(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 splits the financing of one investment project across lenders or not, and whether such multiple lending is symptomatic of financial constraints or rather a well-designed strategy. By setting up a controlled laboratory experiment we are able to uncover the conditions favoring multiple versus single lending strategies of borrowers, as well as improving the probability to get funding from lenders.

Our results can be summarized as follows: first, we do find that, keeping everything else equal, risky and untrustworthy borrowers are more likely to choose multiple *vis-à-vis* single bank lending relationships. Second, the choice of multiple bank lending relationships is identified by lenders as a signal of "bad quality" and borrowers who decide to spread their funding request among several lenders suffer higher credit rationing. Third, we do observe, from the lenders' side, that being chosen as first as well as the length of the relationship positively affect the probability to lend. Finally, when information upon borrowers' 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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† LEM, Sant'Anna School of Advanced Studies and University of Namur

‡ OFCE-DRIC, GREDEG, Université Nice-Sophia Antipolis, SKEMA Business School and LEM, Sant'Anna School of Advanced Studies

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1 Introduction

Early theoretical contributions on financial intermediation suggest that borrowing from one bank is optimal as it reduces monitoring costs (Diamond, 1984) and the use 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), while this share reaches 80% for Italian firms (Detragiache et al., 2000). As most of the interactions between firms and banks are repeated through time, it may be optimal, both for firms and banks, to establish more than one link. Indeed, it has been shown 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 uncover the determinants of multiple bank links: 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), to firms with a poor credit or performance record (Farinha and Santos, 2002) and to more opaque firms (Guiso and Minetti, 2010). 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 relationship 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. 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 favoring long term relationships, 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 due 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 questions: is multiple lending explained by difficulties to build a stable relationship or rather a strategy in order to diversify the sources of credit? 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. We first design 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. 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 cooperation 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 three directions: 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, contrary to our expectations, relationship lending does not seem to have an impact on the choice between single and multiple bank lending relationships. Finally, 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, have shown that firms with higher borrowing concentration have been less hit by the credit tightening.

The rest of the paper is organized as follows. Section 2 describes the experimental design, outlining predictions. Results are reported in Section 3. Section 4 concludes.

2 The Model

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. 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 has no access to any 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 a Credit Register, as in Brown and Zehnder (2007)). Our experimental credit market involves three subjects, one borrower and two lenders. Each participant is randomly assigned to her role at the beginning of a session. The roles remain the same throughout the session, which lasted T periods. The number of periods was not disclosed to the subjects in order to prevent any backward induction strategies, and was randomly drawn for each session.

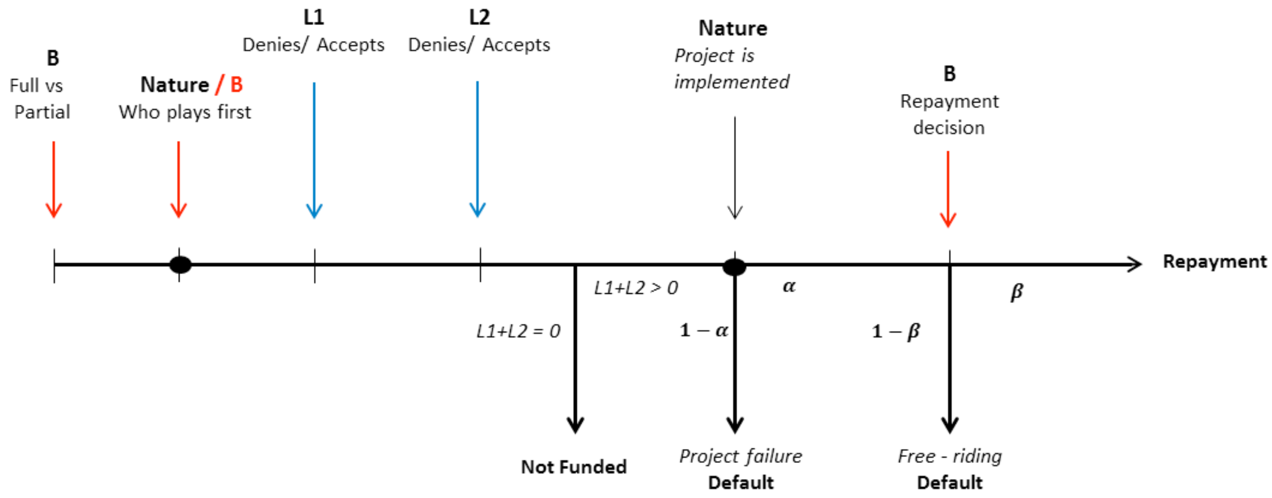
2.1 Basic Setup

We start with an ex-post moral hazard model with an infinite number of identical games. For each game ϕ_i, a borrower i 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 k identical lenders where $k = \{1, 2\}$, who 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 (mainly administrative and bureaucratic costs)[1]. We assume that the borrower has enough collateral to advance her funding request to both lenders ($c = 2s$, where $c < D$).
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 lender (*Partial* decision). This is how we design single versus multiple bank lending relationships. In the basic setup, Nature then determines who between l_1 or l_2 enters the game first, with equal probability. After receiving the application fee s, the chosen 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 will lend with probability γ_k, where $k = \{1, 2\}$[2].
Neither the borrower nor the lenders know who has been chosen to enter the game first. The lenders only know whether in the round they have been requested to enter the game or not, and the size of loan requested by the borrower.
After the first lender has made his decision, the second lender might be asked to enter the game if the borrower has obtained less than D (this is the case in the *Partial* subgame and in the *Full* subgame conditional on the first lender having denied credit). In that

[1] In other words, s represents the fee the borrower has to pay in order to open the account, or the transaction fee, and it enters the bank's turnover. The lender will receive s irrespectively of whether the loan is issued or not.

[2] For ease of notation, we call γ_1 (γ_2) the probability that the lender (randomly) chosen to play first (the lender chosen to play second) gives the loan.

Figure 1: The timeline of decisions



case, the second lender receives the application fee s and chooses to accept or deny the loan request. If the obtained amount is positive, the borrower implements the project (or the small project) that yields I (or $I/2$) with probability α and 0 with probability $1-\alpha$[3]. 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, $L = \{\frac{D}{2}; D\}$). 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. 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 decisions of each lender, however she is not able to identify l_1 from l_2.

Once the borrower has made her repayment decision, the game ends. The next game, ϕ_{i+1} is identical to the game described so far. The timeline of decisions in each game ϕ_i is shown in Figure 1.

The decision problem of the agents is displayed in Figure 5, in the appendix. In particular,

[3] If the borrower has obtained D he cannot implement two small projects, he 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.

the borrower's profit will be:

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

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

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

and

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

2.2 Case with complete information

In a first step we present the equilibrium in the setting with complete information, then we will 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.

2.2.1 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 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:

$$\Pi_{B,repay} \geq \Pi_{B,default} \tag{1}$$

If the borrower chooses to request the entire amount to one lender at the time (playing *Full*), condition 1 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 (therefore the amount repaid $D(1+r)$ is equal to zero).
When asked to enter the game, the lender's maximization problem is to choose a value of γ_k ($k = \{1,2\}$), his probability to give the loan to the borrower, which maximizes his profit.
We proceed by backward induction and compute the lender's profit as follows:

$$\max_{\gamma} \Pi_{L,k} = \gamma_k(s - D) + (1 - \gamma_k)s \tag{2}$$

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, as the probabilities that the two lenders are chosen to play first are i.i.d., the solution of the game as presented in 2 is identical for both lenders. Besides, as the probability that the second lender will enter the game depends upon the decision of lending of the first lender, 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 finding his optimal solution in not-lending, himself ($\gamma_2^* = 0$). In the equilibrium of the single lending case, players thus reach the end node number 3.
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 1 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 1 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.

2.2.2 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 to the present value from defecting V_d. We solve the model in the case of a "trigger" strategy: there is no cooperation after the first defection. 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:

$$V_{c,B} > V_{d,B} \tag{3}$$

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 to both lenders in all subsequent periods without receiving any loan [5]:

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

the borrower thus cooperates if the following condition is satisfied:

$$\alpha > \frac{-\delta s}{\delta I - D(1+r)} \tag{4}$$

We call α^* the threshold value at which the borrower changes her decision, with $\alpha^* = \frac{-\delta s}{\delta I - D(1+r)}$ [6]. 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,

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

[6] 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.

