004)	(0.003)	(0.010)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
Interest rate surprise$_{t-1}$	0.002	0.002	0.006**	0.003**	0.005***	0.002	0.002	0.002	0.002	0.002
	(0.003)	(0.004)	(0.002)	(0.001)	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)
Firm variables (i)										
Risk Scoring$_{it-1}$	0.014***	0.016***	0.004*	0.004*	0.030***	0.015**	0.014**	0.016**	0.017***	0.018***
	(0.005)	(0.006)	(0.003)	(0.002)	(0.011)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Unknown borrower$_{ijt-1}$	0.230***	0.263***	0.120***	0.102***	0.413***	0.250***	0.231***	0.251***	0.266***	0.264***
	(0.012)	(0.014)	(0.008)	(0.006)	(0.028)	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)
Specialized in firm's same province$_{ijt-1}$	-0.071***	-0.078***	-0.061***	-0.046***	-0.154***	-0.076***	-0.074***	0.000	-0.046***	-0.075***
	(0.014)	(0.016)	(0.007)	(0.005)	(0.026)	(0.016)	(0.015)	(.)	(0.011)	(0.016)
log(No. of loan applications made$_{it}$)	0.077***	0.086***	0.054***	0.059***	0.183***	0.082***	0.077***	0.077***	0.086***	0.082***
	(0.012)	(0.014)	(0.007)	(0.006)	(0.023)	(0.014)	(0.013)	(0.013)	(0.015)	(0.014)
Local competition variables										
HHI (number of loans)$_{it-1}$	0.237***	0.284	0.020	0.012	0.544***	0.270***	0.251***	0.292***		
	(0.038)	(0.044)	(0.018)	(0.014)	(0.119)	(0.043)	(0.040)	(0.045)		
HHI (volume of loans)$_{it-1}$									0.224*	
									(0.119)	
log(No. of banks in the province$_{it-1}$)										-0.106*
										(0.062)
Bank variables (j)										
Δlog(Total loans in the province$_{jt-1}$)	-0.109***	-0.126***	-0.064***	-0.043***	-0.245***	-0.124***	-0.117***	-0.142***	-0.127***	-0.120***
	(0.028)	(0.033)	(0.019)	(0.015)	(0.064)	(0.032)	(0.030)	(0.033)	(0.033)	(0.027)
log(Total assets$_{jt-1}$)	0.165***	0.190***	0.066***	0.048***	0.290***	0.186***	0.176***	0.188***	0.192***	0.169***
	(0.023)	(0.027)	(0.011)	(0.008)	(0.038)	(0.026)	(0.024)	(0.026)	(0.026)	(0.027)
Capital ratio$_{jt-1}$	0.986**	0.925**	1.596***	1.260***	1.590**	0.978**	1.036**	0.943**	1.040**	0.652
	(0.394)	(0.423)	(0.335)	(0.256)	(0.625)	(0.418)	(0.410)	(0.409)	(0.408)	(0.489)
Liquidity ratio$_{jt-1}$	-0.458***	0.572***	0.047	0.059	-0.946***	-0.549***	-0.493***	-0.557***	-0.572***	-0.638***
	(0.127)	(0.149)	(0.082)	(0.069)	(0.312)	(0.143)	(0.135)	(0.152)	(0.154)	(0.156)
ROA$_{jt-1}$	-3.329***	-3.712***	-2.583***	-2.032***	-7.681***	-3.634***	-3.520***	-3.637***	-4.031***	-3.659***
	(0.979)	(1.109)	(0.944)	(0.735)	(2.404)	(1.105)	(1.051)	(1.030)	(1.089)	(0.954)
Total losses/Interest margin$_{jt-1}$	-0.007	-0.008	-0.006	-0.006	-0.004	-0.007	-0.007	-0.006	-0.007	-0.010
	(0.010)	(0.012)	(0.012)	(0.009)	(0.025)	(0.012)	(0.011)	(0.012)	(0.012)	(0.013)
No. of loan applications received/ No. branches$_{jt-1}$	-0.065***	-0.071***	-0.037***	-0.039***	-0.131***	-0.070***	-0.067***	-0.073***	-0.073***	-0.092***
	(0.013)	(0.015)	(0.013)	(0.010)	(0.021)	(0.015)	(0.015)	(0.015)	(0.015)	(0.020)
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal (Month) Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Province & Bank*Industry Fixed Effects	No	No	No	No	No	No	No	Yes	No	No
No. of Observations	1,418,909	1,418,909	604,950	604,950	1,418,909	1,418,909	1,418,909	1,416,996	1,418,909	1,418,909

Note. This table reports estimates from a Poisson model for the period 2002:02 to 2015:12 except for columns (4) and (5), where OLS and Tobit models are used respectively. The dependent variable is loan origination time, which measures the number of days or months a bank takes to approve a loan application and to grant the loan for which the request was made. 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%.