(Just) first time lucky?

The impact of single versus multiple bank lending relationships on firms and banks' behavior[*]

Giorgia Barboni[†] and Tania Treibich[‡]

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Abstract

The widespread evidence of multiple bank lending relationships in credit markets suggests that firms are interested in setting up a diversity of banking links. However, it is hard to know from the empirical data whether a firm's observed number of lenders is symptomatic of financial constraints or rather a well-designed strategy. By setting up a model and testing it in a controlled laboratory experiment we are able to uncover the conditions favoring multiple versus single lending strategies of borrowers, as well as the probability to get funding from lenders.

Our results suggest that lenders evaluate borrowers' debt exposure towards other banks as a "free-riding" strategy - and indeed borrowers do so - when they are not able to gather further information upon their quality and interactions are only seldom repeated. On the contrary, when borrowers and lenders engage in a committed relationship, multiple bank lending relationships serve as a diversification strategy.

Keywords: Repeated Games, Information Asymmetries, Multiple Lending, Relationship lending.

JEL codes: C72 C73 C92 G21.

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[†] LEM, Sant'Anna School of Advanced Studies; giorgia.barboni@gmail.com

[‡] OFCE-DRIC, GREDEG, Université Nice-Sophia Antipolis, SKEMA Business School and LEM, Sant'Anna School of Advanced Studies; tania.treibich@gmail.com

1 Introduction

Early theoretical contributions on financial intermediation suggest that borrowing from one bank is optimal as it reduces banks' monitoring costs (Diamond, 1984) and the requirement of collateral (Boot and Thakor, 1994). Consolidated evidence on multiple bank lending relationships appears then to be at odds with these models: multiple bank lending relationships have been extensively documented in credit markets, among firms of all size and ages. In the US, for instance, 50% of firms borrow from more than one bank (Petersen and Rajan, 1994; Guiso and Minetti, 2010), while this share reaches 80% for Italian firms (Detragiache et al., 2000). Firms may indeed benefit from multiple lending. It has been shown theoretically that multiple bank lending relationships represent a mean to restore competition among lenders and to limit ex post rent extraction (von Thadden, 1995), to mitigate ex-post moral hazard behaviors (Bolton and Scharfstein, 1996) and to reduce the probability of an early liquidation of the project (Diamond, 1991; Detragiache et al., 2000).

On the empirical ground, several works have tried to explain the variety observed in the number of bank relationships, both across countries and within one country. Cross-country studies have shown that a higher frequency of multiple bank lending relationships is associated to countries with inefficient judicial systems and poor enforcement of creditor rights (Ongena and Smith, 2000). Moreover, in their study on a sample of Portuguese firms, Farinha and Santos (2002) have revealed that firms with a poor credit or performance record have a higher probability to switch from single to multiple lending relationships. Guiso and Minetti (2010) further add that among American firms multiple lending is more frequent among financially opaque companies, that is young or small ones. In analyzing the determinants of multiple bank lending relationships, these works encounter several endogeneity issues which are only partly solved by appropriate econometric instruments. From one end of the spectrum, firms' quality is strictly correlated to their access to funds, and this in turn affects their decision upon single versus multiple bank lending relationships. We refer to this point as the "credit rationing story": as the borrower's quality deteriorates, her access to credit becomes more difficult, and she might split her loan requests and ask smaller amounts to a higher number of lenders. Such poor quality firm would therefore maintain several credit links. It might also be the case that a firm chooses multiple lending as a "diversification" strategy: maintaining diverse sources of funds helps to limit hold-up costs associated with single lending. Moreover, playing the competition between banks might further improve the firm's contract conditions. On the other end of the spectrum, firm's creditworthiness is inherently related to relationship lending, that is the ability to create a stable relationship with one lender, i.e. the firm's main bank. With respect to this, Petersen and Rajan (1994) and Berger and Udell (1995) have shown that when a borrower builds a long-term relationship with the same lender,

she can benefit from better credit terms as well as access to further funds. The "relationship lending story" thus affirms that the firm's quality, by facilitating relationships' stability, is positively correlated with borrowing concentration.
Both stories are plausible, and have been verified both theoretically and empirically.

From lenders' perspective, benefits of relationship lending are related to a reduction of information asymmetries from repeated interactions, and increased incentives for the firm to behave in a good manner. However, observational data do not allow to identify which channel develops more frequently and under which conditions. Therefore, a controlled laboratory experiment seems the most appropriate setting to answer to the following research question: what drives a firm's number of bank links: is it the firm's choice or rather the banks'? Indeed, multiple lending can be observed as the outcome of a firm's diversification strategy as well as the result of credit rationing, the firm having to split the funding request in order to get enough funds. Similarly, relationship lending can be the outcome of a concentration of borrowing strategy or the result of credit rationing, the firm only being able to get funding from the lender who has soft information about her quality. To our knowledge, this is the first experimental credit market to study the determinants of single versus multiple bank lending relationships.
We build a laboratory experiment in which, in a similar spirit as Carletti et al. (2007), lenders have limited diversification opportunities and are subject to ex-post moral hazard problems. We then allow borrowers' quality to vary exogenously and test how this affects lenders' funding decisions as well as borrowers' choice between single and multiple bank lending relationships. Besides, in the first treatment borrowers and lenders can't create any long term relationships, because the latter are randomly chosen. In the second treatment, however, we let relations be established through time, by giving the borrower the possibility to choose her lender. By comparing funding decisions and repayment behavior, keeping riskiness constant, we are able to detect the impact of relationship lending as well as credit rationing on firms' borrowing strategies. Finally, we further modify the relationship lending setting by making the source of moral hazard (if any) public.
Our experimental design also allows to test for the emergence of social preferences in addition to self-interested actions. In particular, by implementing a treatment in which borrowers have the possibility to choose to which lender they want to address their funding request first, we are able to study lenders' decision along two dimensions: from one side, by comparing randomness with intentionality, we can study whether in a relationship lending setting borrowers and lenders engage in a committed relationship, and reach the cooperative equilibrium. From the other side, we can also test for the impact of "not being chosen" on the lender's decision. In other words, we can analyze whether lenders change their behavior depending on their rank in the borrowers' lending requests. Besides, we can also condition lenders' decisions to single versus multiple bank lending strategies, and see whether, *ceteris paribus*, lenders do behave differently. Laboratory experiments

are not new in the credit market literature: using an experimental credit market, Brown and Zehnder (2007) show that information sharing between lenders works as an incentive for borrowers to repay, when repayment is not third-party enforceable, as they anticipate that a good credit history eases access to credit. This incentive becomes negligible when interactions between lenders and borrowers are repeated, as banking relationships can discipline borrowers. Similarly, Brown and Zehnder (2010) find that asymmetric information in the credit market has a positive impact on the frequency of information sharing between lenders, whereas competition between them may have a negative, though smaller, effect on information sharing.

Closer to our paper are the laboratory experiments conducted by Fehr and Zehnder (2009) and Brown and Serra-Garcia (2011): both papers analyze how borrowers' discipline is affected by debt enforcement and find that (strong) debt enforcement has a positive impact on borrowers' discipline. However, when debt enforcement is weak, Brown and Serra-Garcia (2011) show that bank-firm relationships are characterized by a lower credit volume.

We contribute to the empirical literature on multiple bank lending relationships along twodirections: first, we show that firms tend to use multiple bank lending relationship in an opportunistic way, as more dishonest firms tend to have multiple bank lending relationships, irrespectively of their riskiness. Second, we show that firms are less credit rationed when they concentrate their credit. This result is in line with the recent work on the financial crisis: De Mitri et al., 2010, for example, show that firms with higher borrowing concentration are less hit by credit tightening.

The paper is organized as follows. Section 2 describes the experimental design and predictions; results are discussed in Section 4. Section 5 concludes.

2 The Experimental Design

Our lending game builds on the investment game introduced by Berg et al. (1995), where the lending as well as repayment decisions relate to the economic characteristics of the borrower and the screening and enforcement capacities of the lender. In order to study borrowers' funding strategies as well as lenders' decisions, we introduce several novelties. Lending contracts and relationships are endogenously formed, as is reputation. However, interest rates and project types are exogenously given, while project returns are stochastic, as in Fehr and Zehnder (2009). The enforcement of debt repayment is incomplete as we allow for strategic default from the borrower. Information about the borrower's risk level as well as her trustworthiness is incomplete, but we allow for information sharing among lenders: they observe default events in a Credit Register (as in Brown and Zehnder, 2007). Again, similar to Fehr and Zehnder (2009), borrowers don't have any initial endowment and cannot use excess returns in the future rounds of the game. However, contrary to their design, we assume that, if the borrower is not able to conclude the credit contract, she can't access an alternative project. Similarly, lenders cannot invest in a safe project and therefore they compete against each other in order to enter the game: the value of both the borrower's and the lenders' outside option is normalized to zero.

Throughout the game, we observe players' decisions keeping constant price (interest rates), risk (the project's fixed success probability) and information (using the Credit Register). In each session, one borrower and two lenders are grouped for T periods. Our main interest lies in understanding the drivers of both the borrower and lenders' decisions. In order to prevent any backward induction strategies and lose control over the players' behavior, we have modified the experiment by Brown and Zehnder (2007) and Fehr and Zehnder (2009) by designing a game with an infinite number of periods. This is implemented by randomizing T[1], which is not disclosed to the subjects.

At the beginning of each period t, the borrower needs to finance an investment project which requires D units of capital to become profitable. We assume that the borrower has not enough wealth to implement her project by herself. Therefore, she has to turn to the credit market, which consists of two identical lenders who she meets in sequential order. As we explain in further detail below, which lender receives the loan request first is either decided by Nature or the borrower. Each lender can lend up to D units of capital. The borrower pays s every time she faces a lender. By s, we identify the "administrative costs" faced by the borrower at each bank, that is, all costs the borrower has to sustain in order to go to a bank and ask for a loan[2]. We assume that the borrower has enough collateral to advance her funding request to both lenders ($c = 2s$, where $c < D$). The decision structure in each period is as follows:

Loan request: The borrower moves first and chooses whether she wants to borrow D from only one lender (*Full* decision), or, rather, to borrow $\frac{D}{2}$ from each (*Partial* decision). The overall sum of the requested amount must always be D. This is how we design single versus multiple bank lending relationships.

