Sharing information on lending decisions: an empirical assessment*

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Abstract

This paper presents the first empirical study of information spillover and signalling on loan search and its outcomes when a bank can observe whether a borrower applying for a loan has been formerly rejected by other lenders. To this end, it exploits a unique dataset that takes advantage of the fact that the Italian Credit Register discloses such information. The empirical strategy makes use of data on loan applications and rejections, as well as of time-varying bank and firm fixed effects, to robustly identify the effect of such information on lending. The results show that disclosing to an intermediary information on an applicant's past rejections affects negatively the probability that he continues the search. At the same time, the information on former rejections is associated with a higher probability of being funded for those borrowers that are not discouraged and continue the search, provided that they are not opaque. A theoretical model shows that banks interpret the information on previous rejections as a signal of unobservable quality for the average borrower, while not for more opaque borrowers, for whom past rejections impact negatively the outcome of latter applications. We also document that credit intermediaries differ in the extent to which they rely on this information, in a way that, at least in part, reflects the different informational content that such signal carries for them.

Keywords: sequential lending decisions, credit supply, winner's curse, informational spillover.

JEL classification: E51, G21, G28.

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1 Introduction

It is well known that credit dynamics feed back to the business cycle in a procyclical way (Ruckes 2004; Dell'Ariccia and Marquez 2006; Panetta et al. 2009). During upturns, the decrease in borrowers' default probability contributes to a more intense competition among intermediaries and lower levels of screening, resulting in a credit boom. Viceversa, in downturns the competitive pressure among intermediaries diminishes, as banks adopt tighter credit standards in order to avoid financing low quality borrowers, leading to a lending crunch.

In addition, during downturns, banks' more pervasive screening may increase the share of rejected applicants in the market and, as long as these stay in the market, also the probability, faced by each bank, of receiving an application from a borrower that has already been rejected by another intermediary. To avoid this, banks operate an extra tightening of credit standards, which exerts an additional contractionary effect on the real economy by further reducing the borrowers' probability to have their applications approved. Such distortionary phenomenon is an instance of the winner's curse in credit markets (Broeker 1990).

In principle, if lenders could observe the outcomes of previous screening processes, this distortion could be abated. However, lenders typically do not have access to such information, even in countries where a Credit Register is in place. A notable exception is Italy, where intermediaries evaluating a new applicant ("perspective" lenders, hereafter) learn from the Credit Register if a borrower was rejected by other banks in the six months preceding the current application.[1] The present paper exploits this unique characteristic of the Bank of Italy's Credit Register to empirically study for the first time the effects of previous lenders' decisions on perspective lenders' decision to finance a borrower.

More precisely, the analysis employs a very detailed dataset tracking the outcome of a large sample of loan applications filed by Italian firms to banks that they are not engaged with at the moment of the application. This dataset contains information on both rejected and approved applications (which allows us to effectively identify loan supply; see for instance Puri et al. 2011). Our empirical strategy consists of regressing the number of past rejections that a borrower has at the moment of a new application on the probability that this is approved. Thanks to the fact that in our dataset firms apply to several banks in the same period (i.e. they make multiple applications), and banks receive more than one application at time, we can include bank/time and firm/time fixed effects to control for all time-varying and invariant, observable and unobservable firm or bank characteristics that may influence lending decisions (Khwaja and Mian 2008 and Jiménez et al. 2012). To further corroborate our findings, we conduct a regression-discontinuity type of exercise, by taking advantage of a normative feature which imposes that a borrower's past rejections should be disclosed only up to the six months preceding his application for credit. Exploiting the fact that

[1] Such data are collected and made available to perspective lenders also in Sweden; however there it is a private company that deals with the collection and dissemination of borrowers' records. To our knowledge, such data have not yet been made available nor used for research purposes.

we have instead access to the whole history of a borrower's rejections, we compare the effect of the observable past rejections with that of those that only we can see, thus assessing the effect of such information, controlling for all other firm-specific factors that may influence the decision.

The main results of the analysis are the following. The information on an applicant's past rejections affects lending decisions in a statistically significant way. On the borrowers' side, past rejections are negatively correlated with the probability of continuing the loan search. At the same time, for those borrowers that continue the search despite former rejections, this information is, on average, positively linked to the probability of being funded. This is however not true for those applicants that are opaque, for whom past rejections affect negatively the outcome of the lending decision.

The first result indirectly shows that there is a winner's curse in the credit market, as the information on the decisions taken by other intermediaries is valuable. Unfortunately, as there is no counterfactual scenario in which lenders do not access this information, estimating directly the extent of the winner's curse is not possible. We lay down a simple theoretical model, which illustrates how the estimated impact of the information on past rejections on the probability of finding credit compounds two opposite effects. The former is a negative "information spillover" effect that captures the impact of previous lenders' rejections on the decision of the perspective lender. The second is a positive "selection" effect, that arises as, in a context of incomplete information on borrowers' quality, applying notwithstanding previous rejections acts a signalling device that allows better applicants to select themselves out from the pool. The theoretical distinction between the two effects, which however we cannot pin down empirically, allows us to argue that the positive effect of past rejections on the probability of approval for the average borrower captures the fact that the decision to apply for credit regardless of past rejections signal the quality of the project. Conversely, this does not apply to worse borrowers, that are deterred out of the market.

Finally, to corroborate our reading of the results, we show that the informational content of past rejections, and hence its impact on banks' decisions, varies with bank, firm and macroeconomic characteristics, in a way that is coherent with the idea that the relative importance of the information spillover and the selection effect compounds differently for different banks, borrowers and general economic environment. In particular, we confirm that the information spillover effect prevails for those intermediaries that have worse access to soft information regarding the applicant, and is more muted for banks that rely more on their own screening technology or that have an appetite for risk. Similarly, the selection effect is more muted for borrowers that have a larger amount of deteriorated outstanding credit at the moment of the new application, or that are already engaged with a larger number of lenders. Finally, when the prospects for the economy improve, the negative impact of the spillover effect diminishes.

The paper is organized as follows. We start by providing a brief overview of the related literature (Section 2); we then introduce the model and discuss its testable implications (Section 3), then describe the data (Section 4) and the empirical methodology (Section 5). We finally show the results (Section 6) and conclude (Section 7).

2 Review of the literature

The empirical literature on winner's curse and informational externalities in the credit market is fairly scant, as it is difficult to access the data needed to test such phenomena. The theoretical literature, on the contrary, is fairly well developed. Broeker (1990) and Nakamura (1993) have characterized the winner's curse in the loan application process as the additional tightening of credit standards that banks operate because they fear to finance ("win") an applicant who has been previously considered as not creditworthy by other lenders. This distortion arises when intermediaries' screening technologies are imperfectly correlated, and the decisions taken by banks are unobservable, in a context in which firms already rejected by a bank are not screened out of the market but turn for credit to other intermediaries. Such phenomenon has been shown to be highly procyclical (Ruckes 2004; Dell'Ariccia and Marquez 2006) as credit risk, and hence the proportion of risky borrowers in the pool of applicants increases in economic downturns.[2]

An additional strand of literature that relates to our analysis is that on information spillover. In our setup, an information spillover occurs when the number of previous rejections influences subsequent banks' choices, regardless of whether it conveys substantial information on the borrower's quality. This phenomenon has been thought as the tendency of some banks to replicate the strategies of others, in terms of investing, for instance, in the same industry or in the same securities (see, for instance, Jain and Gupta 1987; Shaffer 1998; Acharya and Yorulmazer 2007 and Bonfim and Kim 2012).

An interesting parallel can be drawn between searching for financing in the credit market and searching for a job in the labor market. In the labor market, in fact, employers generally observe the length of the unemployment spell of the workers who apply for a job. As low productivity workers are likely to have longer unemployment spells, just as worse borrowers are likely to take more time to find financing, the duration of the unemployment spell is a signal that employers take into account in their hiring decisions. Lockwood (1991) studies a setup in which employers can individually screen applicants and also use the information conveyed by the unemployment spell, a situation analogue to that we consider for the Italian credit market, where lenders screen their applicants and take into account the duration of the "search" for credit. Lockwood shows that in equilibrium employers always do the screening and take into account the information conveyed by the unemployment spell (which is related to the probability that the worker has been screened by another employer and found of low productivity). Furthermore, he demonstrates that employers vary the length of unemployment period that they are willing to tolerate in hiring an unemployed worker depending on exogenous supply and demand factors, among which the state of the economy and the cost of keeping a vacancy. Many of Lockwood's theoretical predictions apply also to the case of credit market, and are confirmed by our empirical

[2] To mitigate this issue, in many countries private and public credit registers have been successfully established with the aim to soothe informational asymmetries among market participants. However, even if the information typically available from these registers can reach a very good level of detail, it will hardly bring a full homogenization of the information sets available to different banks.

analysis. We as well find that perspective banks use the information "externality" generated by the screening process of the other intermediaries and that they do so to different extent, depending on the characteristics of both the bank and the applicant.

3 The model

We consider an economy that lasts two periods, populated by two banks and a continuum of competitive firms, which need to borrow L units of funds for their investment project. The search for credit is assumed to be sequential: firms make one application per period, turning to a bank in the second period only if their first application is rejected. This implies that applying for credit in the second period reveals that the applicant was rejected by its competitor.

