Burning Money?

Government Lending in a Credit Crunch

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Abstract

We analyze new lending to firms by a state-owned bank in crisis times, the potential adverse selection faced by the bank, and the causal real effects associated to its lending. For identification, we exploit: (i) a new credit facility set up in Spain by its state-owned bank during the credit crunch of 2010-2012; (ii) the bank's continuous scoring system, together with firms' individual credit scores and the threshold for granting vs. rejecting loan applications; (iii) the rich credit register matched with firm- and bank-level data. We show that, compared to privately-owned banks, the state-owned bank faces a worse pool of applicants, is tighter (softer) in lending to firms with observable (unobservable) riskier characteristics and has substantial higher loan defaults. Using a regression discontinuity approach around the threshold, we show that the supply of credit causes large positive real effects on firm survival, employment, investment, total assets, sales, and productivity, as well as crowding-in of new credit by private banks.

JEL Codes: E44; G01; G21; G28; H81.

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"The recent global financial crisis underscored the countercyclical role of state-owned banks in offsetting the contraction of credit from private banks, leading to arguments that this function is an important one that can potentially better justify their existence."

Global Financial Development Report, World Bank (2013)

1. Introduction

Financial crises imply persistent negative real effects on economic activity (Kindleberger, 1978; Schularick and Taylor, 2012; Freixas et al., 2015). A key channel is the reduction in the supply of bank credit (Bernanke, 1983; Jordà et al., 2013). Bank illiquidity problems may be solved by the provision of liquidity by central banks, but credit crunches may stem from the scarcity of bank capital in crisis times (Bernanke and Lown, 1991), or from banks flying to securities such as government debt rather than lending to small and medium sized firms (Shleifer and Vishny, 2010; Stein, 2013).

Direct public lending via state-owned banks might therefore have a useful role to play during financial crises by ameliorating the credit crunch (Allen, 2011; World Bank, 2013).[1] A state-owned bank can support lending to the real economy by relying not only on its explicit capital, but also on the implicit capital derived from its access to taxpayer funds. The expansion of the supply of credit during a crisis may bring positive spillovers for the real economy (Holmstrom and Tirole, 1997). However, such lending may be associated with large defaults due a general scarcity of creditworthy borrowers (a demand problem, including the firm balance sheet channel of Bernanke et al., 1996) compounded with an adverse selection problem, as state-owned banks may face a very risky pool of borrowers that were rejected by their past private lenders (Broecker, 1990; Shaffer, 1998; Ruckes, 2004; Dell'Ariccia and Marquez, 2006).[2]

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[1] As noted by Allen (2011): "The real advantage of public banks would become evident during a financial crisis. Such banks (…) would also be able to provide loans to businesses—particularly small and medium size enterprises—through the crisis. They could expand and take up the slack in the banking business left by private banks." By public banks, he refers to state-owned banks; private banks are privately-owned. In this paper, we also use private banks as privately-owned banks.

[2] There is also the fact that state-owned banks are generally more inefficient than privately-owned banks (Shleifer and Vishny, 1994; La Porta et al., 2002).

Identification of causal real effects of credit supply has been elusive as the literature has only used data on granted loans (e.g., Chodorow-Reich, 2014; Paravisini et al., 2015; and Jiménez et al., forthcoming), which require strong identification assumptions. Instead, we use data on loan applications in a quasi-experimental design, where we exploit the bank's continuous scoring system used in a new, small credit facility (550 million euros), together with firms' individual credit scores and the threshold for granting vs. rejecting applications (Angrist and Pischke, 2009; Imbens and Wooldridge, 2009). These new data allow us –in a regression discontinuity approach– to exploit individual firms' scoring around the threshold to obtain exogenous variation –at the firm level– in the supply of credit, and hence to identify its real effects.

In April 2010, the Spanish government announced that its state-owned bank, Instituto de Crédito Oficial (ICO), would set up a new credit facility to directly lend to SMEs and entrepreneurs. Credit conditions by privately-owned banks had substantially tightened,[3] so the idea was to fill this gap by lending directly to firms. The tightening of bank lending conditions could reflect not only an increase in credit risk, following the worst recession in decades, but also a credit supply problem, due to private banks' insufficient capital (especially given the problems with their real estate exposures),[4] liquidity hoarding, and crowding out by sovereign debt.

The main novelty of the public credit facility was that ICO would lend directly to firms and would assume all the credit risk of these loans. Thus, ICO performed the credit risk analysis of the loan applications. The approval or rejection of these applications was essentially based on a scoring system that used hard information, and not on relationship-lending based soft information, since ICO did (still does) not have a network of branches, which limited its ability to screen and monitor borrowers, which were mostly opaque non-listed SMEs. All this implied that ICO resorted to a scoring method based on hard information to accept or reject loan applications.

The new lending program covered both investment- and liquidity-purpose loans to firms, with a maximum amount of 200,000 euros per borrower. Loan interest rates for

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[3] See, for example, the bank lending survey (http://www.bde.es/webbde/en/estadis/infoest/epb.html), the survey on credit conditions for SMEs (www.ecb.europa.eu/stats/ money/surveys/sme/html/index.en.html) and actual credit and survey data (https://www.ecb.europa.eu/pub/pdf/other/mb201307_focus06.en.pdf).

[4] Jiménez et al. (2012 and forthcoming) show that there was a significant credit crunch by private banks due to their lack of capital.

both types of loans were 6-month Euribor + 3.5%, with a fee of 0.5%, independently of the credit risk of the borrower (personal guarantees were required if deemed necessary for both types of loans). For investment-purpose loans, the maturity was seven years, while for liquidity-purpose loans, the maturity was three years. The program had available funds up to 2.5 billion euros, but was abruptly discontinued in 2012, due to the large loan loss provisions that ICO had to make. The total credit amount granted was close to 550 million euros. The percentage of applications that were granted never exceeded 30%, that is, ICO rejected more than 2/3 of the applicants. We focus our analysis on loans to SMEs, which amounted to around 300 million euros, serving around 5,500 firms, as we do not have key data on entrepreneurs' businesses.

We exploit the exhaustive Spanish credit register (CIR), a proprietary database owned by Banco de España in its role as supervisor of the Spanish banking system, which contains all corporate bank loans granted in Spain by all operating banks since 1984 on a monthly basis. Since 2002, CIR also stores data on new loan applications of firms that are not currently borrowing from the requesting bank, including applications by firms to the new public credit facility. Moreover, we know whether a loan application is granted, and for those granted applications, we observe the loan amount, and the future credit performance of the loan (defaults).

We match the credit datasets with other administrative datasets for firm- and bank-level variables. The information on non-financial firms comes from the balance sheets and income statements that corporations must submit yearly to the Spanish Mercantile Register. We also exploit another administrative dataset managed by the National Statistics Institute (INE), called the Central Business Register (DIRCE), to obtain all firms that closed down during a calendar year to analyze firm survival. We also use supervisory information on banks' balance sheet and income statements.

Importantly –and new in the literature– we also exploit the continuous scoring function used by the state-owned bank, which was based on eighteen different firm variables (related to leverage, profitability, liquidity, and credit history among others), to accept or reject loan applications, as well as the applicants' individual scores. The scoring function was proprietary information, not known by the applicants, and firm variables were cross-checked by the bank with government and private registers.

We use these datasets for the empirical identification of the main two issues addressed in the paper, namely the determinants of lending decisions and the real effects of loans granted. First, on the lending analysis, we exploit the loan applications to ICO and to private banks by firms not currently borrowing from them. We analyze the characteristics of the pool of applications to both types of banks. We also analyze the granting of loan applications depending on borrower observed and unobserved risk, exploiting data on applications by the same firm in the same month to both ICO and private banks. Furthermore, conditional on granting the loan, we analyze its amount and future default. Second, as the credit register is matched (via the unique tax identifier code) with firms' characteristics (survival, investment, and growth in employment, sales, total assets, and productivity) and firm new private bank credit, we analyze the real effects associated to the credit granted in a regression discontinuity approach.

The results show that the pool of new applicants is riskier for the state-owned bank than for the private banks in basically all observed characteristics, such as firm profitability, capital, sales, age and liquidity, as well as on previous loans' interest rates, drawn-down of existing credit lines, and bad credit history. The results also show that the state-owned bank is more restrictive than the private banks both in granting new loan applications (extensive margin) and in the volume granted conditional on approval (intensive margin). However, a substantial part of these effects is due to the riskier pool of applicants to the state-owned bank in observable as well as unobservable risk characteristics. Importantly, in both the extensive and intensive margins, the state-owned bank is softer than private banks in its supply of credit to firms with higher *unobservable* risk, which we proxy at the firm level either (i) by the absence of ex-ante granted loans following applications to private banks by the firm during the previous year, or (ii) by ex-post loan defaults not related to ex-ante firm observable characteristics.

The results imply that the ex-post loan defaults of the state-owned bank are 32 percentage points higher compared to private banks. Moreover, a substantial part of these defaults is due to firms' unobserved risk characteristics. Overall our results indicate that the new public credit facility faces significant adverse selection problems which, despite its restrictive lending policy, translate into substantially higher defaults.

At the same time, we show that there are positive real effects associated with the new supply of credit. A crucial problem in the literature to identify the real effects of credit supply is that banks reject applications from risky firms with poor investment opportunities, especially in crisis times when there is flight to quality (see Bernanke et al., 1996). Therefore, a positive correlation between lending and real effects at the firm level does not necessarily imply causality from lending to real outcomes. We tackle this endogeneity problem in a regression discontinuity approach by exploiting the continuous scoring rule of the state-owned bank in granting applications around the cutoff, where there is a very strong increase –of almost 40 percentage points– in the likelihood of obtaining a loan from ICO.[5]

We find that the public credit facility causes positive real effects at the firm level. In quantitative terms, if the state-owned bank grants a loan to a firm, the probability that the firm survives increases at the mean by approximately 26%, compared to a basically identical firm (around the cutoff) that is rejected. We also find that getting a loan at the cutoff implies higher investment (79%), employment growth (51%), total asset growth (65%), sales growth (69%), and productivity growth (81%).[6]

Moreover, after obtaining the public loan, those firms (compared to almost identical firms that survive without the public loan) have a 75% average increase of the likelihood of ex-post access to new loans from private banks that were not previously lending to them (which corresponds to 22 percentage points), and a 31% increase in private credit volume, thereby suggesting that such public lending causes ex-post crowding-in effects, reinforcing the initial public funds with additional private funds.

We contribute to the literature in four main directions. First, there is a theoretical literature that shows that, in crisis times, rejected borrowers as well as new firms may have difficulties to obtain credit from other banks due to asymmetric information

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[5] It should be noted that, unlike in the standard FICO score, in the scoring rule used by ICO higher scores mean higher credit risk.

[6] Importantly for the validity of the regression discontinuity analysis, we perform several different placebo tests (all with insignificant results), and we show that the firm observable characteristics around the cutoff point at the time of the loan application are not different. Our robustness checks also show similar results with different parametric and non-parametric specifications, with different controls, and find insignificant effects in the McCrary test, which suggests that firms did not choose to be above or below the cutoff point. Moreover, the fact that the credit facility was small (550 million euros over two years in a country with 1 trillion euros of annual GDP) is key for avoiding significant general equilibrium effects that might contaminate the research design.

problems (Broecker, 1990; Ruckes, 2004; Dell'Ariccia and Marquez, 2006). However, there is no empirical paper that shows the costs and benefits associated to a new provider of credit, considering the riskier pool of applicants that the new bank will face. The policy experiment that we exploit provides important findings: if credit crunches could just be solved by creating new banks or new public credit facilities, then public policy could easily address credit crunches and their associated negative real effects. However, we show that the pool of applicants to the new bank or facility tends to be biased towards high risk firms (also in unobservable ways), leading to large defaults.

Second, we advance on the causality front of the real effects of credit supply by obtaining exogenous variation at the firm level in a regression discontinuity setting, exploiting the continuous scoring function around the threshold between accepting and rejecting applications by a bank that does not use soft information.[7] The key difference with the literature (Chodorow-Reich, 2014; Paravisini et al., 2015; Cingano et al., 2016; Amiti and Weinstein, forthcoming; Jiménez, Mian et al., forthcoming; Jiménez et al., forthcoming) is that previous papers did not have the pool of loan applications nor the scoring function based on firm characteristics to grant loans, including the applicants' individual scores.[8] Hence, we avoid potential biases (and strong identification assumptions) due to the correlation between firm and bank characteristics and lending decisions. Our estimates of the real effects are large, as we analyze SMEs in a period of a strong credit crunch, and are in line with the theoretical macro-finance literature that shows how a negative shock in (private) bank capital may lead to a reduction in the supply of credit with negative spillovers in real activity (see e.g. Holmstrom and Tirole, 1997; Repullo and Suarez, 2013; He and Krishnamurthy, 2013; Brunermeier and Sanikov, 2014).

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[7] The literature on identifying *credit supply* has advanced substantially using Khwaja and Mian (2008)'s firm fixed effect estimator, which exploits loan decisions by different banks to the same firm, requiring multiple observations (loans) for the same firm in the same period. However, unless in restrictive settings (Paravisini et al., 2015; Jiménez, Mian et al., forthcoming), this fixed effect estimator does not allow for the identification of the *real effects of credit supply*, as there are no multiple observations of real effects for the same firm in the same period (i.e., there is only one observation of employment for a particular firm in a given period).

[8] The contemporaneous paper by Berg (2016) also exploits a cutoff lending rule. The main differences are that: (i) we exploit a new public lending facility, and by a bank that is not specialized in screening or monitoring using soft information, but just uses a lending rule; (ii) we have access to all the loans by all banks, not just one; (iii) we analyze a state-owned bank lending policy in a strong credit crunch period.

Third, we contribute to the literature that shows the costs and benefits of state ownership in general and of banks in particular.[9] State ownership of firms is common across the world. Atkinson and Stiglitz (1980) argue that state-owned firms are a second best way to overcome market failures, while Shleifer and Vishny (1994) highlight their inefficiencies. State ownership is particularly prevalent in the banking sector and there is evidence of these inefficiencies (La Porta et al., 2002; Sapienza, 2004; Dinç, 2005; Khwaja and Mian, 2005; Carvalho, 2012; Englmaier and Stowasser, 2013). All these papers are about capture by politicians. In contrast, we stress the limits of state-owned banks in fighting a credit crunch, even when their lending policies are driven by an external credit scoring system and not controlled by politicians.

Finally, we provide a theoretical framework to interpret our results. We contrast the behavior of a privately-owned vs. a state-owned bank, where the latter differs in that its objective function has, in addition to profits, a term that captures a government concern about the amount of lending, proxying for the real effects to the economy. Banks face an adverse selection problem that is mitigated by a scoring system that provides a noisy signal about the borrowers' risk types.[10] Lending decisions of both banks are characterized by a cutoff signal. We show that the state-owned bank will have higher loan defaults, which will be higher the worse the quality of its pool of applicants and the precision of its scoring system. At the same time, from a welfare perspective, the objective function of the state-owned bank internalizes the benefits of lending to firms, which implies that a positive lending bias is in fact optimal.

Our results suggest limitations of public policy to fight credit crunches, as asymmetric information is pervasive in loan markets, especially in crisis times. At the same time, we show that direct public lending to firms can bring strong, positive effects on the real economy, which may be especially valuable when expansionary monetary and/or fiscal policy may be either not feasible or not effective.