Loan acceptance: After receiving the application fee s, the requested lender is asked to take the second move which is to accept or deny the loan request. Lenders can only accept or reject the loan request they have received (e.g. they cannot lend $\frac{D}{2}$ if they have been requested D). We assume that each lender gives credit with probability γ.

Project Implementation: If the obtained amount is positive, the borrower implements the project that yields P with probability α and 0 with probability $1-\alpha$. If the borrower

[1] After the twentieth round, there is a 1/10 probability that the session continues for another round. In the experiment, the number of rounds ranged from 20 to 30 across sessions.

[2] In other words, s represents the fee the borrower has to pay to ask for loan review, and it enters the bank's turnover. The lender will receive s irrespectively of whether the loan is issued or not.

has only obtained $\frac{D}{2}$ she can implement a small project which yields $I/2$ in case of success[3].

Repayment Decision: Conditional on the project being successful, the borrower then chooses to repay the loan (with probability β) or to free-ride (with probability $1-\beta$). If the borrower repays, lenders will receive $L(1+r)$, with L the amount they lent in that round, that is $L = \{\frac{D}{2}; D\}$.

If the borrower free-rides or the project is not successful, lenders observe default, and receive no repayment. Throughout the game, the lenders can recall (and observe) the borrower's repayment behavior in all previous games in a "Credit Register"[4], irrespectively of whether they received a loan request or not[5]. Given that both lenders observe default events in the Credit Register, this signal is public. Besides, they observe the loan size request, even in rounds of play for which they don't enter the game. However, they have no direct information on α and no information on their position in the game. On the contrary, the borrower knows α and the lenders' decisions.
Once the borrower has made her repayment decision, the period ends. The next game is identical to the game described so far.
The timeline of decisions in each period is shown in Figure 1.

The decision problem of the agents is displayed in the Game Tree, Figure 2, in the Appendix. In particular, the borrower's profit will be[6]:

$$\Pi_B = \begin{cases} -2s & \text{if no loan } (\gamma_1=\gamma_2=0);\ [3] \text{ or } [7] \\ \alpha[I-D(1+r)]-s & \text{if loan is repaid, } \textit{Full} \text{ strategy } (\gamma_1=1;\beta=1);\ [1] \\ \alpha[I-D(1+r)]-2s & \text{if loan is repaid, } \textit{Full} \text{ strategy } (\gamma_1=0;\gamma_2=1;\beta=1);\ [2] \\ & \text{or } \textit{Partial} \text{ strategy } (\gamma_1=1;\gamma_2=1;\beta=1);\ [4] \\ \alpha[\frac{I}{2}-\frac{D}{2}(1+r)]-2s & \text{if loan is repaid, } \textit{Partial} \text{ strategy } ((\gamma_1=0;\gamma_2=1)\vee(\gamma_1=1;\gamma_2=0);\beta=1);\ [5] \text{ or } [6] \\ \alpha I - s & \text{if strategic default, } \textit{Full} \text{ strategy } (\gamma_1=1;\beta=0);\ [1] \\ \alpha I - 2s & \text{if strategic default, } \textit{Full} \text{ strategy } (\gamma_1=0;\gamma_2=1;\beta=0);\ [2] \\ & \text{or strategic default, } \textit{Partial} \text{ strategy } (\gamma_1=1;\gamma_2=1;\beta=0);\ [4] \\ \alpha\frac{I}{2}-2s & \text{if strategic default, } \textit{Partial} \text{ strategy } ((\gamma_1=0;\gamma_2=1)\vee(\gamma_1=1;\gamma_2=0);\beta=0);\ [5] \text{ or } [6] \end{cases}$$

On the contrary, the first and second lender's profit will be respectively:

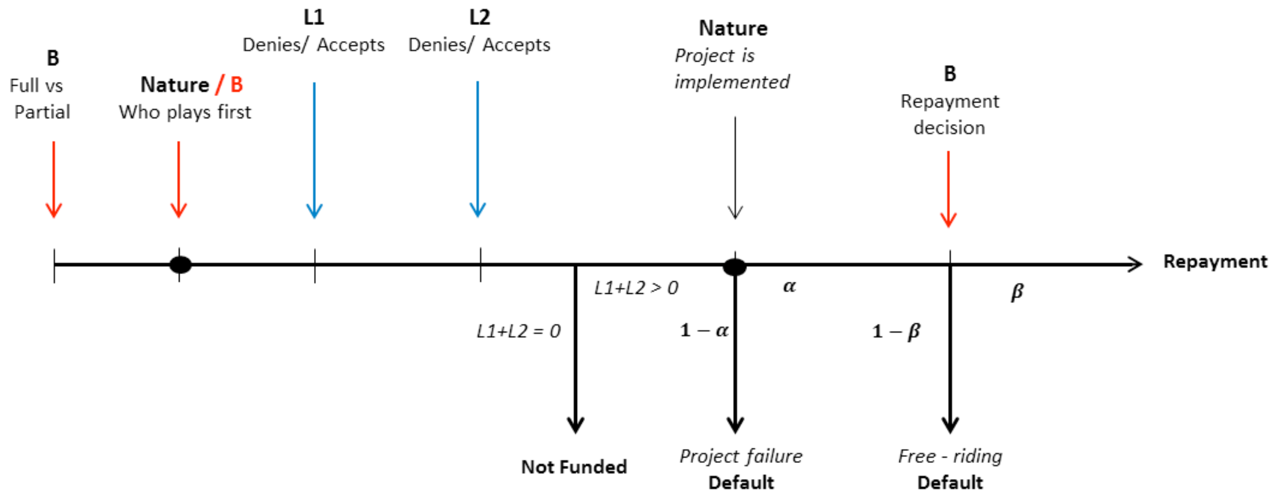
[3] However, if she has obtained D, she cannot implement two small projects, and has to invest the full amount in one project.

[4] In the experiment that we describe in section 6, such information will be further specified in a "Credit Register" shared database which collects the information about the borrower's repayment behavior in all periods.

[5] At the end of each round, the Credit Register is updated with the outcome of the round, that is either *Not Funded*, *Repaid*, or *Default*. Therefore at the beginning of round t, lenders can observe the outcomes of all rounds up to $t-1$.

[6] We display the end node number corresponding to each payoff between brackets.

Figure 1: The timeline of decisions



$$\Pi_{L,1} = \begin{cases} s & \text{if no loan } (\gamma_1 = 0);\ [2],\ [3],\ [5] \text{ or } [6] \\ \alpha D r + s & \text{if loan is repaid, } \textit{Full} \text{ strategy } (\gamma_1 = 1; \beta = 1);\ [1] \\ \alpha \frac{D}{2} r + s & \text{if loan is repaid, } \textit{Partial} \text{ strategy } (\gamma_1 = 1; \beta = 1);\ [4] \text{ or } [5] \\ -D + s & \text{if strategic default, } \textit{Full} \text{ strategy } (\gamma_1 = 1; \beta = 0);\ [1] \\ -\frac{D}{2} + s & \text{if strategic default, } \textit{Partial} \text{ strategy } (\gamma_1 = 1; \beta = 0);\ [4] \text{ or } [5] \end{cases}$$

and

$$\Pi_{L,2} = \begin{cases} 0 & \text{if } \textit{Full} \text{ strategy } (\gamma_1 = 1);\ [1] \\ s & \text{if no loan } (\forall \gamma_1; \gamma_2 = 0);\ [3],\ [5] \text{ or } [7] \\ \alpha D r + s & \text{if loan is repaid, } \textit{Full} \text{ strategy } (\gamma_1 = 0; \gamma_2 = 1; \beta = 1);\ [2] \\ \alpha \frac{D}{2} r + s & \text{if loan is repaid, } \textit{Partial} \text{ strategy } (\forall \gamma_1; \gamma_2 = 1; \beta = 1);\ [4] \text{ or } [6] \\ -D + s & \text{if strategic default, } \textit{Full} \text{ strategy } (\gamma_1 = 0; \gamma_2 = 1; \beta = 0);\ [2] \\ -\frac{D}{2} + s & \text{if strategic default, } \textit{Partial} \text{ strategy } (\forall \gamma_1; \gamma_2 = 1; \beta = 0);\ [4] \text{ or } [6] \end{cases}$$

2.1 Treatments

The experiment was implemented at the EXEC, University of York in October 2011. The experiment was programmed and conducted with the experiment software z-Tree (Fischbacher, 2007). All subjects were volunteers, and each subject could only take part in one session. All participants were undergraduate students of the University of York. We conducted six experimental sessions, for a total of 129 subjects. To ensure that the subjects understood the game, the experimenters read the instructions aloud and explained final payoffs with the help of tables provided in the instructions[7]. Before the

[7]Instructions are available upon request

game started, the subjects practiced three directed test runs. In each session, groups of three subjects were formed: one borrower (player A) and two lenders (players B and C). All subjects received a show-up fee of 5 pounds to which their payoff in the game was added in order to compute their final payoff. The players earned an average of 13 pounds from participating in the game. At the end of the game, the subjects randomly selected one of the periods of play to be the one that was actually paid. If the payoff achieved in this period were to be negative, subjects lost part of the show-up fee. Each session lasted approximately one hour and a half.

We implement three treatments in order to detect the effect of borrowers' riskiness, the identification of lenders and information disclosure on subjects' decisions. Treatments were constructed as follows:

- In the *Random treatment* (hereafter "*RA*", the baseline treatment), the sequential order of player B and player C is randomly set[8];

- In the *Relationship lending treatment* (hereafter, "*RL*"), the sequential order of player B and player C is decided by the borrower. In other words, at the beginning of each round, player A is asked to choose to play first with player B or player C[9];

- The *Information Disclosure treatment* (hereafter "*ID*") is identical to the *RL* treatment with the only exception that it allows player B and player C to know whether player A's default has to be accounted for investment failure or free-riding. This information is only accessible to the player(s) who have lent in this particular round of play[10].

