Burning Money?

Government Lending in a Credit Crunch

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Abstract

We analyze a small, new credit facility of a Spanish state-owned-bank during the crisis, using its continuous credit scoring system, firm-level scores, and credit register data. Compared to privately-owned banks, the state-owned bank faces worse applicants, softens (tightens) its credit supply to unobserved (observable) riskier firms, and has much higher defaults. In a regression discontinuity design, the supply of public credit causes: large positive real effects to financially-constrained firms (whose relationship banks reduced substantially credit supply); crowding-in of new private-bank credit; and positive spillovers to other firms. Private returns of the credit facility are negative, while social returns are positive.

JEL Codes: E44; G01; G21; G28.

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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 (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 countercyclical lending may be associated with large defaults due to a general scarcity of creditworthy borrowers (a demand problem, including the firm balance sheet channel of Bernanke et al., 1996) compounded with adverse selection problems, as state-owned banks (or any new lenders) may face a riskier pool of borrowers in crises –e.g. borrowers rejected by their private lenders (see Broecker, 1990; Shaffer, 1998; Ruckes, 2004; Dell'Ariccia and Marquez, 2006).[2]

We analyze lending to firms by a state-owned bank in crisis times, the potential adverse selection and the causal real effects associated to this lending (including crowding-in of private credit and spillovers to other firms and banks). Identification of causal real effects of credit supply policies has been elusive, as the literature has only used data on granted loans (e.g., Banerjee and Duflo, 2014; Jiménez et al., 2017), which require strong identification assumptions. Instead, we use data on loan applications in a quasi-experimental design, where we exploit the continuous scoring system used in a new, small credit facility (550 million euros), in conjunction with firms' individual credit scores and the threshold for granting vs. rejecting applications. These new data allow us –in a

[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. We also use private banks as privately-owned banks.

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

regression discontinuity approach (Angrist and Pischke, 2009; Imbens and Wooldridge, 2009)– 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 addition, the context we analyze is different from the related literature, i.e. a new public credit facility during a severe banking crisis. Moreover, new to the (empirical) literature,[3] by observing the (pool and granting of) loan applications to private banks and the new credit facility of the state-owned bank, including observable and unobserved (hidden) borrower firm risk characteristics, we can study adverse selection in credit markets during crisis times.

We find that public lending (in crisis times) causes large, positive, and persistent real effects, but at the same time results suggest large adverse selection problems in the public credit (with large loan defaults and differences between observable and hidden information about firm risk), and in private credit (with strong frictions for firms that were previously borrowing from private banks that significantly reduced credit supply during the crisis). Overall, the net social returns of public lending are positive (and large), while the private net returns of the state-owned bank are negative.

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 small and medium-sized enterprises (SMEs) and entrepreneurs.[4] Credit conditions by privately-owned banks had substantially tightened, so the idea was to fill this gap. The tightening of bank lending conditions could reflect not only an increase in credit risk, following the worst recession in many decades, but also a credit supply problem, due to e.g. private banks' insufficient capital and liquidity hoarding. The main novelty of the public credit facility was that ICO would lend directly to SMEs, assuming all the credit risk of these loans (ICO was basically lending before to strategic sectors, mainly large exporting firms). The approval or rejection of these applications was mainly based on a credit scoring system that used hard information. 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.

[3] The theory papers by Broecker (1990), Ruckes (2004), Dell'Ariccia and Marquez (2006), among others, on adverse selection in lending have not been analyzed empirically because of lack of granular data (and shocks).

[4] The maximum loan amount was 200,000 euros per borrower, with interest rates at 6-month Euribor + 3.5%, with a fee of 0.5%, independently of the risk of the borrower (personal guarantees were required if deemed necessary). The maturity was between 3 and 7 years depending whether the loan was for liquidity or for investment purposes.

We exploit the exhaustive Spanish credit register (CIR), an administrative database owned by the Bank of Spain in its role as supervisor of the Spanish banking system, which contains all bank loans granted in Spain by all banks on a monthly basis. 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 (ICO). Moreover, we know whether a loan application is granted, and (for those granted ones) the loan amount and the future credit defaults. We match the credit datasets with other administrative datasets for firm- and bank-level variables. To analyze firm survival, we know whether a firm closes down, via the administrative dataset called the Central Business Register (DIRCE). The information on non-financial firms comes from the balance sheets and income statements that firms must submit yearly to the Spanish Mercantile Register. Finally, we use supervisory information on banks' balance sheet and income statements.

Importantly, we also exploit the continuous scoring function used by the state-owned bank (based on eighteen different firm variables, related to leverage, profitability, liquidity, and credit history, among others), the cutoff point 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 ICO with government and private registers.

We use these datasets for the empirical identification of the main two questions addressed in the paper. First, on the lending side, we exploit loan applications to ICO and to private banks by firms not currently borrowing from them. We analyze the applicants' differential riskiness. We also analyze the granting of loan applications depending on borrower *observed* and *unobserved* (hidden) risk, exploiting data on applications by the same firm (even 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, we analyze –in a regression discontinuity approach– the real effects, private credit crowding-in, and other firm and bank spillovers associated to the public credit supply.

The results (not surprisingly) first 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. Moreover, the results also show that the state-owned bank is more restrictive than the private banks in granting new loan applications (extensive margin), in the loan volume granted conditional on approval (intensive margin), and in both margins combined. However, a substantial part of this tightening is due to the riskier pool of applicants that the state-owned bank faces, in both observable and unobserved risk characteristics.

Importantly, the state-owned bank is *softer* than private banks in its supply of credit to firms with higher *unobserved* 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 (for this specific, hidden information, we follow Broecker, 1990, and Dell'Ariccia and Marquez, 2006);[5] or more generally (ii) by ex-post loan defaults not related to ex-ante firm observable characteristics. These effects are present in both the extensive and intensive margins, or in a combination of both. In contrast, the state-owned bank is *tighter* in its supply of credit to firms with *observable* riskier characteristics.

The ex-post loan defaults (delinquencies) of the state-owned bank are 32 percentage points (p.p.) higher compared to private banks. Moreover, most of these defaults are due to firms' unobserved risk characteristics (among both the pool of all loans, and inside the pool of borrowers with loan applications lodged on the previous year but without loans granted). 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 very large 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 may 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 fuzzy regression discontinuity approach by exploiting the cutoff of the continuous scoring rule used by the state-owned bank in granting applications, where there is a very strong increase –of almost 40 p.p., which corresponds to approximately 400% increase– in the likelihood of obtaining a loan from the state-owned bank.[6]

We find that the public credit facility causes positive real effects at the firm level. If the state-owned bank grants a loan to a firm, the probability that the firm survives increases (at the mean) by

[5] The supervisor has this information (and we do as well), but not the banks.

[6] Figure 1 shows the strong discontinuity in the likelihood of obtaining a public loan (note that, unlike in the standard FICO score, in the scoring rule used by ICO higher scores mean higher credit risk). As the percentage increase in the likelihood is not infinite (from 0 to 1 in probability), we use the fuzzy RD instead of the sharp RD (Angrist and Pischke, 2009; Imbens and Wooldridge, 2009). There are firms with a credit risk score above the cutoff that are nevertheless granted the loan (2% of all firms), as well as firms with a risk score below the cutoff that do not get the loan (28% of all firms). This latter figure may be explained by either firms not complying with some requirements or not wanting to take the loan because they may have (other) private loans or enough internal cash flows (our results confirm this). It should be also noted that the firms with a risk score above the cutoff that get the public loan do not have worse fundamentals than the firms just below the cutoff.

approximately 33%, 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 (88%), employment growth (56%), total asset growth (76%), sales growth (73%), and productivity growth (88%).[7]

However, the real effects are only positive for financially constrained firms that receive the public loans around the cutoff, where constrained firms are the ones whose relationship banks substantially reduced credit supply during the crisis (a reduction higher than the median, where credit change is independent of borrower fundamentals, following Amiti and Weinstein, 2018). Therefore, the results indicate that lack of credit substitution across private banks is of first order (a decrease in granting of applications to non-main private banks also corroborates this), thereby suggesting adverse selection in private credit markets during the crisis.

After obtaining the public loan, those firms (compared to almost identical firms that survive without the public loan) have a 106% 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 32 p.p.), and a 30% 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.[8] Moreover, after obtaining the public loan, there are positive spillovers to other firms, via a reduction in future loan defaults to private bank credit (32 p.p.) and in average time to pay suppliers (96%).

All in all, the new public credit facility causes strong, persistent real effects. However, in assessing the public policy program in a credit crunch, one should balance the positive real effects against the large loan defaults when government funds are costly. Taking into consideration these two opposite effects, the social net returns to capital are positive and large (from 37%, using change in value added, to 118%, using change in sales), while the private net returns to capital (for the state-owned bank) are negative (-16%).

Contribution to the literature We contribute in three 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 banks due to asymmetric information problems (Broecker,

[7] For the validity of the regression discontinuity analysis, we perform different placebo tests (all with insignificant results), and show that the firm observables around the cutoff at the time of the loan application are not different. Our robustness checks show similar results with different parametric and non-parametric specifications and 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.

[8] This crowding-in is by banks that were not currently lending to the firm, thus suggesting no loan ever-greening (zombie lending). The new private (versus public) credit also has a longer maturity and very similar defaults as the other private loans.

1990; Ruckes, 2004; Dell'Ariccia and Marquez, 2006, as well as a growing literature on adverse selection in credit markets originated after the start of the crisis). However, there was no empirical paper showing the costs and benefits associated to a new provider of credit, considering the riskier pool of applicants that it may face, including the very different results for observed and unobserved (hidden) borrower risk. We exploit two pieces of unobserved information: (i) the existence of loan applications not granted in the previous year, and (ii) the variation of ex-post loan defaults not predicted by ex-ante firm characteristics, including the ex-ante risk score.[9] Moreover, our results on real effects are only significant for those firms that have a previous (strong) relationship with banks that substantially reduced credit supply in the crisis (and hence have higher need of other sources of finance). 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 (or the private market) could easily address credit crunches and their associated negative real effects.

