Risk aversion and signalling in single and multiple-bank lending

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Abstract

This paper studies the conditions under which banks prefer to engage in single versus multiple bank lending relationships in funding small businesses. Our theoretical model supports the view that relationship lending and risk aversion operate as opposite forces in the choice for the optimal number of bank links. We test our hypotheses in an experimental credit market in which we vary the quality of lenders' information upon borrowers' default strategies. Our results suggest that risk aversion can explain why multiple lending is observed in strong enforcement environments. Indeed, only when borrowers' repayment behaviour can be well monitored are risk-averse lenders more likely to grant group than single loans. On the contrary, when borrowers' behaviour can't be precisely assessed, single lending acts as a commitment device, and allows borrowers to *signal* their trustworthiness. In this sense, single bank lending relationships become particularly important in opaque environments.

Keywords: Laboratory experiment; Information Asymmetries; Risk Aversion; Multiple Lending; Relationship lending

JEL codes: C72; C73; C92; G21

1 Introduction

Notwithstanding the extensive literature that explores the motives and benefits for small firms to engage in one or several bank lending relationships, the conditions under which banks prefer to enter single versus group loans are still under debate (see Neuberger and Räthke, 2009, for a review). Single bank lending relationships appear predominant in the case of opaque (young or small) borrowers (Farinha and Santos, 2002; Guiso and Minetti, 2010) because of larger credit availability, smaller borrowing costs and collateral requirement (Boot and Thakor, 1994). However, multiple bank links are equally diffused (Petersen and Rajan, 1994; Detragiache et al., 2000), one reason being that with multiple bank lending relationships, small firms can avoid hold-up problems induced by long-term relationships (Klein et al., 1978; von Thadden, 1995). From the lenders' perspective, the advantages of relationship lending, where firms rely on a single bank for most of their financial needs, are related to a reduction in information asymmetries from repeated interactions, and increased incentives for the firm to behave in a good manner. This, in turn, mitigates ex-post moral hazard behaviours (Bolton and Scharfstein, 1996a), even in the case of opaque borrowers (Carletti et al., 2007). Therefore, single lending, or similarly, large loan size, reduces banks' monitoring costs (Diamond, 1984; Khalil and Parigi, 1998) and the requirement of collateral (Boot and Thakor, 1994). In particular, Khalil and Parigi (1998) infer that the magnitude of the loan can be used by the bank as a *commitment device* to fight free-riding behaviours when it has imperfect information on the borrower's income. Indeed, Ahn and Choi (2009) have shown a significant negative effect of loan size on firms' opportunistic behaviour. In addition, it is difficult for lenders to negotiate with each other in order to coordinate on a (potentially) defaulting firm in the case of multiple lending. Thus they might prefer to act as a single source of lending and obtain more information on the borrower's investment projects. Conversely, single lending can increase the variance of the bank's returns. When a lender becomes excessively exposed towards one or more borrowers, the resulting concentration risk may undermine his stability, as the evidence from the 2008-2009 financial crisis suggests. This risk, however, may be limited in the case of small business lending, where the average size of loans (and lenders' exposure) is significantly smaller. Still, even when loan concentration does not represent a threat, particularly risk-averse lenders could prefer to reduce their loan exposure towards a borrower whose repayment performance is uncertain. The tightening of evaluation criteria for larger loans also suggests that risk aversion is an important driver in banks' lending decisions.

Relationship lending and risk aversion thus seem to operate as opposite forces in the choice for the optimal number of bank links. Yet, isolating banks' risk taking behaviour from relationship lending decisions is hardly an easy task, especially because, in both cases, the presence of information asymmetries between borrowers and lenders is central to the financial intermediation structure (Sufi, 2007). Note that banking theory has mostly neglected risk aversion on the lender side,[1] with the exception of studies on the role of loan officers' gender (Beck et al., 2013; Bellucci et al., 2010). On the contrary, borrowers' risk-taking behaviour has received greater attention, especially when studying weak-enforcement environments (Brown and Serra-Garcia, 2014).[2]

Based on a simple static model of imperfect information and different degrees of risk aversion, we build an experimental credit market which allows to disentangle the roles played by information asymmetries and risk aversion in assessing lenders' willingness to lend under single versus multiple bank lending relationships. Our experiment addresses the following research questions: What are the main determinants of single versus multiple bank lending relationships? In particular, what are the respective roles of relationship lending and risk aversion in determining the optimal number of bank links SMEs engage in? Finally, does the quality of lenders' information upon their borrowers (or, in other words, clients' opaqueness) influence their lending choices, and through which channel? The purpose of this paper is therefore to present a clear framework to understand the mechanisms linking lenders' relationship lending and risk-taking strategies in different informational settings. In addition, our paper offers an innovative way to test whether lenders' behaviours are mutually influenced, as an effect of information sharing.