For each treatment, we ran two separate sessions[11], a high-risk (α_{low}) and a low-risk (α_{high})[12] session. In the experiment, we set $\alpha_{low} = 0.6$ and $\alpha_{high} = 0.9$. The value of α was only disclosed to borrowers[13]. Therefore, we ran a total of six sessions (see Table 1 below).

2.2 Predictions

If subjects were playing a one-shot game, the predictions for the entire experiment would be straightforward assuming perfect rationality and selfishness: the borrower would never repay and, by backward induction, lenders would always deny credit. However, as the game is infinitely repeated, we expect the agents to act strategically in order to maximize

[8] with equal probability that either player B or player C is selected as the first lender. In the experiment, the choice of Nature was generated by computer.

[9] At the beginning of each round, a window appears on player A's screen asking to whom between player B and player C she wants to address her funding request in the first instance.

[10] The information appeared as a message in the screen at the end of each period.

[11] Each participant played in only one session

[12] where $I\alpha_{low} < I\alpha_{high}$.

[13] However, lenders knew that borrowers knew their own α.

Table 1: Treatments

Session 1 *RA* α low	***Session 2*** *RA* α high
Session 3 *RL* α low	***Session 4*** *RL* α high
Session 5 *ID* α low	***Session 6*** *ID* α high

both present and future payoffs. Moreover, as both α and β are not disclosed to lenders, they end up playing a game with incomplete information. Having no information about the borrower's trustworthiness and project riskiness, we assume that lenders will decide whether to deny or grant credit on the basis of the borrower's expected probability of default $\hat{p}_t^D$. Its proxy is computed as the frequency of observed defaults in the past periods, $\hat{p}_t^D$, where:

$$\hat{p}_t^D = \frac{\#Default_t}{t} \tag{1}$$

The number of defaults up to period t $\#Default_t$ is public information, as the lenders can always recall the borrower's past repayment history through the Credit Register. Starting from a low prior, that is:

$$\hat{p}_0^D < \tfrac{r}{1+r}$$

where r is the (exogenous) interest rate, lenders may stop lending if observed defaults are too frequent and $\hat{p}_t^D$ exceeds the threshold. Conversely, starting from a high prior

$$\hat{p}_0^D \geq \tfrac{r}{1+r},$$

and if some contracts are actually formed between the borrower and the other lender, a lender can start giving funds after observing enough repayments. However, if both lenders start with high priors, no contracts will be formed in any subsequent period.

In what follows, we summarize the predictions for the experiment. For a more detailed discussion of the theoretical underpinnings, please refer to the model discussed in Appendix C.

RA versus RL treatment

The difference between the **RA and RL treatments** lies in the possibility to build long-term bank relationships. As the literature on relationship lending suggests (Berger and

Udell, 1995; Petersen and Rajan, 1994), we should expect that when firms have the opportunity to establish repeated interactions with the same bank, this results into a higher concentration of their borrowing. Therefore, the main prediction for the **RL treatment** is that borrowers are more likely to choose single-bank relationships than in the **RA treatment**. At the same time, also banks should positively react to firms' borrowing concentration when they are engaged in long-term relationships, by granting credit to a higher extent than in the RA treatment.

RL versus ID treatment

The **ID treatment** differs from the **RL treatment** in the type of information the lenders receive when the borrower does not repay: while in the latter they only observe generic default, in the former they get a perfect signal upon the source of default; in other words, they know whether default is driven by the project failure or is voluntary. Besides, this supplement information introduces asymmetry across lenders. The ID treatment not only allows long-term relationship building, but also tests the idea that, through repeated interactions, the lenders acquire more (soft) information about the borrowers' quality. This should have several effects. First, borrowers should opt for single-bank lending relationships to a higher extent. Therefore, we expect that, compared to the **RA and RL treatments**, the **ID treatment** increases the likelihood of single-bank lending relationships. Second, because of the perfect signal, borrowers should repay more, and, as a consequence, lenders should also increase their lending rates. A second prediction is therefore that both β and γ will be higher in the **ID treatment** respectively to the other two treatments. At the same time, we might expect untrustworthy borrowers to switch lenders more often than in the other treatments, as only the lender they have been funded by receives information about their default. As a consequence, lenders could perceive the switching behavior as a negative signal from the borrower: therefore, they should lend less to switching borrowers in the ID treatment than in the other treatments.

Proposition 1 (Demand Side): *Borrowers are more likely to choose single-bank relationships when long-term relationship are feasible and in particular when full disclosure implies high informational rents within relationships.*

Proposition 2 (Supply Side): *Lenders are less likely to participate in multiple bank lending relationships when relationship lending is feasible.*

Proposition 3 (Winner's curse): *Borrowers who successfully established a lending re-*

lationship are less likely to switch, especially in the disclosure treatment. Lenders are less likely to lend to switching borrowers in the disclosure that in the non-disclosure treatment.

Safe versus Risky treatments

As previously mentioned, for each treatment we ran two separate sessions, one with a low-risk (α_{high}), safer project, the other with a high-risk (α_{low}) project. If lenders had perfect information on the borrower's riskiness, we might have expected a higher share of successful contracts in the case of the low-risk treatments from the beginning. In a setting with asymmetric information about α, through repeated interactions, players should adapt their beliefs over the borrowers' overall quality (the combination of her riskiness and trustworthiness). Thus, we might expect that the share of accepted requests should increase in the case of safe treatments and decrease in the case of risky treatments, with a significant difference between the two. In the former case, players should approach a "Cooperative equilibrium" (lenders accept requests and get repaid) while in the latter case they should converge to a "Defecting equilibrium" (no contracts formed). Thus the following should be observed:

Proposition 4 (Project Riskiness): *Lenders are more likely to grant credit in low-risk than high-risk treatments. In turn, borrowers are more likely to repay low-risk than high-risk treatments. .*

3 Results

In this section we report the results of the six experimental sessions. After presenting descriptive statistics, we further investigate the determinants of players' choices.

3.1 Descriptive Statistics

We start investigating our data with summary statistics in order to get a first intuition on players' behavior. Table 4 summarizes statistics for all sessions; the values reported are the average at group level by session. At a first glance, borrowers appear to have strong preferences towards single bank lending relationships, which have been chosen in 77% of the cases; moreover, the repayment rates appear to be very high. There is instead more variability on the supply side: on average, lenders have accepted to give credit about half of the times. When we condition the lending acceptance rate by the size of the loan request (Full or Partial), differences emerge. Indeed, first players seem to lend more under single lending than multiple lending, while the opposite is observed for second lenders.

Tables 5 and 6 report the mean difference tests between treatments. We use two-sided Wilcoxon-Mann-Whitney tests to verify whether differences between treatments are significant, using means per group as independent observations[14]. Reporting descriptive statistics at the treatment level (RA, RL and ID), table 5 reveals that borrowers' behavior (as shown by statistics over $Full$ choice and β) is very stable across sessions. Therefore, **Proposition 1** which anticipated a higher share of single lending strategies when relationship is possible does not seem to be confirmed. Determinants of the $Full$ decision will be investigated more in depth below. When we consider lenders, several elements can be noted. In the Random treatment, the first and second lenders show similar levels of the acceptance rate (0.42 against 0.44), while the subject chosen to play first seems to lend more than the second in the RL and the ID treatments (0.57 against 0.45 and 0.57 against 0.49 respectively). This could be interpreted as first evidence that lenders positively react to being chosen to play first. However, we are not able to detect any significant difference across treatments through the tests. Indeed, between-treatments effects appear strongly confounded by the riskiness level, as shown in table 6[15]. The performed two-sided tests show that, when comparing safe and risky sessions, differences are statistically significant for all variables of interests. We find that borrowers are significantly more likely to concentrate their borrowing in safe (0.81) than in Risky treatments (0.72). Similarly, the repayment behavior in Safe treatments ($\beta = 0.91$) is significantly higher than in Risky treatments ($\beta = 0.68$). From the lenders' side, banks are more likely to lend when project risk is low ($\gamma_1 = 0.67$; $\gamma_2 = 0.63$), than when it is high ($\gamma_1 = 0.37$; $\gamma_2 = 0.32$). These results thus confirm predictions made in **Proposition 4**: in safe treatments, lenders are more likely to lend and borrowers are more likely to repay.

A second learning from table 6 relates to differences in behavior under single or multiple lending. Although borrowers seem to be more trustworthy under single lending ($\beta = 0.82$ against 0.69), this difference is not significant. However, we find that lenders positively react to the single lending decision, since γ_1 is significantly higher in $Full$ (0.54) than $Partial$ (0.38). We believe this result supports the relationship lending argument introduced in **Proposition 2** by showing that when firms concentrate their borrowing they experience less credit rationing, particularly by establishing a long-term relationship with the bank they have chosen.

To strengthen the validity of the test, table 7 reports M-W tests comparing the behavior between the first and second lender, when subjects know their position in the game[16]. Although the statistics show that overall first lenders lend more than second ones, this difference is only significant when we condition on the borrower opting for single bank

[14] Contrary to standard t-tests, the two-sided Wilcoxon-Mann-Whitney tests do not assume that differences are normally distributed. Given the low number of observations, the latter method is preferred.

[15] We are not able to test differences between treatment-risk sessions, since only 7 or 8 observations are obtained from each of the six sessions.

[16] That is, observations from the Random treatment are discarded.

lending relationships. Instead, when the funding of the project is syndicated (*Partial*), second lenders (0.52) seem to be more inclined to lend than first lenders (0.44), although the difference is not significant.