The paper proceeds as follows. Section 2 presents our theoretical model. Section 3 describes the new credit facility and the datasets. Sections 4 and 5 discuss the empirical strategy and the results on lending and on real effects, respectively. Section 6 concludes.

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[9] See also the cross-country evidence by Bertay et al. (2015).
[10] See Eslava and Freixas (2016) for a related model of bank screening.

Appendices A, B and C, respectively, contain the proofs of the theoretical results, the definition of the variables used in the empirical analysis, and further robustness results.

2. Theoretical model

This section presents a stylized model of bank lending under asymmetric information that rationalizes the different behavior of privately-owned and state-owned banks. Its main objective is to provide a framework for understanding the empirical results of Section 4.

The model features a single bank that provides funding to entrepreneurs with heterogeneous risk profiles. The bank cannot observe the risk of the entrepreneurs' projects. To mitigate this adverse selection problem, the bank has a scoring system that provides a noisy signal about entrepreneurs' risk. We start the analysis by characterizing the screening and lending behavior of a privately-owned, profit-maximizing bank. Then we consider a state-owned bank that, in addition to profits, cares about the amount of lending to the economy.

2.1. Private bank

Consider an economy with two dates ($t = 0,1$), a risk-neutral bank, and a measure one continuum of penniless entrepreneurs that can be of two types: high and low risk. Let γ denote the (publicly known) proportion of high risk entrepreneurs.

Entrepreneurs have investment projects that require a unit investment at $t = 0$ and yield a stochastic payoff Y at $t = 1$ given by

$$Y = \begin{cases} 1+y, & \text{with probability } 1-p, \\ 1-\lambda, & \text{with probability } p, \end{cases}$$

where $p = p_L$ for low risk and $p = p_H$ for high risk entrepreneurs, with $p_L < p_H$. Let $\bar{p} = (1-\gamma)p_L + \gamma p_H$ denote the average probability of failure of investment projects.

The bank lends funds at an exogenous rate r and the opportunity cost of these funds is r_0, with $r_0 < r < y$.[11] We assume that parameter values are such that lending to a low risk entrepreneur is profitable, while lending to a high risk entrepreneur is not, i.e.

$$\pi_L = (1+r)(1-p_L) + (1-\lambda)p_L - (1+r_0) = r - r_0 - (r+\lambda)p_L > 0,$$
$$\pi_H = (1+r)(1-p_H) + (1-\lambda)p_H - (1+r_0) = r - r_0 - (r+\lambda)p_H < 0.$$

We also assume that

$$\bar{\pi} = (1-\gamma)\pi_L + \gamma\pi_H = r - r_0 - (r+\lambda)\bar{p} < 0,$$

so lending to an entrepreneur chosen at random is also unprofitable.

The bank does not observe the entrepreneurs' types, but has a *scoring system* that provides a signal $s = p + \varepsilon$ for a borrower of type p, where $\varepsilon : N(0,\sigma^2)$. Thus, the lower the standard deviation σ the better the quality of the scoring system. Note that, as in the scoring system used by ICO; higher values of s signal riskier borrowers.

The profit-maximizing lending policy is characterized by a cutoff signal $\bar{s}$ such that the bank lends to entrepreneurs with scores $s \le \bar{s}$. The corresponding supply of credit is

$$L(\bar{s}) = \Pr(s \le \bar{s}) = (1-\gamma)\Phi\left(\frac{\bar{s} - p_L}{\sigma}\right) + \gamma\Phi\left(\frac{\bar{s} - p_H}{\sigma}\right),$$

where $\Phi(\cdot)$ denotes the cdf of a standard normal random variable. Clearly $L'(\bar{s}) > 0$, so the higher the cutoff signal $\bar{s}$ (i.e. the weaker the lending standards) the higher the credit granted.

Bank profits per unit of loans are given by

$$\pi(\bar{s}) = r - r_0 - (r+\lambda)p(\bar{s}),$$

where $p(\bar{s}) = E(p \,|\, s \le \bar{s})$ is the *default rate* of the loans in its portfolio. Since

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[11] Note that the model incorporates an important feature of the ICO program, namely that the terms of the loans (including interest rates) were fixed by the government.

$$p(\overline{s}) = \frac{1}{L(\overline{s})}\left[(1-\gamma)\Phi\left(\frac{\overline{s}-p_L}{\sigma}\right)p_L + \gamma\Phi\left(\frac{\overline{s}-p_H}{\sigma}\right)p_H\right],$$

total bank profits are given by

$$\Pi(\overline{s}) = \pi(\overline{s})L(\overline{s}) = (1-\gamma)\Phi\left(\frac{\overline{s}-p_L}{\sigma}\right)\pi_L + \gamma\Phi\left(\frac{\overline{s}-p_H}{\sigma}\right)\pi_H.$$

The bank chooses the cutoff signal $\hat{s}$ that maximizes its total profits $\Pi(\overline{s})$. Let us define $\hat{L} = L(\hat{s})$, $\hat{\Pi} = \Pi(\hat{s})$, and $\hat{p} = p(\hat{s})$. Then we can prove the following result.

Proposition 1 *The cutoff signal chosen by a profit-maximizing bank is*

$$\hat{s} = \frac{1}{2}(p_H + p_L) - \frac{\sigma^2}{p_H - p_L}\ln\left(-\frac{\gamma\pi_H}{(1-\gamma)\pi_L}\right).$$

The supply of credit $\hat{L}$ and bank profits $\hat{\Pi}$ are decreasing and the default rate $\hat{p}$ is increasing in the proportion γ of high risk entrepreneurs and in the noise σ of the scoring system.

Thus, we have a closed form solution for the cutoff signal $\hat{s}$, which depends on two key parameters: the proportion γ of high risk entrepreneurs and the noise σ of the scoring system. A worse pool of applicants or a lower quality of the scoring system leads the bank to tighten its credit standards, although this does not fully offset the effects on the default rate, which goes up.

2.2. State-owned bank

After characterizing the screening and lending behavior of a profit-maximizing bank, we next consider the behavior of a state-owned bank. We postulate that this bank is characterized by an objective function that differs from the one of the privately-owned bank in an additive term that captures a government concern about the amount of lending to the economy. Formally, we assume an objective function of the form

$$U(\overline{s}) = \Pi(\overline{s}) + \delta L(\overline{s}),$$

where $\delta > 0$ is the weight given to lending in the bank's objective function, called the *lending bias*. Substituting $\Pi(\bar{s})$ and $L(\bar{s})$ into this expression gives

$$U(\bar{s}) = (1-\gamma)\Phi\left(\frac{\bar{s}-p_L}{\sigma}\right)(\pi_L+\delta) + \gamma\Phi\left(\frac{\bar{s}-p_H}{\sigma}\right)(\pi_H+\delta).$$

The state-owned bank chooses the cutoff signal $\hat{s}$ that maximizes its objective function $U(\bar{s})$. Let us define $\hat{L} = L(\hat{s})$, $\hat{\Pi} = \Pi(\hat{s})$, and $\hat{p} = p(\hat{s})$, and assume that the lending bias is not too large, in particular $\bar{\pi} + \delta < 0$. Then we can prove the following result.

Proposition 2 *The cutoff signal chosen by the state-owned bank is*

$$\hat{s} = \frac{1}{2}(p_H + p_L) - \frac{\sigma^2}{p_H - p_L}\ln\left(-\frac{\gamma(\pi_H+\delta)}{(1-\gamma)(\pi_L+\delta)}\right).$$

The supply of credit $\hat{L}$ and the default rate $\hat{p}$ are increasing and bank profits $\hat{\Pi}$ are decreasing in the lending bias δ of the state-owned bank.

Since $\delta = 0$ corresponds to the case of a profit-maximizing bank, this result implies that the state-owned bank will have laxer credit standards, and will be less profitable and have a higher default rate than the corresponding private bank.

Figure 1 illustrates the effect of the lending bias δ on the supply of credit (Panel A) and the default rate (Panel B) of the state-owned bank. The solid line in both panels corresponds to given values of the proportion γ of high-risk entrepreneurs and the noise σ of the scoring system. The dashed lines show the effect of an increase in γ (for the given value of σ), while the dotted lines show the effect of an increase in σ (for the given value of γ).[12] Panel A shows that the supply of credit L is increasing in the lending bias δ, but it is decreasing in the proportion γ of high-risk entrepreneurs and the noise σ of the scoring system. Panel B shows that the default rate p is increasing in the lending bias δ, and it is also increasing in the proportion γ of high-risk entrepreneurs and the noise σ of the scoring system.

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[12] The following parameter values are used: $p_L = 0$, $p_H = 1$, $r_0 = 0$, $r = 0.1$, $\lambda = 0.5$, $y = 0.15$, $\gamma = 0.4$ (solid) and 0.5 (dashed), and $\sigma^2 = 0.75$ (solid) and 1 (dashed). Since the magnitude of the shifts depends on the size of the changes in γ and σ, what it is relevant is the position of the dashed and the dotted lines with respect to the solid lines, and not their relative position.

It is interesting to note that when choosing the cutoff signal $\hat{s}$, the profit-maximizing bank does not take into account the entrepreneurs' surplus generated by a successful project, which is $y - r$. A social planner would take this into account, so its objective function would be

$$W(\overline{s}) = w(\overline{s})L(\overline{s}),$$

where

$$w(\overline{s}) = (1+y)(1-p(\overline{s})) + (1-\lambda)p(\overline{s}) - (1+r_0) = \pi(\overline{s}) + (1-p(\overline{s}))(y-r).$$

Hence, by our previous results we have

$$W(\overline{s}) = (1-\gamma)\Phi\left(\frac{\overline{s}-p_L}{\sigma}\right)[\pi_L + (1-p_L)(y-r)] + \gamma\Phi\left(\frac{\overline{s}-p_H}{\sigma}\right)[\pi_H + (1-p_H)(y-r)].$$

Let us now define $W(\delta) = W(\hat{s}(\delta))$. Then by the proof of Proposition 1, it follows that

$$\left.\frac{dW(\delta)}{d\delta}\right|_{\delta=0} = \left.\frac{dW(\hat{s})}{d\hat{s}}\right|_{\hat{s}=\hat{s}} \hat{s}'(0) > 0,$$

Hence, setting a positive lending bias for a state-owned bank is socially optimal.[13] Figure 2 illustrates this result by plotting the function $W(\hat{s})$. Social welfare first goes up, reflecting the under-provision of lending by a profit-maximizing bank, but then it quickly goes down with further increases in the bias.

Summing up, we have presented a model that rationalizes the lending behavior of a state-owned bank. Two key results are especially relevant to understand the empirical evidence that follows. First, the state-owned bank has laxer credit standards, but it tightens them when facing a worse pool of applicants (e.g., including those rejected by other banks) or has a worse credit scoring system (e.g., because it lacks soft or relationship-based information). Second, this tightening does not fully offset the effects on the default rate, which goes up. Thus, the state-owned bank may be more restrictive in granting loans than private banks, but nevertheless may have much higher defaults.

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[13] An important caveat to this result is that it assumes that reducing profits or generating losses for the state-owned bank carries no social cost. To the extent that public sector funds are obtained from distortionary taxation, a lending bias may not be optimal.

3. Public policy and datasets

This section describes the lending program launched by the Spanish government through its state-owned bank, Instituto de Crédito Oficial (ICO), and the different datasets that we use in the empirical analysis.

3.1. New public lending facility

In April 2010, the Spanish government entrusted ICO with a new program to lend to SMEs and entrepreneurs.[14] The main novelty was that the ICO would lend *directly* to SMEs and entrepreneurs, and would assume *all* the credit risk of these loans. The program was a challenge for ICO because it was the first time it granted such loans. Since ICO did (still does) not have a network of branches and no direct relationship with potential borrowers (to obtain soft information), and almost no experience on screening and monitoring SMEs borrowers, the state-owned bank used a scoring system based on hard information to accept or reject loan applications (see more details below). The program started in June 2010 with the aim of improving access to credit for SMEs and entrepreneurs at a time where private banks were retrenching from lending.

The new public credit facility granted two types of loans: Investment-purpose loans to support the acquisition of fixed production assets, and liquidity-purpose loans to provide for specific cash flow needs. The maximum amount lent was 200,000 euros per borrower. The terms of the loans varied according to the purpose of the loan: For investment loans the maturity was seven years, while for liquidity loans the maturity was three years. For both types of loans, the interest rate was 6-month Euribor + 3.5%, with a fee of 0.5%, independently of the credit risk of the borrower, although personal guarantees could be required.

The new credit facility had available funds up to 2.5 billion euros over a minimum of two-years. The facility was terminated early, in July 2012, due to the cost for ICO, both in terms of staff devoted to the program and, more importantly, the impact on loan loss provisions, as previously granted ICO loans started to default. In mid-2012, ICO

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[14] ICO is attached to the Ministry of Economic Affairs and Competitiveness. Legally, the state-owned bank is a credit institution with a banking license. It finances itself on international capital markets, and has access, as any euro area bank, to the European Central Bank. Its main mission is to promote activities contributing to economic growth. Before the new credit facility was set up, ICO had lent to mostly large firms but with the credit risk shared with private banks.

had to make loan loss provisions of around 80 million euros, for a bank with a yearly profit around 50 million euros.

The total amount granted under the new credit facility was close to 550 million euros, slightly above 20% of total funds available. About 300 million euros were granted to SMEs, reaching 5,500 companies, so the average loan stood at around 55,000 euros. The percentage of applications that were granted never exceeded 30%, that is, ICO rejected more than 2/3 of the applicants.

To screen borrowers, ICO acquired a scoring system based on eighteen firm variables, described below in datasets, that provided a continuous rating and a threshold for accepting or rejecting applications (in line with the scoring system and the cutoff point in the theoretical model in the previous section). There were different thresholds depending on the purpose of the loan, investment or liquidity.

3.2. Datasets

We use several datasets. First, the Credit Register (CIR) owned and managed by the Bank of Spain CIR contains information about all loans above 6,000 euros (a very low threshold for firms) granted by any bank operating in Spain since 1984 on a monthly basis, which for loans to firms is an extremely low threshold. Moreover, since February 2002 CIR also contains data on loan applications from firms that are not currently borrowing from the requesting bank. We know whether a loan application is granted. We also know the future performance of each loan (default status). See Jiménez et al. (2012, 2014, and forthcoming) for a detailed description of these datasets.

In Section 4 we analyze loan applications from firms that are not currently borrowing from private banks or from the state-owned bank. We have information on the set of the loan applications, whether the loan is granted or not, and for those loans that were granted, we observe the loan amount and whether the firm defaults or not on the loan in the future.

We then match these loan datasets stemming from CIR with the one on non-financial firm variables and the one on bank variables. The economic and financial information on firms comes from the balance sheets and income statements that Spanish corporations must submit yearly to the Spanish Mercantile Register. We enhance the

firm information dataset with another administrative dataset, the Central Business Register (DIRCE), which is a dataset managed by the National Statistical Institute (INE) that collects data on all the firms that close down during a calendar year. We are able to match all these datasets since we have for each firm its unique tax identifier code. In addition, we also use the Bank of Spain dataset containing the balance sheet and income statement of Spanish banks at a monthly frequency.