Our model design 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). Further, the enforcement of debt repayment is incomplete as we allow for strategic default from the borrower. Therefore, the borrower's type (trustworthy or not) is endogenous and unknown to the lender, who can only infer it from observing the borrower's repayment behaviour.

[1] In that case, banks' preference towards single or multiple lending is explained by the cost of monitoring (Carletti et al., 2007) or available information (Detragiache et al., 2000).

[2] It is therefore not surprising that the micro-finance literature has largely dealt with risk-averse borrowers (see Fischer, 2013, among others).

Information about the borrower's risk level is also incomplete: only the borrower knows the project success rate α,[3] and she also observes the lenders' decisions. Finally, we allow for information sharing among lenders through a "Credit Register" (as in Brown and Zehnder, 2007[4]).

The use of controlled laboratory experiments is not new in the banking literature (Brown and Zehnder, 2007, 2010; Brown and Serra-Garcia, 2014; Fehr and Zehnder, 2009; Cornée et al., 2012). In particular, Fehr and Zehnder (2009), Brown and Serra-Garcia (2014) and Cornée et al. (2012) are interested in the impact of debt enforcement or information disclosure on borrowers' repayment behaviour. They find that (strong) debt enforcement has a positive impact on borrowers' discipline. However, if Cornée et al. (2012) don't report any impact of information disclosure on the granting of credit by lenders, Brown and Serra-Garcia (2014) observe that bank-firm relationships are characterized by a lower credit volume when debt enforcement is weak. Still, to the best of our knowledge, we make the first attempt at analysing the determinants of bank links variety using this methodology. Because lenders' preference towards single or multiple lending may depend on borrowers' opacity, our design includes two different treatments. We exogenously vary the quality of information lenders can acquire upon borrowers' (endogenous) repayment behaviour, which we use as a proxy for their trustworthiness. More specifically, we allow for different levels of information disclosure upon borrowers' failure in repaying.

Our results show that lenders' willingness to engage in single or multiple bank lending relationships depends both on their information set (our proxy for the strength of contract enforcement) and their risk aversion. When lenders can perfectly observe borrowers' behaviour, as we allow in the first treatment, we find that risk-averse lenders have a relatively lower probability to lend when asked for single loans than risk-loving ones, as predicted by our model. Indeed risk-averse lenders prefer multiple lending for it allows them to diversify risks. On the contrary, and in line with Khalil and Parigi (1998), when borrowers' behaviour can't be precisely assessed, single lending acts as a commitment device, and allows borrowers to *signal* their trustworthiness. In this sense, single bank lending relationships become particularly important in opaque environments, as they insulate borrowers from the higher default costs they might experience when a coordination failure among lenders occurs (Bolton and Scharfstein, 1996b).

In what follows, we discuss in detail our experiment and the model it builds upon. In particular, Section 2 describes the experimental design and procedures and Section 3 presents

[3]However, lenders know that borrowers know their project's probability of success.

[4]In our experiment, we include a Credit Register in both treatments.

theoretical underpinnings and predictions. Empirical results are then discussed in Section 4. Section 5 concludes.

2 Experimental design

Our experiment mirrors a situation in which a borrower needs to finance her investment activity and seeks funds from one or more lenders. Therefore, we design a game with a borrower and two lenders. They interact to fund an investment opportunity whose probability of success is only known to the borrower. In advancing her funding request, the borrower must choose whether she wants to engage in a single or in multiple bank lending relationships. Conditional on receiving funds and project success, the borrower then decides to repay or free-ride on her debt.[5] We describe the game and the different treatments in greater detail below.