We also use graphical tools in order to explore subjects' behavior, as shown in Figures 3 and 4. Figure 3 shows the evolution of the lending decision over periods, in the safe and risky treatments. To do so, we compute the mean value of γ for each period. If in the safe treatment, the average lending acceptance rate is stable over time, we observe a decreasing trend in the risky sessions. Indeed, the low level of observed defaults confirms lenders in their decision in the safe treatment. Instead, when default events accumulate in the risky treatment, lenders revise their proxy on the probability of default and stop lending, as expected from section 2.2.
Figure 4 (top) tests whether borrowers' repayment rate responds to the length of the relationship with a particular lender. We find that borrowers increase their probability to repay when the relationship length exceeds two periods as compared with their overall behavior. Thus the length of relationship should be used as a possible determinant of β. Finally, Figure 4 (bottom) complements previous results on the effect of the borrower's choice between single and multiple lending on the chosen lender's decision. This graphical inspection confirms that lenders have a higher probability to accept the loan request if it is concentrated.

3.2 Determinants of players' decisions

We build our identification strategy in order to test two main hypotheses. From the borrowers' perspective, we want to understand to what extent the choice of single versus multiple bank lending relationships depends upon the firm's characteristics and behavior, or on the lenders' decisions towards her. From the lenders' perspective, we investigate the determinants of the lending decision, and more precisely, whether being chosen by the borrower to play first has an impact on lending behavior. We estimate our main equations using both a linear probability and a probit model on our panel throughout 22 periods[17]. We compare how subjects' behavior changes across treatments using subsamples. This will reveal whether, when we control for the exogenous risk level, differences between treatments emerge.

We are interested in the determinants affecting the choice of single versus multiple bank lending relationships. If the previous section has pointed towards risk as a possible determinant, we also test whether lenders' behavior in the previous round also impacts such

[17] Our sessions lasted between 22 and 30 periods. In order to prevent biases due to session length, we censor all observations above period 22.

decision. Indeed, although our theoretical model defines single lending as the best strategy, previous works on multiple lending (Detragiache et al., 2000, Farinha and Santos, 2002) have shown that financially constrained borrowers tend to spread their lending requests in order to maximize their chances to get funding. Thus we estimate the main equation as follows, for each borrower i and period t. Standard errors are clustered at the group level[18]:

$$Full_{i,t} = \theta_0 Rationed_{i,t-1} + \theta_1 Safe + \epsilon_{i,t} \tag{2}$$

where $Rationed_{t-1}$ is a dummy which takes value one if the borrower has been credit rationed in the previous round[19]. We also include controls for riskiness ($Safe$ is equal to one in α_{high} sessions) A borrower might also choose to concentrate her borrowing after having stabilized a relationship with one lender, and gained reputation towards the bank. We thus introduce the variable $Length_{t-1}$, which reports the number of periods the chosen lender has cooperated with the borrower, up to period $t-1$, when relationship lending is possible (treatments RL and ID). Given the negative correlation between our variables, we test the effect of credit rationing ($Rationed_{t-1}$) and relationship length ($Length_{t-1}$) on the borrower's repayment decision in two separate regressions. The second regression that we estimate is therefore :

$$Full_{i,t} = \theta_0 Length_{i,t-1} + \theta_1 Safe + \epsilon_{i,t} \tag{3}$$

Results for equations 2 and 3 are shown in table 8. As expected, we find that having experienced credit rationing in the previous period leads the borrower to spread its credit requests at present (the coefficient θ_0 is negative and statistically significant) , for each one of our treatment subsamples. Therefore, multiple bank lending relationships are used as a means to overcome credit rationing. The exogenous risk level instead does not impact on such decision. Besides responding to credit rationing, borrowers also tend to concentrate their borrowing when they have established a stable relationship with a chosen lender. Indeed, the variable *Length* is positively associated with the probability to choose a single lending strategy, both in the RL and the ID treatments.

After choosing between single and multiple lending requests, the borrower decides to repay the loan or not when the project is a success. We investigate whether β is impacted by the exogenous risk level, but also the lenders' decisions in the previous period as well as the length of the lending relationship. We estimate the following regressions:

$$\beta_{i,t} = \theta_0 Rationed_{i,t-1} + \theta_1 Safe + \epsilon_{i,t} \tag{4}$$

[18] As a robustness check, we have also run the regressions clustering the standard errors at the subject *and* group level. Since we observe no significant differences, we report results clustered at the group level.

[19] We classify a borrower as credit rationed if he is not able to implement the whole project, that is, both if she receives 0 or $\frac{D}{2}$ in the round.

$$\beta_{i,t} = \theta_0 Length_{i,t-1} + \theta_1 Safe + \epsilon_{i,t} \tag{5}$$

Results for equations 4 and 5 are shown in table 9. In all treatments, credit rationed borrowers have a higher probability to free-ride on their loan, given that $Rationed_{t-1}$ has a negative impact on β. Contrary to what we could have expected from our mean difference tests, it's not the risk level *per se* that explains a reduced trustworthiness of the borrower in risky sessions, but lender behavior. Indeed, the dummy $Safe$ has no impact on β in the RA and RL treatments. However, we find that when repayment behavior is revealed to the lenders, in treatment ID, borrowers are more likely to repay in the safe treatments. In order to test whether the repayment decision is driven by the possibility to establish long term relationships, our second regression tests whether the probability to repay is affected by the relationship length, with the expectation that it has a positive impact. This hypothesis is confirmed in the information disclosure treatment but is refuted in the relationship lending one, in which $Length_{t-1}$ has no significant impact on β. Therefore, releasing the information on the source of default efficiently constrains borrowers to collaborate if they want to maintain their stable relationship with the lender. Instead, when the borrower knows that the source of default is ambiguous, relationship length does not act as a safeguard against free-riding behavior.
The third decision of the borrower, in treatments RL and ID concerns to which lender the borrower wants to address her loan request first. Again, we test how such decision is influenced by credit rationing as well as relationship length. The dependent variable $Switch_t$ takes value 1 if the borrower has chosen a different lender to play first in period t as compared to period $t-1$. It takes value 0 if the chosen lender is the same across periods. The estimated regressions are therefore:

$$Switch_{i,t} = \theta_0 Rationed_{i,t-1} + \theta_1 Safe + \epsilon_{i,t} \tag{6}$$

$$Switch_{i,t} = \theta_0 Length_{i,t-1} + \theta_1 Safe + \epsilon_{i,t} \tag{7}$$

Results for equations 6 and 7 are shown in table 10. As expected from **Proposition 3**, credit rationed borrowers have a higher probability to switch lenders, but only in the RL treatment. Instead, relationship length reduces the borrowers' probability to switch lenders: borrowers appear to be captive. We have also performed other tests, shown in Table **??** in order to understand how the probability to switch lenders relates to the duration of the relationship. We estimate the following regression:

$$Switch_{i,t} = \theta_0 Length1_{i,t-1} + \theta_1 Length2_{i,t-1} + \theta_2 Length3_{i,t-1} + \theta_4 LengthMore_{i,t-1} + \theta_5 Safe + \epsilon_{i,t} \tag{8}$$

where $Lengthk_{i,t-1}$ is equal to one if $Length_{i,t-1} = k$, for $k = 1, 2, 3$; and $LengthMore_{i,t-1}$ is equal to one if $Length_{i,t-1} > 3$, and zero otherwise. We find that the negative link between the probability to switch and relationship length starts to be significant after two periods in the RL treatment and three periods in the ID one. Also, the absolute value of the impact increases with the duration of the relationship.

Our analysis of the determinants of borrowers' behavior has revealed the following. Credit rationed borrowers have a higher probability to split their loan requests, to free-ride and to switch lenders. Instead, borrowers that have been able to establish a long-term relationship with a lender concentrate their borrowing requests, and, to a lower extent, repay more their loans. Finally, the duration of the credit relationship is negatively associated with the probability to switch lenders.

In what follows, we study the determinants of the lenders' decision. In a first step we test general determinants of the lending decision across all treatments. In a second step we focus on the RL and ID treatments in order to measure the effect of being chosen to play first and other default probability proxies. As a first investigation of the data, we thus estimate the following regression equation, for each lender j playing with borrower i in each period t:

$$\gamma_{1,j,t} = \theta_0 Full_{i,t} + \theta_1 Default_{hist,i,t-1} + \theta_2 Safe + \epsilon_{j,t} \tag{9}$$

Results are displayed in table 12. The dependent variable, identified as $\gamma_{1,j,t}$, is a dummy which takes the value of one if the borrower has received credit from the first lender to enter the game, and it is 0 if he has denied. As regressors, we use a series of variables related to the bank-firm relationship: the loan size request, as defined by the borrower's choice $Full$, and the borrower's credit history. In this first specification, the borrower's default probability is thus proxied by the dummy variable $Default_{hist}$, which takes the value of one if the borrower has defaulted at least once in the past periods. We also control for the riskiness level.

As expected by **Proposition 4**, we observe a negative relation between observed defaults and the probability that lenders give funds, in all treatments but the ID one. Indeed, observed defaults is public information, and if it the best proxy for the probability of future defaults in the first two treatments, it is only the second best in the ID one. We will study below other possible determinants for the lending decision in this treatment (see Table 14), in particular those related to the free-riding information. Moreover, we find that in the RL treatment, safer borrowers get more funds (θ_2 is positive and significant) while in the two other treatments (RA and ID) it is the choice between single and multiple lending that is used as a proxy for borrowers' quality, θ_0 being positive and significant.

As a second step, we focus on the RL and ID treatment (tables 13 and 14, respectively). Our dependent variable is now the decision of all lenders, would they be first or second to enter the game. This allows us to measure the effect of being chosen to play first on the lending decision, using the $Chosen$ variable. Further, we add a variable defining the number of periods the lender has cooperated with the borrower, $Length$, in order to test whether the stability of the relationship also impacts the lending decision. Besides $Default_{hist}$, we also test other proxies for the borrower's probability of default. $High_{default}$ (Model 2) tests whether the frequency of default events matters. It is a dummy taking value 1 if the frequency of defaults ($Default_t/t$) is higher than the threshold computed in section 4, that is $\frac{1}{1+r}$. Then $Freeride_{hist}$ (Model 3), is a dummy which takes the value of 1 if the borrower has ever free-ridden. Finally β (Model 4), the borrower's trustworthiness in the previous period, is the last default proxy we use. Note that comparing models 3 and 4 will help to see whether one single free-riding event has the same effect as recent free-riding.