$\delta > \frac{D(1+r)}{I}$. 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 his decision, the lender compares his expected value from cooperating or not. The lender accepts to give the loan if :

$$V_{c,L} > V_{d,L} \tag{5}$$

with

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

and

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

Expression 5 is true if $\beta\alpha > \frac{1}{1+r}$ [7]. 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, for $k = 1, 2$ 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 (defined by her discount factor δ) that conditions lending.

We now turn to the analysis of 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:

$$V_{single,B} > V_{multiple,B} \tag{6}$$

[7] 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 4 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.

with

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

and

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

Figure 2: Single vs Multiple lending choice, $\beta = 1$

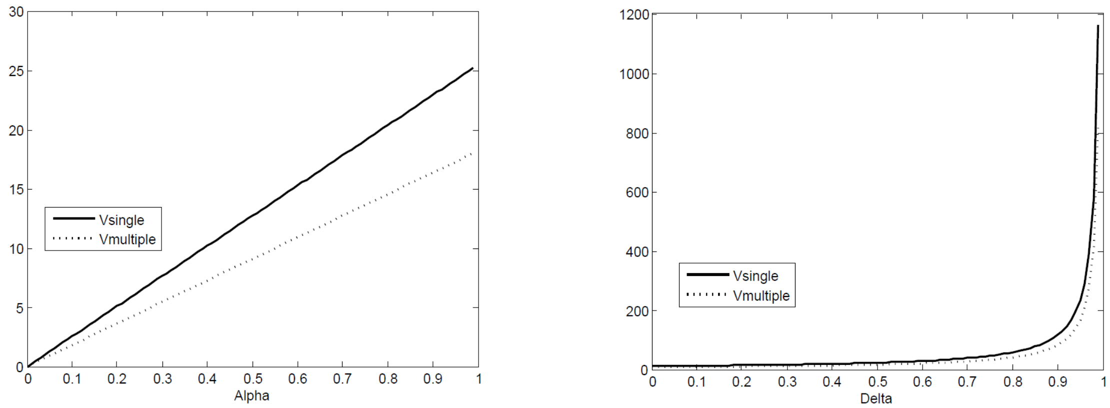
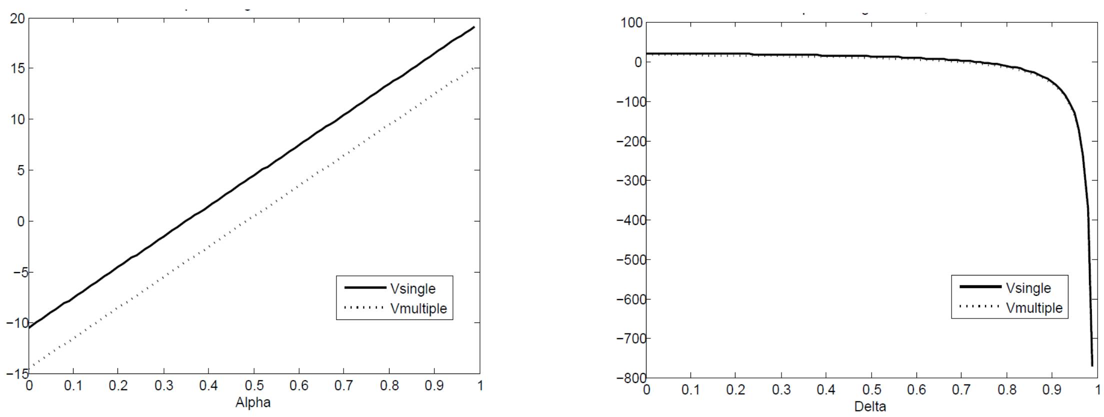
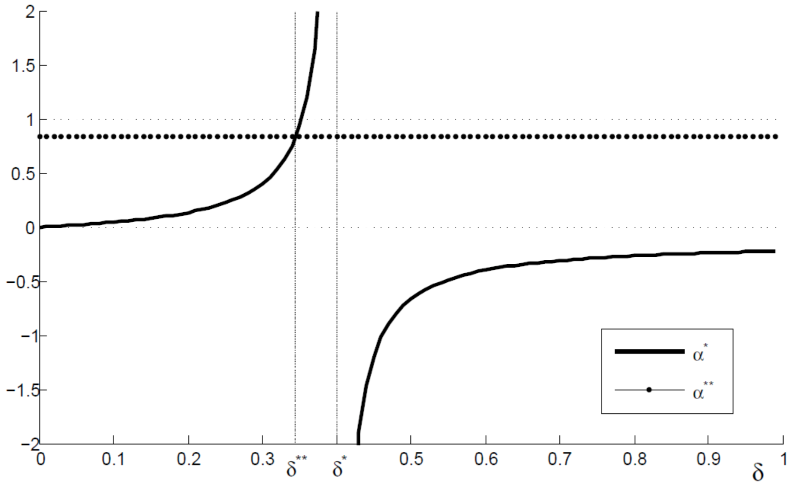


Figure 3: Single vs Multiple lending choice, $\beta = 0$



With few algebraic passages it is easy to see that the borrower should always prefer single to multiple bank lending relationships if she believes that $\gamma_1 = 1$, that is she will receive credit in the first period. What may further affect such decision is the possibility that the probability to receive credit in the first period depends on the size of the loan request. However, we have seen above that loan size does not affect lending, if the

Figure 4: 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 $\delta = \delta^*$.

borrower repays. Figures 2 and 3 show that keeping the borrower's repayment strategy riskiness level fixed, the difference in her payoffs when choosing a single or multiple lending strategy is marginal whatever the value of δ. However, when considering such difference across riskiness levels, keeping the borrower's discount factor fixed (figures on the left), the single lending bonus is increasing in the value of α when the borrower is trustworthy. Therefore the safer the borrower's profile, the higher the incentive to choose single lending. Untrustworthy borrowers in turn benefit from a fixed bonus when choosing single lending. Indeed, single lending reduces the cost associated to the loan request as long as the first lender accepts to give funding, which is the case only in the first period when the borrower is untrustworthy. We can therefore introduce the following hypotheses:

Hypothesis 1: *The single lending strategy strictly dominates the multiple lending one.*

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

2.3 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 accepts to lend if the probability to be repaid is high enough: $p^R > \frac{1}{1+r}$. However, with no information on β and α, lenders need to compute a proxy $\hat{p}_t^R$ 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* $\hat{p}_0^R$ on the value of the probability to be repaid in order to decide whether to lend or not in the first period. If the prior is above $\frac{1}{1+r}$ 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 compute his belief over p^R in each period. The frequency of defaults is the proxy used by lenders:

$$\hat{p}_t^R = \frac{Default_t}{t} \tag{7}$$

Lenders can both recover the number $Default_t$ in each period using the Credit Register, which is public information[8]. Starting from a high prior ($\hat{p}_0^R > \frac{r}{1+r}$), a player can stop lending if observed defaults are too frequent. On the contrary, starting from a low prior ($\hat{p}_0^R \leq \frac{r}{1+r}$), 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 low priors, no contracts will be formed in all subsequent periods.
Introducing asymmetry of information about the project riskiness and borrower's patience constrains lenders to reevaluate the borrower's probability to repay in each period, based on the available information. We can therefore introduce the following hypothesis:

Hypothesis 2: *There is a negative relation between observed defaults and the probability to get funds.*

3 Treatments

The experiment was implemented at the EXEC, University of York in October 2011. All subjects were volunteers, and each subject could only take part in one session. All

[8]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: $p^R = \alpha$ if $\alpha > \alpha^*$ and $p^R = 0$ 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.

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[9]. Before the 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 an 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. In each treatment, we identify the borrower as player A, while the two lenders as player B and player C. Treatments were constructed as follows. In the *Random treatment* (hereafter "RA", the baseline treatment), who plays first between player B and player C is randomly set[10]. In the *Relationship lending treatment* (hereafter, "RL"), at the beginning of each round, player A is asked to choose to play first with player B or player C. In the *Relationship lending treatment* (hereafter, "RL"), at the beginning of each round, player A is asked to choose to play first with player B or player C. 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 entered this particular round of play.