We focus our analysis on SMEs because we have access to their economic and financial information (i.e. balance sheet, profit and loss, as well as employment and investment) while for entrepreneurs we do not have such data.[15] Moreover, as there are limitations on personal insolvency in Spain, we do not have information on entrepreneurs' closing down their businesses.

In Section 5 we analyze the real effects of the credit supply. Following the terminology in Angrist and Pischke (2009) and Lee and Lemieux (2010), we have quasi-experimental data, namely not only do we have the pool of applicants and whether they were rejected or not, but also the continuous scoring function and the threshold to accept or reject applications employed by ICO, and random sample of applicants with their individual credit scores matched with firm real and financial variables.[16] Since there were two different thresholds depending on the purpose of the loan, investment or liquidity, we have normalized all scores by subtracting, for each firm, the threshold from the score. As a result, the normalized cutoff point is zero for all firms, with negative values indicating higher credit quality. Moreover, to assess the real effects, we add to this database information on the future performance of the firms, in investment, and growth in employment, sales, total assets, and productivity, as well as firm survival.

The ICO scoring system is based on eighteen firm variables: short-term indebtedness; credit line usage ratio (that is, drawn-down over committed credit); average cost of debt; bank loans over own funds; bank loans over gross operating profit;

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[15] We follow the definition of SME used by ICO that follows the European definition, based on the EU recommendation 2003/361.

[16] We have compared this sample with the database used in the rest of the paper and there are not significant differences (see summary statistics in Table 1 for all ICO applicants). For instance, the average log of total assets is 6.99 (compared to 6.98 of the main dataset), the average age is 13.48 (13.56), the average ROA is 2.84 (2.82), and the average capital ratio, liquidity ratio, productivity, and interest paid are 24.56 (25.01), 6.09 (5.42), 4.61 (4.65), and 4.26 (4.33), respectively. See Appendix B for the definition of the variables.

leverage ratio (that is, own funds over total assets); net current assets over total assets; profitability measures such as ROE, ROA and sales' profitability; industry; age; numbers of years of experience of the manager; temporary employees ratio; owned or rented premises of the firm; bank loan defaults and two variables related to firm payment compliance with external providers (e.g. unpaid phone and electricity bills).[17] Each of the firms' variables is assigned to a specific area: financial indebtedness, solvency, liquidity, profitability, business information as well as default history. Each variable is categorized around six intervals and a different rating value is assigned depending on the allocation to each of the six buckets. Then, each rating value is weighted inside its corresponding area, and each of the six areas is again weighted to get the final score, which is just the weighted sum of the ratings assigned to the different firm characteristics. Ratings are such that the score is increasing in the firm's credit risk. In the empirical analysis we use the loan applications that were not rejected by lack of data or were withdrawn by firms before it reached the ICO analysts.

4. Empirical strategy and results on lending decisions

In this section we present the empirical strategy and the results on lending. We study loan applications (and granted outcomes) by the state-owned bank and privately-owned banks to firms which are not currently borrowing from them, which implies that all banks face a similar screening problem. Table 1 analyzes the pool of firms that apply only to privately-owned banks versus firms that also apply to the state-owned bank, and Table 2 shows the descriptive statistics of the variables used in the econometric analysis. In Tables 3 and 4, we analyze the difference in lending between the state-owned bank and the private banks, in particular on the granting of loan applications, the loan granted volume, and the future loan defaults. In the next section, we will present the empirical strategy and the results on the real effects of credit supply. Appendix B contains the definition of all the variables used in the empirical analysis and Appendix C contains some robustness results.

We start with a description of the pool of SMEs that apply to the state-owned bank (ICO) and to privately-owned banks that are not currently lending to them during the period in which the public credit facility was operative (years 2010, 2011 and

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[17] The scoring system is proprietary information and hence we cannot disclose its exact formula.

2012).[18] In Table 1 we analyze the characteristics of the pool of firms that apply only to privately-owned banks, I(ICO APPLICANT)$_f$ = 0, and of firms that apply to the state-owned bank (and possibly to other banks), I(ICO APPLICANT)$_f$ = 1. The aim is to assess whether the state-owned bank faces a riskier pool of applicants than private banks. In Table 1, we report data on all applicant firms, even if they have only one loan (in Tables 3 and 4, we will restrict the sample to firms with at least two loan applications or granted loans, respectively, to apply firm fixed effects). There are 82,184 applicant firms in Table 1, of which 20% are ICO applicants.

Table 1 shows that firms that apply to the state-owned bank are, in basically all characteristics, riskier: younger firms, with less profits, less capital (more leverage), less sales and liquidity, higher (previous) loan interest rates paid, higher usage (drawn to committed) of credit lines, and with a worse credit history.[19]

Table 1 also shows that the differences in average firm characteristics (at the time of the applications) are both statistically and economically significant. For example, without controlling for other variables, firms that apply at least to the state-owned bank as compared to firms that apply just to private banks pay 101 basis points more in loan interest rates, have 33% lower capital ratios and 25% lower profits, almost half of liquidity, previous year loan defaults of 10% as compared to 3% for firms that did not apply to the public credit facility, and credit drawn over committed of 85%, 15 percentage points higher than for firms that did not apply to the public credit facility. All these dimensions are captured through the scoring measure, which is 12% higher for ICO applicants (recall that higher values of scoring imply riskier firms).

The variables with the highest difference in value between the firms that apply to the state-owned bank versus the ones that only apply to privately-owned banks are scoring, capital ratio, liquidity ratio, and credit line usage ratio (drawn amount over committed).[20] Figure 3 shows the kernel probability density function (pdf) of these

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[18] We focus of SMEs, following the definition in the EU recommendation 2003/361, given that the public credit facility was restricted to lend to these firms.

[19] The relationship between credit line usage and defaults can be seen in Jiménez et al. (2009).

[20] To avoid the mechanical increase with the number of observations in the t-statistic of the difference in means, following Imbens and Wooldridge (2009) we also analyze the normalized differences, which are the differences in averages over the square root of the sum of the variances. Imbens and Wooldridge (2009) propose as a rule of thumb the 0.25 threshold in absolute terms, i.e. two variables have "similar" means when the normalized difference does not exceed one quarter. We find that the four variables in

variables. The differences in risk between the two types of firms go beyond average values, and are indeed present in their pdfs –Figure 3 suggests first-order stochastic dominance in all the four variables. In sum, the applicants to the public credit facility are riskier across the board.[21]

In Tables 3 and 4 we examine the lending policy of the new credit facility of the state-owned bank, its relative supply of credit versus the privately-owned banks, and the associated (ex-post) loan defaults. We start with the analysis of the probability that a loan application is granted (i.e. the extensive margin) in Table 3, Panel A. Then, we study the size of the granted loan (Panel B). Finally, Table 4 analyzes ex-post loan defaults.

We analyze average loan outcomes of the state-owned bank versus privately-owned banks, but also outcomes that depend on firm risk, in particular firm scoring (using the proprietary scoring system of ICO) and an unobserved firm risk related to the lack of granted loans corresponding to last year's applications. We use the scoring system here to summarize into one variable the many different firm observable variables, although our results are very similar if we directly use them as in Table 1.

To make results comparable across different specifications depending on the controls (mainly fixed effects), we restrict the sample to only firms with at least two applications, which allows us to include firm fixed effects; this reduces the number of firms to 63,924 (compared to 82,184 in Table 1) over the period that spans from 2010:06 to 2012:04.[22] The analysis is at the loan level and the specification of our baseline regression is the following linear model:

$$(1) \quad y_{fbt} = \eta_t + \eta_f + \beta I(ICO\ BANK_b) + Firm\ Controls_{ft-1} + Bank\ Controls_{bt-1} + \varepsilon_{fbt}$$

where η_t captures global time effects and η_f captures unobserved firm-specific time-invariant effects. Firm controls include the scoring measure that proxies for time-

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Figure 3, together with a fifth variable on number of banking relationships, are the only ones with values higher than 0.25.

[21] In Table 1, we also perform a multivariate analysis controlling for all firm characteristics at the same time and including province*industry*year fixed effects to control for time-varying firm characteristics proxying for industry and location demand effects. Multivariate analysis also brings very similar results.

[22] Note that Table 3 (with 210,651 observations) uses firm-bank loan applications, while Table 1 uses firm-level data.

varying observable firm risk, and the outcome of previous loan applications that proxies for unobservable firm risk. To control for bank characteristics (which are not related to state-owned and private ownership), we include in all regressions a broad set of bank characteristics such as bank total assets as a measure of bank size, capital ratio as a measure of the bank's net worth, ROA as a measure of bank profitability, and doubtful loan ratio as a measure of bank risk. See the exact list of controls in Tables 3 and 4, their definition in Appendix B, and their summary statistics in Table 2. ε_{fbt} is an error term. The standard errors are corrected for clustering at the level of the firm, industry, province, and bank.

Our main variable of interest is the dummy variable I(ICO BANK)$_b$ that takes the value of one for a loan application (or a granted loan in Table 3 Panel B and Table 4) to this bank, and zero otherwise. The coefficient β of I(ICO BANK)$_b$ captures the lending policy of the state-owned bank relative to privately-owned banks for a similar pool of borrowers. For instance, when firm fixed effects are included, we identify the lending behavior of the state-owned bank compared to private banks for the *same* firms. Moreover, to isolate all time-varying unobserved (and observed) firm fundamentals, in some regressions we control for firm*time fixed effects, thereby analyzing the supply of credit of the state-owned bank compared to private banks for the *same* firm in the *same* month (see Jiménez et al., 2012).

The first dependent variable is I(LOAN APPLICATION IS GRANTED)$_{fbt}$, which equals one if the loan application of firm f to bank b in month t is successful and the loan is granted in t to $t+3$, and equals zero otherwise. As shown in Table 2, it has a mean of 0.29 and a standard deviation of 0.45. We analyze this variable proxying the extensive margin of lending in Table 3, Panel A. The other two dependent variables are only for those granted loan applications. Ln(CREDIT AMOUNT)$_{fbt}$, that we analyze in Table 3, Panel B, equals the logarithm of the committed loan amount (in thousands of euros) granted to firm f by bank b in month t. Its mean and standard deviation are 4.00 and 1.09, respectively (if we do the average for loan volume directly, without log, the average value is 103,000 euros). I(FUTURE DEFAULT)$_{fb}$, that we analyze in Table 4, is a dummy variable which takes the value of 1 if firm f that is granted the loan at time t

by bank *b* defaults at some point in the future (until 2014:08) to bank *b*. Its mean and standard deviation are 0.13 and 0.34, respectively.[23]

We start the analysis without any firm control, and then we control progressively for firm characteristics, given that the pool of borrowers that applied to ICO is different to the one that applied to the private banks, as shown previously in Table 1. We first include a set of time fixed effects (Model 1); then we include the scoring of the firm to capture its observed risk profile, while the unobserved risk is proxied by the outcome of previous loan applications (Model 2); then we also add firm fixed effects to control for unobserved firm heterogeneity (Model 3), and finally we include firm*month fixed effects, which control fully for time-variant unobservable firm quality and risk (Model 4). All firm characteristics are taken at the end of the previous year (t-1).[24]

We are also interested in the heterogeneous effects of the public policy with respect to firm risk. The equation we estimate is the following:

$$(2) \qquad y_{fbt} = \eta_t + \eta_f + \eta_b + \gamma I(ICO\ BANK_b) * Firm\ Controls_{ft-1} + Firm\ Controls_{ft-1}$$
$$+ Bank\ Controls_{bt-1} + \varepsilon_{fbt}$$

where η_b is a bank fixed effect that absorbs the ICO dummy. The coefficient of interest is now γ, which is the coefficient for the double interactions between the ICO bank dummy and firm variables that proxy for firm observed and unobserved risk. This allows us to test the heterogeneous effects of the state-owned bank lending policy, controlling for the overall average effects by introducing bank fixed effects. Finally, we add in Model 6 of Table 3 and Model 5 of Table 4 firm*time fixed effects to equation (2). Standard errors are also corrected for clustering at the level of the firm, industry, province, and bank.

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[23] Note that the sample size (i.e. in terms of number of observations and number of firms) declines drastically for the second and third dependent variables in Panel B of Table 3 and in Table 4 as both variables focus only on applications granted, and to apply firm fixed effects, at least two granted loans are needed.

[24] In Model 5 we also control for the contemporaneous variable I(ICO BANK APPLICANT)$_f$, which is a dummy that equals one if the firm asked for at least a loan to the new public credit facility. Therefore, this variable takes the value of 0 if the firm did not apply to ICO. We use this variable in Model 5 to control for time-varying unobservable trends in demand-side effects. We get similar results when these trends are not introduced. The average value of this variable is 0.23 and its standard deviation is 0.42. Note that 0.23 does not mean that 23% of loan applications were made to the state-owned bank, but within the sample of SMEs we have during the 2 year-program, 23% of firms at least applied once to ICO.

In Panel A of Table 3 we analyze the determinants of granting a loan application. We find that the estimated coefficient for I(ICO BANK)$_b$ is negative and statistically significant for all specifications, thereby implying that, on average, ICO was more restrictive in granting loan applications than the private banks.

It is also interesting to highlight that the coefficient is -0.121*** for Model 1 and gradually decreases to -0.116*** in Model 2, to -0.107*** in Model 3, and finally to -0.094*** for Model 4, a reduction of approximately 25% in absolute value for Model 4 as compared to Model 1.[25] As we control progressively for firm fundamentals, this reduction is due to the biased pool of borrowers that applied to ICO, worse than the one faced by the private banks (as shown in Table 1).

The estimated coefficient of Model 4 implies that the likelihood of having the application granted by the state-owned bank compared to the private banks is 33% lower.[26] Therefore, keeping the quality of the borrower identical, the new public credit facility was more restrictive on average than the private banks in the extensive margin of lending.[27]

Models 5 and 6 further analyze the heterogeneous lending behavior. The estimated coefficients of interactions of the ICO dummy with scoring and "none of the applications were granted last year" in Model 5 equal -0.021*** and 0.103*** respectively, and in Model 6 equal -0.022* and 0.064*** respectively. This implies that the state-owned bank grants less loan applications than the private banks to the riskier firms in observable characteristics (higher scoring). However, within the firms that apply to banks in the previous year, the state-owned bank grants more new loan applications than the private banks to those firms that did not get any granted loan application in the previous year.

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[25] *** implies statistically significant at 1%, ** significant at 5%, * significant at 10%.

[26] The models that include firm*month fixed effects are the best to isolate credit supply, both average and heterogeneous effects, but are restrictive given that the number of firms (observations) decreases by 27% from Model 4 to 3 for average effects and by 22% from Model 6 to 5 for heterogeneous effects, as we require having at least two loan applications in the same month by the same firm. Given that our sample period is short (about two years), firm fixed effects also control well for borrower unobserved risk characteristics.

[27] Scoring has a negative and statistically significant coefficient, which means that, on average, riskier firms in observables are less likely to get a loan application granted. In Model 2, without firm fixed effects, the coefficient on those firms that have been not granted previous applications is negative. Model 3 with firm fixed effects gives mechanically a positive coefficient for this variable.