Second, we obtain very large real effects of credit supply and also advance on the causality front of the real effects of credit supply policies by obtaining directly *exogenous variation at the firm level* in a regression discontinuity setting, exploiting the continuous scoring function around the threshold between accepting and rejecting applications. The key difference with the literature (Banerjee and Duflo, 2014; Chodorow-Reich, 2014; Paravisini et al., 2015; Jiménez et al. 2017; Jiménez et al., 2018; Amiti and Weinstein, 2018) is that previous papers did not have the pool of loan applications nor the credit scoring rule based on firm characteristics to grant loans, including the applicants' individual scores.[10] 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 quantitative very 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 strong negative spillovers in real activity (see e.g. Holmstrom and Tirole, 1997; Repullo and Suarez, 2013;

[9] These are almost 20 variables in levels, and in addition polynomials of them. These variables are also the ones with higher predictive power in ex-post loan defaults.

[10] The literature on identifying *credit supply* has advanced substantially using Khwaja and Mian (2008) firm fixed effect estimator (see also Paravisini, 2008), which exploits loan decisions by different banks to the same firm, requiring multiple observations (loans) for the same firm in the same period. However, (i) unless in restrictive settings (Paravisini et al., 2015; Jiménez et al., 2018), 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); (ii) not even credit supply may be well identified as differences in loans granted from different banks to the same firm may be demand driven (Paravisini et al., 2017). In addition, it should be noted that a capital or a liquidity shock to a bank (e.g. a loss in part of its portfolio) may be correlated to its credit demand (as bank asset portfolios and liabilities are correlated due to bank specialization or risk management), thereby potentially biasing the firm-level real effects of credit supply.

He and Krishnamurthy, 2013; Brunermeier and Sanikov, 2014).[11] We also find crowding-in of private loans after the public loan, and positive spillovers to other firms and banks.

The paper closest to ours is Banerjee and Duflo (2014), with the following main differences: (i) the identification (quasi-experimental vs. observational data); (ii) the context (the worst financial and economic crisis since the 1930s, vs. normal times); (iii) the results (very large quantitative effects, but only for a subset of firms, those that had a relationship with banks that significantly reduced credit supply during the crisis, 50% of banks); (iv) large differences in loan defaults and between the social and private net returns of capital; and (v) evidence of adverse selection.[12] Our results also show strong persistence after the worst effects of the crisis disappeared, and hence financial frictions in borrowing with private banks diminish.

Third, we contribute to the literature that shows the costs and benefits of state ownership in general and of banks in particular.[13] 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 large 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 focus on the ability of state-owned banks to fight a credit crunch, when their lending policies are driven by an external credit scoring system.

We also provide a theoretical framework to interpret our empirical 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 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. Lending decisions 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. However, from a welfare perspective, the objective function of the state-owned bank internalizes the benefits of lending, which implies that a positive lending bias is in fact optimal.

[11] The contemporaneous paper by Berg (forthcoming) also exploits a lending rule and the main differences are: (i) we exploit a shock, in particular a new public lending facility; (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; (iv) we analyze adverse selection in lending, and spillovers to other firms and banks. Our results are also different.

[12] See also Bach (2014), a paper close to Banerjee and Duflo (2014) and with similar differences with our paper.

[13] See also the cross-country evidence by Bertay et al. (2015).

Summing up, our results suggest limitations of public policy to fight credit crunches, as asymmetric information in crisis times is pervasive in loan markets. At the same time, we show that direct public lending to firms can bring very large, positive effects on the real economy in a relatively high developed country, which may be especially valuable when expansionary monetary and/or fiscal policy may be either not feasible or not effective.[14] Overall, the net social returns to capital are substantially higher than the private ones (especially for firms previously borrowing from banks that reduced substantially credit supply), thereby implying not only that such public lending may be valuable, but also that there are significant frictions in the private lending market.

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. 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. The model features a single bank that provides funding to entrepreneurs with heterogeneous investment projects. The bank cannot observe the risk of the projects. To mitigate this adverse selection problem, the bank has a scoring system that provides a noisy signal about entrepreneurs' risk.[15] 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.

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

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

[14] For theoretical underpinnings of government lending to firms in crisis times, see Bebchuk and Goldstein (2011).
[15] See Eslava and Freixas (2016) for a related model of bank screening.

where $p = p_L$ for low risk and $p = p_H$ for high risk entrepreneurs, with $p_L < p_H$. Let $\overline{p} = (1-\gamma)p_L + \gamma p_H$ 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 $r_0 < r < y$.[16] 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 $\overline{\pi} = (1-\gamma)\pi_L + \gamma\pi_H = r - r_0 - (r+\lambda)\overline{p} < 0,$ 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 $\varepsilon \sim N(0, \sigma^2)$. Thus, the lower the standard deviation σ the better the quality of the scoring system.[17]

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

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

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

Bank profits per unit of loans are given by

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

where

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

is the *default rate* of the loans in its portfolio. Hence, total bank profits are given by

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

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[16] 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.

[17] Note that, as in the scoring system used by ICO, higher values of s signal riskier borrowers.

The bank chooses the cutoff signal $\hat{s}$ that maximizes its total profits $\Pi(\bar{s})$. 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

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

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 $\tilde{s}$ that maximizes its objective function $U(\bar{s})$. Let us define $\tilde{L} = L(\tilde{s})$, $\tilde{\Pi} = \Pi(\tilde{s})$, and $\tilde{p} = p(\tilde{s})$, 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*

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

The supply of credit $\tilde{L}$ and the default rate $\tilde{p}$ are increasing and bank profits $\tilde{\Pi}$ 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 equivalent private bank.

Figure 1 (Appendix C) 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).[18] 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.

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

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

Let us now define $W(\delta) = W(\tilde{s}(\delta))$. Then by the proof of Proposition 2, it follows that

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

[18] 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 (dotted). 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.

Hence, setting a positive lending bias is socially optimal.[19] Figure 2 (Appendix C) illustrates this result by plotting the function $W(\delta)$. Social welfare first goes up, reflecting the under-provision of credit by a profit-maximizing bank, but then it quickly goes down with further increases in the bias.

Two key results on the lending behavior of a state-owned bank are especially relevant to rationalize 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., 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. 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.

3. Public policy and datasets

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

New public lending facility In April 2010, the Spanish government entrusted ICO with a new program to lend to SMEs and entrepreneurs.[20] The main novelty was that ICO would lend to them. The program was a challenge for ICO because it was the first time it granted such loans. Since ICO did not have a network of branches and no direct relationship with potential borrowers, and almost no experience on lending to small borrowers, the state-owned bank used a credit scoring system based on hard information to accept or reject loan applications. The program aimed at improving access to credit for SMEs and entrepreneurs at a time where private banks were tightening lending standards.[21]

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

[19] A caveat is that the result 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.
[20] ICO is a public credit institution with a banking license. It finances itself on international capital markets. 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 and the credit risk was shared with private banks.
[21] 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). Jiménez et al. (2012 and 2017) show evidence of a credit crunch in Spain by private banks due to their lack of capital.

varied according to the purpose of the loan: For investment loans the maturity was 7 years, while for liquidity loans the maturity was 3 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 2 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 loans started to default. In mid-2012, ICO 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. 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 SMEs because we have access to their economic and financial information (i.e. balance sheet, employment and investment, profit and loss) while for entrepreneurs we do not have such data.[22] Moreover, we do not have information on entrepreneurs' closing down their businesses.

To screen borrowers, ICO acquired a scoring system based on 18 firm variables: short-term indebtedness; credit line usage ratio (drawn over committed amount); average cost of debt; bank loans over own funds; bank loans over gross operating profit; leverage ratio (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 (unpaid phone and electricity bills).[23] Each of the firms' variables is assigned to a specific area: financial indebtedness, solvency, liquidity, profitability, business information, and default history. Moreover, each variable is categorized in six intervals and a different rating value is assigned depending on the allocation to each of the 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 the weighted sum of the ratings assigned to the different characteristics. Ratings are such that the (risk) score is increasing in the firm's credit risk.[24]

[22] We follow the definition of SME used by ICO, based on the EU recommendation 2003/361.
[23] The scoring system is proprietary information and hence we cannot disclose its exact formula.
[24] In the empirical analysis, we use the loan applications that were not rejected by lack of data and that passed some filters used by ICO: the age of the firm higher than one year, no large defaults in private or public credit bureaus, provision of personal guarantees, and positive total assets, number of employees and own funds.

Datasets We use several datasets. First, the Credit Register (CIR) managed by the Bank of Spain. CIR contains information about all loans above 6,000 euros 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 (which we analyze in Section 4). We know whether a loan application is granted, its volume and future performance (default status, delinquencies over 90 days or more).[25] We then match these data with data on non-financial firm and bank variables. To analyze firm survival, we have information on whether a firm closes down during a calendar year, via the administrative dataset managed by the National Statistics Institute (INE) called the Central Business Register (DIRCE). In addition, 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 (not mandatory for the smallest firms). We can match all these datasets since we have for each firm its unique tax identifier code. Finally, we also use the Bank of Spain supervisory bank balance sheet and income statement data at a monthly frequency.

In Section 5 we analyze the real effects of the new 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 credit scoring function and the threshold to accept or reject applications, and a random sample of applicants with their individual credit scores matched with firm real and financial variables.[26] Since there were two 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. Hence, the normalized cutoff point is zero for all firms, with negative values indicating higher credit quality. Moreover, to assess the real effects, we know firm future performance in investment, and growth in employment, sales, total assets, and productivity, as well as survival. We also assess private credit crowding-in effects and spillovers to other firms (suppliers) and private banks.