For each treatment, we ran two separate sessions[11], a safe project session (α_{low}) and a risky project one (α_{high})[12]. Therefore, we ran a total of six sessions (see Table 1 below).

3.1 Safe vs Risky treatments

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 safe treatments ($\alpha = \alpha_{high}$) from the beginning. In a setting with asymmetric information about α, through repeated interaction, players should adapt their beliefs over the borrowers' overall quality (combination

[9]See the instructions in the Appendix. We only provide here the instructions for the "Random" treatment. Instructions for the "Relationship Lending" and the "Information Disclosure" treatments are also available upon request.

[10]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.

[11]Each participant played in only one session

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

Table 1: Treatments

Session 1 Random α low	***Session 2*** Random α high
Session 3 Relationship Lending α low	***Session 4*** Relationship Lending α high
Session 5 Information Disclosure α low	***Session 6*** Information Disclosure α high

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 "Cooperation 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:

Hypothesis 3 (Risk): *The number of contracts should be higher in the safe than in the risky treatments. Indeed, the share of accepted requests should increase over periods in the case of safe treatments and decrease in the case of risky treatments .*

3.2 The Random treatment

The game with incomplete information predicts that both lenders should converge to the same lending rate[13], if they have the same priors. If their priors on the probability to be repaid differ, players' lending decision might differ as well. However, differences should not be systematic: not knowing their position in the game their decisions should be the same when they play first or second. Therefore, we expect $\gamma_1 = \gamma_2$. Moreover, through repeated interaction lenders should also adapt their behavior to the observed frequency of default. As a consequence, overall, we should expect a higher credit volume in the sessions with safer projects. The model also predicts that all borrowers choose single lending. Finally, loan size should not have any impact on lenders' decision. Specific to this treatment, we should observe that:

Hypothesis 4 (Anonymity): *The probability to get funding from the first or second*

[13]By lending rate we mean the share of accepted loan requests, not their cost, the latter being always fixed in our setting.

lender should be equal.

3.3 The Relationship Lending treatment

We modify the above described game (defined as the *Random treatment*), by allowing the borrower to choose l_1 or l_2 to enter the game first, at the beginning of each round of play, instead of Nature. Furthermore, lenders are informed of their position in the game. We define as p_{chosen_1} the probability that player l_1 is chosen as first (such that $p_{chosen_2} = 1 - p_{chosen_1}$), with p_{chosen_1} being endogenously determined by the borrower's choice in each period. The game then proceeds exactly as in the Random Game. However, this time, when one lender receives a loan request from the borrower, his decision about lending not only will depend upon the borrower's past repayment behavior (that is, by his beliefs over α and β), but also upon the fact that the borrower has *voluntarily* chosen him instead of the other lender.

Assuming complete information, in the finite-horizon game, the borrower's incentive-compatibility constraint will be exactly as in equation 1: therefore, her optimal decision will be to default. Besides, she will also be at most indifferent between choosing one lender instead of the other. Therefore, lenders' optimal strategy under the finite-horizon game is to deny credit, knowing that the borrower would never repay.

However, with the repetition of the game, the issue for lenders becomes to know whether they gain from being chosen to play first or not. As before, if the project is too risky or the borrower untrustworthy ($\beta\alpha < \frac{1}{1+r}$), their decision will be to deny funding, whatever their position in the game. However, if the project is safe enough, and the borrower chooses the single lending strategy, she will form a contract with the first lender to play, and the second lender will not enter the game. In that case, the first lender makes a positive profit and the second lender no profit at all. Therefore, both lenders compete in order to play first, that is increase their probability to be chosen $p_{chosen,k}$, for $k = a, b$. However, because lenders are only incentivized to increase $p_{chosen,k}$ in the profitable range of α, where they both would accept to give the loan anyway, there is no way they can differentiate one from the other. Therefore the predictions of the relationship lending game are exactly the same as the random one.

Interesting effects can however emerge when we consider the game with imperfect information, as implemented in the experiment. Indeed, when lenders are uncertain about the default probability, they might interpret repeated matching as a signal of trustworthiness, and increase their expected repayment probability as a consequence. This can be tested by measuring the probability to give funds conditional on the length of relationship between the borrower and one of the lenders.

The possibility to identify the lender and choose which lender plays first (in the *RL* and *ID* treatments) should increase lending and repayment behavior probability, as well as relationship length: as trust is built up both players have higher incentives to cooperate. Relationship lending could therefore mitigate risk: if the borrower's fixed quality element is poor (the project is risky), its endogenous element is improved (the borrower is trustworthy). Thus a trade-off between risk and trustworthiness could help improve risky borrowers' access to funding.

In the case that both lenders do not take their decisions simultaneously, but sequentially, additional information can be inferred from the unfolding of the stage game. This is the case in the "Full" branch, when l_1 denies funding and the borrower goes to the second lender. The second lender knows his position in the game and thus this is the only case in which the action of l_1 is disclosed to l_2 (if l_1 had accepted, l_2 would not play). This indirect information might also affect γ_2: the second lender can reevaluate the probability to be repaid based on the decision of the first lender.

Hypothesis 5 (Lender order): *The probability to get funding from the first or second lender should be different in the full branch only. However, being chosen should not affect the probability to give funds.*

3.4 The Information disclosure treatment

In this third treatment lenders participating in the round are told when default is caused by the borrower's voluntary free-ride. As commented above, after being given such information, the lender should stop lending at all: whatever the value of α, the probability to be repaid in all subsequent rounds is expected to be zero, if $\beta = 0$. This effect should act as an enforcement device and increase borrowers' repayment probability, and, in turn, credit volume conditional on no free-riding history should be relatively higher than in the RL treatment. The possibility given to lenders to disentangle riskiness from trustworthiness in the Information Disclosure treatment should therefore drastically limit free-riding behaviors: borrowers could no longer use the benefit of the doubt to free-ride.

Hypothesis 6 (Free-riding disclosure): *Free-riding behaviors should be lowest in the ID treatment as compared to the RA and RL ones.*

Corollary: *The probability to give funds (γ_k) should be highest in the ID treatment as compared to the RA and RL ones.*

4 Results

In this section we report the results of the six experimental sessions. After presenting descriptive statistics over the entire sample as well as by session, we investigate further the determinants of players' choices.

4.1 Descriptive Statistics

We start investigating our data with summary statistics in order to get a first intuition on players' behavior. Figure 6 in the Appendix shows borrower's repayment behavior, while figure 8 reports the lending decision by the first and the second lender. By comparing the three figures, it is straightforward to see that lenders' behavior displays a higher variability than borrowers'. While the distribution of borrowers' decisions is clearly unimodal, or, in other words, we observe a very low degree of strategic default, the distribution of lenders' decisions is, instead, bimodal. Indeed, although a significant share of lenders always accept the borrowers' request, most of them deny funding most of the time.

When it comes to multiple vs single lending strategies, Hypothesis 1 seems verified: the full choice is observed most of the times (above 68% in all sessions), although not always (see tables 4 to 6).

Next we test whether the size of the loan request affects lenders' decision: when we condition γ on the choice of single versus multiple bank lending relationship, we see that lending rates increase with loan size (figure 11, bottom).

We also perform a series of paired t-tests in order to compare different values of γ both across lenders (by order) and treatments. When chosen as first, 48% of lenders accepted the funding request , while only 28% gave credit when chosen as second. Such difference is statistically significant. Results from the t-test don't change when we restrict the sample only to the Relationship Lending and Information Disclosure treatments, where the borrower's choice upon which lender she wants to address her funding request first is made voluntary. Both t-tests thus run in favour of the argument that lenders tend to positively respond to borrowers' willingness to cooperate. At the same time, however, they confute the predictions we made under Hypothesis 4: the order in which lenders enter the game matters for the borrower's probability to receive funding.