Results reveal that $Default_{hist}$, $High_{default}$ and $Freeride_{hist}$ all have the same predictive in the RL treatment, while using β reduces a bit the goodness of fit. This shows that lenders have memory: they base their lending decision not only upon the borrower's behavior in the past period, but on her overall credit history. If in the RL treatment lenders cannot identify the type of default (thus $Default_{hist}$ and $Freeride_{hist}$ have the same predictive power), in the ID treatment only the measures related to trustworthiness ($Freeride_{hist}$ and β) have a significant impact on the probability to lend (the former having a negative effect and the latter a positive one, as expected).

Tables 13 and 14 also report that besides the credit history, the determinants of the lending decision differ in both treatments: in the RL treatment, the borrower's decisions, i.e. choosing which lender to play first or the concentration of borrowing don't impact the lenders' decision. What do are the "objective" elements, that is the riskiness level and the credit history. The length of the relationship has a positive effect on the probability to lend in models 1 and 3, which are the most imperfect proxies for the default probability. In the ID it is the exact opposite. What matters is the borrower's behavior, the fact that she has chosen the lender to play first, cooperated over time and repaid her loans in the past. Indeed, both the length of the relationship up to $t-1$ and the continuing effort of the borrower to cooperate, as signaled by $Chosen$, positively impact the probability to get funds.

Our investigation of the determinants of the decision to lend has revealed the following. Our results only partially validate the the prediction from **Proposition 2**: when relationship lending is not feasible (in the RA treatment), the borrower's choice to concentrate her loan request is used as a proxy for her willingness to collaborate. When the borrower openly decides which lender to play first, and whether she seeks a stable relationship or not (by repeatedly choosing the same lender), the decision between $Full$ and $Partial$ does not matter any more. Moreover, in the RL and ID treatments, lenders base their decision on the probability of default, using the best proxy available (the default event in the RL treatment and the free-riding event in the ID one).

4 Conclusions

Uncovering the determinants underlying the choice between single and multiple bank lending relationships through the use of observational data often implies the resolution of endogeneity issues which are not easy to tackle. We thus build an experimental credit market in which a borrower can implement an investment opportunity either through single or multiple bank lending relationships by addressing her funding request to either one or two identical lenders. We first implement a market in which there is no opportunity to create long term relationships between borrowers and lenders. We then modify it by allowing relations to be established through time. Besides, lenders have limited diversification opportunities and are subject to ex-post moral hazard problems. Throughout the game, we allow the borrower's quality to vary exogenously and study how this affects lenders' funding decisions as well as borrowers' choice between single and multiple bank lending relationships. In particular, the use of a controlled laboratory experiment helps us to address the following research questions: are multiple bank lending relationships explained by difficulties to build a stable relationship or rather a strategy in order to diversify the sources of credit? Moreover, as the borrower can choose to which lender she wants to address her funding request first, does the rank in which the lender appears in the borrower's preferences play a role in his funding decision?

We find that multiple bank lending relationships are preferred by those borrowers who have experienced credit rationing in the past. In turn, those that have established a stable relationship with one lender tend to concentrate their borrowing, repay more, and repeatedly choose the same lender. From the other side, we observe that lenders are less likely to give credit to borrowers that spread their loan requests among several financial intermediaries, but only in absence of relationship lending, while when relationship lending is possible, lenders will base their funding decisions upon borrowers' riskiness and past defaults. Taken together, our results suggest that lenders evaluate borrowers' debt exposure towards other banks as a "free-riding" strategy - and indeed borrowers do so - when they are not able to gather further information upon their quality and interactions are only seldom repeated. On the contrary, when borrowers and lenders engage in a committed relationship, multiple bank lending relationships serve as a diversification strategy. From the lenders' side, we find that being chosen as first by the borrower as well as the length of the relationship positively affect their willingness to lend. Last, when information upon borrower's repayment behavior is made available, lenders are more likely to punish free-riding behaviors than simple default due to project failure: our results thus show that the reason why borrowers default matters for the continuation of the relationship lending.

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Appendix A

Proof of equation 14 for all values of γ_1 and γ_2

When the borrower doesn't assume that lenders will accept to lend in the first period, the value from cooperating $V_{c,B}$ integrates the probability to be given the funds from the first or the second lender:

$$V_{c,B} = \sum_{t=1}^{\infty} \delta^{t-1} \{ \gamma_1 \left[\alpha [I - D(1+r)] - s \right] + (1-\gamma_1) [\gamma_2 \left[\alpha (I - D(1+r)] - s \right] + (1-\gamma_2)(-2s)] \}$$

Similarly, the value from defecting $V_{d,B}$ becomes:

$$V_{d,B} = \gamma_1(\alpha I - s) + (1 - \gamma_1)[\gamma_2(\alpha I - 2s) + (1 - \gamma_2)(-2s)] + \sum_{t=2}^{\infty} \delta^{t-1}(-2s)$$

As a consequence, the borrower will cooperate if the following condition is satisfied:

$$\alpha > \frac{-\delta s \gamma_1}{(\delta I - D(1+r))(\gamma_1 + \gamma_2 - \gamma_1 \gamma_2)} \tag{10}$$

Note that for $\gamma_1 = \gamma_2 = 0$ the condition is true for all values of α.

Appendix B

Figure 2: The game tree

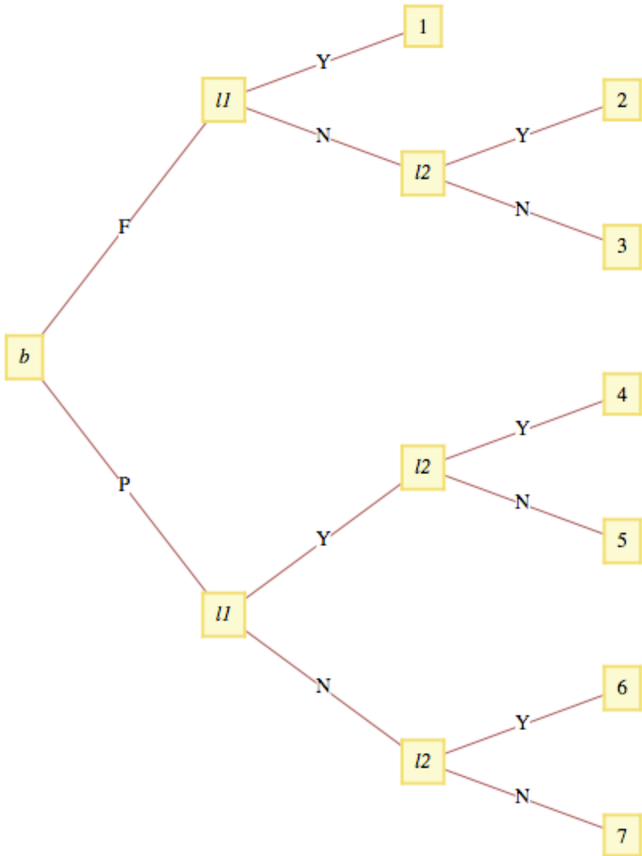


Table 2: Construction of variables used in the regressions

Variable	Description
$Rationed_t$	$= 1$ if the borrower was denied credit by at least one lender in the period
$Safe$	$= 1$ for sessions with a high value of α
$Switch_t$	$= 0$ if the chosen lender is the same across periods. $= 1$ if the borrower has chosen a different lender to play first in period t as compared to period $t-1$
$Default_{hist,t}$	$= 0$ if the borrower has never defaulted up to period t $= 1$ if the borrower has defaulted at least once since the game started
$Freeride_{hist,t}$	$= 0$ if the borrower has never free-ridden up to period t $= 1$ if the borrower has free-ridden at least once since the game started
$Length_{i,t}$	length of relationship between the borrower and the chosen lender
$Lengthk_{i,t-1}$	$= 1$ if $Length_{i,t-1} = k$, for $k = 1, 2, 3$
$LengthMore_{i,t-1}$	$= 1$ if $Length_{i,t-1} > 3$
$High_{default,t}$	$= 1$ if the frequency of defaults (defined as $\frac{Default_t}{t}$) is above the threshold value of $\frac{r}{1+r}$ (that is 0,166 according to our parametrization) $= 0$ otherwise

Figure 3: Evolution of lending over time by riskiness level

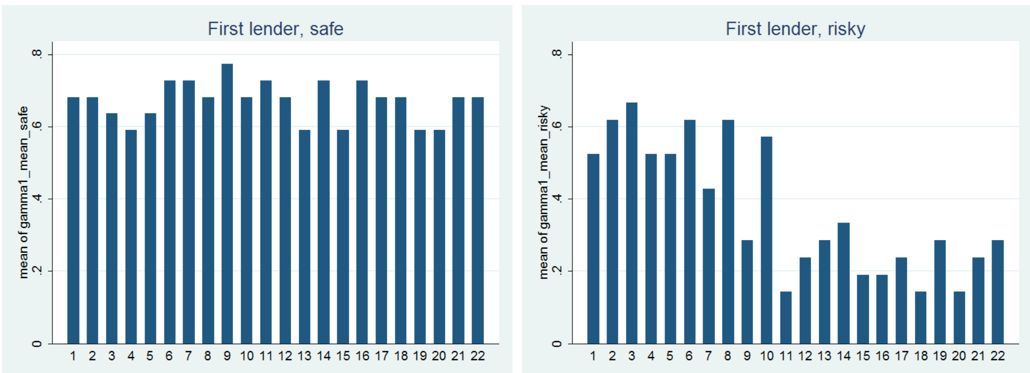


Table 3: Parameters and treatments

	Random treatment	**RL treatments**
Parameters		
Risk level: α	p	p
Project size: D	p	p
Revenue: I	p	p
Interest rate: r	p	p
Decisions		
Full vs. Partial	$d(b)$	$d(b)$
l_1 (or l_2) enters the game first	Nature	$d(b)$
Accept vs Deny the loan	$d(l_1)$ and/or $d(l_2)$	$d(l_1)$ and/or $d(l_2)$
Repay the loan if project successful	$d(b)$	$d(b)$
Information		
α	only b	only b
Loan size request	all players	all players
l_1 (or l_2) enters the game first	None	all players
Success of the project	only b	only b
Default /repayment/not funded	all players	all players

Note: p are parameters; $d(x)$ is the decision of player x, where b = *borrower* and l_k = *lender*, with $k = \{1,2\}$

Table 4: Descriptive statistics, all sessions

	mean	sd	min	max	Nb obs
Full choice	0.77	0.24	0.18	1	43
β	0.79	0.25	0	1	42
γ_1	0.52	0.30	0.05	1	43
γ_2	0.46	0.34	0	1	40
γ_1 if Full	0.54	0.30	0	1	43
γ_1 if Partial	0.38	0.39	0	1	33
γ_2 if Full	0.41	0.38	0	1	39
γ_2 if Partial	0.47	0.37	0	1	33
Rationed	0.41	0.35	0	1	43

Note: Each observation is the mean value of the variable for a subject-group across all periods.