4. Empirical strategy and results on lending decisions

In this section we present the empirical strategy and the results on lending decisions. We study loan applications (and granted outcomes) by the state-owned bank and privately-owned banks

[25] See Jiménez et al. (2012, 2014, and 2017) for a detailed description of these datasets.

[26] 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.

to firms that 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 possibly to other banks), 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 volume, and the future defaults.

We start with a description of the pool of SMEs that apply to the state-owned bank and to private banks that are not currently lending to them during the period in which the public credit facility was in operation (years 2010, 2011 and 2012). In Table 1 we analyze the characteristics of the pool of firms that apply only to private banks, I(ICO APPLICANT$_f$) = 0, and of firms that at least apply to the state-owned bank, I(ICO APPLICANT$_f$) = 1. In Table 1, we report data on all applicant firms, even if they have only one application (in Tables 3 and 4, we restrict the sample to firms with at least two 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, with less profits, less capital (more leverage), less sales and liquidity, higher (previous) loan interest rates paid, higher usage of credit lines, and with a worse credit history. Table 1 also shows that the differences in average firm characteristics (at the time of the applications) are statistically and economically significant. For example, without controlling for other variables, firms that apply 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 ICO, and credit drawn over committed of 85% as compared to 70% for firms that did not apply to ICO. All these dimensions are captured through the risk scoring measure, which is 12% higher for ICO applicants.

The variables with the highest differences between firms that apply to the state-owned bank vs. the ones that only apply to private banks are scoring, capital ratio, liquidity ratio, and credit line usage ratio (drawn over committed amount).[27] Figure 3 (Appendix C) shows the kernel probability density function (pdf) of these variables. The differences in risk between the two types of firms go

[27] To avoid the mechanical increase with the number of observations in the t-statistic of 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. They propose as a rule of thumb a 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 variables in Figure 3 of Appendix C (and the number of banking relationships) are the only ones with values higher than 0.25.

beyond average values, and are indeed present across their pdfs, suggesting first-order stochastic dominance. In sum, the applicants to ICO are riskier across the board.[28]

In Tables 3 and 4 we examine the lending policy of the new credit facility, its relative supply of credit versus the private 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 control for firm risk, in particular firm scoring,[29] and an unobserved (hidden) firm risk measured by the lack of granted loans corresponding to last year's applications.[30]

To make results comparable across different specifications, 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.[31] The analysis is at the loan level and our baseline regression is as follows:

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

where η_t captures time effects and η_f unobserved firm-specific time-invariant effects. Firm controls include the scoring measure that proxies for time-varying observable firm risk, and the outcome of previous loan applications that proxies for unobserved (hidden) firm risk. To control for bank characteristics (which are not related to state or private ownership), we include a broad set of bank characteristics (total bank assets as a measure of size, capital ratio as a measure of solvency, ROA as a measure of profitability, and doubtful loan ratio as a measure of bank risk). The standard errors are corrected for multi-clustering at the level of the bank, firm, industry, and province.

Our main variable of interest is the dummy variable I(ICO $BANK_b$) that takes the value of one for an ICO loan application (or an ICO granted loan in Table 3 Panel B, and Table 4), 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* firm. Moreover, to isolate all time-varying unobserved (and observed) firm fundamentals, in some regressions we control for firm*time fixed effects (where time is

[28] In Table 1, we also perform a multivariate analysis with similar results controlling for all firm characteristics at the same time and including province*industry*year fixed effects to control for unobservables.
[29] 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.
[30] This variable (which proxies for hidden information) is observed by the supervisor (and us), but not by banks, especially by a bank (ICO) that is new in the SME segment of the credit market.
[31] Note that Table 3 (with 210,651 observations) uses firm-bank loan applications, while Table 1 uses firm-level data.

year:month), thereby analyzing the supply of credit of the state-owned bank compared to private banks for the *same* firm in the *same* month.

The first dependent variable in Table 3, Panel A is I(LOAN APPLICATION 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 zero otherwise. This variable proxies the extensive margin of lending. As shown in Table 2, it has a mean of 0.29 and a standard deviation of 0.45. The other two dependent variables are only defined for those granted loan applications. Ln(CREDIT AMOUNT$_{fbt}$), that we analyze in Table 3, Panel B, equals the log 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 average loan volume directly, without log, the mean is 103,000 euros). I(FUTURE DEFAULT$_{fbt}$), 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 (delinquencies over 90 days) at some point in the future (until 2014:08) to bank *b*. Its mean and standard deviation are 0.13 and 0.34.[32]

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 previously shown 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 unobserved heterogeneity (Model 4). All firm controls are taken at the end of the previous year (*t*-1).[33]

To assess the heterogeneous effects of the public lending facility on firm risk we estimate the following equation:

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

where η_b is a bank fixed effect that absorbs the ICO dummy. The coefficient of interest is now γ, which captures 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-

32 Note that the sample size declines drastically for the second and third dependent variables, since at least two granted loans are needed, whereas for the first dependent variable only at least two loan applications are needed.

33 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, and zero otherwise. We use this variable 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, which means that, within our sample of SMEs, 23% of them applied at least once to ICO.

owned bank lending policy, controlling for the overall average bank fixed effects. In Model 5 of Table 3 we add firm fixed effects and, in Model 6 of Table 3, firm*time fixed effects.[34]

In Panel A of Table 3 we analyze the determinants of granting a loan application. The estimated coefficient of 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 interesting to highlight that the coefficient gradually declines (in absolute value) from -0.121*** in Model 1 to -0.094*** in Model 4.[35] 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 private banks (as shown in Table 1). Model 4 implies that the likelihood of having the application granted by the state-owned bank compared to private banks is 33% lower (at the mean of granting applications).[36] Therefore, for the same borrower quality, the new public credit facility was more restrictive on average than the private banks in the extensive margin of lending.[37]

Models 5 and 6 further analyze the heterogeneous lending behavior. The estimated coefficients of interactions of the ICO dummy with scoring and with "none of the applications were granted last year" are -0.021*** and 0.103*** respectively in Model 5, and -0.022* and 0.064*** respectively in Model 6. This implies that the state-owned bank grants less loan applications than private banks to riskier firms in observable characteristics (higher scoring). However, within the firms that applied for loans in the previous year, the state-owned bank grants more new loans than private banks to those firms that did not get any loan in the previous year.[38]

The structure of Panel B of Table 3 is the same as Panel A. 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* unobserved), the state-owned bank provides more credit (between 20.7% and 26.7% higher) than private banks. Moreover, in the model with the strongest specification (with firm*month fixed effects), the higher loan volume of the state-owned

[34] When interactions terms are included, all variables in levels are demeaned to keep its economic meaning unaltered.

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

[36] The models that include firm*month fixed effects are the best to isolate credit supply, 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.

[37] 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 not been granted previous loan applications is negative (whereas Model 3, with firm fixed effects, gives mechanically a positive coefficient for this variable).

[38] Although this information was not observed either by the private banks, they could rely on their previous experience in granting loans to SMEs. Note also that for a firm that does not have granted applications in the previous year, the current private banks that we analyze are different.

bank is even larger for riskier firms in unobserved characteristics (those that were not granted an application in the previous 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 softer than private banks in a crucial segment of risky firms: those that were not granted any loan application in the previous year despite seeking finance.

The interaction of the ICO dummy and firm scoring gives somewhat different results in Panels A and B of Table 3. Although it is not statistically significant in the strongest specification (Model 6) of Panel B, it is always negative and significant in Panel A.

Moreover, as Table 1, Panel A, in Appendix C shows, when we combine the extensive and intensive margins, the results show opposite (statistically significant) coefficients for observed and unobserved (hidden) risk. Therefore, for observable risk characteristics (summarized in the risk scoring), the results suggest that the state-owned bank is tighter in its lending to observable riskier firms, whereas the opposite happens for unobserved riskier firms.

In Table 4, we find that loans granted by the state-owned bank have a substantially higher probability of default (delinquencies) than those granted by private banks (32 p.p. higher).[39] 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^{***}).[40] Note that this is even though the state-owned bank is more restrictive in granting applications than the private banks. Interestingly, the coefficient in Model 2 is only reduced to 0.27 if we control (in addition to the firm scoring) by all firm observable characteristics from Table 1 (not only in levels, but also in the square and other polynomial degrees). Hence, most loan defaults are due to unobserved borrower characteristics, which further indicate that –controlling for observable characteristics– the state-owned bank is softer with unobserved riskier firms that tend to default more ex-post.

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 unobserved characteristics.[41] Model 4 shows that the ex-ante firm risk variable "none of the previous year loan applications granted"

[39] The definition of defaults follows the policy and academic literature (at least 90 days of delinquency). Note that delinquency does not necessarily imply firm-level failure: For ICO loans, 69% of defaulting firms do not end up failing.
[40] Note that despite that we do not have the loss given default (LGD) at the loan level, the average LGD for the portfolio of ICO loans is 32%.
[41] In Table 1, Panel B, of Appendix C we show additional robustness exercises for Tables 3 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). Since we have very few firms that have private and public loans with similar maturity, strategic defaults to some banks are not driving the results.

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.

All in all, our results suggest that the new public credit facility faces significant adverse selection problems. The state-owned bank has (not surprisingly) a worse pool of borrowers and consequently restricts its lending (even more to the observed riskier borrowers). However, it is substantially softer on unobserved riskier firms, proxied by either the inability of getting credit ex-ante (previous loan applications to private banks not granted) or by the tendency to default more ex-post (that is not explained by ex-ante firm observable characteristics), which 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 public credit facility causes positive real effects, and if so, how large these effects are. We focus on firm survival, change in employment, investment, total assets, sales (proxying for overall production), and productivity (sales over employees). We also analyze whether the public lending implies subsequent lending by private banks (crowding-in effects), thereby amplifying the effects of the initial public funds lent, and whether there are spillovers to other firms (suppliers) and private banks (defaults).