We then relate lenders' order and their willingness to lend to the borrowers' choice in terms of single versus multiple bank lending relationships. Further, we find that the order of requests matters only when the borrower has chosen the single-lending strategy (as proxied by the *Full* choice), while we find no statistically significant difference between the willingness to lend by the first and the second lender when the borrower has chosen the multiple-lending strategy (as proxied by the *Partial* choice).

4.1.1 Safe vs risky treatments

We then compare players' decisions across treatments. Although borrowers' repayment rate is always high (above 70% in all sessions), they repay more in safe treatments compared to risky ones. The effect of riskiness on players' decisions is therefore in accordance with Hypothesis 3. This is further confirmed by figures 7 and 10 (top): lenders are able to identify borrowers' probability to repay given that they mostly refuse lending in the risky treatments, while they accept significantly more[14] in safe treatments. Moreover, figure 9 compares the evolution of lenders' decisions over time in the case of safe or risky treatments. It is very clear that starting from a similar prior ($\gamma_0 = 0,6$), lenders adapt their beliefs over the probability to be repaid over time, following expectations from the game with incomplete information. In the case of the safe treatments, with a low rate of default, lending rates are very stable and comprised between 60 and 80%. In the case of risky treatments on the contrary lending rates are strictly decreasing, reaching 20% at the end of the game. Indeed, it takes time for lenders to learn the risk level of the borrower. Table 4 presents summary statistics for our two corresponding sessions when the order of the lenders in each period is randomly determined (Random Treatment-α_{low} and Random Treatment-α_{high}[15]). As shown in columns (5) and (6), we test whether mean differences across levels of riskiness are significant, for each decision variable. Not surprisingly, there is more cooperation between players in the safe sessions, and the mean distribution of all variables is significantly higher in the α_{high} session than in the α_{low} one. In the safer session, borrowers are more willing to repay and lenders are more willing to lend. This is further confirmed by the fact that in the safer session, even in the absence of relationship lending, borrowers experience less credit rationing (the share of *Rationed* borrowers is significantly lower)[16].

Moreover, borrowers exogenously endowed with a risky project are more willing to opt for multiple bank lending relationships than safe borrowers (the share of *Full choice* is lower). However, the analysis here doesn't allow us to understand whether this result is driven by risk-diversification motives or, rather, by strategic behavior. We will specifically test the determinants underlying borrowers' choices in the following section.

Finally, when lenders don't know their position in the game (RA sessions), the first and second lender's behavior should not differ systematically (Hypothesis 4). If we find that in the risky session there is no significant difference between the willingness to lend of the first and the second borrower, this difference becomes significant in the safe one, against theoretical expectations.

4.1.2 Random vs relationship lending treatments

Introducing relationship lending (RA vs. RL, figure 10, middle) also affects lenders' willingness to lend. As in Petersen and Rajan (1994), when relationship lending is possible, we observe a stronger commitment from the parts. In particular, we find that the prob-

[14] Mean tests confirming the differences across treatments are shown in tables 4 to 6 and commented below.

[15] Tables 5 and 6 show that similar results are found in the Relationship Lending and Information Disclosure treatments.

[16] The construction of all variables is detailed in the Appendix.

ability to be given funds increases in RL treatments as compared with RA ones, and repayment rates (figure 11) are higher when the lending relationship is stable.

The intuition behind these results is that, as theory predicts, in a stable relationship lenders acquire more information on the borrowers' riskiness and creditworthiness. Moreover, being chosen here plays a role, along two directions: from one side, being chosen increases the lending rate; from the other, not being chosen seems to trigger a retaliation behavior. Indeed, the lender who enters the game by default (because the first lender denied funding) is less likely to give the loan as compared to when the decision is randomly set. Results from table 5 also indicate that relationship lending doesn't seem to mitigate moral hazard behavior: repayment rates across risk levels are not statistically different. A possible explanation for this latter evidence is that the repayment rate is already very high (greater or equal than 80%) in both sessions.

Furthermore, the share of single bank lending relationships in the risky session of the Relationship Lending Treatment is significantly lower than the share of single bank lending relationships in the risky session of the Random Treatment. A possible explanation is that borrowers need to signal their creditworthiness to lenders in order to increase their probability to receive funds. In the random treatment they only have one means to do this and it is by choosing a single lending strategy. In the RL treatments however the signaling process is more directly made by repeatedly choosing the same lender. In that case, the choice of single vs multiple lending strategies loses its signaling importance. We will further test this statement in the regression analysis.

4.1.3 Relationship lending vs Information Disclosure treatments

The Information Disclosure treatment only differs from the Relationship Lending Treatment in the type of information lenders receive about the borrower's behavior. Indeed, while in the Relationship Lending treatment the source of default - whether it depends upon project's failure or borrower's unwillingness to repay - was kept undisclosed, in the ID sessions, instead, it is revealed to the lender suffering losses.

Disclosing information (RL vs ID, figure 10, bottom) also affects lenders' willingness to lend, however, not exactly as predicted in Hypothesis 6: as predicted, lending rates are higher than the RL treatment in risky sessions, however they are lower in safe ones. This latter element can be related to perfect monitoring: when free-riding is observed early in the game, lenders refuse to cooperate in all subsequent periods, bringing mean lending rates down. On the contrary, in risky sessions, lenders are told when default is related to project failure, and show leniency in that case. Such behavior is consistent with model predictions: if default is due to free-riding ($\beta = 0$), the probability to be repaid is null. However, if default is due to risk, lenders' belief over the probability to be repaid is decreased, but positive. Moreover, repayment rates (β) are not significantly higher when information is disclosed. This is because, as already stated above, they are already very high in the other sessions. Summary statistics for our two corresponding sessions, the Information Disclosure Treatment-α_{low} and Information Disclosure treatment-α_{high} and ttests are shown in table 6. The main result of these tables is that there is no significant difference between the share of single versus multiple bank lending relationships across sessions.

This first look into the data points that risk, loan size and lender order might be important determinants of lenders' decisions. On the borrower side, risk, but also the stability of the relationship with a lender seem to matter.

4.2 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]. Besides running the analysis over the entire sample, we compare how subjects' behavior changes across treatments using subsamples.

4.2.1 The borrower's decisions

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 the borrower's trustworthiness (β), or lenders' behavior in the previous round also impact such 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[18]:

$$Fullchoice_{i,t} = \theta_0 Rationed_{i,t-1} + \theta_1 \beta_{i,t-1} + \theta_2 Safe + \theta_3 Final_{Period} + \epsilon_{i,t} \quad (8)$$

where $Rationed_{t-1}$ is a dummy which takes value one if the borrower has been credit rationed in the previous round[19] and β is a dummy which is one if the borrower has

[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.

[18] Standard errors are 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.

voluntarily repaid in the previous period. We also include controls for riskiness ($Safe$ is equal to one in α_{high} sessions) and time ($Final_{period}$)[20]. Results for equation 8 are shown in table 7. 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). However running the regression over treatment subsamples reveals that such effect is significant only for the Relationship Lending and Information Disclosure treatments. Therefore, when reputation building is possible, multiple bank lending relationships are used as a means to overcome credit rationing. On the contrary, in the Random treatment, that is, in absence of relationship building, dishonest borrowers are more likely to establish multiple bank lending relationships (θ_1 is positive and statistically significant).
Evidence from table 7 suggests that borrowers choose multiple lending for two reasons, each one holding under different conditions. From one side, when borrowers have the possibility to establish long-term relationships, they will be more likely to opt for multiple bank lending relationships if they have experienced credit restrictions, irrespectively of their riskiness and creditworthiness. On the other side, when relationship lending is not allowed, the choice of multiple versus single bank lending relationships is closely related to the borrower's trustworthiness.