2.1 The game

We assume that the borrower has an initial endowment, e, which is however not sufficient to implement her investment project by herself, as it requires an initial amount of minimum size $D/2$, where $e < D/2$. Therefore, she has to turn to the credit market, which consists of two identical lenders who she can meet in sequential order. The project is risky, with a success rate α only known to the borrower. We model the lending game as a two-stage game: in the first stage, the borrower chooses her preferred loan size, and in the second stage the lender decides whether to lend or not. We refer to the decision of the borrower in favour of single lending as "Full" funding and to the alternative case as "Partial" funding. Indeed, in the case of multiple lending, the borrower asks each of the two lenders for half the amount. Thus from lenders' perspective, the choice of single or multiple relationships affects loan size, L, where $L = \{D; D/2\}$ for the Full and Partial strategies, respectively. We also assume that making a funding request to a lender is costly for the borrower. Therefore, the Partial strategy is more expensive than the Full one. We call s the "administrative costs" faced by the borrower each time she applies for a loan.[6] The game is then repeatedly played for a certain number of rounds. The decision structure in each round is as follows (the timeline of decisions in each period is shown in Figure 1) :

[5]Moreover, similar to Fehr and Zehnder (2009), borrowers cannot use excess returns in the future rounds of the game. 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.

[6]In other words, s represents the fee the borrower has to pay to ask for loan review, and it enters the bank's turnover as the bank acquires information on the borrower's funding needs. The lender will receive s irrespectively of whether the loan is issued or not. We assume that the initial wealth the borrower is endowed with (e) is sufficient to advance her funding request to both lenders ($e \geq 2s$).

i) *Loan request*: The borrower moves first and chooses whether she wants to borrow D from only one lender (Full funding), or, rather, to borrow $\frac{D}{2}$ from each (Partial funding).[7]

ii.a) *First lender decision*: 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[8]).

ii.b) *Second lender decision*: If the borrower did not obtain D from the first lender (either because he refused or because he granted $\frac{D}{2}$), she proceeds with the second lender.

iii) *Project Implementation*: If the obtained amount is positive, the borrower implements the project that yields I with probability α and 0 with probability $1 - \alpha$. If the borrower has only obtained $\frac{D}{2}$ she can implement a small project which yields $I/2$ in case of success.[9]

iv) *Repayment decision*: Conditional on the project being successful, the borrower chooses to repay the loan or to free-ride. 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 payment. Once the borrower has made her repayment decision, the round ends. The next round is identical to the one described so far.

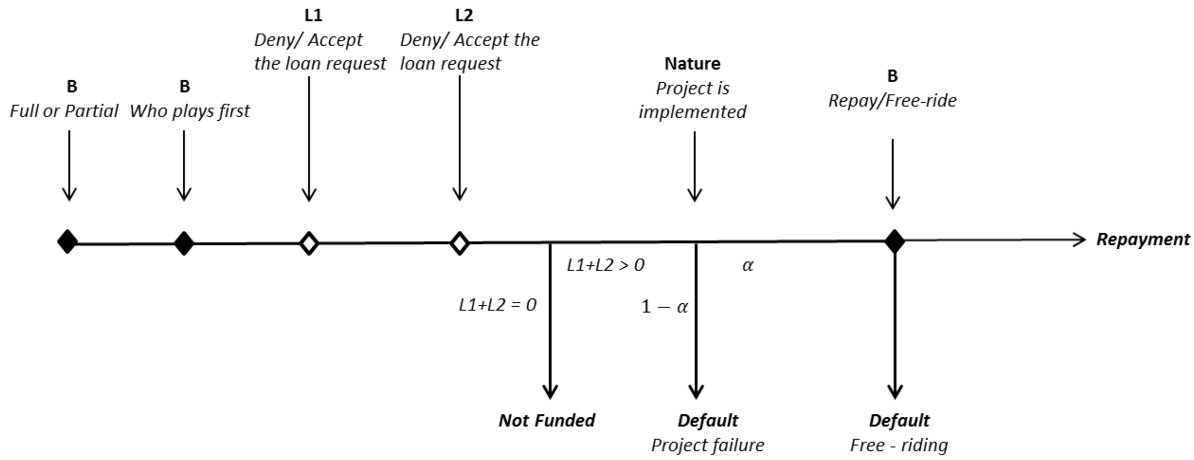
Throughout the game, the lenders can recall (and observe) the borrower's repayment behaviour in all previous rounds in a Credit Register, irrespectively of whether they received a loan request or not. Therefore, at the beginning of round t, lenders can observe the outcomes of all rounds up to $t - 1$, classified either as "Not funded" (i.e. the borrower didn't receive any funding), "Repayment" (i.e. the borrower received funding and repaid the loan), or "Default" (i.e. the borrower received funding but didn't repay). Given that both lenders observe project default in the Credit Register, this event is public. Besides, they observe the loan size request, even in rounds of play for which they don't enter the game, as well as their position in the game (whether they have been chosen to play first or not).