Summarizing, in Table 3, Panel A, we find that the state-bank is more restrictive in granting applications as compared to the private banks, not only because it has a riskier pool of applicants, but also when we control for observable and unobservable firm characteristics. The difference in the probability of granting applications is around 10 percentage points, which is quantitatively important (around 33%). Moreover, the state-owned bank is more cautious to observable riskier borrowers than the private banks. However, within the firms that apply to banks in the previous year, the state-owned bank grants more new loan applications than the private banks to the firms that did not get any granted loan application on the previous year. This is interesting as this information cannot be observed by the state-owned bank.[28]

The structure of Panel B of Table 3 is the same as Panel A. In this panel we find first that, without conditioning on firm characteristics, the state-owned bank provides less loan volume (18.2%) to the granted applications. However, this reduction is just because the pool of applicants is riskier. Once we control for firm characteristics (observable and even unobservable ones), the state-owned bank provides a higher credit volume (between 20.7% and 26.7% higher) than the private banks.

Moreover, following Model 6, the strongest specification (with firm*month fixed effects), the higher loan volume of the state-owned bank is even larger for riskier firms in unobservable ways (firms that were not granted an application in the last year). Therefore, considering only applications from the same firm in the same month to the state-owned bank and to private banks, for both the likelihood of granting applications and loan volume granted, the state-owned bank is more generous than the private banks in a crucial segment of risky firms: the firms that did not get any granted loan application in the previous year despite seeking finance.

The interaction of the ICO dummy and firm scoring gives different results in Panels A and B. Although it is not statistically significant in the strongest specification (Model 6) of Panel B, it is always significant in Panel A. Therefore, for observable characteristics (summarized in the scoring), the results suggest that the state-owned bank is tighter in its lending to observable riskier firms.

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[28] Although this information was not observed either by the private banks, they could rely on their previous experience in granting loans to SMEs.

In Table 4, we find that loans granted by the state-owned bank have a substantially higher probability of default than those granted by private banks (32 percentage points higher). However, around half of this number is due to the riskier pool of borrowers, as we can see from comparing Model 1 or 2 to Model 3 (e.g. 0.327*** versus e.g. 0.165***).[29] Note that this is even though the state-owned bank is more restrictive on average in granting loan applications than the private banks. This result further suggests that –controlling for observable characteristics– the state-owned bank is softer in unobserved riskier firms that tend to default more ex-post.[30]

In addition, the higher defaults for the state-owned bank as compared to the private banks are especially higher for riskier firms in both observable and unobservable characteristics.[31] Both Model 4 and 5 show that the ex-ante firm risk variable "none of the last-year loan applications is granted" implies higher ex-post defaults only for the state-owned bank, but not for the private banks, which suggests that the state-owned bank takes the riskier firms within the pool of firms that were trying to borrow before the new public credit facility was launched.

Our results indicate that the new public credit facility faced significant adverse selection problems, the state-owned bank restricted lending because of the worse pool of borrowers, but it was substantially softer on unobserved riskier firms, proxied by either the inability of getting credit ex-ante or by the tendency to default more ex-post. This basically explains the substantial higher ex-post defaults of the public lending facility.

5. Empirical strategy and results on the real effects of credit supply

In this section we analyze whether the granting of loans by the state-owned bank causes some positive real effects, and if so, how large these effects are. To test for the real effects, we focus on the main firm-level real outcomes such as firm survival,

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[29] Note that despite that we do not have the loss given default for each loan, the average is 34% for all the portfolio of ICO loans.

[30] The coefficient in column 2 is only reduced to 0.27 if we control (in addition to the firm scoring) by the firm observable characteristics from Table 1 (not only in levels, but also in the square and other polynomial degrees). Therefore, a substantial part of loan defaults is due to unobserved ex-ante characteristics.

[31] In Appendix C we show additional robustness exercises for Tables 3, Panel B, and 4, by including loan controls (maturity, loan amount and collateral) and the possible selection bias of granted loan outcomes to the granting of loan applications (following Jiménez et al., 2014).

change in employment, investment, total assets, sales (proxying for overall production), and productivity (measured by sales over employees). We also analyze whether the public lending implies sub-sequent lending by private banks (crowding in effects), thereby multiplying the effects of the initial public funds lent.

ICO is a bank without soft information on borrowers (e.g., without branches or previous experience in lending directly to SMEs) that relied for the new credit facility on hard information and a lending rule to grant applications. Thus, we exploit –in a regression discontinuity approach– the state-owned bank's continuous lending rule (i.e. the scoring system) based on firm fundamentals to accept or reject loan applications around the cutoff point, where we get –at the firm level– an exogenous variation in credit supply.

Therefore, we can push on the causality of credit supply because, apart from exploiting a new credit facility in a matched firm-bank-credit register data, we know both the loan applications and the lending rule of the state-owned bank –with the individual firm scoring values and the cutoff to grant the loans– which give us quasi-experimental data, following the terminology of Angrist and Pischke (2009) and Lee and Lemieux (2010).

The regression discontinuity design (see e.g. Imbens and Wooldridge, 2009) is used in situations where the probability of being enrolled into the treatment changes discontinuously (in our case, granting vs. rejection of the firm loan application by the state-owned bank) with some continuous variable (in our case, the continuous scoring value that the state-owned bank uses to evaluate a borrower).[32] Figure 4 shows the probability of receiving the ICO loan depending on the firm scoring. A firm is selected to be treated if the numerical value of the scoring is below a certain threshold (the cutoff point); then, the probability of receiving the treatment (the ICO loan) is discontinuous at the cutoff point. Figure 4 shows clearly that this is the case in our paper, with a

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[32] As we focus on firm-level results, in this section we analyze the data at the firm level, thus aggregating applications at the firm level. Results do not depend on this. As explained in Section 3, the database that we use allow us to have a random sample of ICO applicants with their individual scoring values, cutoff point and the result of the application, which we match (via the unique tax number) with firm-level real and financial variables, both at the time of the loan application and in the future. This sample has a large coverage, representing 25% of all applications. As shown in Section 3, there are not significant differences in firm variables between the sample and the set of all ICO applicants.

discontinuity in the likelihood of granting the loan of almost 40 percentage points around the cutoff point (almost 400% increase in probability of receiving the loan).

Our results are based on a fuzzy regression discontinuity approach. As Figure 4 shows, there are a number of firms with a credit scoring above the cutoff that are nevertheless granted the loan (2% of all firms), as well as a higher number of firms below the cutoff that do not obtain the loan (28% of all firms).[33] Therefore, the fuzzy approach corrects for the endogeneity of getting an ICO loan by instrumenting it via a dummy variable defined by whether the particular firm score is below the cutoff point or not (see e.g. Angrist and Pischke, 2009; Imbens and Wooldridge, 2009; Lee and Lemieux, 2010).[34]

There are different strategies to perform this analysis. We focus on the nonparametric (local) one, which requires that in a small interval around the threshold the allocation is almost random. In fact, as Table 2 Panel A of Appendix C shows, the firm observable characteristics around the cutoff point (below and above) at the time of the loan application are not statistically different, but (following Figure 4) the firms have a very different probability of being granted the loan.

Moreover, Figure 5 also suggests that firms do not choose whether to be above or below the cutoff point. This is confirmed using the McCrary test.[35] Note that the formula applied by the state-owned bank is confidential and proprietary and it provides a value out of eighteen firm variables (for example leverage and profits), which are double-checked with the Mercantile Register, the Bank of Spain, private registers and the tax authority. Hence, manipulation is difficult. In consequence, we can interpret the direction and magnitude of the change in the real variables for firms around the cutoff point as a direct measure of the casual effects of the public policy.

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[33] In the latter case, it is mainly because the cross-checking of some information reveals problems, or because the firm does not need anymore the loan, although we do not know the specific firm-level reason.

[34] If instead of an increase of almost 40 p.p. of the likelihood of being treated (obtaining the ICO loan) around the cutoff, it would have been 100 p.p., i.e. to go from 0 to 1 in probability, then we could have used the sharp approach in regression discontinuity. Nevertheless, if we use the sharp approach eliminating the non-compliers (observations based on firms that get the loan despite of having a score above the cutoff and those that do not get the loan despite of having a score below the cutoff), results are also statistically and economically significant.

[35] This statistical test studies whether there is a discontinuity in the density of the assignment variable, where the null hypothesis is that there is continuity. In our case, the estimated value is 0.0727 (with 0.0605 standard error), so we do not reject the null hypothesis.

Our main econometric analysis is based on a non-parametric method using local polynomials where the optimal bandwidth is selected automatically by the program. The equation we estimate is the following:

$$(3) \qquad Y_i = \alpha + \beta I(ICO\ APPLICANT\ GRANTED_i) + f(r_i) + \varepsilon_i,$$

where Y_i is the an outcome measure for firm i from 2009:M12 to year t;[36] I(ICO APPLICANT GRANTED)$_i$ is a dummy variable that takes the value of one if the firm got an ICO loan, and zero otherwise; r_i is the rating (scoring value) for firm i centered at the cutoff point; and ε_i is an error term. $f(\cdot)$ is a function of the rating variable that is included to correct for the possible bias due to the selection on observables; it is usually assumed to be linear (see Gelman and Imbens, 2016), though we also use quadratic and higher degree polynomials for robustness. As we use the fuzzy approach, we instrument I(ICO APPLICANT GRANTED)$_i$ with a dummy variable that equals one if the firm specific score is below the cutoff, and zero otherwise.

The firm outcome Y_i is: a dummy variable whether the firm survives or not; the percentage change in total assets; the percentage change in total sales; the percentage change in the number of employees; the investment; the percentage change in productivity; and two credit-related variables, a dummy variable that equals one if the firm receives (after the acceptance or rejection of the ICO loan) new credit from private banks that were not lending to the firm during the period, and zero otherwise, and the percentage change in total private bank credit.[37]

Table 5 shows the estimation results of the regression discontinuity model of firm survival between 2010:M1 and different times t, where t is end of December of either 2011, 2012, 2013 and 2014 (columns 1 to 4).[38] The coefficient of I(ICO APPLICANT GRANTED)$_i$ is positive and statistically significant. In addition, the instrument has a first stage F-test between 86 and 121, where the rule of thumb for not having weak instruments problems is above 10. In terms of magnitude, the granting of a

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[36] Note that the public lending facility starts in mid 2010, and the previous firm-level information is from end of 2009.

[37] Appendix B contains the definition of all the variables used in the empirical analysis.

[38] Table 2 also contains the descriptive statistics used for the econometric analysis of the real effects of the new credit supply. Note that the average effects of all the real variables are negative, and therefore our results imply that these effects are alleviated by the lending policy of the state-owned bank (e.g. employment declines less for firms that get an ICO loan than otherwise).

loan by the new credit facility causes a positive impact on the likelihood for a firm to survive until the end of 2014 of 19 percentage points, which corresponds to 26% increase at the mean.

We also show different specifications for robustness to check the consistency of the estimated coefficients (following Angrist and Pischke, 2009; Imbens and Wooldridge, 2009; Lee and Lemieux, 2010)). For example, we use a quadratic polynomial instead a linear one (column 5); we test the sensitivity of the results to the change of the optimal bandwidth from half (column 6) to double (column 7), and also show the estimated results for a parametric specification (column 8). Moreover, Figure 6 plots the estimates against the continuum of bandwidths to show the stability of the baseline model.[39] Additionally, Table 2 Panel B of Appendix C also performs a robustness exercise, exploring the sensitivity of the results to the inclusion of firm observable characteristics (those of Panel A) as controls in addition to the scoring. Results are all statistically and economically significant, and very similar (and statistically not different) to those of the baseline regressions.[40]

In Table 6 we analyze other firm outcomes. The estimated coefficients for employment growth, total assets growth, total sales growth, productivity growth, investment, ex-post access to private loans, and total private bank credit growth are all statistically significant and economically large. As some real effects cannot have values below -100%, we also perform a Tobit analysis with very similar results. Quantitatively, the granting of a public loan by the new public credit facility causes a 51% to 59% increase in employment growth, 65% to 70% increase in total assets growth, 69% to 83% in total sales growth, 79% to 94% increase in investment, 81% to 97% increase in productivity,[41] and a 75% average increase of the likelihood of ex-post access to new private loans (which corresponds to 22 percentage points), and a 31% increase in total

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[39] The estimated optimal bandwidth for column 4 is 0.966.

[40] In addition, we also analyze the heterogeneity effects depending on some firm or loan characteristics. However, we do not find significant heterogeneity. Nevertheless, we find than the real effects are higher for firms without internal capital markets (non-reported), which is consistent with limited alternative sources of funding.

[41] We find similar results when selecting firms that continue operating over the 2010-2013 period, with 29%, 60%, 76%, 94% and 48%, respectively. For access to new private credit after the ICO loan, we select (and only analyze) firms that continue operating, as otherwise they could not obtain new credit from private banks.

private bank credit.[42] Figure 7 shows the economic effects; in all the output variables, there is a clear jump just below and above the cutoff point.[43]

Therefore, not only are the real effects large, but also, after obtaining public funds, these firms obtain new loans from private banks, not their old main banks. These banks are not affected by loan ever-greening (zombie lending). The new private credit increases the initial public funds, thus consistent with crowding in effects. Importantly, as the size of the program was small, the research design is not contaminated with general equilibrium effects that would imply a significantly impact on firms that were rejected by the public lending facility.

As Table 3 of Appendix C shows, results are not statistically (or economically) significant before the law was passed in mid 2010, i.e. up to December 2009, which serves as a placebo test. Following Lee and Lemieux (2010), we also use another placebo test (non-reported) by testing at points different from the official threshold (by adding or subtracting a multiple of the optimal bandwidth to the cutoff) whether there are also significant jumps in firm outcomes. In all cases, the estimated discontinuities are insignificant. Therefore, the different placebo tests suggest that it is the public lending that causes the real effects.

All in all, the new credit facility set up by the state-owned bank causes positive, strong real effects on average. However, given our results in Section 4, there is significant firm heterogeneity: (i) one set of firms which have large loan defaults (and in fact with similar firm exit likelihood than the firms that did not get the loan by the state-owned bank); and (ii) another set of firms with very strong positive real effects, low defaults and entering again in the private credit market.[44] Thus, in assessing the public policy program, one should balance the positive real effects in a period of credit crunch against large loan defaults where government funds are scarce and costly.

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[42] An important part of the new private lending has maturity higher than the residual maturity of the public loans (in particular, in 69% of the cases).

[43] Note that the quantitative effects in Figure 7 are different from those in Tables 5 and 6, as the figures are just reporting the real effects and the firm scoring, whereas the tables are based on the fuzzy regression discontinuity estimates (where the scoring firm value instruments the public loan granted to analyze the real effects).

[44] Our strong results on real effects are for all firms that get the public loans versus the ones that are rejected. However, analyzing those firms that obtained the public loans, there is an important group with high loan defaults (see Section 4) that have survival rates similar to those firms that did not obtain the public loans.

6. Concluding remarks

We analyze the role of lending by a state-owned bank in a credit crunch, the potential adverse selection faced by the bank, and the causal real effects of the supply of new credit to firms. In a crisis, actions by central banks via public liquidity injections to banks may not reach the real side of the economy if banks do not have enough capital, prefer to hoard liquidity or invest in securities such as government debt.[45]

Direct public lending via state-owned banks might therefore have a useful role to play in financial crises by reducing the credit crunch. A state-owned bank can support lending to the real economy by relying not only on its explicit capital, but also on the implicit capital derived from its access to government and taxpayer funds. This increase in the supply of credit may bring strong positive effects for the real economy. On the other hand, there is evidence that state-owned banks are generally more inefficient than privately-owned banks. Moreover, a higher willingness to provide more lending in the crisis may imply substantial defaults due to lack of high quality firm applicants (demand side), including the potential winners' curse in new loans.