Table 7, however, is not enough to draw the whole picture. Indeed, we also need to fully understand what explains credit rationing in order to identify further the link between credit rationing and the choice of single versus multiple bank lending relationships. We therefore estimate how the probability of being credit rationed is affected by a set of variables at the firm level as follows, for each borrower i and period t:

$$Rationed_{i,t} = \theta_0 Rationed_{i,t-1} + \theta_1 Rationed_{i,t-2} + \theta_2 \beta_{i,t-1} + \theta_3 Full_{i,t} + \theta_3 Safe + \theta_4 Final_{Period} + \epsilon_{i,t} \tag{9}$$

Results for equation 9 are displayed in table 8. First, we see that credit rationing is strongly autocorrelated : borrowers rationed in the previous periods have a higher probability to stay rationed in period t. Then, the main result is that, controlling for project riskiness, the probability of being credit rationed is negatively and significantly correlated with the choice of single bank lending relationships, under all treatments: the more the borrower has concentrated her borrowing, the less credit tightened she will be. What this finding suggests is that lenders perceive multiple bank lending strategies as a signal of bad borrower quality, and protect themselves by denying credit. More importantly, when relationship lending is possible (that is, both in the Relationship Lending and the Information Disclosure treatments), the more honest the borrower is, the less likely she will be to experience credit rationing. The link is not significant in the Random treatment. We

[20]The time dummy, $Final_{period}$, is equal to one for the second half of the session.

interpret this result as further evidence of the impact of relationship lending on lenders' behavior: through repeated interaction, the lender gets a more precise evaluation of the borrower's quality, both in terms of riskiness and trustworthiness. The latter is rewarded by relaxing credit conditions.

We also perform some robustness checks. In particular, table 9 shows the determinants of borrowers' switches from single to multiple lending. In doing so, we regress the number of switches the borrower makes throughout the game on a series of variables like credit rationing in past periods, borrower's repayment behavior in past periods, and we control for project riskiness. In line with previous findings, results show that borrowers are more likely to switch between single and multiple bank lending relationships if they have experienced credit rationing in the past or if they have been dishonest. These effects are significant across all treatments.

4.2.2 Lenders' decisions

In what follows, we study the determinants of the lenders' decision. In a fist step, we analyze the decision of the first lender, and in a second step we will focus on the Relationship Lending and Information Disclosure treatments in order to test the effect of being chosen to play first. 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:

$$\gamma_{1,j,t} = \theta_0 Full_{i,t} + \theta_1 Default_{hist,i,t-1} + \theta_2 Safe + \theta_3 Final_{Period} + \epsilon_{j,t} \tag{10}$$

Results are displayed in table 10. 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 ($Default_{hist}$, a dummy 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 and time.

As expected by Hypothesis 2, we observe a negative relation between observed defaults and the probability that lenders give funds, in all treatments but the Information Disclosure one. We will study below other possible determinants for the lending decision in this treatment.

Moreover, we find that in the Relationship Lending treatment, safer borrowers get more funds (θ_2 is positive and significant) while in the two other treatments (Random and Information Disclosure) 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 Relationship Lending and the Information Disclosure treatment (tables 11 and 12, 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 number 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 2.3, that is $\frac{r}{1+r}$. Then $Freeride_{hist}$ (Model 3), is a dummy which takes the value of 1 if the borrower has ever free-ridden and β (Model 4), the borrower's trustworthiness in the previous period.

Results reveal that $Default_{hist}$, $High_{default}$ and $Freeride_{hist}$ all have the same predictive in the Relationship Lending treatment, while using β reduces the goodness of fit. This reveals that lenders have memory : the lender bases his lending decision not only upon borrower's behavior in the past period, but on her overall credit history. If in the Relationship Lending treatment lenders cannot identify the type of default (thus $Default_{hist}$ and $Freeride_{hist}$ have the same predictive power), in the Information Disclosure 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 11 and 12 also reveal that besides the credit history, the determinants of the lending decision differ in both treatments : in the Relationship lending treatment, when the asymmetry of information is high, being chosen to play first or having a stable relationship with the borrower don't impact the lenders' decision. What do are the "objective" elements, that is the riskiness level and the credit history. In the Information Disclosure it is the exact opposite. What matter are the borrower's trustworthiness, as we have noted above, but also the stability of the relationship. 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.

Finally, we investigate what drives borrowers' preferences towards one of the lenders. The regressions in table 13 shows that lenders' behavior can affect their probability of being chosen: the more they are willing to give credit, and the more stable the relationship, the more likely it is that the borrower will choose them in the following period.

5 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 the choice of multiple bank lending relationship is highly correlated with borrowers' untrustworthiness only if relationship lending is not possible. When we allow for repeated interactions between lenders and borrowers, we show instead that multiple bank lending relationships are preferred by those borrowers who have experienced credit rationing in the past, irrespectively of their trustworthiness. 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. 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 lending, 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 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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6 Appendix

Figure 5: The game tree

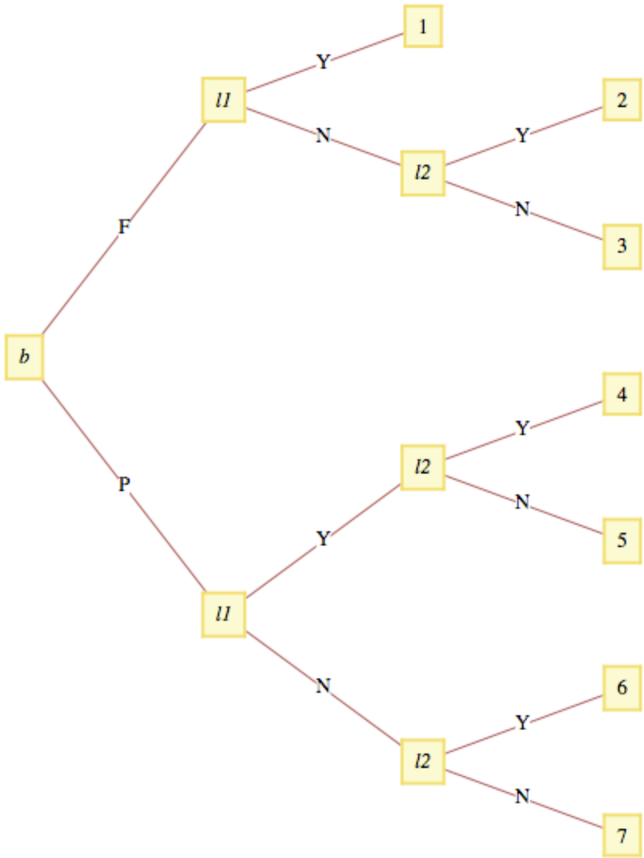
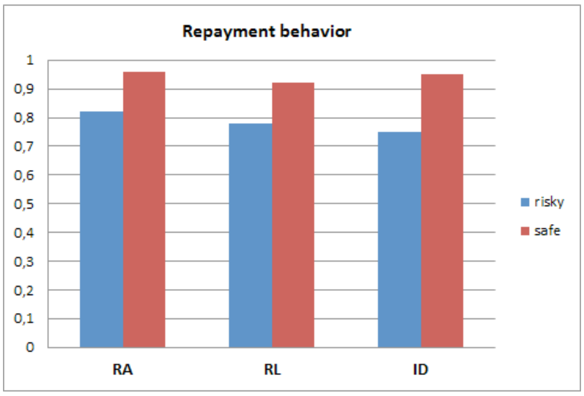


Figure 6: Borrowers' repayment decision (Left : by session ; Right: overall distribution)



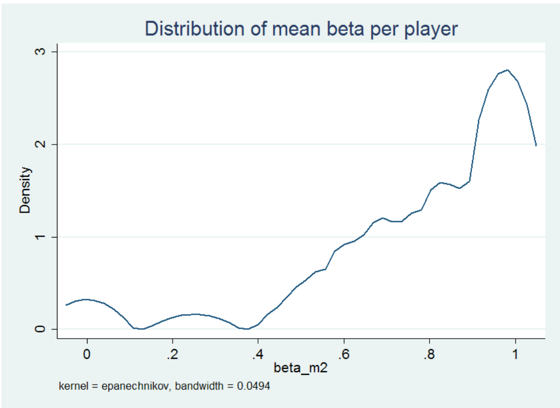


Table 2: Construction of variables used in the regressions

Variable	Description
$Rationed_t$ (v)	= 1 if the borrower was denied credit by at least one lender in the period
$Safe$ (d)	= 1 for sessions with a high value of α
$Final_{period}$ (d)	= 1 for the second half of the game
$Default_{hist,t}$ (v)	= 0 if the borrower has never defaulted up to period t = 1 if the borrower has defaulted at least once since the game started
$Freeride_{hist,t}$ (v)	= 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
$Length_{first,t}$ (v)	in sessions allowing for relationship lending, length of relationship between the chosen lender and the borrower in number of periods (the lender gives the loan and the borrower repays)
$High_{default,t}$ (v)	= 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

Note : (d) Dummy variable ; (v) variable.