Firms applying for a loan sustain a cost $k_i > 0$, with $i = 1, 2$, with $k_1 \neq k_2$, which represents the cost of applying in periods 1 and 2, and can be either material or immaterial (time). Firms can be of two types τ, high and low, which we denote Θ and θ, respectively. If the loan finances the project of a high type the return to the bank is gL, with $g > 0$, otherwise it is $-lL$.

The applicant's type is his private information, and therefore unknown to the bank. However, before taking a lending decision, in each period banks freely observe a signal σ_i, that is informative about the applicant's type. This may represent the outcome of a screening process or of a scoring system. The probablity of theobserved signal is

$$p(\sigma_i = \Theta|\Theta) = p(\sigma_i = \theta|\theta) = \frac{1}{2} + \gamma \tag{1}$$

If a loan is approved, entrepreneurs enjoy a private benefit equal to B: this defines the benefits the entrepreneur derives from running an investment project independently of its actual success, which may be related to non-pecuniary aspects of the activity (e.g. prestige, visibility, relations and career prospects), but also to the possibility to divert resources to his own benefit. We can then assume that B is a measure of the degree of opacity of the borrowing firm.

For notational simplicity and with no substantial loss of generality, we make the following parameter normalizations and simplifying assumptions. The size of the loan is assumed to be equal to one, $L = 1$; bad projects to not pay back anything, $l = 1$, and the rate of return for the high type's project is strictly less than one, $g < 1$. High and low types are present in the population proportion $q_1 \in (0, 1)$ and $1 - q_1$. Further, the signal is sufficiently informative

$$\gamma > \frac{1-g}{1+g}\frac{1}{2} \tag{2}$$

Finally, the cost of filing an application is not too large

$$\frac{k_i}{B} < \frac{1}{2} - \gamma \tag{3}$$

that is, for both types the cost of applying is lower than the benefits weighted by the probability that an applicant receives the high signal.

The situation represented in this model is highly stylized, as are its assumptions. However, we do not aim at providing a realistic description of the search for credit, but rather a parsimonious setup in which to isolate the key forces at play. We are also aware that other, alternative dynamics could be advanced to explain the results. Here we purposefully choose to limit our attention to the interplay of the information spillover and signalling effects because this mechanism can reconcile in a simple framework all the empirical findings; this does however not exclude that other forces could be at play.[3]

3.1 The equilibrium with selection

To gain intuition, it is useful to point out that k_i, the ex ante loan application cost, makes the decision to apply more expensive for the low type borrowers, since the smaller probability with which they receive a favorable signal realization diminishes the expected value of the benefits from applying. For this reason, applying for a loan can act as a signalling device for applicants of the high type.

To capture the selection process that arises thanks to this signalling, we establish the existence (although not the uniqueness) of a Perfect Bayesian Equilibrium in which each bank optimally takes its lending decisions conditional on the borrower's type and based on rationally updated posteriors on the probability that a given realization of the signal is generated by a high (low) type. Firms optimally decide their application strategies by considering the banks' lending decisions and posterior beliefs. More formally, the equilibrium is defined as follows.

Definition 1 *A Perfect Bayesian Equilibrium is a strategy profile for banks and firms and posterior beliefs for banks such that at any stage of the game strategies are optimal given the beliefs, and the beliefs are obtained from equilibrium strategies and observed actions using the Bayes' rule.*

Let us denote as Bank 1 the bank where the first application is filed and Bank 2 the other. In this stylized representation, sequentiality implies that Bank 2 knows that its applicants come from a pool characterized by a different distribution of types than that of period 1, which creates an informational spillover from the decisions taken in the first period by Bank 1 to those taken by Bank 2. This fact, together with the assumption of costly application, creates the possibility for borrowers of the high type to use the decision to apply to signal their type and select away from lower types.

[3] In particular, one could argue that searching for bank credit is one of the possible options that a firm has to satisfy its financing needs (the other being venture capital, bond emission etc.). Then, firms could leave the credit market not because of discouragement but because they learn better their financing preferences. This may be true, but first it is outside the narrower scope of our research question (i.e. how do past rejections impact the search for banking credit), and second the predictions of such conjecture cannot explain the findings in Table 2, that show that the probability of firms leaving the credit market increases with the number of past rejections received.

In an equilibrium with selection, lending policies in period 2 are tighter than in period 1, reflecting the worsening of the pool of applicants (information spillover). Moreover, low types are discouraged from applying once the fact that they have been rejected in the previous period is made known (selection), while the probability of application of good types is instead assumed to be the same in both periods. Let the subscript i indicate both the time period of the game and the Bank that is moving in that period. We denote with λ_i and Λ_i the probability of applying for the low and the high type respectively in period 1, 2, and with ψ_{b_i} and Ψ_{b_i} the probability that a loan application is approved by Bank b_i, conditional on a low and high signal. Proposition 1 shows that:

Proposition 1 (Equilibrium with Selection) *There exists a Perfect Bayesian Equilibrium with selection where in period* 1 *all borrowers apply* ($\lambda_1^* = \Lambda_1^* = 1$) *and Bank* 1 *grants credit only upon receiving a good signal* ($\psi_{b_1}^* = 0$, $\Psi_{b_1}^* = 1$). *In period* 2*, low type borrowers are discouraged from applying and Bank* 2 *funds borrowers that receive a high signal, with a probability strictly lower than in the previous period, and updates its beliefs using Bayes' rule:* $\lambda_2^* < \lambda_1^*$, $\Lambda_2^* = \Lambda_1^*$ *and* $\psi_{b_2}^* = 0$ *and* $\Psi_{b_2}^* < 1$.

Proof. See the Appendix. ■

In the equilibrium with selection, then, the information on a borrower's previous rejections is associated with two effects on the probability of having the application approved in the second period. One is the negative impact coming from the information spillover that renders the pool of second period applicants worse due to the decisions taken by the bank operating in the first period; the other is the positive impact that arises for borrowers of the high type, that, thanks to the fact that applying is costly and that they are more likely to receive the high signal, can successfully signal their unobservable quality. Note that this model is meant to discipline the interpretation of the empirical results, and it singles out mechanisms that may coexist with others. In this respect, it is worth highlighting once more that we have not derived under which conditions the equilibrium with selection is unique, and, for now, it remains only one of the possible equilibria of the game.

3.2 Testable predictions

The equilibrium with selection described above has testable implications on firms' behavior in response to the rejections they receive, conditional on them being observable by future lenders.

Testable prediction #1 *In an equilibrium with selection some firms are discouraged from applying as they receive rejections.*

In other words, there is selection at work. Note that in our model in equilibrium, given how it is constructed, such tightening will drive out of the market only low quality firms, which makes the (disclosure of the) information on a borrower's past rejections a welfare enhancing policy. However, this conclusion cannot be taken outside the model, where both low and high type firms may not find it profitable to apply after having received a certain number of rejections, with unclear consequences in terms of welfare.

Second, we focus on the equilibrium probabilities that a loan application is approved in the two periods, π_i, for $i = 1, 2$, to observe how these vary between the two periods (recall that the fact that a firm applied in the second period is equivalent to disclose that it was rejected in the previous period). Conditional on observing a loan application, the probability π_1 that it is approved in the first period (unconditional on the signal, which we do not observe, and on the borrower's type) is equal to

$$\begin{aligned}\pi_1 &= q_1 \Lambda_1^* \left[p(S|\Theta) \Psi_{b_1}^* + p(s|\Theta) \psi_{b_1}^* \right] + (1-q_1)\lambda_1^* \left[p(S|\theta) \Psi_{b_1}^* + p(s|\theta) \psi_{b_1}^* \right] \\ &= q_1 \left(\frac{1}{2} + \gamma \right) + (1-q_1) \left(\frac{1}{2} - \gamma \right)\end{aligned} \tag{4}$$

and the corresponding for the second period is

$$\begin{aligned}\pi_2 = & \frac{q_1 \Lambda_2^* p(s|\Theta)}{q_1 \Lambda_2^* p(s|\Theta) + \lambda_2^* (1-q_1) p(s|\theta)} \left[p(S|\Theta) \Psi_{b_2}^* + p(s|\Theta) \psi_{b_2}^* \right] \\ &+ \frac{(1-q_1) \lambda_2^* p(s|\theta)}{q_1 \Lambda_2^* p(s|\Theta) + \lambda_2^* (1-q_1) p(s|\theta)} \left[p(S|\theta) \Psi_{b_2}^* + p(s|\theta) \psi_{b_2}^* \right] \\ &= \frac{\frac{k_2}{B} \left(\frac{1}{2} + \gamma \right)}{q_1 \left(\frac{1}{2} - \gamma \right) + g(1-q_1) \left(\frac{1}{2} + \gamma \right)} \left[q_1 + g(1-q_1) \right]\end{aligned} \tag{5}$$

Depending on whether π_1 is larger or smaller than π_2, the equilibrium parameters may or not allow the selection effect to (more than) compensate the negative impact deriving from the information spillover. In fact, as long as π_1 is larger than π_2, the informational spillover effect prevails, and a borrower rejected in the first period is less likely to be financed. However, it turns out that there are parameter values such that in equilibrium $\pi_2 - \pi_1 > 0$, namely for which the signalling effect prevails: borrowers that re-apply are more likely to be financed, as they successfully signal themselves as high type borrowers.