For identification of these effects, we exploit a new (small) credit facility in Spain during the financial crisis provided by its state-owned bank, a bank without soft information on borrowers that relied on hard information included in a lending scoring system. Importantly, we have access to the bank's continuous value scoring function based on borrower firm fundamentals to grant or reject loan applications, the cutoff used for granting or rejecting applications, including the specific individual applicant's score, and the exhaustive credit register, including loan applications, matched with administrative firm and supervisory bank balance-sheet data.

Our empirical results suggest that the public credit facility faces significant adverse selection problems. In response to these problems, the state-owned bank restricts its lending, but nevertheless it is substantially softer in its lending to unobservable riskier firms (i.e., firms to whom none of their previous loan applications were granted, or firms that tend to default more ex-post but these defaults are not related to the ex-ante observable firm scoring or other observable firm characteristics). Thus,

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[45] See for example Abassi et al. (2016) or Peydró et al. (2017).

the public lending facility has 32 percentage points higher ex-post loan defaults, compared to defaults of privately-owned banks (lending to new firms).

Importantly, in a regression discontinuity approach –to obtain exogenous variation in credit supply at the firm level– we exploit the continuous value scoring function based on eighteen firm fundamentals to grant loan applications around the cutoff point. We find that the public credit facility causes large real effects on firm survival, employment, investment, total assets and sales, productivity as well as subsequent substantially higher probability of getting new loans from private banks that they were not previously lending to the firm and higher total private credit volume (crowding in effects). Quantitatively, the granting of a public loan by the state-owned bank causes a 26% increase in firm survival, 51% increase in employment growth, 65% increase in total assets growth, 69% in total sales growth, 79% increase in investment, 81% increase in productivity, a 75% increase of the likelihood of ex-post access to new private loans, and a 31% increase in total private credit volume. The quantitative effects are large as these are small firms in an economy with a strong credit crunch.

Commentators and academics have extensively argued about the limits of expansionary monetary policy to reach the real sector in crisis times. Another countercyclical solution, as the World Bank for instance argues, is via state-owned banks by granting directly loans to firms in crisis times. Overall, our results show that when there is a (private sector) credit crunch, a state-owned bank can ameliorate it with significant real effects in the economy, including firm survival, employment, output, investment and productivity. However, a significant part of its lending is very risky, which suggests that also a substantial part of the rationed credit demand is not solvent. Hence, the effectiveness of public policy in combating credit crunches via state-owned banks seems severely limited by informational asymmetries that are especially pervasive in crisis times.

References

Angrist, J. D., and J.-S. Pischke (2009), *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton: Princeton University Press.

Atkinson, A., and J. E. Stiglitz (1980), *Lectures on Public Economics*, New York: McGraw-Hill.

Abbassi, P., R. Iyer, J. L. Peydró, and F. R. Tous (2016), "Securities Trading by Banks and Credit Supply: Micro-Evidence from the Crisis," *Journal of Financial Economics* 121 (3), 569-594.

Amiti, M., and D. Weinstein (forthcoming). "How Much do Bank Shocks Affect Investment? Evidence from Matched Bank-Firm Loan Data," *Journal of Political Economy*.

Berg T. (2016), "Got Rejected? Real Effects of Not Getting a Loan," ECB WP 1960, September.

Bernanke, B. S. (1983), "Nonmonetary Effects of the Financial Crisis in Propagation of the Great Depression," *American Economic Review* 73, 257-76.

Bernanke, B. S., and C.S. Lown. (1991), "The Credit Crunch," *Brookings Papers in Economic Activity* 22, 205-39.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1996), "The Financial Accelerator and the Flight to Quality," *The Review of Economics and Statistics* 78, 1-15.

Bertay, A., A. Demirgüç-Kunt, and H. Huizinga (2015), "Bank Ownership and Credit over the Business Cycle: Is Lending by State Banks less Procyclical?" *Journal of Banking and Finance* 50, 326-339.

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

Brunnermeier, M., and Y. Sannikov (2014), "A Macroeconomic Model with a Financial Sector," *American Economic Review* 104, 379-421.

Carvalho, D. (2014), "The Real Effects of Government-Owned Banks: Evidence from an Emerging Market," *Journal of Finance* 69, 577-609.

Chodorow-Reich, G. (2014), "The Employment Effects of Credit Market Disruptions: Firm-Level Evidence from the 2008-09 Financial Crisis," *Quarterly Journal of Economics* 129, 1-59.

Cingano, F, Manaresi, F., and E. Sette (2016), "Does Credit Crunch Investments Down?" *Review of Financial Studies* 29, 2737-2773.

Dell'Ariccia, G., and R. Marquez (2006), "Lending Booms and Lending Standards," *Journal of Finance* 61, 2511-2546.

Dinç, I. S. (2005), "Politicians and Banks: Political Influences on Government-owned Banks in Emerging Markets," *Journal of Financial Economics* 77, 453-479.

Englmaier, F., and T. Stowasser (2013), "Electoral Cycles in Savings Bank Lending," SSRN working paper.

Eslava M, and X. Freixas (2016), "Public Development Banks and Credit Market Imperfections," Barcelona GSE Working Paper No. 874.

Freixas, X., L. Laeven, and J. L. Peydró (2015), *Systemic Risk, Crises, and Macroprudential Regulation*, Cambridge: MIT Press.

Gelman, A. and G. Imbens (2016), "Why High-Order Polynomials Should not be Used in Regression Discontinuity Designs," Stanford and Columbia Mimeo.

He, Z., and A. Krishnamurthy (2013), "Intermediary Asset Pricing," *American Economic Review* 103, 732-770.

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

Imbens, G. M., and Wooldridge, J. M. (2009), "Recent Developments in the Econometrics of Program Evaluation," *Journal of Economic Literature* 47, 5–86.

Jiménez, G., Salas, V., and, J. Saurina (2006), "Determinants of Collateral," *Journal of Financial Economics* 81, 255-281.

Jiménez, G., Lopez, J. A., and J. Saurina (2009), "Empirical Analysis of Corporate Credit Lines," *Review of Financial Studies* 22, 5069 –5098.

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

Jiménez, G., S. Ongena, J. L. Peydró, and J. Saurina (2014), "Hazardous Times for Monetary Policy: What do Twenty-Three Million Bank Loans say About the Effects of Monetary Policy on Credit Risk-Taking?" *Econometrica* 82, 463-505.

Jiménez, G., A. Mian, J. L. Peydró, and J. Saurina (forthcoming), "The Real Effects of the Bank Lending Channel," *Journal of Monetary Economics*.

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

Jorda, O., M. Schularick, and A. M. Taylor (2013), "When Credit Bites Back," *Journal of Money, Credit and Banking* 45, 3-28.

Khwaja, A. I., and A. Mian (2005), "Do Lenders Favor Politically Connected Firms? Rent Provision in an Emerging Financial Market," *Quarterly Journal of Economics* 120, 1371-1411.

Khwaja, A. I., and A. Mian (2008), "Tracing the Impact of Bank Liquidity Shocks," *American Economic Review*, 98, 1413-1442.

Kindleberger, C. P. (1978), *Manias, Panics, and Crashes: A History of Financial Crises*, New York: Basic Books.

La Porta, R., F. Lopez-de-Silanes, and A. Shleifer (2002), "Government Ownership of Banks," *Journal of Finance* 57, 265-301.

Lee, D. S., and T. Lemieux (2010), "Regression Discontinuity Designs in Economics," *Journal of Economic Literature* 48, 281–355.

Paravisini, D., V. Rappoport, P. Schnabl, and D. Wolfenzon (2015), "Dissecting the Effect of Credit Supply on Trade: Evidence from Matched Credit-Export Data," *Review of Economic Studies* 82, 333-359.

Peydró, J.-L., A. Polo, and E. Sette (2017), "Monetary Policy at Work: Security and Credit Application Registers Evidence," CREI working paper.

Repullo, R., and J. Suarez (2013), "The Procyclical Effects of Bank Capital Regulation," *Review of Financial Studies* 26, 452-490.

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

Sapienza, P. (2004), "The Effects of Government Ownership on Bank Lending," *Journal of Financial Economics* 72, 357-384.

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

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

Shleifer, A., and R. W. Vishny (1994), "Politicians and Firms," *Quarterly Journal of Economics* 109, 995-1025.

Shleifer, A., and R. W. Vishny (2010), "Unstable Banking," *Journal of Financial Economics* 97, 306-318.

Stein, J., (2013), "The Fire-Sales Problem and Securities Financing Transactions," https://www.federalreserve.gov/newsevents/speech/stein20131004a.htm.

World Bank (2013), "Global Financial Development Report."

FIGURE 1

The effect of the lending bias on the supply of credit
and the default rate of the state-owned bank

A - Supply of credit   B - Default rate

This figure shows the effect of the lending bias δ on the supply of credit (Panel A) and the default rate (Panel B) of the state-owned bank. The solid line in both panels corresponds to given values of the proportion γ of high-risk entrepreneurs and the noise σ of the scoring system. The dashed lines show the effect of an increase in γ (for the given value of σ), while the dotted lines show the effect of an increase in σ (for the given value of γ).

FIGURE 2

The effect of the lending bias of the state-owned bank on social welfare

Welfare

This figure shows the effect of the lending bias δ of the state-owned bank on social welfare W.

FIGURE 3

Densities of some characteristics of firm applicants to ICO and to other banks

SCORING

CAPITAL RATIO

LIQUIDITY RATIO

DRAWN OVER COMMITTED
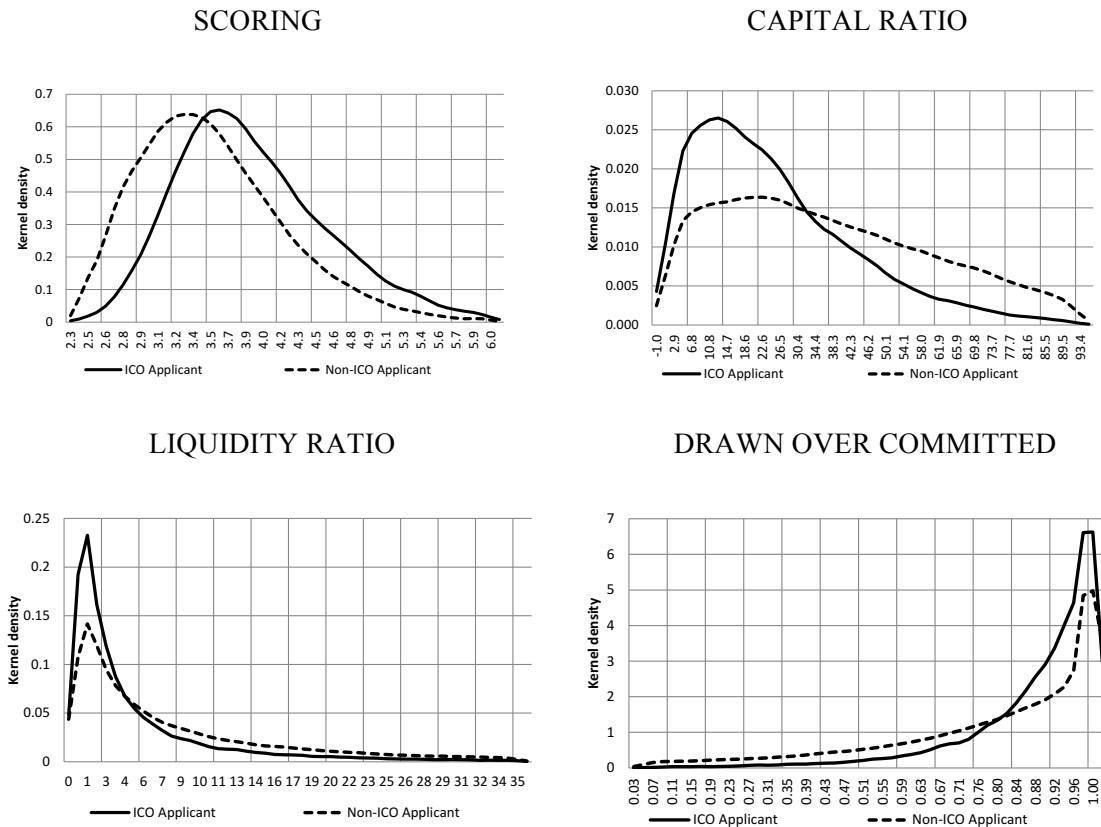
This figure shows the estimated kernel densities of some firm characteristics. SCORING is a variable that measures the financial risk of a firm through a weighted average of firm characteristics (note that higher values of SCORING are associated to riskier firms). CAPITAL RATIO is the own funds of the firm over total assets. LIQUIDITY RATIO is the current assets of the firm over total assets. DRAWN TO COMMITMENT is the ratio between the drawn amount over the total committed amount of all bank loans of the firm.

FIGURE 4

State-owned bank's granted loans by bin
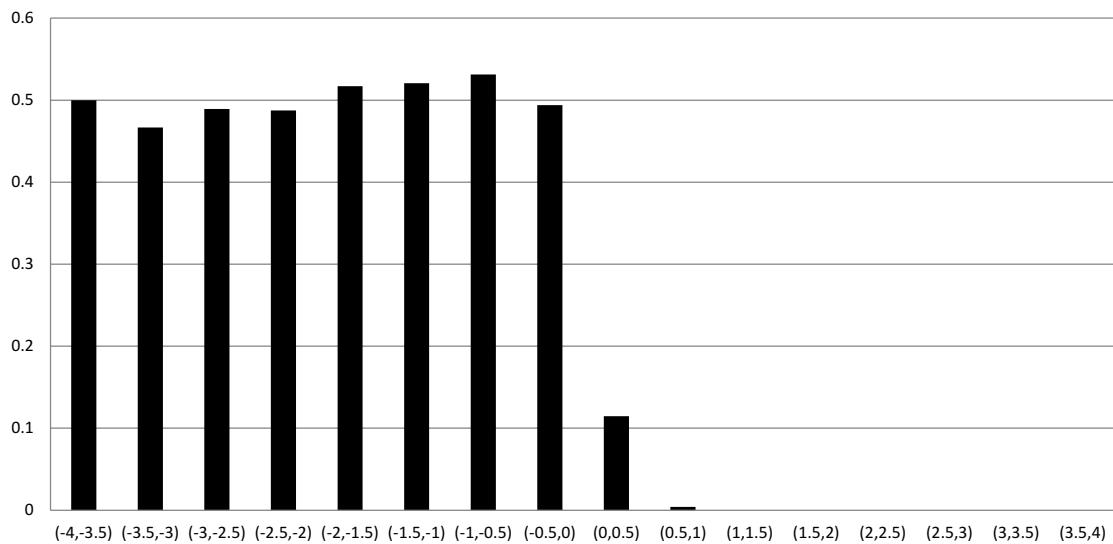
This figure shows the frequencies of granted loans by the State-owned bank for each bin of the scoring minus the cutoff point.