We exploit –in a regression discontinuity approach– ICO's continuous lending rule 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. The regression discontinuity design (see Imbens and Wooldridge, 2009) is used in situations where the probability of being enrolled into the treatment changes discontinuously (in our case, granting vs. rejecting the loan application) with some continuous variable (in our case, the continuous scoring value that the state-owned bank uses to evaluate a borrower).[42] Figure 1 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 the cutoff point. The probability of receiving the treatment (the ICO loan) is discontinuous at the cutoff point, with a discontinuity in the likelihood of granting the public loan of almost 40 p.p. around the cutoff point (almost 400% increase in probability of receiving the loan).

[42] As we focus on firm-level results, in this section we aggregate 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 outcome 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.

Our results are therefore based on a fuzzy regression discontinuity approach.[43] As Figure 1 shows, there are a number of firms with a credit scoring above the cutoff that are granted the loan (2% of all firms), and a number of firms below the cutoff that do not obtain the loan (28% of all firms).[44] 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 Angrist and Pischke, 2009; Imbens and Wooldridge, 2009; Lee and Lemieux, 2010).[45]

Figure 4 (Appendix C) suggests that firms do not choose to be below the cutoff point. This is confirmed using the McCrary test.[46] Note that the risk scoring formula applied by the state-owned bank is confidential and proprietary and it provides a value out of 18 firm variables that are double-checked by ICO with administrative and private registers, so manipulation is difficult. Therefore, 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.

For our main estimation, we use Calonico et al. (2014), and Calonico et al. (forthcoming) non-parametric method using local polynomials where the optimal bandwidth is symmetric. The estimated equation is the following:

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

where y_i is the an outcome measure for firm i from 2009:M12 to year t;[47] I(ICO APPLICANT GRANTED$_i$) is a dummy variable that takes the value of one if the firm was granted 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. The function $f(r_i)$ is included to correct for the possible bias due to the selection on

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[43] 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 noncompliers (observations based on firms that get the loan despite of having a risk score above the cutoff and those that do not get the loan despite of having a risk score below the cutoff), results are also statistically and economically significant.

[44] Although we do not know the specific firm-level reason for the noncompliers, it must be the case that either the loan applications were successful but finally they did not take the loan or they lacked some requirements such as enough guarantees. Analyzing in a regression the compliers vs. noncompliers, below and above the threshold, we find: (i) for firms below the threshold, those that get the public loan are the ones with higher profits and the ones that obtained less private loans; (ii) for firms above the threshold, those that get the public loan have a better scoring (as suggested in Figure 1) and better access to private loans. Finally, we have analyzed the similarity between the firms that, having received a loan from ICO, were in different sides of the threshold. A regression discontinuity design shows that ex-ante firm characteristics (e.g. size, age, ROA, capital ratio, productivity, interest paid, liquidity, credit history and past loan applications) are not statistically different. Therefore, the results suggest that the firms above the threshold that got the ICO loan are not different from those just below the threshold.

[45] 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. As robustness we also perform the parametric (global) strategy that gives similar results.

[46] This statistical test analyzes 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).

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

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 risk score is below the cutoff (0), and zero otherwise.

The firm outcome y_i measures the change in different firm-level outcomes once the firm obtains the public loan: 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; three private 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, the percentage change in total private bank credit, and future loan defaults with private banks); and, finally, the change in the average payment time to suppliers.[48]

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).[49] The coefficient of I(ICO APPLICANT GRANTED$_i$) is positive, statistically significant, and persistent over time. In addition, the instrument has a first stage F-test between 63 and 77, where the rule of thumb for not having weak instrument problems is above 10. In terms of magnitude, the granting of a loan by the new credit facility causes a positive impact on the likelihood of survival until the end of 2014 of 24 p.p. (over a four-year period), which corresponds to 33% increase at the mean.

We also show different specifications to check the consistency of the estimated coefficients (following Angrist and Pischke, 2009; Imbens and Wooldridge, 2009; Lee and Lemieux, 2010). In particular, we use a quadratic polynomial instead a linear one (column 5); we allow for asymmetric bandwidth (column 6); we test the sensitivity of the results to the change of the optimal bandwidth from half (column 7) to double (column 8), and also show the estimated results for a parametric specification (column 9). Moreover, Figure 5 in Appendix C plots the estimates against the continuum of bandwidths to show the stability of the baseline model.[50] Finally, Table 2, Panel B, of

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

[49] 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 on all the real variables are negative, and therefore our results imply that these negative 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).

[50] Following Calonico et al. (2014), the estimated optimal bandwidth for column 4 is 0.602. What we show with Figure 5 in Appendix C is the stability of the coefficient for different values of the bandwidth. Obviously, as the neighborhood of the cutoff gets smaller, the sample used significantly decreases, and the estimates get less precise; however, the coefficients are stable.

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.

In addition, Table 6 shows the heterogeneity effects of two key firm characteristics that proxy for financial constraints. Since we are interested in adverse selection, we split firms depending on whether (at the time they apply for the ICO loan) the impact of the public loan on firm outcomes is higher for firms whose relationship banks substantially reduced credit supply during the crisis (and hence they are more financially constrained if substitution across banks is difficult in crisis times).[51] We use a dummy variable that takes the value of one for firms which their main private banks had reduced more credit supply (constrained banks), where the bank shock is computed using Amiti and Weinstein (2018) methodology (bank credit growth orthogonal to borrower fundamentals), and we define it as those with the change in credit supply below the median.[52] We also consider the impact of ICO loans for firms with a significant (higher than 10%)[53] fraction of their debt with short-term maturity (lower than one year), and we also use the two firm measures at the same time (short-term maturity and ex-ante borrowing from constrained banks).

As Table 6 shows, we find that the real effects on firm survival are only positive for financially constrained firms (either their main relationship banks were constrained banks or/and with substantial short-term liabilities). The real effects are zero for the other (unconstrained) firms.

In Table 7 we analyze other firm-level outcomes. The estimated coefficients for employment growth, total assets growth, total sales growth, investment, and productivity growth are all statistically significant and large.[54] Quantitatively, the granting of a loan by the new credit facility causes a 56% to 86% increase in employment growth, 75% to 101% increase in total assets growth, 73% to 93% in total sales growth, 88% to 115% increase in investment, and 88% to 115% increase

[51] We indeed find that granting of applications from private banks that were not lending previously to the firm becomes substantially lower during crisis times.
[52] The approach is similar to analyzing change in (bank-firm) credit on firm*time and bank*time dummies, where the bank dummies capture the change in credit not explained by time-varying unobserved and observed borrower fundamentals (thereby, isolating bank credit supply); see also Jiménez et al. (2014). For a firm with multiple banks we compute the bank shock as the weighted average by loan volume of each bank (where each bank has a value based on Amiti and Weinstein (2018) bank shock), and then, if the firm value is below the median, then the firm is associated to financially constrained banks. As we weight by (firm-bank) loan size (before the public credit facility), we give more importance to the main banks of each firm, thereby mainly capturing relationship banks.
[53] The 10% corresponds to the 10th percentile of the distribution of the percentage of short-term over total bank debt. We have also used either the 25th percentile (22%) or to have positive (vs. 0) short-term debt with very similar results.
[54] As some real effects cannot have values below -100%, we also perform a Tobit analysis yielding very similar results.

in productivity.[55] Figure 6 of Appendix C shows the economic effects; for all these variables, there is a clear jump at the cutoff point.[56]

Moreover, Table 8 replicates Table 6 for the rest of firm-level outcomes yielding very similar results. Effects are only significant (and very large) for constrained firms, and zero for other firms. These findings suggest that the program is not an implicit subsidy that automatically makes firms more likely to survive or grow if they receive a public loan.

Finally, in Table 9 we analyze private credit crowding-in and some externalities (spillovers) to other firms and banks. Columns 1 and 2 show that, after obtaining the public loan, those firms (compared to almost identical firms that survive without the public loan) have a 106% 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 31.6 p.p.), and a 30% increase in private credit volume, thereby suggesting that such public lending causes ex-post crowding-in effects (that is, reinforcing the initial public funds with additional private funds).[57] Therefore, after obtaining public funds, these firms obtain new loans from private banks that were not currently lending to them, and hence not affected by loan ever-greening (zombie lending).

Moreover, columns 3 and 4 show that the average time in paying suppliers decreases by 96% after obtaining the public loan, while future loan defaults (at the end of 2015) to private banks decrease by 32 p.p..[58]

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.[59] Following Lee and Lemieux (2010), we also use another placebo (non-reported) by testing at points different from the official threshold through adding or subtracting a multiple of the optimal bandwidth to the cutoff. In all cases, the estimated discontinuities are insignificant.

All in all, the new public credit facility causes strong positive real effects, but against large loan defaults in a credit crunch period when government funds are very costly and scarce. We

[55] We find similar results when selecting firms that continue operating over the 2010-2013 period (economic effects are 56%, 76%, 73% and 72 and 44%, respectively). For access to new private credit after the ICO loan, we focus on firms that continue operating, as otherwise they could not obtain new credit from private banks.

[56] Note that the quantitative effects in Figure 6 of Appendix C are different from those in Tables 5 and 7, 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).

[57] The new private (versus public) credit has on average a longer maturity (in 67% of the firms). Moreover, the default rate of these "crowding-in" private loans is not statistically different from those other private loans (10% vs. 11%, respectively).

[58] These spillovers are not large for the whole economy since the size of the public lending program was very small.

[59] Note that we cannot perform the placebo before 2010 for the variable firm survival, as all firms in our sample, by definition, survived until 2010.

estimate the private net returns of the state-owned bank by subtracting from the ex-post returns the fixed costs per unit of loans:

$$(1+r)(1-PD)+(1-LGD)PD-(1+r_0)-\frac{c}{L},$$

where r is the loan rate, PD is the default rate, LGD is the loss given default, r_0 is the financing cost, c is the fixed cost of setting up the credit facility, and L is the total loan volume.[60] The net private returns computed in this manner are -16%.