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 $k = \{1,2\}$

Figure 7: Lenders' acceptance rate by lender order; by session

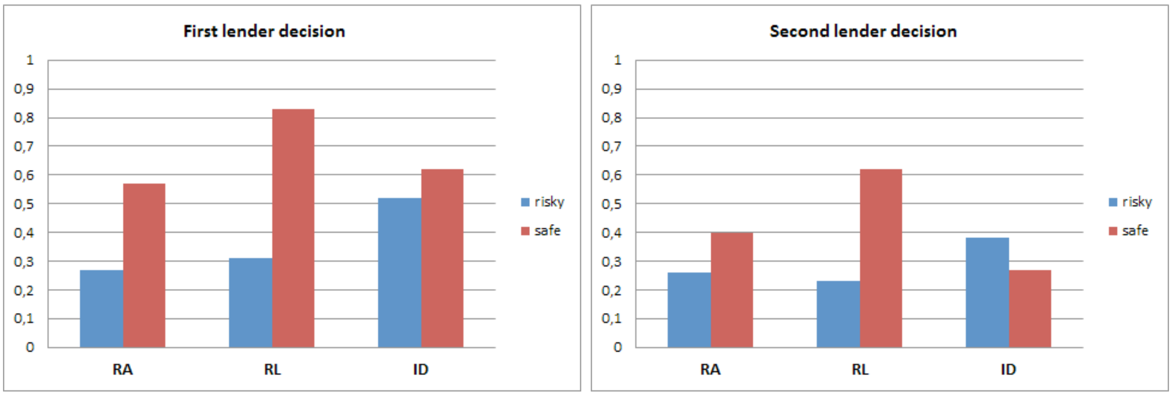


Figure 8: Lenders' acceptance rate by lender order; overall distribution

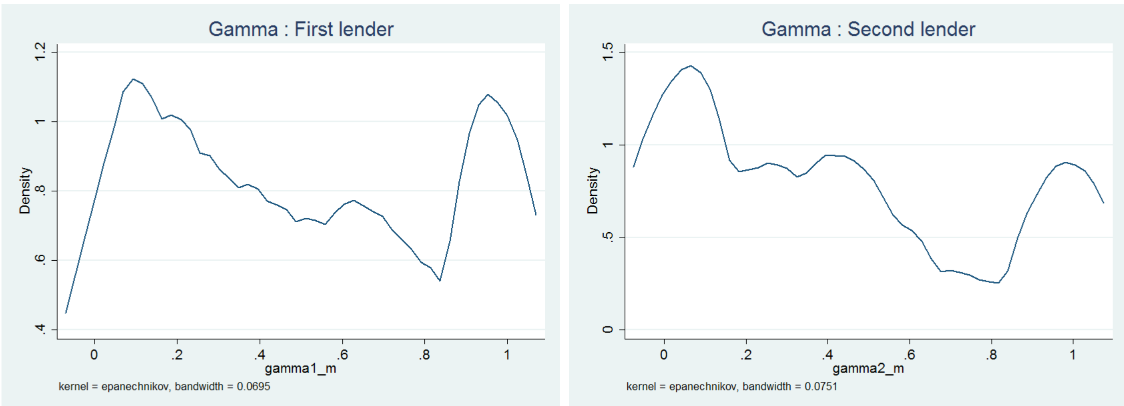


Figure 9: Evolution of lending over time by riskiness level

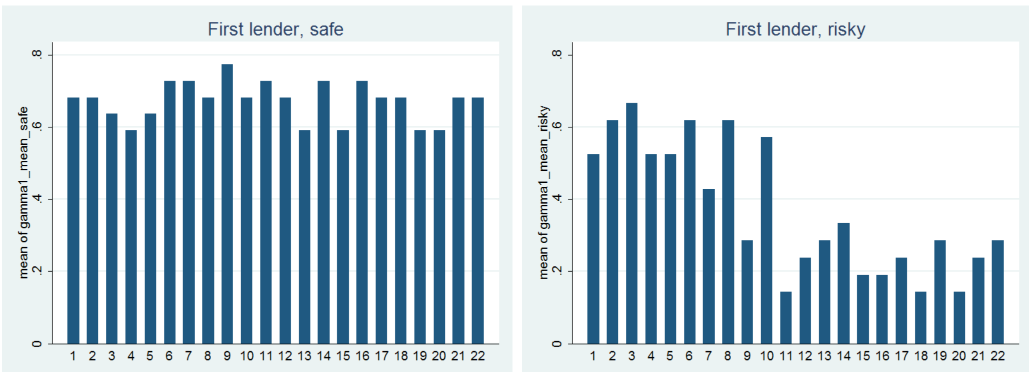


Figure 10: Distribution of lenders' decisions across treatments

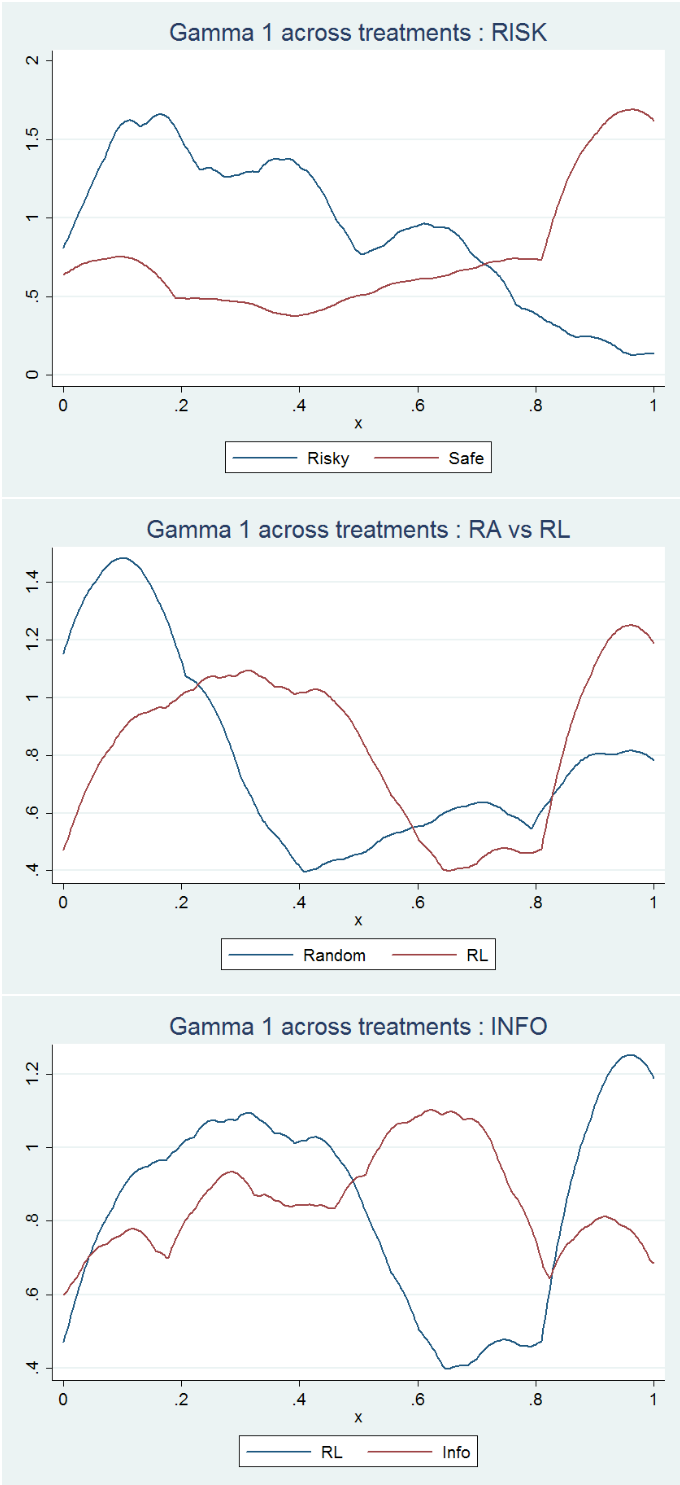


Figure 11: Conditional distributions

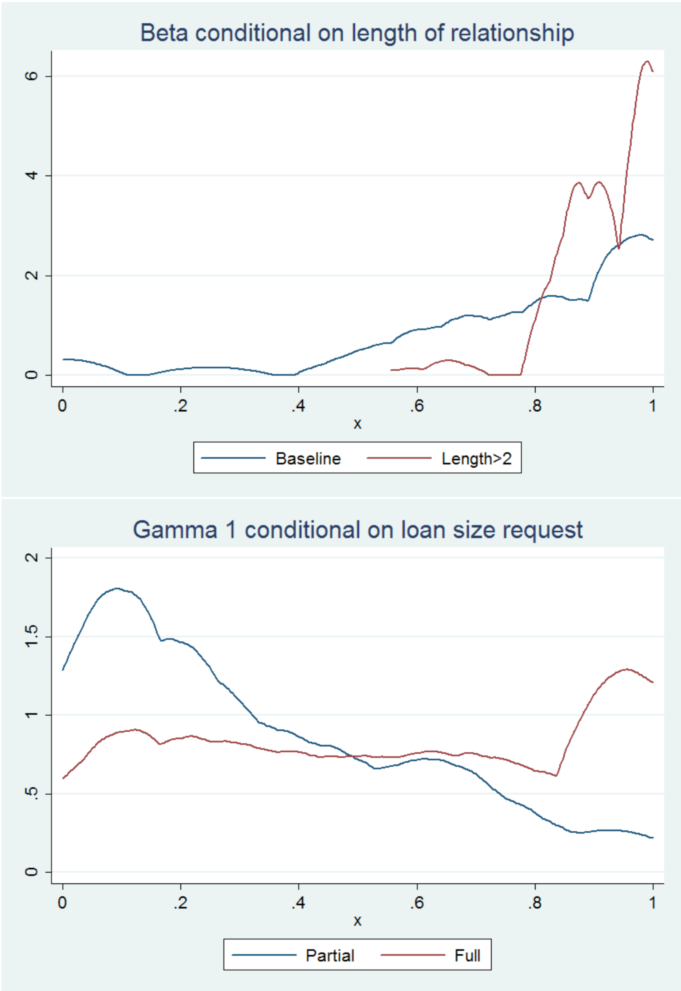


Table 4: Summary statistics: Random treatment

	Random - α_{low}		**Random - α_{high}**		**ttest**	
	mean	sd	mean	sd	ttest	t stat
β	0.82	0.39	0.96	0.19	0.138**	2.30
γ_1	0.21	0.41	0.57	0.49	0.362***	13.56
γ_2	0.21	0.41	0.39	0.49	0.178***	4.89
Full choice	0.73	0.44	0.82	0.38	0.0956***	3.97
Avg volume lent	3.36	2.29	7.33	3.86	3.978***	12.17
Avg volume repaid	1.94	4.30	8.01	5.64	6.068***	20.49
Rationed	0.70	0.46	0.27	0.44	0.435***	9.54
n. switches	0.18	0.38	0.06	0.23	0.116***	3.64

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Summary statistics: Relationship Lending treatment

	Rel Lend - α_{low}		**Rel lend - α_{high}**		**ttest**	
	mean	sd	mean	sd	ttest	t stat
β	0.8	0.40	0.92	0.27	0.121*	1.78
γ_1	0.27	0.44	0.83	0.37	0.565***	22.76
γ_2	0.16	0.37	0.62	0.49	0.456***	9.82
Full choice	0.68	0.47	0.84	0.36	0.163***	6.50
Avg volume lent	3.33	1.44	9.02	1.36	5.693***	38.40
Avg volume repaid	1.77	1.44	9.74	4.54	7.969***	29.50
Rationed	0.70	0.46	0.13	0.34	0.570***	13.65
n. switches	0.14	0.35	0.06	0.23	0.080***	2.61

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Summary statistics: Information Disclosure treatment

	Info Disc - α_{low}		**Info Disc -** α_{high}		**ttest**	
	mean	sd	mean	sd	ttest	t stat
β	0.75	0.43	0.95	0.21	0.204***	3.33
γ_1	0.52	0.50	0.62	0.48	0.106***	3.46
γ_2	0.38	0.49	0.26	0.44	-0.120***	-3.03
Full choice	0.75	0.43	0.76	0.42	0.0182	0.68
Avg volume lent	6.27	1.27	6.67	3.87	0.409	1.40
Avg volume repaid	3	5.04	7.23	5.77	4.230***	1.52
Rationed	0.43	0.50	0.35	0.48	0.080	1.08
n. switches	0.15	0.36	0.11	0.31	0.039	1.08