[7] The overall sum of the requested amount must always be D.

[8] Although simplifying, this assumption enables to limit the number of equilibria in the game, especially related to lenders' strategic choices.

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

Figure 1: The timeline of decisions



The decision problem of the agents is displayed in the Game Tree, Figure 7 in the appendix (section A1), together with their payoffs, Figure 8.

2.2 Treatments

We implemented two treatments, constructed as follows:

- In the **Information Disclosure treatment** ("**ID**" treatment) at the beginning of each round, the borrower chooses which lender to play first with. At the end of each round, both lenders can access a shared window (the Credit Register) as described above. Besides, in case of default, the lender(s) who have lent in the current round of play receive a private message on their screen revealing whether the borrower's default has to be accounted for investment failure or free-riding (i.e. the borrower decided not to repay despite project success).

- The **Relationship Lending treatment** ("**RL**" treatment) is identical to the ID treatment, except for the quality of information on the borrower's default. Indeed, in case of default, lenders in the RL treatment cannot disentangle investment failure from borrower's free-riding behaviour. Instead, they only receive a generic message on their screen stating that the borrower didn't repay.

Note that the more precise information provided in the ID treatment in case of default introduces an information asymmetry across lenders: private information (within the banking relationship) is better than the public information (accessible to all lenders through the Credit Register). Thus the ID treatment tests how the acquisition of more information about the borrowers' repayment behaviour, through repeated interactions, affects lenders' decisions. To some extent, we can think of the ID treatment as mirroring the "true" effects of relationship lending: as Sharpe (1990) points out, relationship lending indeed allows a bank to acquire more (private) information about its customers than other banks do; on the contrary, the RL treatment introduces a confounding element in the firm-bank relationship, reducing the accuracy of the received information.

For each treatment, we ran two separate sessions, a risky (α_{low}) and a safe (α_{high}) one,[10] for a total of four sessions (see Table 1 below). In the experiment, we set $\alpha_{low} = 0.55$ and $\alpha_{high} = 0.95$; $I = 30$; $D = 10$; r=0.2 and s=4.[11]

Table 1: Treatments

Treatment	**Conditions**	**Sessions**	**Riskiness**
Information Disclosure (ID)	In case of default, lenders entering the game know whether it was driven by project failure or by the borrowers' free-riding behaviour.	Session 1	α_{high}=0.95
		Session 2	α_{low}=0.55
Relationship Lending (RL)	In case of default, lenders only know that the borrower was not able to repay, but not the exact reason why.	Session 3	α_{high}=0.95
		Session 4	α_{low}=0.55

2.3 Implementation and procedures

The experiment was computerized and implemented at the EXEC laboratory (University of York, UK) in October 2011, over three days. It was programmed and conducted with the experiment software z-Tree (Fischbacher, 2007). All subjects were volunteers who registered to our experiment through the ORSEE Online Recruitment System,[12] which design is adapted to economic experiments. Notice that the system automatically excludes subjects with a bad record (i.e. who have registered to previous experiments and did not show up). Moreover, we imposed that each subject could only take part in one session. All participants were undergraduate students or personnel of the University of York. We conducted four experimental sessions, for a total of 96 subjects (32 groups of 3 players, that is, 32 borrowers and 64 lenders in total). To ensure that the subjects understood the game, the experimenters read the instructions aloud

[10] The riskiness of a session was determined by the different probabilities of success of the investment project. In particular, $I\alpha_{low} < I\alpha_{high}$.

[11] Payoffs were computed in tokens and then converted in pounds.

[12] `www.orsee.org`.

and explained final pay-offs with the help of tables provided in the instructions.[13] Before the game started, the subjects practised three directed test runs. In each session, groups of three subjects were formed for T periods: one borrower (player A) and two lenders (players B and C). In order to prevent any backward induction strategies and lose control over players' behaviour, we designed a game with an infinite number of periods. This was implemented by randomizing T,[14] which was not disclosed to the subjects. Throughout the game, we observed players' decisions keeping constant price (interest rate), risk (the project's fixed success probability) and information (using the Credit Register).