FIGURE 5

Density of the scoring variable
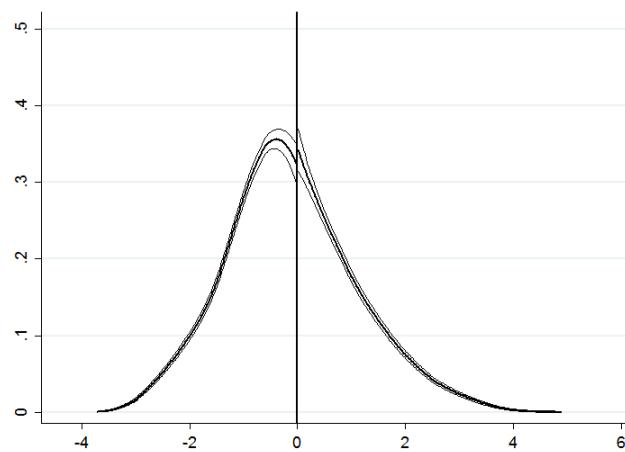
This figure shows the estimated kernel densities of the scoring minus the cutoff point on both sides of the cutoff using the McCrary methodology. In thin lines, the 95% confidence bands are reported.

FIGURE 6

Fuzzy design estimation of firm survival (2010-2014) with varying bandwidth
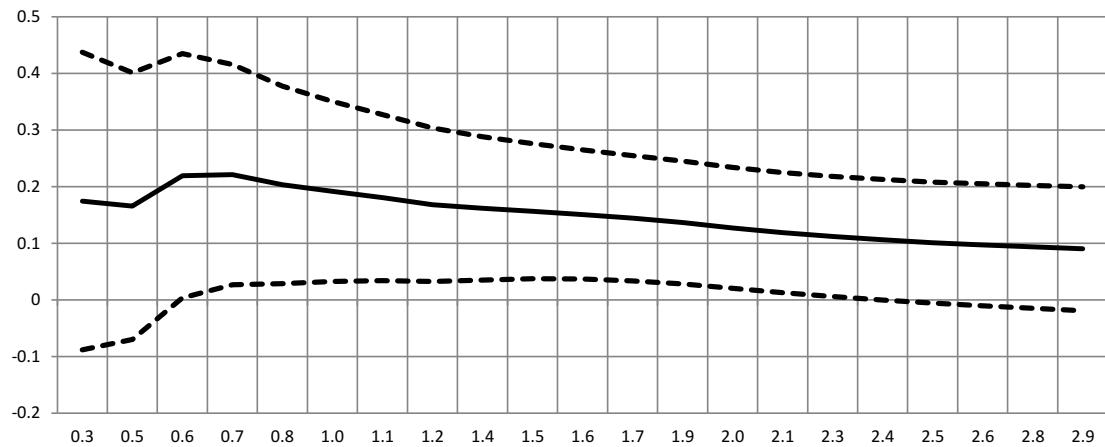
This figure shows the estimation of the analogous to column 4 of Table 5, where the survival of the firms is analyzed for a continuum of bandwidths. Plotted lines show the 90% percent confidence bands.

FIGURE 7

Graphical representation of the regression discontinuity results

Firm survival

Employment growth

Assets growth

Sales growth

Investment

Productivity growth

New bank loan

Bank loan growth
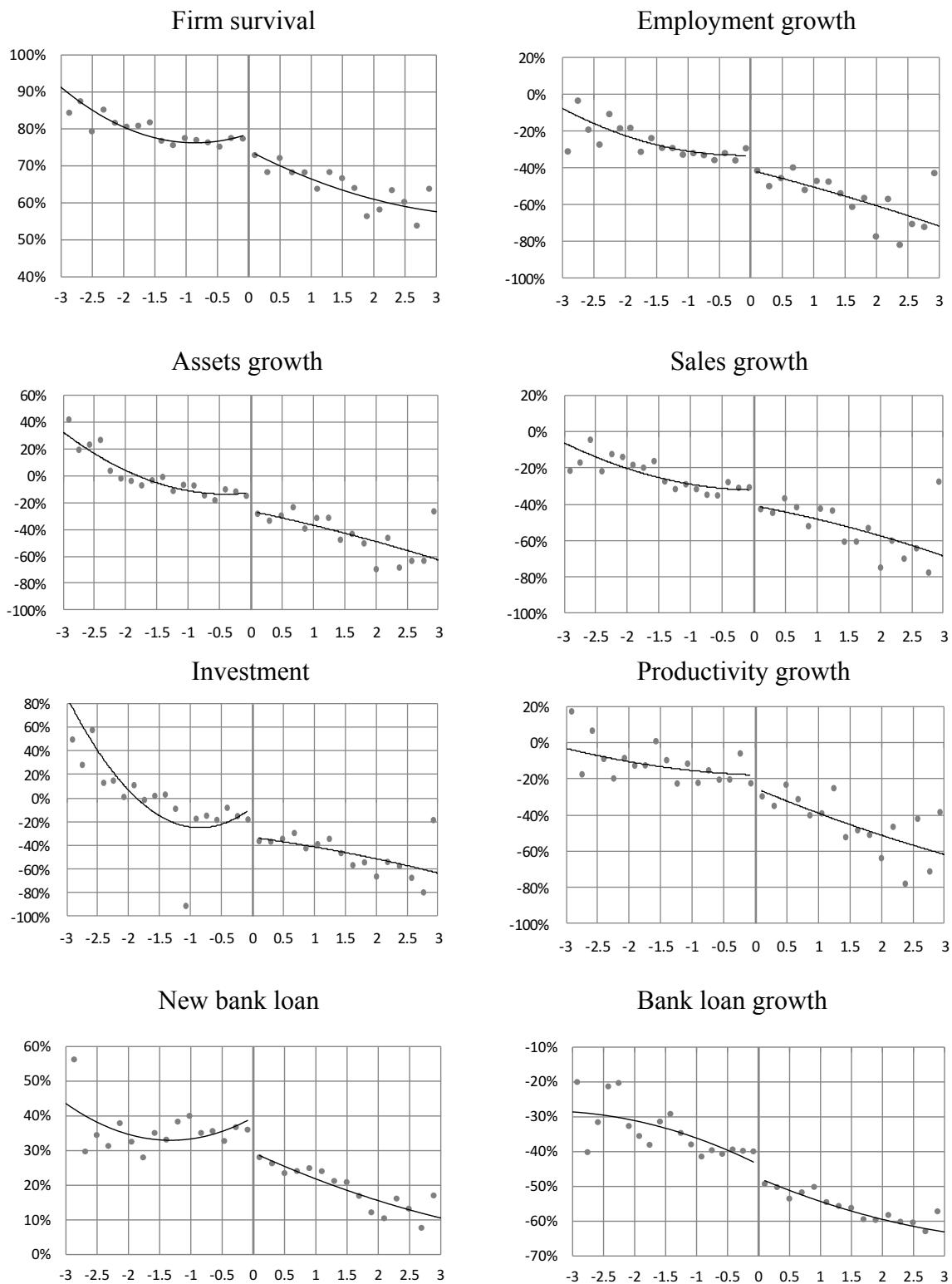
X-axis: the scoring minus the cutoff point. Y-axis: the average value of each firm variable within bin. A 2nd order polynomial is adjusted. For a description of the variables, see Appendix B.

TABLE 1

Descriptive statistics of firm applicants to ICO and to other non-current banks

	ICO Applicant				Non-ICO Applicant				Mean Test ICO vs. Non-ICO	Dependent variable: I(ICO APPLICANT)$_f$	
	Mean	S.D.	P25	P75	Mean	S.D.	P25	P75	t-test	Coeff.	S.E.
SCORING$_{ft-1}$	3.98	0.80	3.44	4.37	3.56	0.71	3.06	3.94	68.57 ***	0.022 **	(0.006)
CAPITAL RATIO$_{ft-1}$	25.01	18.26	11.08	35.02	37.55	24.21	17.68	54.86	-63.36 ***	-0.027 **	(0.008)
LIQUIDITY RATIO$_{ft-1}$	5.42	8.76	0.79	6.02	10.21	13.17	1.65	13.42	-45.10 ***	-0.015 **	(0.006)
Ln(TOTAL ASSETS)$_{ft-1}$	6.98	1.27	6.13	7.83	6.87	1.37	5.94	7.77	9.69 ***	-0.025 **	(0.012)
AGE$_{ft-1}$	13.56	9.26	7.00	19.00	14.78	9.96	7.00	20.00	-14.76 ***	-0.009 **	(0.002)
ROA$_{ft-1}$	2.82	9.11	1.35	5.92	3.76	10.18	1.15	6.89	-11.19 ***	-0.003	(0.004)
Ln(SALES/EMPLOYEES)$_{ft-1}$	4.65	0.86	4.12	5.13	4.80	0.95	4.20	5.35	-19.31 ***	-0.021 **	(0.006)
INTEREST PAID$_{ft-1}$	4.33	3.37	2.31	5.44	3.32	3.76	1.03	4.28	32.10 ***	0.019 **	(0.006)
Ln(NUMBER OF BANKS)$_{ft-1}$	1.53	0.59	1.10	1.95	1.16	0.62	0.69	1.61	71.86 ***	0.071 ***	(0.016)
DRAWN OVER COMMITTED$_{ft-1}$	0.85	0.21	0.81	0.98	0.70	0.33	0.54	0.97	56.33 ***	0.016 *	(0.009)
NON COLLATERALIZED LOANS/TOTAL LOANS$_{ft-1}$	0.71	0.33	0.46	1.00	0.68	0.40	0.30	1.00	9.44 ***	-0.021 **	(0.006)
LOAN MATURITY 1-5y/TOTAL LOANS$_{ft-1}$	0.29	0.26	0.08	0.43	0.26	0.31	0.00	0.42	11.46 ***	0.005 *	(0.003)
I(BAD CREDIT HISTORY)$_{ft-1}$	0.10	0.30	0.00	0.00	0.03	0.16	0.00	0.00	43.26 ***	0.020 **	(0.004)
I(LOAN APPLICATION)$_{ft-1}$	0.57	0.50	0.00	1.00	0.43	0.50	0.00	1.00	32.64 ***	0.019 **	(0.003)
I(NONE LOAN APPLICATION GRANTED)$_{ft-1}$	0.29	0.45	0.00	1.00	0.25	0.43	0.00	0.00	10.41 ***	-0.004	(0.003)

Notes: This table reports means, standard deviations, 25th and 75th percentiles of firm characteristics depending whether the firm asked or not to the state-owned bank (ICO). Last two columns report estimates from a linear probability model using ordinary least squares. The dependent variable is I(ICO APPLICANT)$_f$ which equals one if the firm asked for a loan to the ICO program and zero otherwise. The definition of the independent variables can be found in Appendix B. All independent variables have been normalized with their mean and standard deviation. The estimation includes province*year*industry (NACE at two digits) fixed effects. Coefficients are listed in the first row, the corresponding significance levels are in the adjacent column and robust standard errors that are corrected for clustering at firm, industry, province and bank level are reported in the last column. I(.) is the indicator function which means that the variable takes only two values: 0 or 1. *** Significant at 1%, ** significant at 5%, * significant at 10%. Number of observations: 105,909. Number of firms: 82,184. Number of observations by ICO applicants: 16,461.

TABLE 2

Descriptive statistics of the variables used in the analysis

Variable	Mean	Standard Deviation	P25	Median	P75
For the Analysis of the Lending Regressions (Tables 3 and 4)					
I(LOAN APPLICATION GRANTED)$_{fbt}$	0.29	0.45	0.00	0.00	1.00
Ln(CREDIT AMOUNT)$_{fbt}$	4.00	1.09	3.26	3.93	4.62
I(FUTURE DEFAULT)$_{fb}$	0.13	0.34	0.00	0.00	0.00
SCORING$_{ft-1}$	3.71	0.76	3.19	3.61	4.11
I(ICO BANK APPLICANT)$_f$	0.23	0.42	0.00	0.00	0.00
I(LOAN APPLICATION)$_{ft-1}$	0.74	0.44	0.00	1.00	1.00
I(NONE LOAN APPLICATION GRANTED)$_{ft-1}$	0.40	0.49	0.00	0.00	1.00
I(ICO BANK)$_b$	0.07	0.26	0.00	0.00	0.00
Ln(TOTAL ASSETS)$_{bt-1}$	18.04	1.37	17.27	18.27	18.73
CAPITAL RATIO$_{bt-1}$	5.75	2.34	4.34	5.21	6.91
ROA$_{bt-1}$	0.31	0.57	0.16	0.31	0.56
DOUBTFUL RATIO$_{bt-1}$	6.39	3.65	4.33	5.71	7.52
For the Analysis of the Real Effects of ICO loans (Tables 5 and 6)					
I(FIRM SURVIVAL)$_{f2014}$	0.73	0.44	0.00	1.00	1.00
EMPLOYMENT GROWTH$_{f2013}$	-0.37	0.58	-1.00	-0.42	0.00
ASSETS GROWTH$_{f2013}$	-0.19	0.70	-1.00	-0.17	0.13
SALES GROWTH$_{f2013}$	-0.33	1.06	-0.73	-0.24	0.13
INVESTMENT$_{f2013}$	-0.25	2.42	-1.00	-0.31	0.00
PRODUCTIVITY GROWTH$_{f2013}$	-0.23	0.70	-1.00	-0.25	0.18
I(NEW BANK LOAN)$_f$	0.30	0.46	0.00	0.00	1.00
BANK LOAN GROWTH$_f$	-0.45	0.47	-0.88	-0.52	-0.15
SCORING$_{ft}$ - CUTOFF POINT$_{ft}$	-0.11	1.21	-0.90	-0.22	0.62
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	0.31	0.46	0.00	0.00	1.00
I(ICO LOAN APPLICATION BELOW CUTOFF POINT)$_{ft}$	0.57	0.49	0.00	1.00	1.00

Notes: This table reports means, standard deviations, 25th and 75th percentiles of the sample used for the lending regressions (Tables 3 and 4), and the one used in the analysis of the real effects of ICO loans (Tables 5 and 6). I(.) is the indicator function which means that the variable takes only two values: 0 or 1. For a description of the variables see Appendix B.