We proxy the gross social returns by the change in sales due to the policy over the public loans received estimated for the median firm, based on the sales prior to the policy (December 2009) and the estimated coefficient in column 5 of Table 7 (results are very similar if we use all the firms around the cutoff point, not just the median firm, based on all the sales prior to the policy).[61] Subtracting the financial costs, the net social returns are 118%.

We use firm sales as (i) sales measure total firm output and are used to pay capital owners (shareholders and debtholders), labor (workers) and the state (taxes); and (ii) payments for intermediate inputs entail positive real effects on other firms, and we are not double-counting sales since the size of the credit facility was tiny. Note that a small program also implies that we do not need to assess general equilibrium effects, but just the partial equilibrium effects on the firms in our sample.[62] An alternative estimation using just the change in value added yields net social returns of 37%.[63]

It is also important to highlight that our positive social returns do not take into account those workers fired from firms (or in firms that do not survive), with the associated costs for unemployment insurance (and for human capital loss) in a country with very high unemployment during the crisis. Note also that there could be some misallocation of capital as some firms should not have survived; however, the results on crowding-in effects (by private banks that were not lending previously to those firms) suggest that these effects are not of first order. Interestingly, most of defaults on public loans are due to unobserved borrower risk; therefore, the costs of the policy for the state-owned bank are mainly stemming from adverse selection in lending.

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[60] The assumed *PD* is 40%, the *LGD* is 32%, the loan rate is 5%, and the fixed costs are 8.5 million euros.
[61] Table 7 is over a four-year period, and hence we divide it by four to get annual returns.
[62] From another administrative dataset, we checked that in our sample there are basically no pairs of firms that sell to each other intermediate inputs or provide services to each other (if that were the case, or in an analysis of the whole or a substantial part of the economy, value added would be better for measuring social returns).
[63] The estimated coefficient for value added in the regression discontinuity is 0.653, which is statistically significant. If we use EBITDA instead of sales, the gross social returns become 12% for the median firm and around 40% for the average one, where the estimated regression discontinuity coefficient is 1.037, and is statistically significant.

6. Concluding remarks

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 to invest in safer assets such as government debt.[64] 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 credit supply may bring 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 public lending in crisis times may imply substantial defaults due to lack of high quality borrowers (demand side) and the potential adverse selection in new borrowers.

We analyze the role of lending by a state-owned bank in a credit crunch, the potential adverse selection faced, and the causal real effects of the supply of new credit to firms, including spillovers to other firms and banks. For identification, we exploit a new (small) credit facility in Spain in 2010-2012 provided by its state-owned bank, a bank that used a credit scoring system based on hard information to grant or reject loan applications. Importantly, we have access to the bank's continuous value scoring function, the cutoff used for granting applications, including the individual applicants' scores, and the exhaustive credit register, including loan applications, matched with administrative firm and supervisory bank balance-sheet data.

Compared to privately-owned banks, the state-owned bank faces worse applicants, softens (tightens) its credit supply to unobserved (observable) riskier firms, and has much higher defaults (32 p.p. more delinquencies). The unobserved (hidden) riskier firms are either based (i) on firms to whom none of their previous loan applications, over the previous year, were granted, or (ii) on 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 (in levels or polynomials).

In a regression discontinuity design, the supply of public credit causes: large positive real effects to financially-constrained firms (whose relationship banks reduced substantially credit supply); crowding-in of new private bank credit; and positive spillovers to other firms and banks. Quantitatively, the granting of a public loan causes a 33% increase in firm survival, 56% increase in employment growth, 76% increase in total assets growth, 73% in total sales growth, 88% increase in investment, 88% increase in productivity, a 106% increase of the likelihood of ex-post access to

[64] See for example Abassi et al. (2016) and Peydró et al. (2017).

new private loans, a 31% increase in total private credit volume, a 96% decrease in the average time in paying suppliers, and a reduction of 32 percentage points of future loan default to private banks.

The quantitative effects are large as these are SMEs in an economy with a strong credit crunch, and the public loans crowds-in subsequent private credit (thereby amplifying the initial funding). Moreover, the quantitatively very large positive real effects are only (economically and statistically) significant for financially constrained firms, where constrained firms are the ones whose relationship banks substantially reduced credit supply during the crisis (above the median). For the other firms, the real effects are zero, which (together with our large quantitative average effects) implies that results are not explained by subsidized loans. Finally, as the new credit facility set up by the state-owned bank causes strong real effects, but it has large defaults, we compare the social with the private returns to capital. We find that private net returns for the state-owned bank are negative (-16%), while social net returns are positive and large (between 37% and 118%).

Commentators and academics have extensively argued about the limits of expansionary monetary policy to reach the real sector in crisis times. Another countercyclical public policy, as the World Bank (2013) for instance argues, is to use state-owned banks to directly grant loans to firms. Overall, our results show that, when there is a credit crunch, a state-owned bank can ameliorate it with significant positive real effects. However, a significant part of its lending is very risky, with most defaults stemming from unobserved borrower risk, so the effectiveness of this policy in combating credit crunches is reduced by informational asymmetries in crisis times. On the other hand, our results also show that, without adverse selection in private credit markets –proxied by those firms whose relationship banks substantially reduced credit supply–, the positive real effects of the public policy would have been zero. That is, without (or with small) frictions in private credit markets, the public policy would not be needed.

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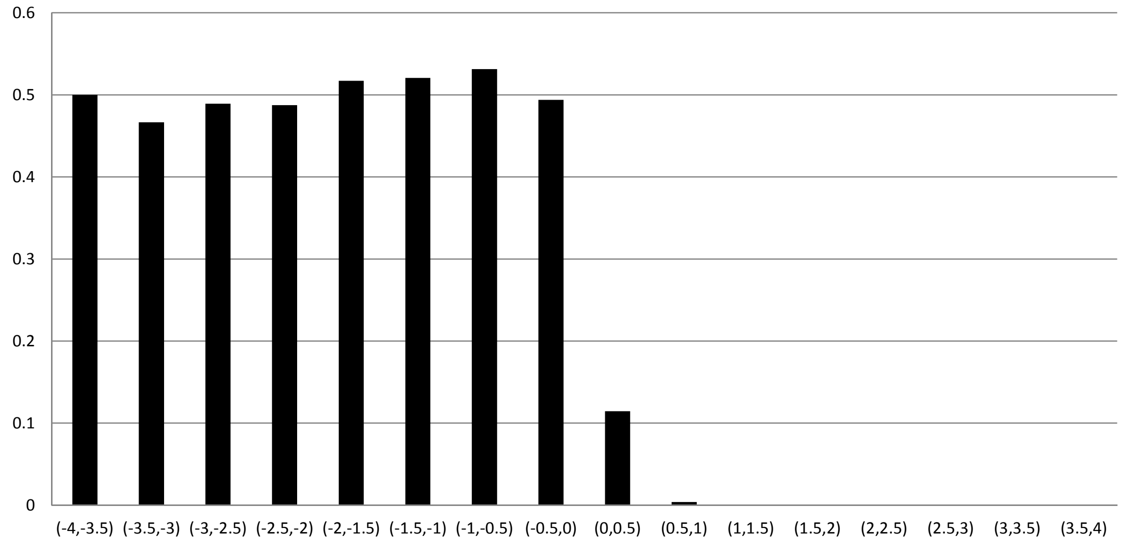
FIGURE 1
State-owned bank's granted loans by bin



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

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: $I(\text{ICO APPLICANT})_f$	
	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)
$\text{CAPITAL RATIO}_{ft-1}$	25.01	18.26	11.08	35.02	37.55	24.21	17.68	54.86	-63.36 ***	-0.027 **	(0.008)
$\text{LIQUIDITY RATIO}_{ft-1}$	5.42	8.76	0.79	6.02	10.21	13.17	1.65	13.42	-45.10 ***	-0.015 **	(0.006)
$\text{Ln(TOTAL ASSETS)}_{ft-1}$	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)
$\text{Ln(SALES/EMPLOYEES)}_{ft-1}$	4.65	0.86	4.12	5.13	4.80	0.95	4.20	5.35	-19.31 ***	-0.021 **	(0.006)
$\text{INTEREST PAID}_{ft-1}$	4.33	3.37	2.31	5.44	3.32	3.76	1.03	4.28	32.10 ***	0.019 **	(0.006)
$\text{Ln(NUMBER OF BANKS)}_{ft-1}$	1.53	0.59	1.10	1.95	1.16	0.62	0.69	1.61	71.86 ***	0.071 **	(0.016)
$\text{DRAWN OVER COMMITTED}_{ft-1}$	0.85	0.21	0.81	0.98	0.70	0.33	0.54	0.97	56.33 ***	0.016 *	(0.009)
$\text{NON COLLATERALIZED LOANS/TOTAL LOANS}_{ft-1}$	0.71	0.33	0.46	1.00	0.68	0.40	0.30	1.00	9.44 ***	-0.021 **	(0.006)
$\text{LOAN MATURITY 1-5y/TOTAL LOANS}_{ft-1}$	0.29	0.26	0.08	0.43	0.26	0.31	0.00	0.42	11.46 ***	0.005 *	(0.003)
$\text{I(BAD CREDIT HISTORY)}_{ft-1}$	0.10	0.30	0.00	0.00	0.03	0.16	0.00	0.00	43.26 ***	0.020 **	(0.004)
$\text{I(LOAN APPLICATION)}_{ft-1}$	0.57	0.50	0.00	1.00	0.43	0.50	0.00	1.00	32.64 ***	0.019 **	(0.003)
$\text{I(NONE LOAN APPLICATION GRANTED)}_{ft-1}$	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 $I(\text{ICO APPLICANT}_f)$ which equals one if the firm asked for a loan to the ICO program and zero otherwise. The definition of the independent variables are 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	Median
For the Analysis of the Lending Regressions (Tables 3 and 4)			
I(LOAN APPLICATION GRANTED)$_{fbt}$	0.29	0.45	0.00
Ln(CREDIT AMOUNT)$_{fbt}$	4.00	1.09	3.93
I(FUTURE DEFAULT)$_{fb}$	0.13	0.34	0.00
SCORING$_{ft-1}$	3.71	0.76	3.61
I(ICO BANK APPLICANT)$_{f}$	0.23	0.42	0.00
I(LOAN APPLICATION)$_{ft-1}$	0.74	0.44	1.00
I(NONE LOAN APPLICATION GRANTED)$_{ft-1}$	0.40	0.49	0.00
I(ICO BANK)$_{b}$	0.07	0.26	0.00
Ln(TOTAL ASSETS)$_{bt-1}$	18.04	1.37	18.27
CAPITAL RATIO$_{bt-1}$	5.75	2.34	5.21
ROA$_{bt-1}$	0.31	0.57	0.31
DOUBTFUL RATIO$_{bt-1}$	6.39	3.65	5.71
For the Analysis of the Real Effects of ICO loans (Tables 5 to 9)			
I(FIRM SURVIVAL)$_{f2014}$	0.73	0.44	1.00
EMPLOYMENT GROWTH$_{f2013}$	-0.37	0.58	-0.42
ASSETS GROWTH$_{f2013}$	-0.19	0.70	-0.17
SALES GROWTH$_{f2013}$	-0.33	1.06	-0.24
INVESTMENT$_{f2013}$	-0.25	2.42	-0.31
PRODUCTIVITY GROWTH$_{f2013}$	-0.23	0.70	-0.25
I(NEW BANK LOAN)$_{f}$	0.30	0.46	0.00
BANK LOAN GROWTH$_{f}$	-0.45	0.47	-0.52
SCORING$_{ft}$ - CUTOFF POINT$_{ft}$	-0.11	1.21	-0.22
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	0.31	0.46	0.00
I(ICO LOAN APPLICATION BELOW CUTOFF POINT)$_{ft}$	0.57	0.49	1.00
PAYMENT TIME TO SUPPLIERS CHANGE$_{f2013}$	0.17	1.11	0.22
FUTURE PRIVATE CREDIT DEFAULTS	0.27	0.44	0.00