All subjects received a show-up fee of 5 pounds to which their pay-off in the game was added in order to compute their final pay-off. The players earned an average of 13 pounds from participating in the game. Once the experimental session had finished, subjects were administered a small questionnaire, again via computer, aimed at collecting socio-demographic information (gender, age, previous participation in other experiments), as well as time preferences and measures of risk aversion.[15] In particular, we construct our risk aversion measure[16] from question 9 of the questionnaire: *How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? (1=you totally try to avoid risks.....9=you are fully prepared to take risks).*[17] 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.

3 Theoretical framework

In what follows, we discuss the theoretical underpinnings of our experiment. We first solve the model in the case of perfect information (Section 3.1), and we then relax this assumption (Section 3.2), as to mirror our experimental design. We then formulate our experimental predictions on this basis (Section 3.3).

[13] Instructions can be provided by the authors upon request.

[14] 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 22 to 30 across sessions.

[15] A printout of the questionnaire is available upon request.

[16] For the regressions, we construct three risk aversion groups by splitting the distribution at its 33rd and 66th percentiles. The variable *Riskaverse* takes values 1 (not risk-averse), 2, or 3 (very risk-averse).

[17] The question is taken from the *Luxembourg Wealth Study* (`http://www.lisdatacenter.org/our-data/lws-database/`). We opted for this measure of risk aversion rather than resorting to other lotteries (as, for instance, Holt and Laury (2002)'s multiple price list) mostly because we believed that playing the risk aversion lottery as a new game could have been too time consuming for our subjects and thus would have affected their ultimate answers.

3.1 Game with perfect information: loan size and risk aversion

In this section, we assume that the borrower's repayment decision, which we define as β_j (with the subscript j identifying the borrower), is observable, corresponding to the ID treatment. Note that the borrower decides to repay or free-ride only if her project is successful, which happens with probability α. Moreover, we call ϕ_j borrower's decision between single and multiple bank lending relationships. In modelling agents' risk preferences, we adopt a mean-variance approach, in a similar spirit as Barboni et al. (2013). The utility function of the lender (who is identified by the subscript i) depends on three elements: i) the expected payoff from his decision to lend or not $E(y_l)$, with $l = lend, notlend$, and the variance of the project payoff $\sigma^2_{y_l}$ in each case; ii) the borrower's strategy about single ($\phi_j = 1$) or multiple lending ($\phi_j = 0$), and repayment choice (β_j) and iii) his coefficient of risk aversion, V_i. The lender's utility can be described as a weighted average of the utilities he would get under the borrower's choice of single versus multiple bank lending relationships:

$$U_{i,l} = \phi_j(E_{l,single} - \frac{1}{2}V_i\sigma^2_{y_{l,single}}) - (1-\phi_j)(E_{l,multiple} - \frac{1}{2}V_i\sigma^2_{y_{l,multiple}}) \tag{1}$$

We now consider the lender's decision of lending versus not lending. The lender agrees to lend if his utility $U_{i,lend}$ is higher than in the alternative case ($U_{i,notlend}$). His decision therefore is given by the sign of the following expression:[18]

$$\begin{aligned} U_{i,diff} = U_{i,lend} - U_{i,notlend} = \phi_j(U_{i,lend,single} - U_{i,notlend,single}) + \\ (1-\phi_j)(U_{i,lend,multiple} - U_{i,notlend,multiple}) \end{aligned} \tag{2}$$

With some computations we get the following:

$$U_{i,diff} = \frac{D}{2}(1+\phi_j)(\alpha\beta_j(1+r)-1) - \frac{1}{2}V_i[\phi_j\sigma^2_{y_{lend,single}} + (1-\phi_j)\sigma^2_{y_{lend,multiple}}] \tag{3}$$

We can now determine how the value of lenders' risk aversion parameter affects their utility and decision. Intuitively, for risk-averse lenders ($V_i > 0$), the second part of equation (3) will be negative. Indeed, agreeing to lend implies a positive variance of payoffs, which represents a

[18] See details in the appendix, section A2.

reduction of their utility from lending. Conversely, risk-loving lenders ($V_i < 0$) should be willing to lend even for a low level of borrowers' repayment probability. In what follows we also need to consider the role of loan size, which affects lenders' decision when they are not risk-neutral. We show below how the borrower's decision $\phi_j = \{0; 1\}$ impacts the willingness to lend.