Figure 4: Conditional distributions

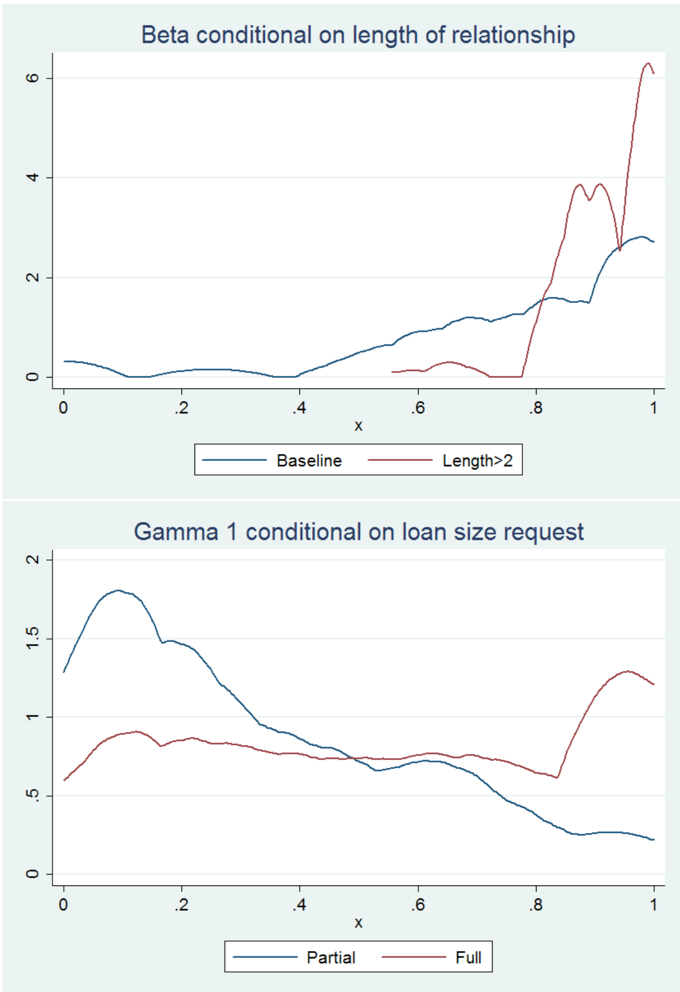


Table 5: Mean difference tests between treatments (1)

	Random	sd	min	max	**RL**	sd	min	max	W-M-W test
Full choice	0.78	0.28	0.18	1	0.77	0.25	0.32	1	$RA = RL$
β	0.79	0.30	0	1	0.78	0.27	0	1	$RA = RL$
γ_1	0.42	0.31	0.05	1	0.57	0.31	0.14	1	$RA = RL$
γ_2	0.44	0.39	0	1	0.45	0.32	0.1	1	$RA = RL$
Nb groups		14				14			

	RL	sd	min	max	**ID**	sd	min	max	W-M-W test
Full choice	0.77	0.25	0.32	1	0.75	0.22	0.32	1	$RL = ID$
β	0.78	0.27	0	1	0.81	0.21	0.25	1	$RL = ID$
γ_1	0.57	0.31	0.14	1	0.57	0.29	0.09	1	$RL = ID$
γ_2	0.45	0.32	0.1	1	0.49	0.35	0	1	$RL = ID$
Nb groups		14				15			

Note: We report the significance of the Wilcoxon-Mann-Whitney equality tests as follows: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 6: Mean difference tests between treatments (2)

	Safe	sd	min	max	**Risky**	sd	min	max	W-M-W test
Full choice	0.81	0.26	0.18	1	0.72	0.22	0.36	1	$Safe > Risky$ *
β	0.91	0.18	0.25	1	0.68	0.26	0	1	$Safe > Risky$ ***
γ_1	0.67	0.33	0.05	1	0.37	0.19	0.09	0.73	$Safe > Risky$ ***
γ_2	0.63	0.41	0	1	0.32	0.19	0	0.83	$Safe > Risky$ **
Nb groups		14				15			

	Full	sd	min	max	**Partial**	sd	min	max	W-M-W test
β	0.82	0.28	0	1	0.69	0.38	0	1	$Full = Partial$
γ_1	0.54	0.30	0	1	0.38	0.39	0	1	$Full > Partial$ **
γ_2	0.41	0.38	0	1	0.47	0.38	0	1	$Full = Partial$
Nb groups		43				43			

Note: We report the significance of the Wilcoxon-Mann-Whitney equality tests as follows: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 7: Mean difference tests between first and second lender decision

	γ_1	sd	min	max	γ_2	sd	min	max	W-M-W test
Overall	0.57	0.29	0.09	1	0.47	0.33	0	1	$\gamma_1 = \gamma_2$
Safe	0.72	0.31	0.09	1	0.64	0.39	0	1	$\gamma_1 = \gamma_2$
Risky	0.42	0.17	0.14	0.73	0.32	0.15	0.1	0.64	$\gamma_1 = \gamma_2$
Full	0.58	0.29	0	1	0.40	0.37	0	1	$\gamma_1 > \gamma_2$ **
Partial	0.44	0.40	0	1	0.52	0.35	0	1	$\gamma_1 = \gamma_2$

Note: We report the significance of the Wilcoxon-Mann-Whitney equality tests as follows: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 8: Determinants of single vs. multiple lending

	RA (1)		RL (1)		ID (1)		RL (2)		ID (2)	
Full choice	ols	probit	ols	probit	ols	probit	ols	probit	ols	probit
$Rationed_{t-1}$	-0.444***	-1.706***	-0.371***	-1.228***	-0.259**	-0.803***				
	(0.122)	(0.453)	(0.069)	(0.218)	(0.087)	(0.269)				
$Length_{t-1}$							0.0292*	0.259***	0.0221*	0.102
							(0.0147)	(0.0879)	(0.0105)	(0.0684)
$Safe$	-0.058	-0.199	-0.017	-0.032	0.008	0.036	0.126	0.342	0.004	0.020
	(0.104)	(0.433)	(0.010)	(0.431)	(0.087)	(0.292)	(0.131)	(0.457)	(0.112)	(0.344)
Constant	0.996***	1.853***	0.919***	1.348***	0.844***	1.009***	0.671***	0.369	0.711***	0.525**
	(0.074)	(0.407)	(0.063)	(0.286)	(0.067)	(0.246)	(0.0835)	(0.239)	(0.078)	(0.239)
N	294	294	294	294	315	315	294	294	315	315
r2	0.25		0.18		0.09		0.06		0.018	
Pseudo r2		0.25		0.16		0.07		0.07		0.02

Standard errors in parentheses; $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 9: Determinants of repayment behavior

	RA (1)		RL (1)		ID (1)		RL (2)		ID (2)	
Repayment (β)	ols	probit	ols	probit	ols	probit	ols	probit	ols	probit
$Rationed_{t-1}$	-0.201*	-0.836**	-0.202**	-0.767***	-0.182	-0.760**				
	(0.099)	(0.359)	(0.088)	(0.276)	(0.108)	(0.351)				
$Length_{t-1}$							0.001	0.001	0.009	0.266*
							(0.011)	(0.064)	(0.006)	(0.151)
$Safe$	0.102	0.612	0.130	0.553	0.178***	0.911***	0.167	0.712	0.209***	0.960***
	(0.078)	(0.440)	(0.097)	(0.408)	(0.047)	(0.309)	(0.118)	(0.509)	(0.064)	(0.345)
Constant	0.870***	1.216***	0.807***	0.939***	0.797***	0.931***	0.749***	0.674**	0.721***	0.375
	(0.073)	(0.342)	(0.086)	(0.299)	(0.030)	(0.117)	(0.101)	(0.318)	(0.056)	(0.234)
N	142	142	165	165	161	161	165	165	161	161
r2	0.12		0.09		0.15		0.04		0.11	
Pseudo r2		0.16		0.09		0.19		0.04		0.18

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table 10: Determinants of switching between lenders

	RL (1)		ID (1)		RL (2)		ID (2)	
Switch	ols	probit	ols	probit	ols	probit	ols	probit
$Rationed_{t-1}$	0.230***	0.601***	-0.031	-0.078				
	(0.059)	(0.154)	(0.111)	(0.280)				
$Length_{t-1}$					-0.083***	-0.261***	-0.057***	-0.211***
					(0.020)	(0.078)	(0.009)	(0.052)
$Safe$	0.204	0.534	0.117	0.293	0.215*	0.593*	0.163	0.424
	(0.127)	(0.337)	(0.112)	(0.282)	(0.119)	(0.336)	(0.099)	(0.267)
Constant	0.346***	-0.405	0.448***	-0.130	0.535***	0.106	0.495***	0.0395
	(0.094)	(0.252)	(0.070)	(0.176)	(0.072)	(0.184)	(0.050)	(0.133)
N	294	294	315	315	294	294	315	315
r2	0.04		0.02		0.13		0.10	
Pseudo r2		0.03		0.01		0.10		0.09