As an illustrative case, we assume $q_1 = \frac{1}{2}$. For selection to prevail, in equilibrium $\pi_2 - \pi_1 > 0$ has to simultaneously hold with the other assumptions of the model, given by (3) and (2); i.e. the system:

$$\begin{cases} \gamma > \frac{(1+g)\left(\frac{1}{4} - \frac{k_2}{2B}\right)}{\frac{k}{B}(1+g) + \frac{1}{2}(1-g)} \\ \gamma > \frac{1-g}{1+g}\frac{1}{2} \\ \gamma < \frac{1}{2} - \frac{k_1}{B} \end{cases}$$

has to be satisfied by some parameter values, where the first equation comes from substituting (4) and (5) in $\pi_2 - \pi_1 > 0$ and rearranging. It turns out to be sufficient to show that there are parameters such that

$$\frac{(1+g)\left(\frac{1}{4}-\frac{k_2}{2B}\right)}{\frac{k_2}{B}(1+g)+\frac{1}{2}(1-g)} < \frac{1}{2}-\frac{k_1}{B}$$

which is satisfied for any k_1, k_2, B, g such that

$$\frac{1}{2}\frac{B-2k_2}{B-2k_1}-\frac{k_2}{B} < \frac{1-g}{1+g}\frac{1}{2} \tag{6}$$

As can be seen, equation (6) is more likely to be satisfied the smaller is B, coherently with the idea that the lower the private benefit that the applicants can embezzle, the more likely it is for the bank to profit from funding them regardless of their past rejections. Conversely, condition (6) is satisfied more easily the higher is k_2, the cost of applying in the second period, that acts as stronger deterrent for applicants of the lower type, which are more likely to receive a bad signal.

Putting these considerations together, we get to a second testable prediction of the model

Testable hypothesis #2 *The effect of past rejections on the probability of approval compounds a negative spillover effect and a positive signalling effect; the latter may dominate for firm/bank matches that are surrounded by a lower degree of asymmetric information, introducing a positive relation between past rejections and the probability of approval.*

In the empirical analysis, we will test for hypothesis 1 by regressing an applicant's past rejections on the probability that he will suspend the search for credit (see Table 2 for the results). As for the second hypothesis, we will regress a firm's past rejections at the moment of the application on the probability that it is approved and check if such relation is more negative for situations that are characterized by a higher degree of asymmetric information (see Tables 3 and 4 for the results).

Ideally, one would like to try disentangling the impact of the two effects. In principle, to capture the selection effect that occurs via signalling (i.e. the fact that by applying with a rejection in its records the firm signals its τ), one could control for a firm's unobservable type (τ in the model) via including time varying fixed effects. Then, the resulting estimates should capture the sole effect of information spillover. However, to fully control for signalling in this way, the fixed effects would have to be set at the frequency with which applications are placed, namely the same frequency of the dependent variable (the probability of being funded). This is not possible, as all the regressors would be collinear with the fixed effects and we are thus constrained to estimating the "compounded" effect of selection and information spillover.[4]

[4] We will nonetheless include firm/time fixed effects to control for all observable and unobservable firm's characteristics (that vary at most at a quarterly frequency, to allow to estimation of the parameters of interest), which may systematically bias downwardly the estimation (see the discussion in Section 5).

Anticipating the results, our estimates confirm that the overall effect is positive for the average firm, once controlling for all relevant characteristics via time varying fixed effects (at a lower frequency). This corroborates the conjecture that firms successfully make use of the decision to apply to signal their quality. For more opaque firms, instead, we document a negative effect, which is coherent with the theoretical finding that in such equilibrium low type firms are discouraged from continue searching (see Tables 3 and 4 for the results).

Finally, to address the issue of the relative importance of the spillover/signalling effects, we exploit the fact that this (and hence the sign of their overall impact, as captured by the estimates) should vary with bank and firm's characteristics. In particular, we expect the information spillover to prevail for those intermediaries that have worse access to soft information regarding the applicant, and to be more muted for those intermediaries that can rely more on their own screening technology or that have an appetite for risk. Indeed, the empirical results confirm these conjectures (see Tables 6 and 7 for the results). Similarly, we expect that an effective selection is less likely to take place for borrowers that have a larger amount of deteriorated outstanding credit at the moment of the new application, or that are already engaged with a larger number of lenders (see Table 8 for the result).

4 The data

Our dataset exploits information drawn from the Italian Credit Register on all loan applications (and their outcome) filed in Italy by a representative sample of 650,000 firms included in the Cerved database, the largest of such kind, that covers Italian firms active in manufacturing and services. A loan application is identified by an enquiry advanced by an intermediary to obtain information on the current credit position of a potential borrower ("*servizio di prima informazione*", preliminary information request). These enquiries can be identified with an actual application as they can be advanced by an intermediary ("perspective" bank) when it formally receives an application from a new borrower. Over the period considered, August 2003 to December 2012, there are about 3,3 millions applications placed to little less than 700 banks.[5]

Note that a bank requires such service only when the request for financing is put forward by a "new" applicant, i.e. not currently borrowing from the bank, as the Credit register regularly updates banks with information on the overall credit position of their existing borrowers.[6] This means that our measure captures only applications placed

[5] The Italian Credit Register, maintained at the Bank of Italy, reports, for all loans exceeding a given threshold (75,000 euro until 2004, 30,000 thereafter), the amount of granted credit as well as other information about credit relationships. Data are reported by banks on a monthly basis. Cerved is a private company providing a database for a large sample of Italian firms (more than 1,000,000) which contains detailed information about firms' activity and balance sheets, reported on a yearly basis.

[6] Note also that, contrary to other countries like Spain, lodging a request to the Credit Register is a service for payment, which corroborates the fact that banks require such service only when evaluating a credit application. Furthermore, anecdotal evidence largely confirms that banks use such service

with banks other than the incumbent ones, including applications placed by borrowers that enter the credit market for the first time. Studying these data is interesting because the informational asymmetry on new borrowers is typically higher. Further, it allows comparability with analogous data used in Jimenez et al. (2012) for Spain.

Our main dependent variable is the dummy $approval_{ijt}$ which takes value 1 if the loan application placed by firm i at bank j in period t is approved, and 0 otherwise. In line with Jiménez et al. (2012), in order to assess whether a loan application has been rejected or not, we inspected the Italian Credit Register for the three months following the month in which the request for information was placed by the bank, to detect if there was any (positive) variation in the credit granted for that particular borrower/lender pair. If so, we infer that the loan application was approved and assign the value 1 to the dummy $approval_{ijt}$.

The information disclosed by the Credit Register, besides allowing us to identify the loan applications advanced by firms and whether they have been approved or not, contains other relevant data regarding the applicants, as in the case of Spain. These include, in particular, information on the applicant firms' total exposure towards the banking system at the moment of the new application, on the quality of its outstanding credit, the number of "incumbent" banks (i.e. the banks that are currently lending to it), on the amount of credit utilized and collateralized etcetera. More importantly, and differently from the Spanish case, the preliminary information records also report the number of other intermediaries which have enquired the Credit Register to obtain information about the same firm over the previous six months, and which did not subsequently grant credit to the borrower. These data represent our main explanatory variable $past\ rejections_{it}$. The six month window ensures that the requests are related to the same investment project, and limits concerns on the issue of changing borrower's quality.

Our empirical analysis is focused on the effect that this information exerts on lending policies. As the signal carried by past rejections may vary with the opacity of the applicant firm, in all the regressions, we include the dummy *small*, which takes value 1 for firms whose total assets fall below the 10th percentile of the distribution. We always control for firms and banks' heterogeneity by including in the regressions: (i) bank/quarter fixed effects and firms' controls via their rating, as measured by the z-score; and (ii) bank/quarter and firm/quarter fixed effects.[7]

To evaluate how the effect of past rejections varies with the perspective bank and

also when evaluating very good or very bad borrowers, which makes us confident that it truthfully captures the number of filed applications.

[7] Cerved produces a synthetic indicator capturing a firm's overall credit worthiness, the Zscore, which we use to construct our *rating* variable. More precisely, following Altman et al. (1994), each firm is assigned a value from 1 to 9 where values from 7 upwards indicate sensible riskiness. Our dummy *good rating* takes value 1 for firms with Zscore below (and including 6); while *bad rating* assigns value 1 for firms with rating higher than or equal to 7. For part of the firms included in the sample, mainly small firms, the balance-sheet information available are so coarse that do not allow the computation of a the Zscore. Furthermore, as Cerved adopts a rotating sample, some firms end up being excluded from the sample for some years. We set *no rating* equal to 1 for these observations (these represent about one fifth of the whole sample).

the applicant firm's characteristics, as well as with the macro environment, we consider a number of other covariates.

Regarding the perspective bank, we consider (i) a measure of geographic proximity, *same province*, an indicator that takes value 1 if perspective bank's headquarters are located in the same province of the applicant firm; (ii) three dummies that capture the intermediary's dimension: *large bank* for banks belonging to the five largest banking groups, *small cooperative bank* and *foreign bank*, for banks that are branches of a foreign banks; (iii) three organizational variables, a *profitability incentive* dummy taking value 1 if the loan officers' incentive schemes are based on realized profitability; a *bad loans incentive* dummy, denoting banks whose loan officers are directly penalized for generating non performing loans, and a *statistical evaluation* dummy that takes value 1 for banks that only use hard information in taking their lending decisions.[8] Regarding firms, we consider the ratio of intangible over total assets as an alternative measure of opacity. Then, we consider other information disclosed in the preliminary information request, namely the share of outstanding credit that is deteriorated and the number of the incumbents.[9]

Finally, we capture the macroeconomic environment with two indicators, *GDP growth* (the real GDP growth rate on the corresponding quarter) and *interest rate* (3-month change in the Euribor rate) to measure the tightness of the monetary policy.