Single bank lending relationship, $\phi_j = 1$

Let's first consider the case of single lending, where the borrower requests the full amount D to lender i. From equation (3), the latter decides on lending if $U_{i,diff} > 0$, with:

$$U_{i,diff} = D(\alpha\beta_j(1+r) - 1) - \frac{1}{2}V_i\sigma^2_{y_{lend;single}} \tag{4}$$

The lender will lend $\iff$ V_i, is below the threshold level $\bar{V}_{single}$:

$$V_i < \frac{2(\alpha\beta_j D(1+r) - D)}{\sigma^2_{y_{lend;single}}} = \bar{V}_{single} \tag{5}$$

What is the intuition of this threshold, $\bar{V}_{single}$? For $V_i < \bar{V}_{single}$,[19] the lender's utility from providing a larger loan is positive. Now, depending on which value $\bar{V}_{single}$ assumes, different types of lenders will lend. If $\bar{V}_{single}$ is strictly positive, this implies that both risk-averse and risk-loving lenders will lend. For values $\bar{V}_{single} < 0$, on the contrary, only risk-loving lenders will lend. In order to define for which values of β_j this happens, we need to look at the sign of $\bar{V}_{single}$:

$$\bar{V}_{single} = \frac{2(\alpha\beta_j D(1+r) - D)}{\alpha\beta_j D(1+r)(1-\beta_j)[\alpha D(1+r) + 4(s-D)^2]} \tag{6}$$

It is easy to see that $\bar{V}_{single} > 0$ for $\beta_j > \frac{1}{\alpha(1+r)} = \beta^*$. In other words, for a repayment probability above the threshold β^*, all risk-loving lenders, as well as risk-averse lenders with $V_i \in (0; \bar{V}_{single}]$ will lend. Conversely, for $\beta_j < \beta^*$, only risk-loving lenders with $V_i < 0$ will lend.

[19] Where this value could be derived by the lender since β_j is public knowledge.

Multiple bank lending relationships, $\phi_j = 0$

We now consider the case of multiple lending, where the borrower requests only half of the amount, $\frac{D}{2}$ to the lender. The latter decides on lending if $U_{i,diff} > 0$, with:

$$U_{i,diff} = \alpha\beta_j(\frac{D}{2}(1+r) - 1) - \frac{1}{2}V_i\sigma^2_{y_{lend,multiple}} \tag{7}$$

In the case of a Partial funding request, the lender agrees to lend $\iff$ his risk aversion coefficient is below the threshold level $\bar{V}_{multiple}$:

$$V_i < \frac{(\alpha\beta D(1+r) - D)}{\sigma^2_{y_{lend,multiple}}} = \bar{V}_{multiple} \tag{8}$$

With a few passages we obtain that the condition for which $\bar{V}_{multiple} > 0$ is, again, $\beta_j > \beta^*$. We are left with understanding the relation between $\bar{V}_{single}$ and $\bar{V}_{multiple}$. The outcome depends on borrowers' trustworthiness. Indeed, a few passages detailed in the appendix (section A2) show that, $\bar{V}_{single} < \bar{V}_{multiple}$ if $\beta_j > \beta^*$. This result suggests that, if borrowers are sufficiently trustworthy, lenders with a risk aversion coefficient V_i up to $\bar{V}_{single}$ will be indifferent between lending under single or multiple bank lending strategies, whereas lenders with a higher coefficient of risk aversion, namely with $V_i \in (\bar{V}_{single}; \bar{V}_{multiple})$, will only lend if they receive a Partial funding request, because they perceive a full exposure towards the borrower as being too risky.

The game thus proceeds as follows. First, the lender observes the type of funding request ($\phi_j = \{0; 1\}$). He then decides whether to lend or not, depending on his level of risk aversion. Finally, conditional on project success, he also observes the borrower's repayment behaviour, β_j, receiving a perfect signal that we call $\hat{\beta}_j = \beta_j$. We summarize our findings into two different cases, also illustrated in Figure 2.

Case 1: $\beta_j > \beta^*$. This condition has two main implications:

(i) $\bar{V}_{single}$ and $\bar{V}_{multiple}$ are strictly positive;

(ii) $\bar{V}_{single} < \bar{V}_{multiple}$.