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table 11: Duration analysis

	RL		ID	
Switch	ols	probit	ols	probit
Length1	-0.107	-0.298	0.000	0.002
	(0.132)	(0.371)	(0.010)	(0.258)
Length2	-0.327**	-0.886**	-0.122	-0.312
	(0.128)	(0.366)	(0.137)	(0.352)
Length3	-0.442**	-1.206**	-0.307***	-0.838***
	(0.173)	(0.540)	(0.091)	(0.275)
LengthMore	-0.691***	-2.243***	-0.482***	-1.450***
	(0.102)	(0.353)	(0.103)	(0.412)
Safe	0.236**	0.675**	0.143	0.380
	(0.109)	(0.344)	(0.0875)	(0.240)
Constant	0.564***	0.153	0.498***	-0.0132
	(0.070)	(0.187)	(0.066)	(0.167)
N	294	294	315	315
r2	0.166		0.113	
Pseudo r2		0.13		0.09

Standard errors in parentheses; $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 12: Determinants of lending decision (1)

	RA		RL		ID	
Lending choice, γ_1	ols	probit	ols	probit	ols	probit
$Full$	0.234***	0.850***	0.122	0.410	0.196*	0.510*
	(0.075)	(0.302)	(0.076)	(0.255)	(0.104)	(0.262)
$DefaultHist_{t-1}$	-0.472***	-1.320***	-0.302***	-1.190***	-0.175	-0.480
	(0.087)	(0.284)	(0.084)	(0.294)	(0.177)	(0.496)
$Safe$	0.051	0.150	0.411***	1.228***	0.006	0.020
	(0.086)	(0.286)	(0.079)	(0.232)	(0.146)	(0.377)
Constant	0.543***	-0.047	0.473***	0.185	0.546**	0.142
	(0.103)	(0.371)	(0.114)	(0.335)	(0.202)	(0.542)
N	294	294	294	294	315	315
r2	0.32		0.39		0.06	
Pseudo r2		0.25		0.33		0.04

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table 13: Determinants of lending decision (RL)

	Model 1		Model 2		Model 3		Model 4	
Lending choice γ	ols	probit	ols	probit	ols	probit	ols	probit
$Chosen$	0.032	0.072	0.055	0.176	0.047	0.146	0.075	0.268
	(0.041)	(0.141)	(0.041)	(0.141)	(0.039)	(0.145)	(0.094)	(0.316)
$Safe$	0.314***	0.901***	0.242***	0.713***	0.371***	1.149***	0.043	0.192
	(0.055)	(0.149)	(0.062)	(0.175)	(0.046)	(0.202)	(0.080)	(0.321)
$Full$	0.029	0.105	0.037	0.128	0.012	0.027	0.050	0.216
	(0.050)	(0.162)	(0.040)	(0.136)	(0.041)	(0.160)	(0.122)	(0.439)
$Length_{t-1}$	0.038***	0.153***	0.012	0.069	0.017*	0.085**	0.010	0.087
	(0.008)	(0.042)	(0.008)	(0.049)	(0.009)	(0.041)	(0.009)	(0.075)
$DefaultHist_{t-1}$	-0.408***	-1.537***						
	(0.072)	(0.267)						
$HighDefault_{t-1}$			-0.389***	-1.139***				
			(0.075)	(0.249)				
$FreerideHist_{t-1}$					-0.366***	-1.156***		
					(0.051)	(0.191)		
β_{t-1}							0.509***	1.462***
							(0.123)	(0.382)
Constant	0.585***	0.581**	0.556***	0.157	0.465***	-0.112	0.211*	-0.956***
	(0.087)	(0.270)	(0.085)	(0.256)	(0.058)	(0.180)	(0.119)	(0.411)
N	444	444	444	444	444	444	209	209
r2	0.38		0.37		0.41		0.28	
Pseudo r2		0.32		0.30		0.34		0.23

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table 14: Determinants of lending decision (ID)

Lending choice γ	Model 1 ols	Model 1 probit	Model 2 ols	Model 2 probit	Model 3 ols	Model 3 probit	Model 4 ols	Model 4 probit
$Chosen$	0.180***	0.474***	0.186***	0.482***	0.153**	0.455***	0.140	0.454
	(0.0475)	(0.135)	(0.0491)	(0.139)	(0.0518)	(0.154)	(0.0965)	(0.277)
$Safe$	-0.108	-0.292	-0.109	-0.328	-0.136	-0.407	0.149	0.508
	(0.112)	(0.308)	(0.123)	(0.336)	(0.0908)	(0.278)	(0.104)	(0.313)
$Full$	0.0435	0.137	0.0403	0.132	0.0719	0.217	0.108	0.411
	(0.0788)	(0.212)	(0.0751)	(0.205)	(0.0789)	(0.235)	(0.0888)	(0.272)
$Length_{t-1}$	0.0483***	0.198***	0.0433***	0.196***	0.0292**	0.130**	0.0124*	0.0793
	(0.0108)	(0.0445)	(0.0132)	(0.0444)	(0.0126)	(0.0535)	(0.00622)	(0.0576)
$DefaultHist_{t-1}$	-0.230	-0.665						
	(0.178)	(0.505)						
$HighDefault_{t-1}$			-0.189	-0.615*				
			(0.132)	(0.363)				
$FreerideHist_{t-1}$					-0.393***	-1.097***		
					(0.104)	(0.276)		
β_{t-1}							0.445***	1.234***
							(0.136)	(0.402)
Constant	0.490**	-0.0501	0.443***	-0.131	0.553***	0.0844	0.0182	-1.535***
	(0.191)	(0.522)	(0.141)	(0.375)	(0.124)	(0.331)	(0.143)	(0.463)
N	483	483	483	483	483	483	212	212
r2	0.172		0.163		0.263		0.265	
Pseudo r2		0.15		0.15		0.22		0.23

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Appendix C

1 The Model

1.1 Case with complete information

Let us assume that each group consists of a borrower i and k identical lenders l_k where $k = \{1, 2\}$. We denote with γ_k the probability that lender k accepts the loan request. In a first step we present the equilibrium in the setting with complete information for the finite-horizon and the infinite-horizon games, then we relieve this assumption and do not let the lenders know the risk level of the project, α, nor the borrower's discount factor, δ. All players observe the outcome of all previous stages before the current stage begins. We assume that all players are risk neutral.

1.1.1 The finite-horizon game

In a game with finite horizon, lenders' problem is to decide whether to accept or deny the borrower's request for funding (with probability γ_k) subject to the borrower's incentive compatibility constraint. As all players know when the game will come to an end, they can use backward induction strategies. In particular, once the project has succeeded, the borrower (player i) will choose to repay or not by comparing her profit in both cases. She will prefer to repay her debt rather than free-ride if and only if the following constraint is satisfied:

$$\Pi_{B,repay} \geq \Pi_{B,default} \tag{11}$$

If the borrower chooses to request the entire amount to one lender at the time (playing *Full*), condition 11 is only satisfied for $D(1+r) \leq 0$. It is straightforward to see that this condition implies that the borrower will always default in this type of game, by choosing to free-ride on the loan. In this case of course, the amount repaid $D(1+r)$ is equal to zero.

When asked to enter the game, the lender's maximization problem is to choose whether or not to lend, that is $\gamma_k = 1$ or $\gamma_k = 0$ ($k = \{1, 2\}$). We proceed by backward induction and compute the lender's profit as follows:

$$\max_{\gamma_k} \Pi_{L,k} = \gamma_k(s - D) + (1 - \gamma_k)s \tag{12}$$

where $\gamma_k^* = 0$ is the decision which maximizes the lender's profit. Therefore, the lender's optimal strategy in the finite-horizon game is not to lend, knowing that the borrower would never repay. It is important to notice in this case that the solution of the game as presented in equation 12 is identical for both lenders. Besides, as the probability that the second lender enters the game depends upon the first lender's lending decision, by backward induction we get that, given that $\gamma_1^* = 0$ for the first lender, the second lender will automatically enter the game but will face the same maximization problem as the first lender. Thus the second lender's optimal decision is also not to lend ($\gamma_2^* = 0$). In the equilibrium of the single lending case, players thus reach the end node number 3 (Cf. figure 2, in the Appendix).

If the borrower instead opts for multiple bank lending relationships (playing *Partial*), her decision conditional on receiving funding will be exactly the same as in 11 only that S is always equal to $2s$. At end nodes 5 and 6, the amount obtained is $L = D/2$ while at end node 4 it is $L = D$. In all cases, condition 11 requires $D(1 + r) \leq 0$ and the borrower never repays.

Lenders' profit in the multiple lending setting is now $\Pi_{L,k} = \gamma_k(s - D/2) + (1 - \gamma_k)s$. Again, the solution of the maximization problem for lenders is to refuse lending. In the equilibrium of the multiple lending case, players thus reach the end node number 7.

Given the equilibria obtained above, the final payoff of the borrower is always $\Pi_B = -2s$. Thus the borrower is indifferent between choosing the single lending or the multiple lending strategy.

1.1.2 The infinite-horizon game

The game ϕ_i is repeated an infinite number of times. In the first period of this model, when the borrower takes the decision of repaying the loan or not, she compares the present value from cooperating, $V_{c,B}$ to the present value from defecting $V_{d,B}$. We solve the model in the case of a "trigger" strategy: there is no cooperation after the first defection[20]. Thus repaying today allows for cooperation in the future while defecting prevents it. If the borrower chooses to play *Full*, she asks the entire amount to one lender at the time, the incentive compatibility constraint of the borrower now becomes:

$$V_{c,B} > V_{d,B} \tag{13}$$

where

$$V_{c,B} = \sum_{t=1}^{\infty} \delta^{t-1} \left[\alpha[I - D(1 + r)] - s\right]$$

and $\delta \in [0;1]$ is the subject's time discount rate.