In order to reproduce the situation faced by the banks when receiving the loan application the information in the dataset is the most updated available at the time of the application: data on banks and macroeconomic variables refer to the quarter preceding the loan application, data on firms refer to the preceding year, data reported by the *preliminary information request* refer to the month before the application.

Table 1 summarizes the definitions of all the variables used and displays some summary statistics.

5 The empirical strategy

Our baseline regression is a linear probability model for the dummy $approval_{ijt}$, that takes value 1 if the application filed by firm i by bank j at time t is approved. The main regressors are $past\ rejections_{it}$, $small_{it}$ and the interaction between the two. This specification allows us to test whether the information on past rejections has an effect on lending decisions, and whether this effect varies with the applicant's opacity. We control for all bank specific factors (observable and unobservable, time invariant and time-varying) that may influence lending policies by including a set of fixed effects for any bank-quarter pair, b_{jt}. To control for firm heterogeneity, we begin with including

[8] These variable are drawn from an ad hoc survey conducted by Bank of Italy, "*L'attività creditizia: aspetti organizzativi e tecniche di valutazione*", to investigate organizational practices. The survey has been conducted on a large sample (about 400) intermediaries in 2007; see Albareto et al. (2008) for details.

[9] A loan is *past due* when its payment has been postponed for at least 180 days. Banks are supposed to classify and report the Credit Register a loan as a *bad loan* when they expect not to be able to recover these funds, although not ruling completely out such possibility.

Table 1. Summary statistics

variable name	description	Obs	Mean	25p	Median	75p
approval	Dummy=1 if the loan application by firm $i$is approved and the loan is granted Frequency: monthly	3334318	0.21	0	0	0
past rejections	Number of past rejections received by firm $i$in the 6 months preceding the application; it corresponds to the number of requests for information advanced during that time period to the Credit Register by intermediaries different from that currently enquiring the Register. Frequency: monthly	3334318	0.91	0	0	1
small	Dummy=1 if the applying firm i's assets fall below the 10th percentile of the distribution. It is missing if information on assets is not available for that firm. Frequency: firm*year	1475400	0.12	0	0	0
opacity	Dummy=1 if firm i's ratio of intangible over total assets is above the 50th percentile of the distribution. Frequency: firm*year	1917661	0.68	0	1	1
no rating	Dummy=1 if there is no rating available for the applying firm $i$at the moment of the request for information. Frequency: firm*year	1917661	0.13	0	0	0
same province	Dummy=1 if the applying firm $i$is located in the same province of the perspective bank's headquarters (at the banking group level). Frequency: firm*year	1874267	0.13	0	0	0
profitability incentive	Dummy=1 if the incentive schemes for the loan officer at the persepctive bank reward branch profitability. Frequency: bank	330	0.12	0	0	0
risk minimization incentive	Dummy=1 if the incentive schemes for the loan officer at the persepctive bank penalize the amount of bad loans. Frequency: bank	330	0.20	0	0	0
statistical evaluation	Dummy=1 if the perspective bank decides only based on statistics criteria Frequency: bank	330	0.09	0	0	0
large bank	Dummy=1 if the perspective banks belong to the 5 largest banking groups Frequency: bank	842	0.10	0	0	0
small cooperative bank	Dummy=1 if the perspective banks is a small cooperative bank. Frequency: bank	842	0.54	0	1	1
foreign bank	Dummy=1 if the perspective banks is a branch of a foreign bank operating in Italy. Frequency: bank	842	0.06	0	0	0
number of incumbent banks	Number of banks lending to firm i at month t-1. Frequency: firm*year	1917661	3.12	1	2	4
deteriorated credit	Percentage of the applicant firm i's outstanding credit that is deteriorated Frequency: firm*year	1917661	5.38	0	0	0
GDP growth	Italian real GDP growth in corresponding quarter, annualized (% change) Frequency: quarterly	38	1.89	0.50	2.06	2.81
interest rate	Quarterly change in the Euribor rate. Frequency: quarterly	38	-0.03	-0.311	0.16	2.81

its rating, which should control for credit risk. The model is described by the following equation

$$\begin{aligned} approval_{ijt} = {} & a_0 + a_1 past\ rejections_{it} \\ & + a_2 small_{it} + a_3 (small^{*} past\ rejections)_{it} \\ & + b_{jt}\ + a_4 (rating_{it})\ + u_{ijt} \end{aligned} \tag{7}$$

The effect of $past\ rejections_{it}$ (coefficients a_1 and a_3) is identified as long as we are correctly controlling for all other factors that may influence a bank's decision over a credit application. To do so, we include bank and firm time-varying, at quarterly frequency, fixed effects. The firm time varying fixed effects, as mentioned in Section 3.2, cannot capture the applicant's unobservable quality (i.e. its type, that is the content of the signalling), but are included to control for all that is observable to the bank but unobservable to the econometrician. The data are in fact characterized by a "survival bias": firms that are credit-worthy are more likely to obtain financing and leave the sample with no, or a low number of, rejections. Thus, firms that "survive" in the dataset with a high number of rejections systematically differ from the average firm, i.e. they are not a random sample. If not properly addressed, this distortion would bias the estimated effect of past rejections on the probability of approval, making it more negative than what it actually is. To control for this bias, we include in our estimates the fixed effects, which allow us to estimate the *within-firm* effect of having been rejected in the past on the probability of having the loan approved.[10]

According to the predictions of the model, the estimated coefficients on $past\ rejections$ will capture the compounded impact of the negative information spillover effect (perspective lenders, upon knowing that the borrower has been evaluated as not creditworthy by another intermediary, are more likely to deny credit as well) and of the positive "selection" effect (capturing the fact that filing a new application once the borrower has been rejected before, and given that applying is costly, has a positive expected value only for high quality applicants that successfully signal themselves out of the pool of applicants). The model then predicts that a_1 may be positive or negative depending on the relative importance of the two effects (see section 3.2). Moreover, it requires a_3 to be always lower than a_1, namely the compounded effect if negative (positive) should be more (less) negative (positive) for opaque firms, as their application process is arguably characterized by higher information asymmetry.

To further corroborate our theoretical conjecture that the effect of past rejections compounds a negative information spillover effect and a positive selection effect, we estimate the following augmented equation (8)

[10] Of course, these estimates are carried out on the subsample of firms that make more than one application (and are rejected more than one time) within a quarter. These are about a million observations.

$$
\begin{aligned}
approval_{ijt} = {} & a_0 + a_1 past\ rejections_{it} \\
& + a_2 small_{it} + a_3(small^{*}past\ rejections)_{it} \\
& + a_4 X + a_5(X^{*}past\ rejections) \\
& + b_{jt}\ + a_6(rating_{it})\ + u_{ijt}
\end{aligned} \tag{8}
$$

which extends the baseline specification by adding the regressor X, as well as the interaction with $past\ rejections_{it}$, which include bank and firm's characteristics, as well as macroeconomic conditions. We expect these variables to tilt the relative importance of the spillover/signalling effect in a predictable way. More precisely, we expect the information spillover effect to prevail for those intermediaries that have worse access to soft information regarding the applicant, and to be more muted for those intermediaries that rely more on their own screening technology or that have an appetite for risk. Similarly, we expect that an effective selection is less likely to take place for borrowers that have a larger amount of deteriorated outstanding credit at the moment of the new application, or that are already engaged with a larger number of lenders. Finally, when the prospects for the general economy improve, the spillover effect should diminish.

6 Results

6.1 The effect of past rejections

We begin with testing the first prediction of the model, namely that as borrowers accumulate rejections, they become more likely to leave the credit market. In practice, we regress the probability that a borrower interrupts the search without having received the loan on the number of past rejections that he has at the moment he suspends the search. The results, displayed in Table 2, confirm that past rejections affect positively and significantly the probability of interrupting the search, both when we control for firm fixed effects (column 1) and for firm/quarter fixed effect (column 2). Moreover, in both cases, the result is stronger for borrowers that are very small (below the 10th percentile of the distribution), and hence more opaque.[11]

[11] The tenth percentile of the distribution stands at firms with assets of about 150 thousands euro, while the median is 1.782 thousands and the mean 14.520.

Table 2. Past requests and search interruption

	probability to interrupt the search	
	(1)	(2)
past rejections	0.010***	0.173***
	(0.000)	(0.001)
small	-0.079***	
	(0.003)	
small#past rejections	0.057***	0.082***
	(0.002)	(0.004)
Observations	2281409	2040979
Prob > F	0.000	0.000
bank-quarter FE	yes	yes
firms' controls	firm FE	firm/quarter FE
Estimation	panel FE	panel FE

Note: these regressions examine the effect of displaying a firm's previous rejections on the probability that it decides to interrupt its search for financing. The dependent variable is a dummy taking value one if the search is interrupted without having found financing. *past rejections* is the number of rejections that the firm has received in the previous 6 months from intermediaries different from the current one. *small* is a dummy taking value 1 if the firm's assets fall below the 10th percentile of the distribution. Sample period is 2003:01 - 2012:12. Robust standard errors in parentheses. Errors are clustered at bank-quarter level. *** p<0.01, ** p<0.05, * p<0.1.