Notes: This table reports means, standard deviations and medians 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 to 9). I(.) is the indicator function which takes only two values: 0 or 1. For a definition of the variables, see Appendix B.

TABLE 3

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

	PANEL A						PANEL B					
Dependent variable:	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*; and I(.) is the indicator function that takes only two values: 0 or 1. 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 defined 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 spanned by the included set of fixed effects. *** 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)
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 ***
				(0.015)
I(ICO BANK)$_b$*I(LOAN APPLICATION)$_{ft-1}$				-0.022
				(0.017)
I(ICO BANK)$_b$*I(NONE LOAN APPLICATION GRANTED)$_{ft-1}$				0.032 *
				(0.018)
Time Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	No	Yes
R2	0.035	0.051	0.778	0.781
No. of Firms	15,743	15,743	15,743	15,743
No. of Observations	39,306	39,306	39,306	39,306

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; and I(.) is the indicator function that takes only two values: 0 or 1. 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 defined 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 spanned by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 5

Firm-level 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	Asymmetric bandwidth	Half Bandwidth	Double Bandwidth	Parametric
Second Stage									
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	0.141 **	0.265 **	0.162 *	0.242 **	0.269 *	0.224 **	0.172	0.166 **	0.218 **
	(0.059)	(0.123)	(0.100)	(0.105)	(0.144)	(0.106)	(0.151)	(0.071)	(0.111)
First Stage. Dependent variable I(ICO LOAN APPLICATION GRANTED)$_{ft}$									
I(ICO LOAN APPLICATION BELOW CUTOFF POINT)$_{ft}$	0.269 ***	0.248 ***	0.252 ***	0.251 ***	0.226 ***	0.250 ***	0.268 ***	0.290 ***	0.254 ***
	(0.031)	(0.031)	(0.030)	(0.029)	(0.035)	(0.029)	(0.037)	(0.024)	(0.026)
F-test instrument	76.9	63.1	72.5	73.9	40.8	77.0	53.7	145.1	96.4
No. of Observations	8,723	9,520	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 different dates, where I(.) is the indicator function that takes only two values: 0 or 1.. 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 defined 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. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 6

Firm-level real effects (1): Fuzzy regression discontinuity analysis of firm survival. Heterogeneity

Dependent variable:	FIRM SURVIVAL 2010-2014											
	Bank-constrained		Non bank-constrained		With Short Term Debt		Without Short Term Debt		Bank-constrained & With Short Term Debt		Non Bank-constrained or Without Short Term Debt	
Second Stage												
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	0.347	***	0.031		0.390	**	0.119		0.586	***	0.032	
	(0.143)		(0.198)		(0.194)		(0.145)		(0.216)		(0.173)	
First Stage. Dependent variable I(ICO LOAN APPLICATION GRANTED)$_{ft}$												
I(ICO LOAN APPLICATION PASS THE SCORING SYSTEM)$_{ft}$	0.283	***	0.233	***	0.215	***	0.332	***	0.268	***	0.241	***
	(0.038)		(0.045)		(0.037)		(0.049)		(0.049)		(0.042)	
No. of Observations	4,202		4,273		5,943		2,532		2,767		5,708	

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 2014, where I(.) is the indicator function that takes only two values: 0 or 1. 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. A firm belongs to the bank-constrained category if the weighted bank-supply shock faced by the firm, computed following Amiti and Weinstein (2018), is below the median of the sample. A firm belongs to the short-term debt category if the weight of the debt with maturity shorter than one year over total debt is at least the 10%. All variables are defined 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. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 7

Firm-level real effects (2): Fuzzy regression discontinuity analysis of firm real and financial outcomes

Dependent variable:	EMPLOYMENT GROWTH$_{09-13}$		ASSETS GROWTH$_{09-13}$		SALES GROWTH$_{09-13}$		INVESTMENT$_{09-13}$		PRODUCTIVITY GROWTH$_{09-13}$	
	Linear	Tobit	Linear	Tobit	Linear	Tobit	Linear	Tobit	Linear	Tobit
Second Stage										
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	0.562 ***	0.861 ***	0.755 ***	1.010 ***	0.729 ***	0.930 ***	0.883 **	1.149 ***	0.879 **	1.151 **
	(0.196)	(0.290)	(0.312)	(0.271)	(0.257)	(0.335)	(0.356)	(0.406)	(0.413)	(0.487)
First Stage. Dependent variable I(ICO LOAN APPLICATION GRANTED)$_{ft}$										
I(ICO LOAN APPLICATION BELOW CUTOFF POINT)$_{ft}$	0.226 ***	0.226 ***	0.244 ***	0.244 ***	0.256 ***	0.256 ***	0.241 ***	0.241 ***	0.231 ***	0.231 ***
	(0.042)	(0.042)	(0.038)	(0.038)	(0.039)	(0.039)	(0.040)	(0.040)	(0.043)	(0.043)
F-test instrument	28.3	28.3	41.0	41.0	43.7	43.7	35.6	35.6	28.6	28.6
No. of Observations	3,810	3,810	4,247	4,247	3,723	3,723	3,683	3,683	3,233	3,233

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; and I(.) is the indicator function that takes only two values: 0 or 1.. All variables are defined 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. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 8

Firm-level real effects (2): Fuzzy regression discontinuity analysis of firm real and financial outcomes. Heterogeneity

Dependent variable:	EMPLOYMENT GROWTH$_{09\text{-}13}$						ASSETS GROWTH$_{09\text{-}13}$					
	Constrained Bank	Non-Constrained Bank	With Short Term Debt	Without Short Term Debt	Constrained Bank & With Short Term Debt	Non-Constrained Bank or Without Short Term Debt	Constrained Bank	Non-Constrained Bank	With Short Term Debt	Without Short Term Debt	Constrained Bank & With Short Term Debt	Non-Constrained Bank or Without Short Term Debt
Second Stage												
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	0.972 ***	0.074	1.039 *	0.462	1.313 **	0.310	0.970 ***	0.506	1.038 ***	0.339	1.360 ***	0.121
	(0.403)	(0.546)	(0.650)	(0.317)	(0.686)	(0.372)	(0.354)	(0.581)	(0.448)	(0.339)	(0.617)	(0.400)
First Stage. Dependent variable I(ICO LOAN APPLICATION GRANTED)$_{ft}$												
I(ICO LOAN APPLICATION PASS THE SCORING SYSTEM)$_{ft}$	0.251 ***	0.171 *	0.137 **	0.379 ***	0.207 ***	0.205 ***	0.278 ***	0.174 *	0.195 ***	0.328 ***	0.247 **	0.211 ***
	(0.062)	(0.072)	(0.054)	(0.082)	(0.076)	(0.056)	(0.059)	(0.064)	(0.049)	(0.077)	(0.077)	(0.058)
No. of Observations	1,728	1,825	2,647	906	1,220	2,333	1,909	1,996	2,829	1,076	1,307	2,598