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Determinants of single vs. multiple lending

	Random		Rel Lend		Info Disc		All sample	
dep var : Full choice	ols	probit	ols	probit	ols	probit	ols	probit
$Rationed_{t-1}$	-0.410	-0.306	-0.628***	-0.675***	-0.319*	-0.309*	-0.483***	-0.484***
	(0.264)	(0.308)	(0.205)	(0.201)	(0.176)	(0.171)	(0.107)	(0.111)
β_{t-1}	0.379**	0.335**	0.160	0.203	-0.021	-0.025	0.097	0.106
	(0.160)	(0.157)	(0.100)	(0.139)	(0.064)	(0.061)	(0.065)	(0.072)
$Safe$	0.020	0.010	0.031	0.047	-0.011	-0.020	-0.042	-0.043
	(0.033)	(0.024)	(0.097)	(0.144)	(0.064)	(0.057)	(0.064)	(0.065)
$Final_{period}$	0.019	0.018	-0.115	-0.129	0.063	0.069**	-0.024	-0.023
	(0.034)	(0.027)	(0.097)	(0.099)	(0.036)	(0.033)	(0.055)	(0.058)
$Constant$	0.586***		0.770***		0.904***		0.867***	
	(0.176)		(0.097)		(0.050)		(0.073)	
Observations	144	144	278	278	207	207	629	629
R-squared	0.47		0.16		0.10		0.14	
Pseudo R-squared		0.52		0.14		0.11		0.12

Marginal effects ; Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Determinants of credit rationing

	Random		Rel Lend		Info Disc		All sample	
dep var : Rationed	ols	probit	ols	probit	ols	probit	ols	probit
$Rationed_{t-1}$	0.327		-0.236	-0.020	0.241**	0.551***	0.095	0.146
	(0.272)		(0.142)	(0.017)	(0.097)	(0.151)	(0.079)	(0.128)
$Rationed_{t-2}$	0.320	0.246	0.174**	0.074*	0.448***	0.481***	0.445***	0.429***
	(0.240)	(0.218)	(0.060)	(0.045)	(0.144)	(0.164)	(0.100)	(0.120)
β_{t-1}	-0.008	0.032	-0.486***	-0.672***	-0.263	-0.410**	-0.311***	-0.367***
	(0.090)	(0.026)	(0.146)	(0.146)	(0.165)	(0.206)	(0.104)	(0.131)
$Full$	-0.458**	-0.992***	-0.653***	-0.764***	-0.224**	-0.608***	-0.344***	-0.494***
	(0.164)	(0.008)	(0.073)	(0.130)	(0.082)	(0.104)	(0.103)	(0.131)
$Safe$	0.000	-0.011	0.018	-0.004	-0.209**	-0.357**	-0.114*	-0.171*
	(0.059)	(0.022)	(0.067)	(0.046)	(0.087)	(0.140)	(0.066)	(0.088)
$Final_{period}$	-0.073	-0.036	-0.015	-0.038	0.130*	0.216**	0.045	0.021
	(0.050)	(0.028)	(0.018)	(0.024)	(0.062)	(0.099)	(0.037)	(0.047)
$Constant$	0.529**		1.135***		0.599**		0.737***	
	(0.181)		(0.137)		(0.208)		(0.141)	
Observations	135	128	268	268	197	197	600	600
R-squared	0.63		0.76		0.66		0.65	
Pseudo R-squared		0.47		0.78		0.63		0.64