We move on with testing the second prediction of the model, namely that the effect of past rejections compounds a negative spillover effect and a positive signalling effect. To do so, we estimate model (7) and present the results in Table 3. Column (1) shows the effect of *past rejections* on the probability that a loan application is approved, controlling for banks' heterogeneity via the inclusion of bank/quarter fixed effects. The effect is negative and more so for opaque applicants. These results are robust to the inclusion of the applicant firm's rating, which comprehensively captures its observable quality at a yearly frequency (column 2).[12]

[12]The positive coefficient for the dummy *small* is difficult to interpret and may reflect specific characteristics (size, industrial sector and so on) which we are not adequately controlling for. This is no concern for us, as we will show below that these findings are confirmed in all the specifications in which we strengthen the controls for firms' characteristics.

Table 3. Baseline estimation

	approval		
	(1)	(2)	(3)
past rejections	-0.007***	-0.007***	0.013***
	(0.000)	(0.000)	(0.001)
small	0.076***	0.079***	
	(0.003)	(0.003)	
small#past rejections	-0.032***	-0.033***	-0.023***
	(0.001)	(0.001)	(0.003)
Observations	2603049	2599464	2603049
Prob > F	0.000	0.000	0.003
bank-quarter FE	yes	yes	yes
firms' controls	no	rating	firm/quarter FE
Estimation	panel FE	panel FE	panel FE

Note: these regressions examine the effect of displaying a firm's previous rejections on the probability that its application is eventually approved. The dependent variable is *approval*, taking value 1 if the loan application is approved. *past rejections* is the number of rejections that the firm has received in the previous 6 months from intermediaries different from the current one. *small* is a dummy taking value 1 if the firm's assets fall below the 10th percentile of the distribution. Sample period is 2003:01 - 2012:12. Robust standard errors in parentheses. Errors are clustered at bank-quarter level. *** p<0.01, ** p<0.05, * p<0.1.

To account for the effect of firms' characteristics that are observable to the bank, but not to us, we include in the regression firm/quarter fixed effects, along with the bank/quarter ones (column 3).[13] These capture not only all observable features of the applicant that vary at quarterly, or lower, frequency (and affect both the number of previous rejections he received and the outcome of the current application), but also those that are unobservable (provided that they vary at most from quarter to quarter). The inclusion of these controls along with the bank/quarter fixed effects provides very robust estimates, as they control for differences across firms in the characteristics linked to the probability of having the application approved. It should also be noted that this exercise represents a very severe test to detect any effect of *past rejections* on the dependent variable, as part of such relationship risks being captured by these fixed effects.

The coefficients, as displayed in column 3, reveal that the effect of *past rejections* remains negative and significant only for those firms that are opaque. For the other

[13] See the discussion in section 3.2 on why these effects are not sufficient to capture firms' type as it signalled to the intermediary, and hence why they do not control for the effect of signalling.

firms, instead, the coefficient is positive and significant, meaning that the probability of approval increases in the number of past rejections. In other words, the empirical results confirm the model's predictions, suggesting that the average borrower uses the strategy to apply notwithstanding past rejections to signal his unobservable quality.

The results in table 3 are also compatible with the presence of winner's curse in the Italian credit market. The fact that such information enters in a statistically significant way in lending decisions indicates that banks value their competitors' previous rejections, coherently with conjecture that lenders tighten credit standards for fear of financing an applicant previously considered not credit worthy (i.e. for fear of the winner's curse).

The findings above are robust to the use of alternative measures of opacity, as shown in Table A1 in the Appendix. We consider first a firm's ratio of intangible over total assets (columns 1 and 2), defining a firm opaque if such ratio falls above the 75th percentile of the distribution. Second, we define opaque those firms for which a rating is not available at the moment of the applications.[14] The results displayed in Table 3 are robust to the use of both alternative definitions.

Summing up, we find that the information on past rejections is used in a context where there is a winner's curse in lending decisions and creates a deterrence effect for firms, that are driven out of the market as they accumulate rejections. Moreover, the effect of this information is heterogenous across firms. For more opaque firms, we document a negative correlation between past rejections and the probability of having a new application approved, which is instead positive for the average firm. These patterns are consistent with those that would arise in an equilibrium with selection, where the overall effect of past rejections compounds the negative impact arising from information spillover and the positive one stemming from signalling. In equilibrium, the former effect prevails for more opaque firms, while for the others the positive selection effect is stronger.

6.1.1 Robustness test: exploiting an asymmetry in the disclosure of past rejections

The estimates presented so far use within-firm variability to control for all firm characteristics that may simultaneously affect the probability of approval and the number of past rejections received by the applicant. Here we corroborate the findings by adopting a different strategy, which takes advantage of a discontinuity in the window over which previous rejections are made observable to the perspective bank. By law, in fact, intermediaries can only observe the rejections received by the applying borrower in the *six* months preceding the date of the current application, but not those made before that. Conversely, we, as econometricians, can observe the whole history of such rejections.

[14] A firm's rating, in fact, can be missing if the firm is not in the Cerved sample or, alternatively, if its balance sheet is too coarse to compute the indicator.

Table 4. Regression discontinuity

	approval	
	(1)	(2)
past rejections$_{[t,t-6]}$	0.010***	0.014***
	(0.000)	(0.000)
past rejections$_{[8,9]}$	0.001	0.004***
	(0.001)	(0.004)
small#past rejections$_{[t,t-6]}$		-0.026***
		(0.003)
small#past rejections$_{[8,9]}$		-0.004
		(0.006)
Observations	3334318	2940871
Prob $> F$	0.000	0.000
bank/quarter FE	yes	yes
firms' control	firm/quarter	firm/quarter
Estimation methodology	Panel FE	Panel FE

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is *approval*, taking value 1 if the loan application is approved. *past rejections* $[t, t-6]$ is the number of previous rejections received in the six months before the current application; *past rejections* $[8, 9]$ is such number in the 8th and 9th month before the application. *small* is a dummy taking value 1 if the firm's assets are below the 10th percentile of the distribution. Sample period is 2003:01 - 2010:12. Standard errors are clustered at the fixed effects' level.

Exploiting this asymmetry, we construct two *past rejections* variables: one referring to the six months preceding the current application (*past rejections*$_{[t,t-6]}$) and a second one counting those received by the borrower in the eight and ninth month preceding the current application (*past rejections*$_{[8,9]}$). We exclude those received in the seventh month for reasons connected with the disclosure policy of the Credit Register; however the results are robust to including them in the variable *past rejections*$_{[8,9]}$.[15]

By adding both variables to the baseline regression, we should be able to pin down

[15] As it takes some days for the Credit Register to update the records, rejections received in the seventh month may or may not be shown in the records. In principle, we could have distinguished rejections by the precise month in which they took place even for the six months period preceding the application (*lodged requests*$_{[t,t-6]}$). However, this would have been inconsistent with the fact that perspective banks do not observe this information (i.e. they only receive information on the total number of rejections occurred for that borrower in the preceding six months but not the date at which these occurred).

the impact of the (compounded) signalling/spillover effect that arises from displaying an additional past rejection, as lenders observe *past rejections*$_{[t,t-6]}$ but not *past rejection*$_{[8,9]}$, meaning that the effect should be concentrated in the former variable. Such empirical strategy would not be valid if firms were strategically placing their application for credit, for instance by delaying a new application until a past rejection were deleted from their records. While we cannot exclude this concern, we argue that it is likely to be very minor in our sample: firms apply for credit because they have contingent needs for liquidity, and strategically waiting is in the majority of cases simply not possible.

In Table 4 we present the results of such exercise, controlling for the varying characteristics of firms by including firm/quarter effects. As can be seen, the coefficient on *past rejection*$_{[8,9]}$ is significant but much lower than that on *past rejections*$_{[t,t-6]}$. Indeed, we can reject the hypothesis that they are equal. For small firms, this is even clearer, as the coefficient on the interaction *past rejection*$_{[8,9]}$ with the dummy *small* is not significant. Table 5 reports the results of the t-tests.

Table 5. Test of significance

	Prob > F	Prob > F
	(1)	(2)
past rejections$_{[t,t-6]}$ = past rejections$_{[8,9]}$	0.0000	0.0000
small#past rejections$_{[t,t-6]}$= small#past rejections$_{[8,9]}$		0.0001
bank/quarter FE	yes	yes
firm/quarter FE	yes	yes

t-test results for the coefficients reported in table 4.

Following the same line of reasonings, we have applied the same method to the model which estimates the impact of *past rejections* on the probability to continue the search for loan (Table 2). The results, displayed in Table A2 in the Appendix, confirm that the effect of *past rejections* is positive. Further, the effect of *past rejections*$_{[t,t-6]}$ is ten times larger than that of *past rejection*$_{[8,9]}$. This corroborates the claim that the estimated impact of such variable is connected with a genuine information content (which we argue arise from information spillover and signalling), and not (only) with unobservable characteristic of the firm as, if this was the case, the effect of the two variables should be comparable.

Therefore the regression discontinuity approach corroborates the conclusion that the information conveyed by an applicant's past rejections carries genuine information that is relevant for the bank, pointing to the indirect evidence on the presence of the winner's curse in the Italian credit market.