Dependent variable:	SALES GROWTH$_{09\text{-}13}$						INVESTMENT$_{09\text{-}13}$					
	Constrained Bank	Non-Constrained Bank	With Short Term Debt	Without Short Term Debt	Constrained Bank & With Short Term Debt	Non-Constrained Bank or Without Short Term Debt	Constrained Bank	Non-Constrained Bank	With Short Term Debt	Without Short Term Debt	Constrained Bank & With Short Term Debt	Non-Constrained Bank or Without Short Term Debt
Second Stage												
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	0.812 ***	0.405	0.945 **	0.660 *	1.159 **	0.570 **	0.831 **	0.567	1.290 **	0.426	1.754 **	0.613
	(0.315)	(0.417)	(0.448)	(0.365)	(0.653)	(0.357)	(0.417)	(0.645)	(0.658)	(0.384)	(0.900)	(0.417)
First Stage. Dependent variable I(ICO LOAN APPLICATION GRANTED)$_{ft}$												
I(ICO LOAN APPLICATION PASS THE SCORING SYSTEM)$_{ft}$	0.300 ***	0.229 ***	0.200 ***	0.354 ***	0.220 *	0.234 ***	0.277 ***	0.212 **	0.178 **	0.386 ***	0.203 **	0.250 ***
	(0.061)	(0.060)	(0.053)	(0.081)	(0.080)	(0.052)	(0.065)	(0.070)	(0.054)	(0.082)	(0.079)	(0.051)
No. of Observations	1,698	1,773	2,567	904	1,188	2,283	1,696	1,762	2,533	925	1,172	2,286

Dependent variable:	PRODUCTIVITY GROWTH$_{09\text{-}13}$					
	Constrained Bank	Non-Constrained Bank	With Short Term Debt	Without Short Term Debt	Constrained Bank & With Short Term Debt	Non-Constrained Bank or Without Short Term Debt
Second Stage						
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	1.240 ***	0.364	1.029 *	0.736 *	1.751 **	0.672
	(0.505)	(0.728)	(0.579)	(0.482)	(0.985)	(0.597)
First Stage. Dependent variable I(ICO LOAN APPLICATION GRANTED)$_{ft}$						
I(ICO LOAN APPLICATION PASS THE SCORING SYSTEM)$_{ft}$	0.259 ***	0.166	0.173 **	0.361 ***	0.192	0.181 **
	(0.067)	(0.072)	(0.058)	(0.094)	(0.086)	(0.062)
No. of Observations	1,484	1,547	2,284	747	1,063	1,968

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. A firm belongs to the constrained bank category if the weighted bank-supply shock faced by the firm, computed following Amiti and Weinstein (2018), is below the median of the sample. A firm belongs to the short-term debt category if the weight of the debt with maturity shorter than one year over total debt is at least the 10%. All variables are defined 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.

TABLE 9

Firm-level externalities and crowding-in effects

Dependent variable:	CROWDING-IN EFFECT		EXTERNALITIES	
	NEW BANK LOAN	BANK LOAN GROWTH	PAYMENT TIME TO SUPPLIERS $CHANGE_{09\text{-}13}$	NEW FUTURE PRIVATE CREDIT DEFAULTS
Second Stage				
$I(\text{ICO LOAN APPLICATION GRANTED})_{ft}$	0.316 **	0.304 **	-0.957 *	-0.324 *
	(0.142)	(0.140)	(0.675)	(0.182)
First Stage. Dependent variable $I(\text{ICO LOAN APPLICATION GRANTED})_{ft}$				
$I(\text{ICO LOAN APPLICATION BELOW CUTOFF POINT})_{ft}$	0.236 ***	0.251 ***	0.230 ***	0.246 ***
	(0.035)	(0.038)	(0.056)	(0.042)
F-test instrument	44.4	44.4	16.9	35.1
No. of Observations	6,968	6,183	2,099	5,208

Notes: This table reports estimates from a non-parametric local-linear regression-discontinuity fuzzy models with robust z-test. The dependent variables of the first stage is $I(\text{ICO LOAN APPLICATION GRANTED})_{ft}$, 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 $I(\text{ICO LOAN APPLICATION BELOW THE CUTOFF POINT})_{ft}$, 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; and I(.) is the indicator function that takes only two values: 0 or 1.. All variables are defined 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. *** Significant at 1%, ** significant at 5%, * significant at 10%.

ONLINE APPENDIX (NOT FOR PUBLICATION)

APPENDIX A

Proofs of the results

Proof of Proposition 1 Let us define

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

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

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

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

if and only if

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

which simplifies to

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

Since

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

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

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

By the properties of normal densities this simplifies to

$$-\left[(1-\gamma)\phi(\hat{x}_L)\hat{x}_L\pi_L + \gamma\phi(\hat{x}_H)\hat{x}_H\pi_H\right] < 0,$$

which implies

$$\frac{\partial\hat{\Pi}}{\partial\sigma} = -\frac{1}{\sigma}\left[(1-\gamma)\phi(\hat{x}_L)\hat{x}_L\pi_L + \gamma\phi(\hat{x}_H)\hat{x}_H\pi_H\right] < 0.$$

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

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

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, by the properties of the normal hazard function, $\hat{x}_H < \hat{x}_L$ and $\hat{x}_H < 0$ imply

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

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 $\tilde{s}$ as well as the effect on $\tilde{s}$ and hence on $\tilde{L}$ of the lending bias δ. Next, since

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

and $L'(\bar{s}),$ we have

$$\frac{\partial\tilde{\Pi}}{\partial\delta} = \left.\frac{d\Pi}{d\bar{s}}\right|_{\bar{s}=\tilde{s}}\frac{\partial\tilde{s}}{\partial\delta} < 0.$$

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

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

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

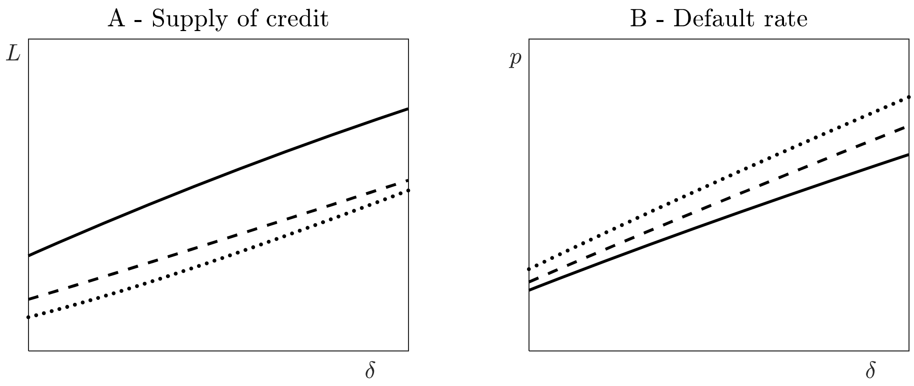
APPENDIX B

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
PAYMENT TIME TO SUPPLIERS CHANGE$_{f2013}$	-	Change in the time to pay to suppliers of firm *f* from 2009 to 2013
FUTURE PRIVATE CREDIT DEFAULTS	0/1	A variable that takes one if the firm *f* defalt in the future (2015) with private banks given that is not defaulted in 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$_{ft-1}$	%	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

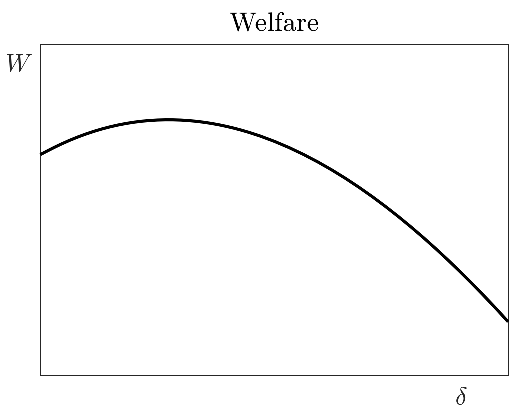
APPENDIX C

FIGURE 1
The effect of the lending bias on the supply of credit and the default rate of the state-owned bank



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

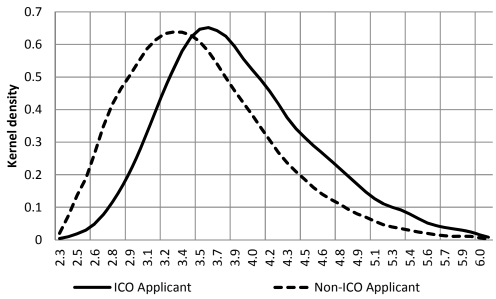


This figure shows the effect of the lending bias δ of the state-owned bank on social welfare W.

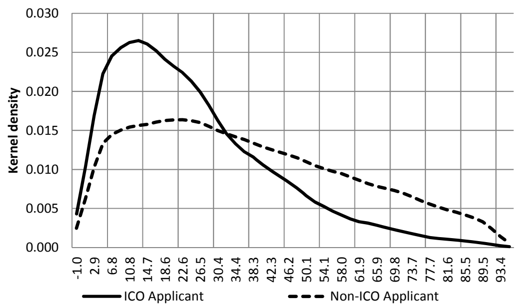
FIGURE 3

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

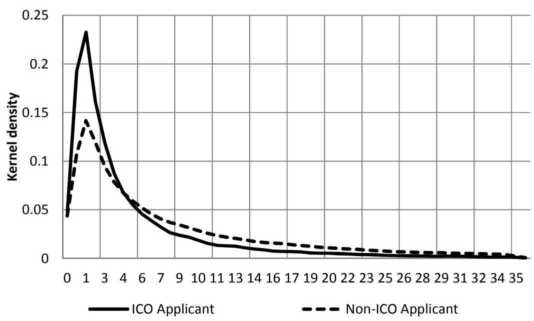
SCORING



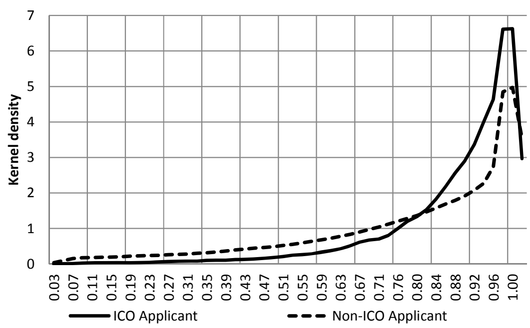
CAPITAL RATIO



LIQUIDITY RATIO

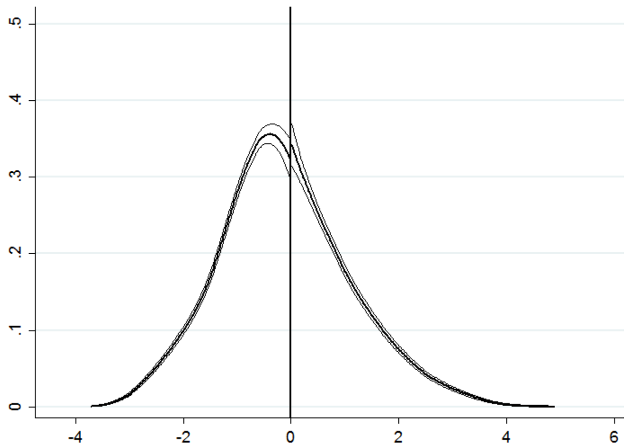


DRAWN OVER COMMITTED



These figures 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.