TABLE 3

Analysis of the likelihood that a loan application is granted and its credit amount

Dependent variable:	PANEL A						PANEL B					
	I(LOAN APPLICATION GRANTED)$_{fbt}$						Ln(CREDIT AMOUNT)$_{fbt}$					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
I(ICO BANK)$_b$	-0.121 ***	-0.116 ***	-0.107 ***	-0.094 ***			-0.182 ***	-0.142 ***	0.267 ***	0.207 ***		
	(0.032)	(0.033)	(0.026)	(0.025)			(0.040)	(0.038)	(0.047)	(0.063)		
SCORING$_{ft-1}$		-0.016 ***	-0.042 ***		-0.044 ***			-0.171 ***	-0.077 ***		-0.080 ***	
		(0.005)	(0.006)		(0.007)			(0.030)	(0.024)		(0.023)	
I(LOAN APPLICATION LAST YEAR)$_{ft-1}$		0.095 ***	-0.111 ***		-0.112 ***			0.304 ***	0.047 ***		0.049 ***	
		(0.012)	(0.013)		(0.012)			(0.022)	(0.012)		(0.016)	
I(NONE LOAN APPLICATION GRANTED)$_{ft-1}$		-0.138 ***	0.268 ***		0.265 ***			-0.046 **	0.002		-0.001	
		(0.021)	(0.025)		(0.023)			(0.021)	(0.016)		(0.016)	
I(ICO BANK)$_b$*SCORING$_{ft-1}$					-0.021 ***	-0.022 *					0.058 **	0.050
					(0.007)	(0.011)					(0.026)	(0.100)
I(ICO BANK)$_b$*I(LOAN APPLICATION)$_{ft-1}$					-0.043 ***	-0.024					-0.090 *	0.089
					(0.009)	(0.020)					(0.051)	(0.105)
I(ICO BANK)$_b$*I(NONE LOAN APPLICATION GRANTED)$_{ft-1}$					0.103 ***	0.064 ***					0.019	0.245 ***
					(0.012)	(0.016)					(0.047)	(0.066)
Time Fixed Effects	Yes	Yes	Yes	-	Yes	-	Yes	Yes	Yes	-	Yes	-
Firm Fixed Effects	No	No	Yes	-	Yes	-	No	No	Yes	-	Yes	-
Firm*Year:month Fixed Effects	No	No	No	Yes	No	Yes	No	No	No	Yes	No	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	No	No	Yes	Yes	No	No	No	No	Yes	Yes
R2	0.012	0.030	0.434	0.485	0.451	0.503	0.007	0.030	0.794	0.787	0.806	0.803
No. of Firms	63,924	63,924	63,924	17,314	63,924	17,314	15,743	15,743	15,743	1,890	15,743	1,890
No. of Observations	210,651	210,651	210,651	46,091	210,651	46,091	39,306	39,306	39,306	4,097	39,306	4,097

Notes: This table reports estimates from a linear probability model using ordinary least squares. The dependent variables are: I(LOAN APPLICATION GRANTED)$_{fbt}$, which equals one if the loan application made to bank b by firm f at time (month) t is approved by the bank and the loan is granted in month t to $t+3$, and equals zero otherwise; and Ln(CREDIT AMOUNT)$_{fbt}$, which is the logarithm of the committed loan amount granted in months t to $t+3$ by bank b to firm f following a successful application filed in month t to bank b by firm f. I(ICO BANK)$_b$ is a dummy variable which equals one if the bank requested was the ICO and zero otherwise. SCORING$_{ft-1}$ is a variable that measures the financial risk of a firm through a weighted average of firm characteristics (note that higher values of SCORING are associated to riskier firms). All bank controls and firm variables are listed in Appendix B. Columns 5 also includes the controls SCORING$_{ft-1}$, I(LOAN APPLICATION)$_{ft-1}$ and I(NONE LOAN APPLICATION GRANTED)$_{ft-1}$ multiplied by ICO Applicant dummy to capture unobserved trends. Coefficients are listed in the first row, robust standard errors that are corrected for multi-clustering at the level of the firm, industry, province and bank are reported in the row below, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. I(.) is the indicator function which means that the variable takes only two values: 0 or 1. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 4

Analysis of the future delinquency of granted loans

Dependent variable:	I(FUTURE DEFAULT)$_{fb}$				
	(1)	(2)	(3)	(4)	(5)
I(ICO BANK)$_b$	0.327 ***	0.320 ***	0.165 ***		
	(0.011)	(0.013)	(0.013)		
SCORING$_{ft-1}$		0.056 ***	-0.004	-0.005	
		(0.005)	(0.007)	(0.006)	
I(LOAN APPLICATION)$_{ft-1}$		0.044 ***	0.006 *	0.006	
		(0.006)	(0.003)	(0.004)	
I(NONE LOAN APPLICATION GRANTED)$_{ft-1}$		-0.012	-0.006 **	-0.005 *	
		(0.008)	(0.003)	(0.003)	
I(ICO BANK)$_b$*SCORING$_{ft-1}$				0.052 ***	0.157 ***
				(0.015)	(0.057)
I(ICO BANK)$_b$*I(LOAN APPLICATION)$_{ft-1}$				-0.022	-0.027
				(0.017)	(0.061)
I(ICO BANK)$_b$*I(NONE LOAN APPLICATION GRANTED)$_{ft-1}$				0.032 *	0.211 ***
				(0.018)	(0.068)
Time Fixed Effects	Yes	Yes	Yes	Yes	-
Firm Fixed Effects	No	No	Yes	Yes	-
Firm*Year:month Fixed Effects	No	No	No	No	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	No	Yes	Yes
R2	0.035	0.051	0.778	0.781	0.781
No. of Firms	15,743	15,743	15,743	15,743	1,890
No. of Observations	39,306	39,306	39,306	39,306	4,097

Notes: This table reports estimates from a linear probability model using ordinary least squares. The dependent variable is I(FUTURE DEFAULT)$_{fb}$, which equals one when firm f that is granted the loan in month t by bank b defaults (doubtful or 90 days overdue) at some point in the future, and equals zero otherwise. I(ICO BANK)$_b$ is a dummy variable which equals one if the bank requested was the ICO and zero otherwise. SCORING$_{ft-1}$ is a variable that measures the financial risk of a firm through a weighted average of firm characteristics (note that higher values of SCORING are associated to riskier firms). All bank controls and firm variables are listed in Appendix B. Column 4 also includes the controls SCORING$_{ft-1}$, I(LOAN APPLICATION)$_{ft-1}$ and I(NONE LOAN APPLICATION GRANTED)$_{ft-1}$ multiplied by ICO Applicant dummy to capture unobserved trends. Coefficients are listed in the first row, robust standard errors that are corrected for multi-clustering at the level of the firm, industry, province and bank are reported in the row below, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. I(.) is the indicator function which means that the variable takes only two values: 0 or 1. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 5

Real effects (1): Fuzzy regression discontinuity analysis of firm survival

Dependent variable:	FIRM SURVIVAL				FIRM SURVIVAL 2010-2014			
	2010-2011	2010-2012	2010-2013	2010-2014	Local Quadratic	Half Bandwidth	Double Bandwidth	Parametric
Second Stage								
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	0.104 **	0.193 **	0.120	0.192 **	0.240 *	0.181	0.132 **	0.218 **
	(0.046)	(0.078)	(0.080)	(0.094)	(0.141)	(0.141)	(0.056)	(0.111)
First Stage. Dependent variable I(ICO LOAN APPLICATION GRANTED)$_{ft}$								
I(ICO LOAN APPLICATION BELOW CUTOFF POINT)$_{ft}$	0.285 ***	0.257 ***	0.272 ***	0.270 ***	0.234 ***	0.248 ***	0.337 ***	0.254 ***
	(0.027)	(0.028)	(0.025)	(0.025)	(0.033)	(0.036)	(0.018)	(0.026)
F-test instrument	113.8	86.3	120.7	115.6	51.5	48.2	345.8	96.4
No. of Observations	8,723	9,520	9,520	9,520	9,520	9,520	9,520	9,520

Notes: This table reports estimates from a non-parametric local-linear regression discontinuity fuzzy models with robust z-test. The dependent variable of the second stage is the dummy I(FIRM SURVIVAL)$_{ft}$, which equals one if the firm f does not close down from 2010:M1 to Date. The dependent variable of the first stage is I(ICO LOAN APPLICATION GRANTED)$_{ft}$, which is a dummy variable that equals one if the loan application made by firm f to ICO at time t is approved and the loan is granted, and equals zero otherwise. I(ICO LOAN APPLICATION BELOW THE CUTOFF POINT)$_{ft}$ is a dummy variable which equals one if the loan application made by firm f to ICO at time t has a scoring below the cutoff point, and equals zero otherwise. All variables are listed in Appendix B. Coefficients are listed in the first row, robust standard errors are reported in the row below, and the corresponding significance levels are in the adjacent column. I(.) is the indicator function which means that the variable takes only two values: 0 or 1. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 6

Real effects (2): Fuzzy regression discontinuity analysis of firm real and financial outcomes

Dependent variable:	EMPLOYMENT GROWTH$_{09\text{-}13}$		ASSETS GROWTH$_{09\text{-}13}$		SALES GROWTH$_{09\text{-}13}$		INVESTMENT$_{09\text{-}13}$		PRODUCTIVITY GROWTH$_{09\text{-}13}$		CROWDING-IN EFFECT	
	Linear	Tobit	Linear	Tobit	Linear	Tobit	Linear	Tobit	Linear	Tobit	NEW BANK LOAN	BANK LOAN GROWTH
Second Stage												
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	0.509 **	0.592 **	0.650 **	0.698 ***	0.687 **	0.828 ***	0.787 ***	0.943 ***	0.807 **	0.969 **	0.224 *	0.313 **
	(0.254)	(0.249)	(0.260)	(0.254)	(0.300)	(0.315)	(0.300)	(0.314)	(0.383)	(0.386)	(0.122)	(0.136)
First Stage. Dependent variable I(ICO LOAN APPLICATION GRANTED)$_{ft}$												
I(ICO LOAN APPLICATION BELOW CUTOFF POINT)$_{ft}$	0.239 ***	0.288 ***	0.255 ***	0.303 ***	0.247 ***	0.281 ***	0.267 ***	0.313 ***	0.222 ***	0.276 ***	0.265 ***	0.264 ***
	(0.043)	(0.039)	(0.039)	(0.036)	(0.048)	(0.043)	(0.041)	(0.037)	(0.051)	(0.046)	(0.028)	(0.032)
F-test instrument	31.1	54.3	42.1	71.2	27.0	42.8	41.7	70.9	19.1	36.0	91.1	69.1
No. of Observations	3,810	3,810	4,247	4,247	3,723	3,723	3,683	3,683	3,233	3,233	6,968	6,183

Notes: This table reports estimates from a non-parametric local-linear regression-discontinuity fuzzy models with robust z-test. The Tobit model is estimated in the same bin that the regression discontinuity. The dependent variables of the first stage is I(ICO LOAN APPLICATION GRANTED)$_{ft}$, which is a dummy variable that equals one if the loan application made by firm f to ICO at time t is approved and the loan is granted, and equals zero otherwise; where the regressor of the first stage is I(ICO LOAN APPLICATION BELOW THE CUTOFF POINT)$_{ft}$, which is a dummy variable that equals one if the loan application made by firm f to ICO at time t has a scoring below the cutoff point, and equals zero otherwise. All variables are listed in Appendix B. Coefficients are listed in the first row, robust standard errors are reported in the row below, and the corresponding significance levels are in the adjacent column. I(.) is the indicator function which means that the variable takes only two values: 0 or 1. *** Significant at 1%, ** significant at 5%, * significant at 10%.

APPENDIX A

Proofs of the results

Proof of Proposition 1 Let us define

$$x_L = \frac{\bar{s} - p_L}{\sigma} \quad \text{and} \quad x_H = \frac{\bar{s} - p_H}{\sigma},$$

and let $\phi(x) = \Phi'(x)$. Differentiating the bank's objective function gives

$$\frac{d\Pi}{d\bar{s}} = \frac{1-\gamma}{\sigma} \phi(x_L)\pi_L + \frac{\gamma}{\sigma} \phi(x_H)\pi_H = \frac{1-\gamma}{\sigma} \phi(x_L)\pi_L \left[1 + \frac{\gamma\phi(x_H)\pi_H}{(1-\gamma)\phi(x_L)\pi_L} \right]$$

$$= \frac{1-\gamma}{\sigma} \phi(x_L)\pi_L \left[1 + \frac{\gamma\pi_H}{(1-\gamma)\pi_L} \exp\left(\frac{1}{2}\left(\frac{\bar{s} - p_L}{\sigma}\right)^2 - \frac{1}{2}\left(\frac{\bar{s} - p_H}{\sigma}\right)^2 \right) \right] \geq 0$$

if and only if

$$1 + \frac{\gamma\pi_H}{(1-\gamma)\pi_L} \exp\left(\frac{1}{2}\left(\frac{\bar{s} - p_L}{\sigma}\right)^2 - \frac{1}{2}\left(\frac{\bar{s} - p_H}{\sigma}\right) \right) \geq 0,$$

which simplifies to

$$\bar{s} \leq \hat{s} = \frac{1}{2}(p_H + p_L) - \frac{\sigma^2}{p_H - p_L} \ln\left(-\frac{\gamma\pi_H}{(1-\gamma)\pi_L} \right).$$

Since

$$-\frac{\gamma\pi_H}{(1-\gamma)\pi_L} > 1 \text{ if and only if } \bar{\pi} = (1-\gamma)\pi_L + \gamma\pi_L < 0,$$

which holds by assumption, it follows that $\hat{s}$ and hence $\hat{L}$ are decreasing in γ and σ.

Next, using the envelope theorem, $\pi_L > 0$ and $\pi_H < 0$ imply

$$\frac{\partial\hat{\Pi}}{\partial\gamma} = -\Phi(\hat{x}_L)\pi_L + \Phi(\hat{x}_H)\pi_H < 0.$$

Since $\Pi(\bar{s})$ is increasing for $\bar{s} < \hat{s}$ and decreasing for $\bar{s} > \hat{s}$ we must have

$$\left.\frac{d^2\Pi}{d\bar{s}^2}\right|_{\bar{s}=\hat{s}} = \frac{1-\gamma}{\sigma^2} \phi'(\hat{x}_L)\pi_L + \frac{\gamma}{\sigma^2} \phi'(\hat{x}_H)\pi_H < 0.$$

By the properties of normal densities this simplifies to

$$-(1-\gamma)\phi(\hat{x}_L)\frac{\hat{s} - p_L}{\sigma}\pi_L - \gamma\phi(\hat{x}_H)\frac{\hat{s} - p_H}{\sigma}\pi_H < 0,$$

which implies

$$\frac{\partial\hat{\Pi}}{\partial\sigma} = -(1-\gamma)\phi(\hat{x}_L)\frac{\hat{s} - p_L}{\sigma^2}\pi_L - \gamma\phi(\hat{x}_H)\frac{\hat{s} - p_H}{\sigma^2}\pi_H < 0.$$

The default rate $\hat{p}$ may be written as

$$\hat{p} = p_L + \frac{1}{1 + \dfrac{1-\gamma}{\gamma}\dfrac{\Phi(\hat{x}_L)}{\Phi(\hat{x}_H)}}(p_H - p_L).$$

To prove that $\hat{p}$ is increasing in γ it suffices to show that

$$\frac{\partial}{\partial \gamma}\left(\frac{1-\gamma}{\gamma}\frac{\Phi(\hat{x}_L)}{\Phi(\hat{x}_H)}\right) = -\frac{1}{\gamma^2}\frac{\Phi(\hat{x}_L)}{\Phi(\hat{x}_H)} + \frac{1-\gamma}{\gamma}\frac{\Phi(\hat{x}_H)\phi(\hat{x}_L) - \Phi(\hat{x}_L)\phi(\hat{x}_H)}{\sigma\left[\Phi(\hat{x}_H)\right]^2}\frac{\partial \hat{s}}{\partial \gamma}$$

$$= -\frac{1}{\gamma^2}\frac{\Phi(\hat{x}_L)}{\Phi(\hat{x}_H)}\left[1 + \frac{\sigma}{p_H - p_L}\left(\frac{\phi(\hat{x}_L)}{\Phi(\hat{x}_L)} - \frac{\phi(\hat{x}_H)}{\Phi(\hat{x}_H)}\right)\right] < 0.$$