6.2 Heterogeneity in the effect of past rejections

In this section we exploit the fact that the relative importance of the spillover/signalling effect varies in a predictable way with bank and firm's characteristics to indirectly test our conjecture that the impact of past rejections compounds the two effects displayed in the model. In particular, we expect the information spillover effect to prevail for those intermediaries that have worse access to soft information regarding the applicant, and to be more muted for those intermediaries that rely more on their own screening technology or that have an appetite for risk. Similarly, we expect that an effective selection is less likely to take place for borrowers that have a larger amount of deteriorated outstanding credit at the moment of the new application, or that are already engaged with a large number of lenders.

We begin by looking at the heterogeneity on the perspective banks' side. One way to test our conjectures is to look at a bank's distance from the borrower. Distance, in fact, makes it more difficult for an intermediary to find out "soft" information about the applicant. The farther away a bank is located, the stronger the incentive to rely on the decisions of other intermediaries. At the same time, for the same reason, a rejection conveys a more precise negative signal about an applicant when it comes from a bank close to him, as it incorporates superior soft information about the borrower or the project. Together, these considerations indicate that the negative informational spillover effect should be stronger for banks that are more distant from the applicant.

Perspective banks, however, do not know the identity of the banks that rejected the borrower in the past, but only the total number of such rejections. Yet, at the same time, banks know that borrowers, as amply documented in the literature, apply for credit following a "distance" criterion, from closer intermediaries to farther away ones (see Hauswald and Marquez 2003, and Bolton et al. 2013). Indeed, this is the case also in our sample (see table A4 in the Appendix, which displays how the percentage of new applications filed to banks in the same province of the applicant decreases with the number of rejections he has in his records, indirectly showing that he applies to more distant banks).

Given that borrowers apply first to nearby intermediaries, the negative information spillover effect of *past rejections* should be larger for banks which are close, but not closest to them. To test this hypothesis, we look at banks located in the same geographical province of the applicant, which in Italy is the second largest administrative unit, the first being the municipality and the largest the region. We expect that the coefficient on the interaction of *past rejections* with a dummy that takes value one for banks in the same province of the applicant should be negative, indicating that for these banks the positive signalling effect conveyed by *past rejections* is muted by the negative impact of the spillover effect.

The results lend support to our hypothesis (Table 6). The interaction of the dummy variable *same province* with *past rejections* is negative and significant, confirming that banks located in the same province of the applicant assign more weight to the decision of previous intermediaries, which they expect to be located closer than themselves to the borrower (column 1). Note also that the baseline coefficients are unchanged from those displayed in Table 3. All the results are left unchanged by the introduction of firm/quarter fixed effects (column 2).

Table 6. Distance of the intermediary from the applicant

	approval	
	(1)	(2)
past rejections	-0.007***	0.013***
	(0.000)	(0.001)
small	0.079***	
	(0.003)	
small#past rejections	-0.033***	-0.026***
	(0.001)	(0.003)
same province	0.029***	0.032***
	(0.002)	(0.003)
same province#past rejections	-0.004***	-0.002**
	(0.001)	(0.001)
Observations	2551601	2555116
Prob > F	0.000	0.000
bank-quarter FE	yes	yes
firms' controls	rating	quarter FE
Estimation methodology	Panel FE	Panel FE

Note: these regressions examine how an applicant firm's distance from the persective bank affects the impact of displaying a firm's previous rejections on the probability that its application is eventually approved. *past rejections* is the number of rejections that the firm has received in the previous 6 months from intermediaries different from the current one. *small* is a dummy taking value 1 if the firm's assets fall below the 10th percentile of the distribution. *same province* is a dummy taking value 1 if the applicant firm is located in the same province of the perspective bank's headquarters. Sample period is 2003:01 - 2012:12. Robust standard errors in parentheses. Errors are clustered at bank-quarter level. *** p<0.01, ** p<0.05, * p<0.1.

Another important dimension of heterogeneity among intermediaries is their size. Larger banks may value less the decision taken by their competitors, as they rely on a number of screening technologies, and may accommodate a larger number of investment projects in their portfolios. For this reason, the negative information spillover effect should be more muted for them. One can also argue that borrowers, anticipating the more pervasive screening that such intermediaries undertake, would apply only if they are very confident in the quality of their project. If this is the case, the impact of the positive selection effect should be stronger. Indeed, we find (Table 7) that for larger banks, both domestic and foreign, the effect of information on past rejections is positive.

Table 7. Size of the intermediary

	approval	
	(1)	(2)
past rejections	-0.009***	0.012***
	(0.001)	(0.001)
small	0.079***	
	(0.003)	
small#past rejections	-0.033***	-0.023***
	(0.001)	(0.003)
large banks#past rejections	0.003***	0.003***
	(0.001)	(0.001)
cooperative banks#past rejections	-0.006***	-0.001
	(0.001)	(0.001)
foreign banks#past rejections	0.007***	0.003**
	(0.001)	(0.001)
Observations	2599464	2940871
Prob > F	0.000	0.000
bank-quarter FE	yes	yes
firms' controls	rating	quarter FE
Estimation methodology	Panel FE	Panel FE

Note: these regressions examine how the perspective bank's size affects the impact of displaying a firm's previous rejections on the probability that its application is eventually approved. *past rejections* is the number of rejections that the firm has received in the previous 6 months from intermediaries different from the current one. *small* is a dummy taking value 1 if the firm's assets fall below the 10th percentile of the distribution. *large bank* is a dummy taking value 1 if the perspective bank's group is one of the five largest banking group operating in Italy. *cooperative bank* is a dummy taking value 1 if the perspective bank is a cooperative bank. *foreign bank* is a dummy taking value 1 if the perspective bank is a branch of a foreign bank. Sample period is 2003:01 - 2012:12. Robust standard errors in parentheses. Errors are clustered at bank-quarter level. *** p<0.01, ** p<0.05, * p<0.1.

Coherently with our reasoning, this is instead not the case for smaller banks, for which the information spillover is more intense, resulting in a negative overall effect of *past rejections*. The effect is however not significant when we include the firm/quarter fixed effects (column 2).

The picture that emerges is corroborated also when looking at another dimension of bank heterogeneity, namely its organization form/business model. We find (table A5 in the Appendix) that the effect of past rejections is more positive for banks that make use of statistical evaluation procedures in the decision to grant their loans (which typically are also large banks: the same explanation applies, that is, the impact of information spillover is lower). At the same time, the effect is more muted (stronger) for banks that adopt more risk averse (riskier) lending policies.

As mentioned above, also the characteristics of the applying firm may tilt the relative importance of the two effects carried by the *past rejection* variable for the perspective bank.

Table 8. Applicant firm's characteristics: other information

	approval	
	(1)	(2)
past rejections	-0.010***	0.018***
	(0.001)	(0.001)
small	0.092***	
	(0.003)	
small#past rejections	-0.032***	-0.026***
	(0.001)	(0.003)
deteriorated credit	-0.001***	
	(0.000)	
deteriorated credit#past rejections	0.000	-0.0007*
	(0.000)	(0.000)
number of current lenders	0.006***	-0.007**
	(0.000)	(0.003)
number of current lenders#past rejections	-0.000***	-0.001***
	(0.000)	(0.000)
Observations	2599464	2603049
Prob > F	0.000	0.000
bank/quarter FE	yes	yes
firms' controls	rating	quarter FE
Estimation methodology	Panel FE	Panel FE

Note: these regressions examine how the applicant firm's characteristics impact the effect of displaying a firm's previous rejections on the probability that its application is eventually approved. *past rejections* is the number of rejections that the firm has received in the previous 6 months from intermediaries different from the current one. *small* is a dummy taking value 1 if the firm's assets fall below the 10th percentile of the distribution. *deteriorated credit* is the share of outstanding credit that is deteriorated; *number of current lenders* is the number of such banks at the moment of the application. Sample period is 2003:01 - 2012:12. Robust standard errors in parentheses. Errors are clustered at bank-quarter level. *** p<0.01, ** p<0.05, * p<0.1.

Here we consider two variables that capture a firm's riskiness, which are observable by the perspective bank at the moment of the application: its overall deteriorated loans (as a percentage of total assets) and the number of banks it is currently engaged with. We expect that both variables exert a negative impact on the effect of the past rejections variable, via making less credible the positive signalling effect.

Indeed, the estimates, presented in Table 8, are in line with our expectations. The coefficients of the interaction terms of both variables with past rejections are negative and significant when we control for firms' heterogeneity with the firm/quarter fixed effects (column 2). When a firm is riskier, the information on past rejections has a more negative impact on the probability of approval, as one would expect.

To conclude, we also look at whether the effect of previous rejections varies with the general economic outlook. A large body of literature (Jiménez et al. 2013 for a recent paper on the topic) studies if banks' lending decisions and credit standards vary with macroeconomic conditions and the stance of monetary policy.

We first test if different stages of the economic cycle also influence the overall effect that the information disclosed in *past rejections* has on the probability that a borrower's application is approved. Intuitively, better macroeconomic conditions should reduce the negative impact of asymmetric information in credit matches, and, accordingly, that of the information spillover effect. A similar reasoning applies to more favorable monetary policy conditions.