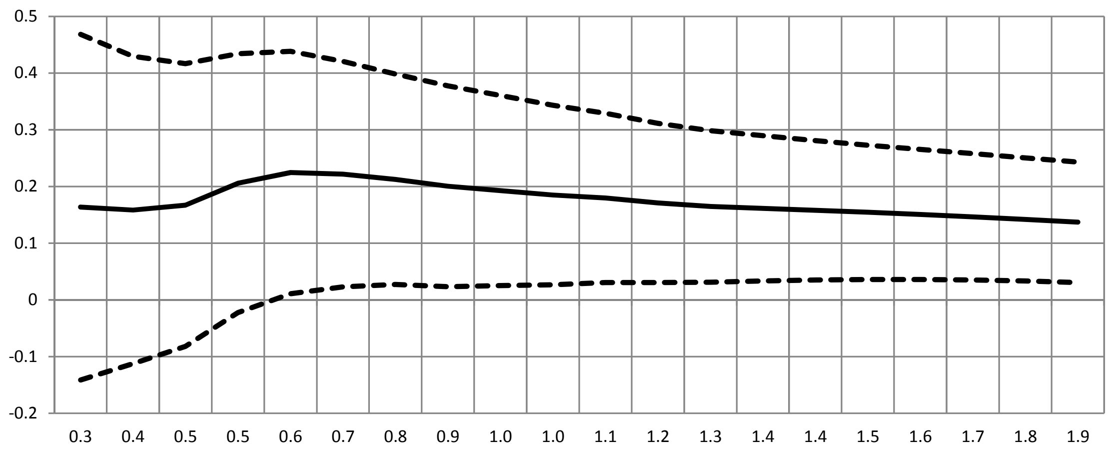
FIGURE 4
Density of the scoring variable



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 5

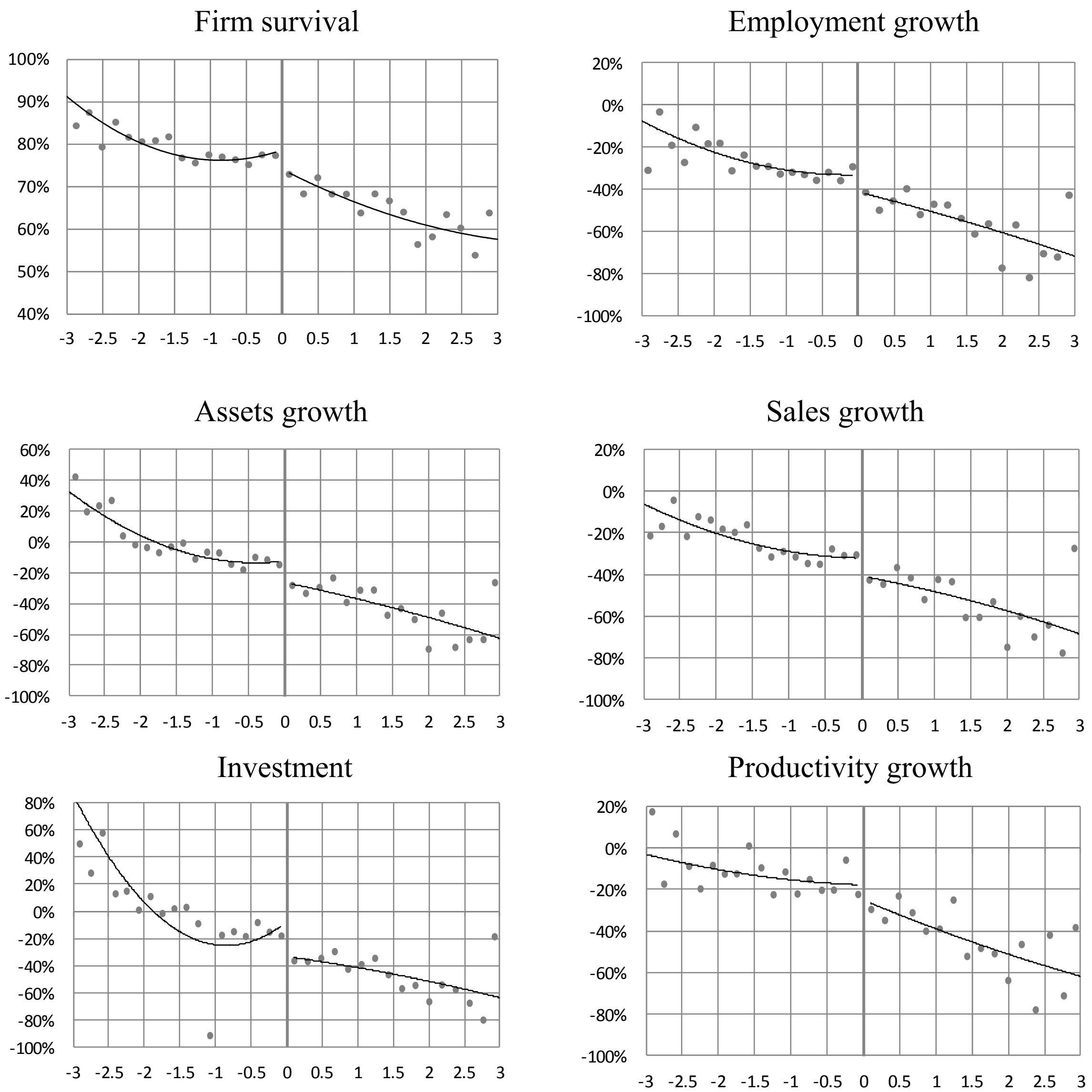
Fuzzy design estimation of firm survival (2010-2014) with varying bandwidth



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 95% percent confidence bands.

FIGURE 6

Firm-level real effects: a graphical representation



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

Robustness of Tables 3 and 4

PANEL A: Estimating the extensive and intensive margins together

Dependent variable:	Ln(1+CREDIT AMOUNT)$_{fbt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
I(ICO BANK)$_b$	-0.530 ***	-0.487 ***	-0.367 ***	-0.326 ***		
	(.127)	(.13)	(.103)	(.101)		
SCORING$_{ft-1}$		-0.104 ***	-0.180 ***		-0.190 ***	
		(.016)	(.025)		(.03)	
I(LOAN APPLICATION LAST YEAR)$_{ft-1}$		0.474 ***	-0.418 ***		-0.421 ***	
		(.051)	(.05)		(.047)	
I(NONE LOAN APPLICATION GRANTED)$_{ft-1}$		-0.593 ***	1.037 ***		1.025 ***	
		(.085)	(.096)		(.09)	
I(ICO BANK)$_b$*SCORING$_{ft-1}$					-0.067 ***	-0.075 *
					(.021)	(.039)
I(ICO BANK)$_b$*I(LOAN APPLICATION)$_{ft-1}$					-0.199 ***	-0.147 **
					(.033)	(.07)
I(ICO BANK)$_b$*I(NONE LOAN APPLICATION GRANTED)$_{ft-1}$					0.367 ***	0.289 ***
					(.047)	(.065)
Time Fixed Effects	Yes	Yes	Yes	-	Yes	-
Firm Fixed Effects	No	No	Yes	-	Yes	-
Firm*Year:month Fixed Effects	No	No	No	Yes	No	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	No	No	Yes	Yes
R2	0.010	0.031	0.423	0.489	0.451	0.505
No. of Firms	63,924	63,924	63,924	17,314	63,924	17,314
No. of Observations	210,651	210,651	210,651	46,091	210,651	46,091

PANEL B: Correcting for selection bias and adding loan controls

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

Notes: This table reports estimates from a linear probability model using ordinary least squares. The dependent variables are: Ln(1+CREDIT AMOUNT)$_{fbt}$, the logarithm of one plus the committed loan amount granted in months *t* to *t+3* by bank *b* to firm *f* , 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 successful 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; and I(.) is the indicator function that takes only two values: 0 or 1.. 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 are 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 spanned by the included set of fixed effects. *** 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. Note that in this table the dependent variables change for each row. 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; and I(.) is the indicator function that takes only two values: 0 or 1. All variables are defined 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. *** 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, where only the 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; and I(.) is the indicator function that takes only two values: 0 or 1. All variables are defined 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. *** 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$_{2009-2008}$
Second Stage					
I(ICO LOAN APPLICATION GRANTED)$_{ft}$	-0.017	0.023	0.008	0.054	0.121
	(0.145)	(0.073)	(0.132)	(0.186)	(0.172)
First Stage. Dependent variable I(ICO LOAN APPLICATION GRANTED)$_{ft}$					
I(ICO LOAN APPLICATION BELOW CUTOFF POINT)$_{ft}$	0.251 ***	0.281 ***	0.274 ***	0.240 ***	0.228 ***
	(0.039)	(0.034)	(0.034)	(0.050)	(0.045)
F-test instrument	42.5	68.7	65.3	23.1	26.1
No. of Observations	5,345	5,720	5,585	3,560	5,043

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; where I(.) is the indicator function that takes only two values: 0 or 1. 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 defined 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. *** Significant at 1%, ** significant at 5%, * significant at 10%.