But given that $\hat{x}_H < \hat{x}_L$, by the properties of the normal hazard function we have

$$1 + \frac{\sigma}{p_H - p_L}\left(\frac{\phi(\hat{x}_L)}{\Phi(\hat{x}_L)} - \frac{\phi(\hat{x}_H)}{\Phi(\hat{x}_H)}\right) = 1 + \frac{\sigma}{p_H - p_L}\left(\frac{\phi(-\hat{x}_L)}{1 - \Phi(-\hat{x}_L)} - \frac{\phi(-\hat{x}_H)}{1 - \Phi(-\hat{x}_H)}\right)$$

$$> 1 + \frac{\sigma}{p_H - p_L}(\hat{x}_H - \hat{x}_L) = 0$$

To prove that $\hat{p}$ is increasing in σ it suffices to show that

$$\frac{\partial}{\partial \sigma}\left(\frac{\Phi(\hat{x}_L)}{\Phi(\hat{x}_H)}\right) = \frac{\Phi(\hat{x}_H)\phi(\hat{x}_L)\dfrac{\partial \hat{x}_L}{\partial \sigma} - \Phi(\hat{x}_L)\phi(\hat{x}_H)\dfrac{\partial \hat{x}_H}{\partial \sigma}}{\left[\Phi(\hat{x}_H)\right]^2}$$

$$= \frac{\Phi(\hat{x}_L)}{\sigma\Phi(\hat{x}_H)}\left(\frac{\phi(\hat{x}_L)}{\Phi(\hat{x}_L)}\hat{x}_H - \frac{\phi(\hat{x}_H)}{\Phi(\hat{x}_H)}\hat{x}_L\right) < 0.$$

But given that $\hat{x}_H < \hat{x}_L$ and $\hat{x}_H < 0$, by the properties of the normal hazard function we have

$$\frac{\phi(\hat{x}_L)}{\Phi(\hat{x}_L)}\hat{x}_H - \frac{\phi(\hat{x}_H)}{\Phi(\hat{x}_H)}\hat{x}_L < (x_H - x_L)\left(\frac{\phi(-\hat{x}_H)}{1 - \Phi(-\hat{x}_H)} + \hat{x}_H\right) < 0,$$

which completes the proof of Proposition 1. □

Proof of Proposition 2 Following the same steps as in the proof of Proposition 1 gives the expression for the cutoff signal $\hat{s}$ as well as the effect on $\hat{s}$ and hence on $\hat{L}$ of the lending bias δ. Next, since

$$\left.\frac{dU}{d\bar{s}}\right|_{\bar{s}=\hat{s}} = \left.\frac{d\Pi}{d\bar{s}}\right|_{\bar{s}=\hat{s}} + \delta L'(\hat{s}) = 0,$$

and $L'(\hat{s}) > 0$, we have

$$\frac{\partial \bar{p}}{\partial \delta} = \frac{d\Pi}{d\bar{s}}\bigg|_{\bar{s}=\bar{s}_0}\frac{\partial \bar{s}}{\partial \delta} < 0.$$

Finally, to show that the default rate $\bar{p}$ is increasing in the lending bias δ notice that by the proof of Proposition 1, it suffices to show that

$$\frac{d}{d\bar{s}}\left(\frac{\Phi(\bar{x}_L)}{\Phi(\bar{x}_H)}\right) = \frac{\Phi(\bar{x}_L)}{\sigma\Phi(\bar{x}_H)}\left(\frac{\phi(\bar{x}_L)}{\Phi(\bar{x}_L)} - \frac{\phi(\bar{x}_H)}{\Phi(\bar{x}_H)}\right) < 0,$$

which holds by the properties of the normal hazard function, given that $\bar{x}_H < \bar{x}_L$. $\square$

APPENDIX B

Definitions of the variables used in the analysis

Variable	Unit	Definition
I(LOAN APPLICATION GRANTED)$_{fbt}$	0/1	A dummy variable which equals one if the loan application made in month t to bank b by firm f is successful and the loan is granted between t to $t+3$, and equals zero otherwise
Ln(CREDIT AMOUNT)$_{fbt}$	ln(000 Euros)	The logarithm of the committed loan amount granted in months t to $t+3$ by bank b to firm f following a succesful application filed in month t to bank b to firm f
I(FUTURE DEFAULT)$_{fb}$	0/1	A dummy variable which equals one when firm f, which obtained the loan in month t by bank b, defaults at some point in the future, and equals zero otherwise
I(FIM SURVIVAL)$_{f2014}$	0/1	A dummy variable which equals one if firm f doesn't close down from the end of 2009 to date 2014, and equals zero otherwise
EMPLOYMENT GROWTH$_{f2013}$	-	Growth of the number of employees of firm f at 2013 with respect the end of 2009
ASSETS GROWTH$_{f2013}$	-	Growth of total assets of firm f at 2013 with respect the end of 2009
SALES GROWTH$_{f2013}$	-	Growth of sales of firm f at 2013 with respect the end of 2009
INVESTMENT$_{f2013}$	-	Change in fixed assets of firm f from 2009 to 2013 over fixed asssets at the end of 2009
PRODUCTIVITY GROWTH$_{f2013}$	-	Growth of the ratio of sales over employees of firm f at 2013 with respect the end of 2009
I(NEW BANK LOAN)$_f$	0/1	A dummy variable which equals one when firm f gets a loan by a non-current private bank after the end of the ICOdirecto program, and equals zero otherwise
BANK LOAN GROWTH$_f$	-	Growth of total bank loans (without ICO loans) of firm f at the end of the ICO program respect the end of 2009
SCORING$_{ft-1}$	-	A variable that measures the financial risk of a firm f through a weighted average of firm characteristics
I(ICO BANK APPLICANT)$_f$	0/1	A dummy variable which equals one if firm f asked for a loan to the ICOdirecto program, and equals zero otherwise
Ln(TOTAL ASSETS)$_{ft-1}$	ln (000 Euros)	The logarithm of the total assets of firm f the year prior to the loan request
AGE$_{ft-1}$	years	Age of firm f during the year prior to the loan request
ROA$_{ft-1}$	%	Return over total assets of firm f the year prior to the loan request
CAPITAL RATIO$_{ft-1}$	%	Own funds over total assets of firm f the year prior to the loan request
Ln(SALES/EMPLOYEES)$_{ft-1}$	-	A measure of productivity as the log of sales over the number of employees of firm f the year prior to the loan request
INTEREST PAID$_{ft-1}$	%	Average interest rate of all outstanding bank loans of firm f the year prior to the loan request
LIQUIDITY RATIO$_{ft-1}$	%	Current assets over total assets of firm f the year prior to the loan request
Ln(NUMBER OF BANKS)$_{ft-1}$	-	The logarithm of 1 plus the average number of number of banking relatiosnhips of firm f during the last year prior to the loan request
DRAWN OVER COMMITED$_{ft-1}$	%	The ratio between the average drawn amount over the average total committed amount of all bank loans of firm f during the last year prior to the loan request
NON COLLATERALIZED LOANS/TOTAL LOANS$_{ft}$	%	The ratio between the average amount of non-collateralized loans over the average amount of total loans of firm f during the last year prior to the loan request
LOAN MATURITY 1-5y/TOTAL LOANS$_{ft-1}$	%	The ratio between the average amount of loans with a maturity between 1 and 5 years over the average amount of total loans of firm f during the last year prior to the loan request
I(BAD CREDIT HISTORY)$_{ft-1}$	0/1	A dummy variable which equals one if firm f had non-performing loans outstanding during the last year prior to the loan request, and equals zero otherwise
I(LOAN APPLICATION)$_{ft-1}$	0/1	A dummy variable which equals one if firm f made a loan application to a non-current bank during the last year prior to the loan request, and equals zero otherwise
I(NONE LOAN APPLICATION GRANTED)$_{ft-1}$	0/1	A dummy variable which equals one if all loan applications made by firm f during the last year prior to the loan request were rejected, and equals zero otherwise
I(ICO BANK)$_b$	0/1	A dummy variable which equals one for the ICO bank and zero otherwise
Ln(TOTAL ASSETS)$_{bt-1}$	ln(000 Euros)	The logarithm of the total assets of bank b the year prior to the loan request
CAPITAL RATIO$_{bt-1}$	%	The ratio of bank equity over total assets of bank b the year prior to the loan request
ROA$_{bt-1}$	%	The ratio of bank return over total assets of bank b the year prior to the loan request
DOUBTFUL RATIO$_{bt-1}$	%	The non-performing loan ratio of bank b the year prior to the loan request

TABLE 1

Robustness of Tables 3 and 4

Dependent variable:	Ln(CREDIT AMOUNT)$_{fbt}$		I(FUTURE DEFAULT)$_{fb}$	
Correcting for Selection Bias				
I(ICO BANK)$_b$	0.283 ***	0.215 ***	0.194 ***	0.141 ***
	(0.044)	(0.075)	(0.019)	(0.018)
Loan Controls				
I(ICO BANK)$_b$	0.137 ***	0.047	0.145 ***	0.161 ***
	(0.039)	(0.083)	(0.014)	(0.036)
Correcting for Selection Bias & Loan Constrols				
I(ICO BANK)$_b$	0.174 ***	0.118 **	0.178 ***	0.137 ***
	(0.039)	(0.059)	(0.020)	(0.028)
Time Fixed Effects	Yes	-	Yes	-
Firm Controls	Yes	-	Yes	-
Firm Fixed Effects	Yes	-	Yes	-
Firm*Year:month Fixed Effects	No	Yes	No	Yes
Bank Controls	Yes	Yes	Yes	Yes
No. of Firms	15,743	1,890	15,743	1,890
No. of Observations	39,306	4,097	39,306	4,097

Notes: This table reports estimates from a linear probability model using ordinary least squares. The dependent variables are: Ln(CREDIT AMOUNT)$_{fbt}$, the logarithm of the committed loan amount granted in months t to $t+3$ by bank b to firm f following a succesful application filed in month t to bank b by firm f; and I(FUTURE DEFAULT)$_{fb}$, a dummy variable which equals one when firm f that is granted the loan in month t by bank b defaults at some point in the future, and equals zero otherwise. I(ICO BANK)$_b$ is a dummy variable which equals one for the ICO bank, and equals zero otherwise. The definition of the rest of independent variables can be found in Appendix B. Coefficients are listed in the first row, robust standard errors that are corrected for multi-clustering at the level of the firm, industry, province and bank are reported in the row below, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. I(.) is the indicator function which means that the variable takes only two values: 0 or 1. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 2

Real effects. Robustness results: Firm covariates

PANEL A: Pre-differences of firm covariates to the assignment.

Non-parametric fuzzy regression discontinuity analysis for firm covariates

Dependent Variables	Treatment variable: I(ICO LOAN APPLICATION GRANTED)$_{ft}$
Ln(TOTAL ASSETS)$_{ft}$	-0.026
	(0.531)
Ln(AGE)$_{ft}$	-0.263
	(0.313)
Ln(SALES)$_{ft}$	-0.861
	(0.555)
CAPITAL RATIO$_{ft}$	-3.519
	(4.862)
ROA$_{ft}$	-3.118
	(3.002)
Ln(SALES/EMPLOYEES)$_{ft}$	0.031
	(0.480)
INTEREST PAID$_{ft}$	1.149
	(1.033)
LIQUIDITY RATIO$_{ft}$	-1.175
	(2.738)
I(LOAN APPLICATION LAST YEAR)$_{ft}$	0.182
	(0.138)
I(BAD CREDIT HISTORY)$_{ft}$	-0.037
	(0.101)

Notes: This table reports estimates from a non-parametric local-linear regression discontinuity model with robust z-test and firm covariates. The dependent variables change for each row. Coefficients are listed in the first row, and the corresponding significance levels are in the adjacent column. I(ICO LOAN APPLICATION GRANTED)$_{ft}$ is a dummy variable which equals one if the loan application made by firm f to ICO at time t is approved and the loan is granted, and equals zero otherwise. All variables are listed in Appendix B. Coefficients are listed in the first row, robust standard errors are reported in the row below, and the corresponding significance levels are in the adjacent column. I(.) is the indicator function which means that the variable takes only two values: 0 or 1. *** Significant at 1%, ** significant at 5%, * significant at 10%.

PANEL B: Sensitivity of the baseline results to the inclusion of firm covariates.

Non-parametric fuzzy regression discontinuity analysis of firm survival

Dependent variable:	FIRM SURVIVAL 2010-2014
Including firm covariates	
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	0.245 *
	(0.143)
Residualizing	
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	0.199 **
	(0.088)

Notes: This table reports estimates from a non-parametric local-linear regression discontinuity fuzzy models with robust z-test. The dependent variables is I(FIRM SURVIVAL)$_{ft}$, which equals one if the firm f does not close down from 2010:M1 to 2014:M12. Only second stage is shown. First stage is similar to the other tables. I(ICO LOAN APPLICATION GRANTED)$_{ft}$ is a dummy variable which equals one if the loan application made by firm f to ICO at time t is approved and the loan is granted, and equals zero otherwise. All variables are listed in Appendix B. Coefficients listed in the first row, robust standard errors are reported in the row below, and the corresponding significance levels are in the adjacent column. I(.) is the indicator function which means that the variable takes only two values: 0 or 1. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 3

Real effects. Robustness results: Placebo test

Dependent variable:	EMPLOYMENT GROWTH$_{2009-2008}$	ASSETS GROWTH$_{2009-2008}$	SALES GROWTH$_{2009-2008}$	INVESTMENT$_{2009-2008}$	PRODUCTIVITY GROWTH$_{2009-2008}$	CROWDING-IN EFFECT	
						NEW BANK LOAN	BANK LOAN GROWTH
Second Stage							
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	-0.017	0.023	0.000	-0.114	0.154	0.072	-0.035
	(0.143)	(0.079)	(0.131)	(0.099)	(0.176)	(0.090)	(0.081)
First Stage. Dependent variable I(ICO LOAN APPLICATION GRANTED)$_{ft}$							
I(ICO LOAN APPLICATION BELOW CUTOFF POINT)$_{ft}$	0.251 ***	0.281 ***	0.266 ***	0.261 ***	0.238 ***	0.275 ***	0.287 ***
	(0.041)	(0.032)	(0.042)	(0.042)	(0.044)	(0.024)	(0.026)
F-test instrument	37.2	76.4	40.3	37.6	29.4	130.2	124.5
No. of Observations	5,345	5,720	5,585	3,560	5,043	9,520	8,475

Notes: This table reports estimates from a non-parametric local-linear regression discontinuity fuzzy model with robust z-test. The dependent variables of the second stage is I(ICO LOAN APPLICATION GRANTED)$_{ft}$, which is a dummy variable that equals one if the loan application made by firm f to ICO at time t is approved and the loan is granted, and equals zero otherwise. The regressor of the second stage is I(ICO LOAN APPLICATION BELOW THE CUTOFF POINT)$_{ft}$, which is a dummy variable that equals one if the loan application made by firm f to ICO at time t has a scoring below the cutoff point, and equals zero otherwise. All variables are listed in Appendix B. Coefficients are listed in the first row, robust standard errors are reported in the row below, and the corresponding significance levels are in the adjacent column. I(.) is the indicator function which means that the variable takes only two values: 0 or 1. *** Significant at 1%, ** significant at 5%, * significant at 10%.