To test these conjectures, we add to the baseline model two business cycle indicators: the 3-month annualized GDP growth and the quarterly change in the 3-month Euribor interest rate. The estimates (Table 9) confirm our hypothesis. With better prospects regard the real economy, the coefficient on *past rejections* interacted with the change in GDP growth is positive and statistically significant, and remains so even after including the firm/quarter fixed effects (column 2). A more favorable economic environment, then, limits the negative effect of information spillover.

Table 9. Macroeconomic conditions

	approval	
	(1)	(2)
past rejections	-0.011***	0.014***
	(0.001)	(0.001)
small	0.078***	
	(0.003)	
small#past rejections	-0.032***	-0.023***
	(0.001)	(0.003)
interest rate#	0.001***	-0.001*
past rejections	(0.000)	(0.000)
GDP growth#	0.005***	0.002***
past rejections	(0.001)	(0.001)
Observations	2599464	2940871
Prob > F	0.000	0.003
bank/quarter FE	yes	yes
firms' control via rating	rating	quarter FE
Estimation methodology	Panel FE	Panel FE

Note: these regressions examine how the macroeconomic environment impacts the effect of displaying a firm's previous rejections on the probability that its application is eventually approved. *past rejections* is the number of rejections that the firm has received in the previous 6 months from intermediaries different from the current one. *small* is a dummy taking value 1 if the firm's assets fall below the 10th percentile of the distribution. *interest rate* is the quarterly change in the Euribor rate; *GDP growth* is the quarterly Italian real GDP growth in corresponding quarter, annualized. Sample period is 2003:01 - 2012:12. Robust standard errors in parentheses. Errors are clustered at bank-quarter level. *** p<0.01, ** p<0.05, * p<0.1.

The results for the short-term interest rate, instead, are mixed in that they swap from positive and highly significant at the bank/quarter fixed effects and the rating as a control for firm's quality to barely significant and negative when we include the firm/quarter fixed effects.

7 Conclusions

This paper investigates lending policies when a bank observes whether a borrower applying for a loan has previously applied to other lenders without success.

Thanks to a robust identification approach based on the use of loan application and rejection data and time-varying bank and firm fixed effects, the analysis has shown that the number of past rejections has a direct discouragement effect on the probability of continuing a loan search. At the same time, continuing the search despite former rejections has a positive effect on the probability of being funded, provided that the borrower is not opaque. A simple theoretical model shows that there is an equilibrium in which banks interpret the information on previous rejections as signalling unobservable quality for the average borrower, while not for more opaque borrowers, for whom the negative informational content of past rejections spills over to latter applications. We also document that credit intermediaries differ in the extent to which they rely on this information, in a way that reflects the different relevance that the two effects take for them.

While positive in spirit, our analysis allows to draw some more normative considerations. Our work suggests that the dissemination of information on previous lenders' decisions can be welfare enhancing. First, it has a direct role in alleviating the winner's curse in credit markets (i.e. the additional tightening of lending supply during downturns deriving from the increase of the probability that applying borrowers have already been rejected by other lenders). Second, it discourages from applying borrowers with past rejections in their records, while it is used by less opaque borrowers to signal their quality. As long as the applicants that are driven out of the market are of low quality, and those that succeed in signalling are of high quality, overall welfare should increase.

8 References

Acharya. V. and T. Yorulmazer 2008. Information Contagion and Bank Herding. *Journal of Money, Credit and Banking*, 40: 215-231.

Albareto, G., M. Benvenuti, S. Mocetti, M. Pagnini and P. Rossi 2008. L'organizzazione dell'attività creditizia e l'utilizzo di tecniche di scoring nel sistema bancario italiano:risultati di un'indagine campionaria. Bank of Italy *Occasional Papers,* n.o. 12.

Altman, E. I., G. Marco and F. Varetto, 1994. Corporate distress diagnosis: comparisons using linear discriminant analysis and neural networks (The Italian Experience). *Journal of Banking and Finance*, 505-529.

Berger, A. N., N. H. Miller, M. A. Petersen, R. G. Rajan and J. C. Stein, 2005. Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics*, 76: 237-269.

Bonfim, D and M. Kim, 2012. Liquidity Risk in Banking: Is There Herding? European Banking Center Discussion Paper No. 2012-024.

Bolton, P., X. Freixas, L. Gambacorta, P. E. Mistrulli, 2013. Relationship and transaction lending in a crisis. NBER Working Paper No. 19467.

Broecker, T.,1990. Credit-worthiness tests and interbank competition. *Econometrica*, 58: 429-452.

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

Hauswald, R. and R. Marquez, 2006. Competition and strategic information acquisition in credit markets. *Review of Financial Studies*, 19, 967-1000.

Jain A. J. and S. Gupta, 1987. Some Evidence on "Herding" Behavior of U. S. Banks, *Journal of Money, Credit and Banking*, 19: 78-89.

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

Khwaja, A. I. and A. Mian, 2008. Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market. *American Economic Review*, 98: 1413-4.

Lockwood, B., 1991. Information Externalities in the Labor Market and the Duration of Unemployment. *Review of Economic Studies*, 58: 733-753.

Nakamura, L. I., 1993. Loan screening within and outside of customer relationships. Federal Reserve Bank of Philadelphia Working Paper n.o 93-15..

Panetta, F., P. Angelini, U. Albertazzi, F. Columba, W. Cornacchia, A. Di Cesare, A. Pilati, C. Salleo and G. Santini, 2009. Financial sector pro-cyclicality: lessons from the crisis. Bank of Italy, *Questioni di Economia e Finanza* (Occasional Papers), No. 44.

Puri, M., J. Rocholl and S. Steffen, 2011. Global retail lending in the aftermath of the US financial crisis: distinguishing between demand and supply effects. *Journal of Financial Economics*, 100: 556-578.

Ruckes, M., 2004. Bank competition and credit standards. *Review of Financial Studies*, 17: 1073-1102.

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

9 Appendix

Proposition 1 (Equilibrium with Selection) There exists a Perfect Bayesian Equilibrium with selection where in period 1 all borrowers apply ($\lambda_1^* = \Lambda_1^* = 1$) and Bank 1 grants credit only upon receiving a good signal ($\psi_{b_1}^* = 0$, $\Psi_{b_1}^* = 1$). In period 2, low type borrowers are discouraged from applying and Bank 2 funds borrowers that receive a high signal, but with a probability strictly lower than in the previous period, and updates its beliefs using Bayes' rule: $\lambda_2^* < \lambda_1^*$, $\Lambda_2^* = \Lambda_1^*$ and $\psi_{b_2}^* = 0$ and $\Psi_{b_2}^* < 1$.

Proof. To construct the equilibrium above, consider the first period and assume that all firms apply, $\lambda_1 = \Lambda_1 = 1$. Then, knowing this and q_1, upon receiving an application, Bank 1 can compute the probability that it is advanced by a high type, q_1^a

$$q_1^a \ = \text{prob}(\tau = \Theta|apply) = \frac{q_1\Lambda_1}{q_1\Lambda_1 + (1-q_1)\lambda_1} = q_1$$

Upon observing the signal σ_1, such probability can be further updated to

$$P_1 = \text{prob}(\tau = \Theta|apply, \sigma_1 = S) = \frac{q_1^a \ \left(\frac{1}{2}+\gamma\right)}{q_1^a \ \left(\frac{1}{2}+\gamma\right) + (1-q_1^a)\left(\frac{1}{2}-\gamma\right)}$$

$$p_1 = \text{prob}(\tau = \Theta|apply, \sigma_1 = s) = \frac{q_1^a \ \left(\frac{1}{2}-\gamma\right)}{q_1^a \ \left(\frac{1}{2}-\gamma\right) + (1-q_1^a)\left(\frac{1}{2}+\gamma\right)}$$

Given the return structure, the expected return to Bank 1 of approving a loan application, conditional on the signal σ_1, is given by the following expression

$$\Pi(\sigma_1) = g * \text{prob}(\tau|apply, \sigma_1) - 1 * (1 - \text{prob}(\tau|apply, \sigma_1))$$

$$\Pi(\sigma_1) = \begin{cases} g * P_1 - 1 * (1-P_1) & \text{if} \quad \sigma_1 = S \\ g * p_1 - 1 * (1-p_1) & \text{if} \quad \sigma_1 = s \end{cases}$$

For the strategy to fund an application with probability one if the signal is high and with probability zero if it is low to be an equilibrium (i.e. $\Psi_{b_1}^* = 1$ and $\psi_{b_1}^* = 0$), we have to have

$$\Pi(\sigma_1 = S) > 0 \Longleftrightarrow P_1 > \frac{1}{1+g}$$

and

$$\Pi(\sigma_1 = s) \leq 0 \Longleftrightarrow p_1 \leq \frac{1}{1+g}$$

which are both always satisfied as long as $g < 1$. Given P_1, p_1, $\Psi_{b_1}^* = 1$ and $\psi_{b_1}^* = 0$, $\lambda_1 = \Lambda_1 = 1$ is also an equilibrium provided that

$$U_1(apply|\tau, \Psi_{b_1}^*, \psi_{b_1}^*) = \left[-k_1 + \left(\frac{1}{2}-\gamma\right)B\psi_{b_1}^* + \left(\frac{1}{2}+\gamma\right)B\Psi_{b_1}^*\right] \geq 0$$

which is true if and only if

$$\frac{k_1}{B} \geq \frac{1}{2} + \gamma$$

which is always satisfied under (3). Then, in the first period,

$$\begin{aligned}\lambda_1^* = \Lambda_1^* &= 1 \\ \psi_{b_1}^* &= 0 \\ \Psi_{b_1}^* &= 1\end{aligned}$$

are an equilibrium given P_1 and p_1.