It follows:

- (very) risk-averse lenders with $V_i > \bar{V}_{multiple}$ will never lend;

- risk-averse lenders with $\bar{V}_{single} < V_i < V_{multiple}$ will only lend if they receive a multiple lending request;

- (moderately) risk-averse lenders with $0 < V_i < \bar{V}_{single}$ and all risk-loving lenders with $V_i < 0$ will lend both under single and under multiple bank lending relationships.

Case 2: $\beta_j < \beta^*$. This condition implies:

(i) $\bar{V}_{single}$ and $\bar{V}_{multiple}$ are strictly negative;

(ii) $\bar{V}_{multiple} < \bar{V}_{single}$.

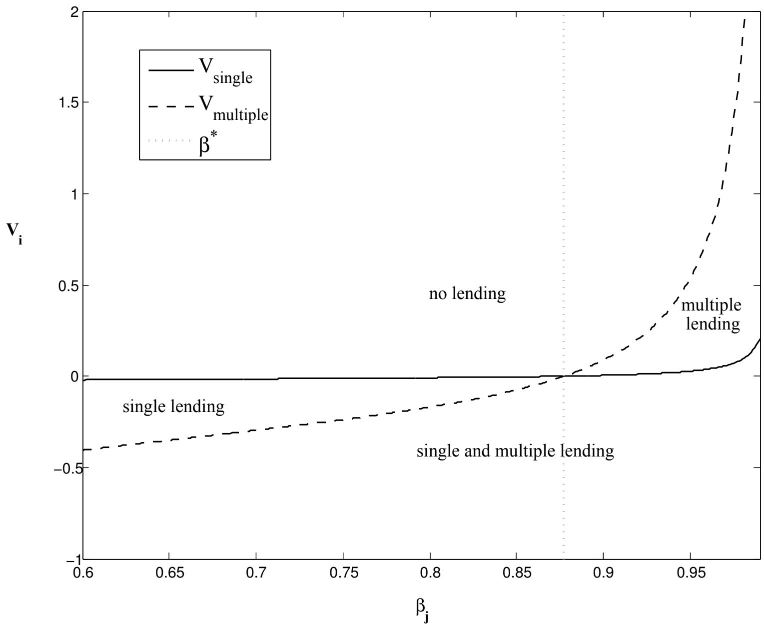
It follows:

- (moderately) risk-loving lenders with $\bar{V}_{single} < V_i < 0$ will never lend;

- risk-loving lenders with $\bar{V}_{multiple} < V_i < \bar{V}_{single}$ will only lend if they receive a single lending request. In this case, given that the likelihood to be repaid is very low, risk-loving lenders will only lend full projects because otherwise they would never break-even.

- very risk-loving lenders with $V_i < \bar{V}_{multiple}$ will lend both under single and under multiple bank lending relationships.

Figure 2: Lending decision as a function of V_i and β_j.



3.2 Game with imperfect information: loan size, risk aversion and signalling

As a final step, we relax the assumption that the borrower's repayment decision β_j is observable, corresponding to the RL treatment. It implies that the lender must base his decision upon something other than the borrower's behaviour. Therefore, in order to be financed, the borrower must send the lender another signal of her trustworthiness. In what follows, we assume that the borrower signals her creditworthiness through the choice of the loan size. To this end, we model the game as a signalling model in a similar spirit as Spence (1973), in a simpler version as described by Bolton and Dewatripont (2005).[20]

Applying such model to a lending game with asymmetric information on borrowers' repayment behaviour, we define two types of principal, denoted by different degrees of trustworthiness. A borrower's trustworthiness can be either β_H or β_L, where $\beta_H > \beta^* > \beta_L$, with $\beta^* = \frac{1}{\alpha(1+r)}$.[21] Lenders do not observe β but the type of funding request: Full (i.e. single bank lending relationship) or Partial (i.e. multiple bank lending relationships). Therefore, they need to infer borrowers' expected repayment behaviour from this signal. We assume, in the same way as in Spence (1973), that the principal chooses the loan type at a cost c which increases with the probability of choosing a higher loan size, where $c(\phi_j) = \psi_j \phi_j$, and which differs according to the borrower's trustworthiness. In particular, we assume $\psi_H < \psi_L$, that is, the marginal cost of asking (and then repaying) a large loan is higher for untrustworthy than for trustworthy borrowers. This cost reflects the inability of the borrower to repay large loans; the intuition is that, once the borrower has the cash ready to make the repayment, he faces a psychological cost to part with that sum.[22] As shown in the appendix (section A2), the Full choice is associated with a larger expected loan size than the Partial choice, and therefore a higher cost c:

$$c(\phi_j = 1) > c(\phi_j = 0) \tag{9}$$

If borrowers' trustworthiness, β_j, were perfectly observable, corresponding to the ID treatment, each borrower would choose the strategy with the lowest expected size ($\phi_j = 0$), therefore minimizing the cost c, irrespectively of her quality. Instead when β_j is not public knowledge (in

[20]Their model shows that education can be used by highly productive workers to signal themselves because the cost of acquiring years of education is lower for them.