Defecting in each period means to receive $\alpha I - s$ in the first period and paying the fee s

[20]There might be other strategies in which lenders start punishment after a higher number of defections, or punishment for a finite number of periods. Instead we are only considering the simplest case, although it might not be a subgame perfect equilibrium.

to both lenders in all subsequent periods without receiving any loan [21]:

$$V_d = \alpha I - s + \sum_{t=2}^{\infty} \delta^{t-1}(-2s)$$

The borrower thus cooperates if the following condition is satisfied[22]:

$$\alpha > \frac{-\delta s}{\delta I - D(1+r)} \tag{14}$$

We call α^* the threshold value at which the borrower changes her decision, with $\alpha^* = \frac{-\delta s}{\delta I - D(1+r)}$ [23]. Thus we get the following decisions of the borrower in the single lending case:

$$\beta = \begin{cases} 0 & \text{if } \alpha < \alpha^* \\ 1 & \text{if } \alpha \geq \alpha^* \end{cases}$$

In the *Partial* case, she asks half of the amount to each lender, and pays the fee $S = 2s$ for sure. As a consequence, the borrower cooperates if $\alpha[\delta I - D(1+r)] > 0$, that is, $\delta > \frac{D(1+r)}{I}$. Setting $\delta^* = \frac{D(1+r)}{I}$, we get the following decisions of the borrower in the multiple lending case:

$$\beta = \begin{cases} 0 & \text{if } \delta < \delta^* \quad \forall \alpha \\ 1 & \text{if } \delta \geq \delta^* \quad \forall \alpha \end{cases}$$

In order to make their decision, lenders compare their expected value from cooperating or not. Lender l_k, $k = 1, 2$ accepts to give the loan if:

$$V_{c,l_k} > V_{d,l_k} \tag{15}$$

with

$$V_{c,l_k} = \sum_{t=1}^{\infty} \delta^{t-1} \left[\beta \alpha L(1+r) - L + s\right]$$

and

$$V_{d,l_k} = \sum_{t=1}^{\infty} \delta^{t-1} s$$

[21] Indeed, both lenders observe free-riding in the first period before taking their decision in the subsequent periods

[22] It is important to note that equation 14 is true if the borrower believes that $\gamma_1 = 1$. In turn, if the borrower doesn't receive funds then he should always choose to cooperate (see proof in the Appendix).

[23] Given our parametrization, we can expect a threshold value $\alpha^* = 0,6$ for a value of the discount factor $\delta = 0,45$. Notice that the expression on the right is negative for $\delta > \frac{D(1+r)}{I} = \delta^*$, therefore cooperation is always satisfied for $\delta \in]\delta^*; 1]$. If $\delta \in [0; \delta^*]$ the equilibrium depends on the value of α. Moreover, if $\delta = 0$ and $\alpha > 0$ then the condition is never satisfied: an extremely impatient individual behaves as if it were a one-shot game.

Expression 15 is true if $\beta\alpha > \frac{1}{1+r}$ [24]. Both the project's risk level and the borrower's trustworthiness matter in lenders' decision. The size of the loan ($L = D$ in the *Full* branch and $L = D/2$ in the *Partial* branch) does not affect the threshold of making lending profitable, however the borrower's trustworthiness is defined differently in the case of single or multiple lending (see above). Thus lenders' decision follow the condition:

$$\gamma_k = \begin{cases} 0 & \text{if } \alpha < \frac{1}{1+r} \quad \forall \beta \\ 1 & \text{if } \alpha \geq \frac{1}{1+r} \quad \text{and } \beta = 1 \end{cases}$$

If the project is too risky, the lender has no incentive to accept the borrower's request, whatever her behavior. However, if the project is safe enough, it is the borrower's behavior, that is β, which conditions lending.

We now turn to the analysis of the borrower's choice between single and multiple bank lending relationship. According to the analysis we have conducted so far, the borrower will prefer single bank lending relationships as long as the following inequality is satisfied:

$$V_{single,B} > V_{multiple,B} \tag{16}$$

with

$$V_{single,B} = \beta \left[\sum_{t=1}^{\infty} \delta^{t-1} [\alpha[I - D(1+r)] - s] \right] + (1-\beta) \left[\alpha I - s + \sum_{t=2}^{\infty} \delta^{t-1}(-2s) \right]$$

and

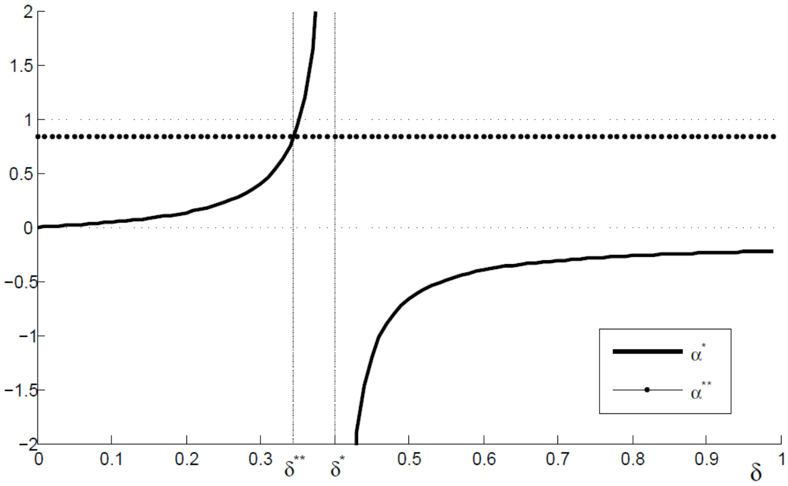
$$V_{multiple,B} = \beta \left[\sum_{t=1}^{\infty} \delta^{t-1} [\alpha[I - D(1+r)] - 2s] \right] + (1-\beta) \left[\alpha I - 2s + \sum_{t=2}^{\infty} \delta^{t-1}(-2s) \right]$$

It is easy to see that the borrower should always prefer single to multiple bank lending relationships. Indeed, the difference between the borrower's payoff under the single lending strategy as compared with the multiple lending one is either s (for a fixed value of δ, whatever the value of α) or $\delta^{t-1}s$ (for a fixed value of α).

The repeated game with complete information predicts that no contract will be formed in the case of risky or untrustworthy borrowers. On the contrary, repeated contracts will be formed between the borrower and the first lender to be chosen if the project is safe and

[24] Notice that for α high enough ($\alpha > \alpha^*$ and $\alpha > \frac{1}{1+r}$), the lenders' and the borrowers' incentives align. Moreover, for $\frac{1}{1+r} > \alpha^*$, the lender's threshold is binding. Figure 5 however shows that which threshold between the lenders' (with $\alpha^{**} = \frac{1}{1+r}$) and the borrower's is binding depends on the borrower's patience.

Figure 5: α^* and α^{**} as function of δ, single lending



Note: both thresholds are equal at $\delta^{**} = \frac{D(1+r)}{I+s(1+r)}$.
Moreover, there is no value of α^* for $\delta = \delta^*$.

the borrower has incentives to be trustworthy. Thus both riskiness and trustworthiness have to be combined to allow for cooperation to emerge.

1.2 Solving the game with incomplete information

We now relieve the assumptions that lenders know the riskiness of the project and the borrower's discount factor. Therefore, a lender has to form beliefs on the probability to be repaid in order to make his lending decision. In the finite horizon game, lenders' decisions do not depend on their knowledge of those parameter values, thus the equilibrium will also be, by backward induction, not to lend, knowing the borrower would free-ride. In the infinite horizon game instead, both the riskiness of the project and the trustworthiness of the borrower matter. In the case with complete information, the probability to be repaid is defined by $p^R = \beta\alpha$. Lenders accept to lend if the probability to be repaid is high enough: $p^R > \frac{1}{1+r}$, or, by construction, if the probability of default is low enough: $p^D < \frac{r}{1+r}$. However, with no information on β and α, lenders need to compute a proxy of the probability of default $\hat{p}_t^D$ which is reevaluated in each period. In the first period of the game, lenders have no information about the riskiness of the project, thus they use their prior $\hat{p}_0^D$ on the value of the probability of default in order to decide whether to lend or not in the first period. If the prior is below $\frac{r}{1+r}$ a lender would accept, and refuse in the alternative. In this latter case, the player will refuse to lend in all subsequent periods if he has no new information. However, if contracts are formed by him or the other lender, the player will use observed default events in order to update $\hat{p}_t^D$ in each period. Such proxy is defined by the frequency of defaults:

$$\hat{p}_t^D = \frac{\#Default_t}{t} \tag{17}$$

Lenders can both recover the number of defaults in each period using the Credit Register, which is public information[25].

Starting from a low prior ($\hat{p}_0^D < \frac{r}{1+r}$), a player can stop lending if observed defaults are too frequent. On the contrary, starting from a high prior ($\hat{p}_0^D \geq \frac{r}{1+r}$), and if some contracts are actually formed by the other two players, a lender can start giving funds after observing enough repayments. However, if both lenders start with high priors, no contracts will be formed in all subsequent periods. Therefore, introducing asymmetry of information about the project riskiness and the borrower's patience constrains lenders to reevaluate the borrower's probability to repay in each period, based on the available information.

[25] There is one way however that lenders can disentangle the borrowers' repayment behavior from the riskiness of the project. Indeed, her decision on repaying or not (β) is defined by the following rule: $\beta = 1$ if $\alpha > \alpha^*$ and $\beta = 0$ if $\alpha \leq \alpha^*$. Therefore we get the following probabilities to repay: $p^D = 1 - \alpha$ if $\alpha > \alpha^*$ and $p^D = 1$ if $\alpha \leq \alpha^*$. Thus any repayment event observed by the lender is enough to signal that the borrower will always repay if she can ($\beta = 1$). Still, we have seen that the order of the thresholds α^* and α^{**} depends on the borrowers' patience δ. The repayment event therefore contains information about α but it is ambiguous due to the uncertainty about the borrower's patience.