In the second period, the equilibrium we are after requires both a spillover effect, ensuring that lending policies are tighter than in the previous period, $\Psi_{b_2}^* < \Psi_{b1}^*$ and $\psi_{b_2}^* = 0$, and a selection effect, according to which low types are discouraged from applying once their past rejections are made available, $\lambda_2^* < \lambda_1^*$, while high types apply with the same probability as in the previous period, $\Lambda_1^* = \Lambda_2^* = 1$. This leaves us with pinning down λ_2^* and $\Psi_{b_2}^*$ and showing that together they make an equilibrium of the game

As in period 1, Bank 2 forms a posterior probability on the type of the applicant, upon receiving an application and given the signal. This is equal to

$$\begin{aligned}P_2 &= \text{prob}(\tau = \Theta | apply, \sigma_2 = S) \\ &= \frac{\left(\frac{1}{2} - \gamma\right)\Lambda_2\left(\frac{1}{2} + \gamma\right)}{\left(\frac{1}{2} - \gamma\right)\Lambda_2\left(\frac{1}{2} + \gamma\right) + \left(\frac{1}{2} + \gamma\right)\lambda_2\left(\frac{1}{2} - \gamma\right)} = \frac{\Lambda_2}{\Lambda_2 + \lambda_2}\end{aligned}$$

$$p_2 = \text{prob}(\tau = \Theta | apply, \sigma_2 = s) = \frac{\left(\frac{1}{2} - \gamma\right)^2 \Lambda_2}{\left(\frac{1}{2} - \gamma\right)^2 \Lambda_2 - \left(\frac{1}{2} + \gamma\right)^2 \lambda_2}$$

Such beliefs are used to compute expected profits

$$\Pi(\sigma_2) = \begin{cases} g * P_2 - 1 * (1 - P_2) & \text{if} \quad \sigma_2 = S \\ g * p_2 - 1 * (1 - p_2) & \text{if} \quad \sigma_2 = s \end{cases}$$

We can pin down λ_2^* via imposing that Bank 2 makes zero profit upon receiving a bad signal,

$$\Pi(\sigma_2 = s) \leq 0 \Longleftrightarrow p_2 \leq \frac{1}{1+g} \quad \Longleftrightarrow \lambda_2^* \leq g$$

we let $\lambda_2^* = g$, which satisfies $\lambda_2^* < \lambda_1^*$, since $g < 1$. To pin down Ψ_{b2}^* we look at borrowers' utility maximizing condition

$$U_2(apply|\tau, \Psi_{b_2}^*, \psi_{b_2}^*) = \left[-k_2 + \left(\frac{1}{2} - \gamma\right)\psi_{b_2}^* + \left(\frac{1}{2} + \gamma\right)\Psi_{b_2}^*\right] = 0$$

which, given $\psi^*_{b_2} = 0$, can be rewritten to isolate the equilibrium $\Psi^*_{b_2}$,

$$\Psi^*_{b_2} = \left(\frac{1}{2} - \gamma\right)^{-1} * \frac{k_2}{B}.$$

Then, it is easy to verify that the tuple

$$\begin{aligned} \lambda^*_1 &= \Lambda^*_1 = 1 \\ \psi^*_{b_1} &= 0 \\ \Psi^*_{b_1} &= 1 \\ \lambda^*_2 &= g \\ \Lambda^*_2 &= 1 \\ \psi^*_{b_2} &= 0 \\ \Psi^*_{b_2} &= \left(\frac{1}{2} - \gamma\right)^{-1} * \frac{k_2}{B} \end{aligned} \tag{9}$$

is a PBE with selection for the game, as at any stage of the game strategies are optimal given the beliefs and the beliefs are obtained from equilibrium strategies and observed actions using Bayes' rule, coherently with Definition (1). ■

Table A1. Baseline estimation: alternative definition of opaqueness

	approval			
	(1)	(2)	(3)	(4)
past rejections	-0.009***	0.012***	-0.010***	0.012***
	(0.000)	(0.001)	(0.000)	(0.001)
opacity	-0.018***			
	(0.001)			
opacity#past rejections	-0.002***	-0.004***		
	(0.000)	(0.001)		
no rating			0.087***	
			(0.004)	
no rating#past rejections			-0.006***	-0.017***
			(0.001)	(0.002)
Observations	3038373	3038373	3038373	3334318
Prob > F	0.000	0.000	0.000	0.000
bank-quarter FE	yes	yes	yes	yes
firms' controls	rating	firm/quarter FE	rating	firm/quarter FE
Estimation	panel FE	panel FE	panel FE	panel FE

Note: these regressions examine the effect of displaying a firm's previous rejections on the probability that its application is eventually approved. *past rejections* is the number of rejections that the firm has received in the previous 6 months from intermediaries different from the current one. *opacity* is a dummy taking value 1 if the firm's ratio of tangible over non tangible assets is higher than the median of the distribution. *no rating* is a dummy taking value 1 if the firm's rating is not available at the moment of the current credit application. Sample period is 2003:01 - 2012:12. Robust standard errors in parentheses. Errors are clustered at bank-quarter level. *** p<0.01, ** p<0.05, * p<0.1.

Table A2. Regression discontinuity

	probability to interrupt the search (1)	(2)
past rejections$_{[t,t-6]}$	0.157***	0.160***
	(0.000)	(0.000)
past rejections$_{[8,9]}$	0.017***	0.017***
	(0.001)	(0.001)
small#past rejections$_{[t,t-6]}$		0.029***
		(0.003)
small#past rejections$_{[8,9]}$		-0.001
		(0.011)
Observations	3334318	2603049
Prob > F	0.000	0.000
bank/quarter FE	yes	yes
firms' control	firm/quarter	firm/quarter
Estimation methodology	Panel FE	Panel FE

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. These regression examine the effect of displaying a firm's previous rejections on the probability that it decides to interrupt its search for financing. The dependent variable is a dummy taking value one if the search is interrupted without having found financing. *previous rejections* $[t, t-6]$ is the number of previous rejections received in the six months before the current application; *lodged requests* $[8, 9]$ is such number in the 8th and 9th month before the application. *small* is a dummy taking value 1 if the firm's assets are below the 10th percentile of the distribution. Sample period is 2003:01 - 2010:12. Standard errors are clustered at the fixed effects' level.

Table A3. Test of significance

	Prob > F	Prob > F
	(1)	(2)
past rejections$_{[t,t-6]}$ = past rejections$_{[8,9]}$	0.0000	0.0000
small#past rejections$_{[t,t-6]}$= small#past rejections$_{[8,9]}$		0.0185
bank/quarter FE	yes	yes
firm/quarter FE	yes	yes

t-test results for the coefficients reported in table A* .

Table A4. The geographical pattern of new applications

Number of past rejections	New applications in different provinces (a)	New applications in the same province (b)	New applications filed (total) (a)+(b)	Percentage (b)/(a+b)
	(1)	(2)	(3)	(4)
0	1.512.339	232.396	1.744.735	13.3%
1	709.173	95.261	804.434	11.8%
2	322.549	40.057	362.606	11.0%
3	150.543	17.594	168.137	10.5%
>= 4	160.277	17.352	177.629	9.8%
Total	37.194	7.505	44.699	17%

The table reports the frequency of new credit applications from firms with 0, 1, 2, and more than 3 previous rejections, lodged with banks headquartered in a different province (a) and in the same province (b); as well as those lodged within the same province as a percentage of the total (b)/ (a) + (b).

Table A5. Aspects of the business model

	approval	
	(1)	(2)
past rejections	-0.008***	0.012***
	(0.001)	(0.001)
small	0.082***	
	(0.003)	
small#past rejections	-0.034***	-0.026***
	(0.002)	(0.004)
risk minimization incentive#	-0.004***	0.000
past rejections	(0.001)	(0.001)
profitability incentive#	0.006***	-0.001
past rejections	(0.001)	(0.001)
statistical evaluation#	-0.000	0.001**
past rejections	(0.001)	(0.001)
Observations	2141462	2424903
Prob > F	0.000	0.000
bank/quarter FE	yes	yes
firms' controls	rating	quarter FE
Estimation methodology	Panel FE	Panel FE

Note: these regressions examine how the perspective bank's business model affects the impact of displaying a firm's previous rejections on the probability that its application is eventually approved. *past rejections* is the number of rejections that the firm has received in the previous 6 months from intermediaries different from the current one. *small* is a dummy taking value 1 if the firm's assets fall below the 10th percentile of the distribution. *risk minimization incentive* is a dummy taking value 1 if the perspective bank's group has a risk minimization incentive policy for its loan officers. *profitability incentive* is a dummy taking value 1 if the perspective bank's group has a profitability maximization incentive policy for its loan officers. *statistical evaluation* is a dummy taking value 1 if the perspective bank's group evaluates loan applications mainly using statistical methods. Sample period is 2003:01 - 2012:12. Robust standard errors in parentheses. Errors are clustered at bank-quarter level. *** p<0.01, ** p<0.05, * p<0.1.