Marginal effects ; Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Determinants of number of switches

dep. var : n. switches	**Random** ols	**Rel Lend** ols	**Info Disc** ols	**All sample** ols
$Rationed_{t-1}$	10.102***	5.166***	3.819***	6.131***
	(1.328)	(1.271)	(0.883)	(0.652)
β_{t-1}	-2.509**	-2.209**	1.357**	-0.404
	(1.085)	(1.040)	(0.657)	(0.510)
$Safe$	-3.709***	-3.523***	-2.925***	-3.224***
	(0.638)	(0.731)	(0.524)	(0.355)
$Constant$	7.402***	8.466***	4.612***	6.056***
	(1.130)	(1.060)	(0.554)	(0.473)
Observations	144	278	207	629
R-squared	0.58	0.19	0.20	0.26

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Determinants of lending decision (1)

	Random		**Rel Lend**		**Info Disc**		**All sample**	
dep var : gamma1	ols	probit	ols	probit	ols	probit	ols	probit
$Safe$	0.052	0.059	0.500***	0.504***	0.095	0.100	0.273**	0.281***
	(0.087)	(0.113)	(0.104)	(0.091)	(0.165)	(0.174)	(0.102)	(0.103)
$Full$	0.235***	0.297***	0.021	0.027	-0.057	-0.057	0.078	0.092
	(0.074)	(0.085)	(0.091)	(0.099)	(0.155)	(0.156)	(0.102)	(0.112)
$Default_{hist,lag}$	-0.470***	-0.488***	-0.246**	-0.331***	-0.127	-0.134	-0.247**	-0.285***
	(0.091)	(0.097)	(0.113)	(0.103)	(0.212)	(0.226)	(0.100)	(0.107)
$Final_{period}$	-0.006	-0.007	-0.058	-0.039	-0.238	-0.244*	-0.058	-0.057
	(0.072)	(0.095)	(0.074)	(0.095)	(0.136)	(0.137)	(0.069)	(0.083)
$Constant$	0.544***		0.526***		0.760***		0.554***	
	(0.109)		(0.175)		(0.240)		(0.149)	
Observations	294	294	448	448	469	469	1,211	1,211
R-squared	0.32		0.37		0.10		0.20	
Pseudo R-squared		0.26		0.33		0.08		0.15

Marginal effects ; Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11: Determinants of lending decision (2, effect of being chosen, RL treatment)

dep var : gamma	**(Model 1)**		**(Model 2)**		**(Model 3)**		**(Model 4)**	
Rel Lend	ols	probit	ols	probit	ols	probit	ols	probit
$Chosen$	0.031	0.028	0.050	0.066	0.046	0.058	0.075	0.072
	(0.042)	(0.058)	(0.043)	(0.060)	(0.040)	(0.059)	(0.095)	(0.090)
$Length_{t-1}$	0.039***	0.059***	0.015	0.027	0.018*	0.034**	0.011	0.022
	(0.007)	(0.015)	(0.009)	(0.019)	(0.009)	(0.016)	(0.010)	(0.018)
$Default_{hist,t-1}$	-0.381***	-0.491***						
	(0.065)	(0.060)						
$High_{default_t-1}$			-0.377***	-0.421***				
			(0.063)	(0.077)				
$Freeride_{hist,t-1}$					-0.346***	-0.416***		
					(0.046)	(0.062)		
β_{t-1}							0.510***	0.491***
							(0.125)	(0.131)
$Safe$	0.319***	0.354***	0.243***	0.282***	0.372***	0.437***	0.050	0.057
	(0.054)	(0.057)	(0.052)	(0.061)	(0.046)	(0.067)	(0.080)	(0.088)
$Full$	0.016	0.026	0.013	0.020	0.003	0.002	0.044	0.049
	(0.047)	(0.062)	(0.037)	(0.052)	(0.043)	(0.065)	(0.122)	(0.120)
$Final_{period}$	-0.100	-0.113	-0.140**	-0.178***	-0.073*	-0.094*	-0.030	-0.032
	(0.058)	(0.081)	(0.050)	(0.069)	(0.039)	(0.052)	(0.048)	(0.052)
Constant	0.630***		0.648***		0.502***		0.223*	
	(0.087)		(0.084)		(0.068)		(0.125)	
Observations	444	444	444	444	444	444	209	209
R-squared	0.39		0.39		0.41		0.28	
Pseudo R-squared		0.33		0.31		0.34		0.24

Marginal effects ; Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note : $High_{default,t} = 1$ if $\frac{Default_t}{t} > \frac{r}{1+r}$

Table 12: Determinants of lending decision (3, effect of being chosen, ID treatment)

dep var : gamma	**(Model 1)**		**(Model 2)**		**(Model 3)**		**(Model 4)**	
Info Disc	ols	probit	ols	probit	ols	probit	ols	probit
$Chosen$	0.166***	0.183***	0.166***	0.180***	0.149**	0.178***	0.140	0.151
	(0.052)	(0.056)	(0.055)	(0.059)	(0.053)	(0.061)	(0.097)	(0.098)
$Length_{t-1}$	0.048***	0.076***	0.045***	0.075***	0.032**	0.054***	0.012*	0.024
	(0.010)	(0.017)	(0.012)	(0.017)	(0.013)	(0.021)	(0.006)	(0.018)
$Default_{hist,t-1}$	-0.170	-0.203						
	(0.183)	(0.202)						
$High_{default_t-1}$			-0.167	-0.218				
			(0.132)	(0.147)				
$Freeride_{hist,t-1}$					-0.340**	-0.368***		
					(0.123)	(0.114)		
β_{t-1}							0.445***	0.448***
							(0.135)	(0.145)
$Safe$	-0.095	-0.108	-0.109	-0.134	-0.126	-0.153	0.149	0.164
	(0.111)	(0.128)	(0.121)	(0.142)	(0.087)	(0.107)	(0.105)	(0.105)
$Full$	0.064	0.080	0.064	0.084	0.080	0.098	0.107	0.134
	(0.077)	(0.087)	(0.073)	(0.084)	(0.080)	(0.095)	(0.086)	(0.093)
$Final_{period}$	-0.216***	-0.230***	-0.236***	-0.249***	-0.121*	-0.143**	0.012	0.018
	(0.064)	(0.068)	(0.051)	(0.056)	(0.067)	(0.072)	(0.069)	(0.079)
Constant	0.562***		0.565***		0.588***		0.013	
	(0.174)		(0.148)		(0.107)		(0.160)	
Observations	483	483	483	483	483	483	212	212
R-squared	0.21		0.22		0.28		0.27	
Pseudo R-squared		0.18		0.18		0.23		0.23

Marginal effects ; Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note : $High_{default,t} = 1$ if $\frac{Default_t}{t} > \frac{r}{1+r}$

Table 13: Determinants of being chosen

	Rel Lend		Info Disc		Rel Lend		Info Disc	
dep var : Chosen	ols	probit	ols	probit	ols	probit	ols	probit
$\gamma_{1,t-1}$	0.254*	0.260*	0.141	0.143	0.089	0.073	-0.012	-0.076
	(0.132)	(0.142)	(0.107)	(0.107)	(0.147)	(0.168)	(0.107)	(0.117)
$Safe$	-0.220	-0.228	-0.130	-0.132	-0.250*	-0.260*	-0.163	-0.165*
	(0.139)	(0.145)	(0.114)	(0.114)	(0.125)	(0.135)	(0.098)	(0.099)
$Final_{period}$	0.021	0.024	0.060	0.062	-0.028	-0.027	0.016	0.024
	(0.067)	(0.071)	(0.062)	(0.064)	(0.059)	(0.064)	(0.058)	(0.058)
$Length_{first,t-1}$					0.076***	0.095***	0.058***	0.099***
					(0.022)	(0.034)	(0.013)	(0.029)
$Constant$	0.419***		0.456***		0.457***		0.500***	
	(0.088)		(0.081)		(0.078)		(0.070)	
Observations	294	294	315	315	294	294	315	315
R-squared	0.05		0.03		0.13		0.10	
Pseudo R-squared		0.04		0.02		0.10		0.09

Marginal effects ; Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1