[21]These values can be interpreted as the average repayment probability of high- and low-quality borrowers, respectively.

[22]This psychological cost represents one of the major barriers to loan repayment, as emphasized in the microfinance literature by Yunus (2003), among others. An alternative interpretation of this psychological cost is borrowers' present-bias. More patient (high quality) borrowers are less likely to be tempted to consume in the present larger sums of money than impatient (low quality) borrowers.

the RL treatment), the borrower also has to consider how loan size choice affects the lender's belief upon her trustworthiness. Once the decision of the principal (the borrower) is known to the agent (the lender), the latter revises his belief $\rho_i(\psi_j|\phi_j)$ about the principal's trustworthiness conditional on having observed ϕ_j. The equilibrium signal for β_j, $\hat{\beta}_j$, is then given by the following relation:

$$\hat{\beta}(\phi_j) = \rho_i(\psi_H|\phi_j)\beta_H + \rho_i(\psi_L|\phi_j)\beta_L \tag{10}$$

In what follows, we define the Perfect Bayesian Equilibrium of the game in two steps. First, we determine the conditional belief $\rho_i(\psi_j|\phi_j)$ for the agent. Second, we infer the principal's best response ϕ_j given this belief. Because untrustworthy borrowers (characterized by $\beta_j = \beta_L$) face a higher marginal psychological cost and the Full funding strategy corresponds to a larger expected loan size, they are only willing to choose a level $L = D/2$. As a consequence, a borrower choosing the Full strategy is signalling a high level of trustworthiness. Therefore, our PBE is to set:[23]

$$\rho_i(\psi_H|\phi_j) = \begin{cases} 0, \text{ if } \phi_j = 0 \\ 1, \text{ if } \phi_j = 1 \end{cases}$$

If the borrowers optimize for these beliefs, trustworthy ones will choose $\phi_j = 1$. Therefore, the lender will interpret the choice for the Full strategy as a signal of trustworthiness. It immediately follows that he will update his belief upon trustworthy borrowers as $\hat{\beta}_j(\phi_j = 1) = \beta_H$, and, similarly, upon untrustworthy borrowers as $\hat{\beta}_j(\phi_j = 0) = \beta_L$.

We now include the lender's risk aversion degree in the present discussion. Lenders' belief about repayment $\hat{\beta}(\phi_j)$ is plugged in equations 5 and 8 instead of β_j. The choice of lending depends on lenders' coefficient of risk aversion, V_i with respect to $\bar{V}_{single}$ and $\bar{V}_{multiple}$, which are function of their belief $\hat{\beta}(\phi_j)$.

The discussion about lenders' decisions will then proceed as before.

[23] For ease of discussion, in this analysis we have only considered the most intuitive PBE, the separating one. Of course, as Bolton and Dewatripont (2005) point out, this equilibrium is not unique. We believe however that, given the discrete nature of the loan size (borrowers can only choose between D and $D/2$), this is the most plausible equilibrium that helps us explain our experimental results.

3.3 Experimental predictions

RL versus ID treatment, and risk aversion

Following our theoretical framework, the choice of single versus multiple lending should be interpreted differently in both treatments. In the ID treatment, trustworthiness can be clearly identified. In that case, lending behaviour conditional on loan size should be solely driven by risk aversion motives. Because of the positive relation between loan size and payoff variance, risk-averse lenders should prefer to lend group loans, while risk-loving ones should give relatively more value to the single ones. When we assume imperfect information upon borrowers' repayment behaviour in the RL treatment, we introduce an "opposite force" acting against lenders' risk aversion. In that case, the choice of single lending is a signal of the borrower's trustworthiness and therefore increases the probability to receive a repayment, everything else equal. On the other side, risk-averse lenders are relatively more willing to enter multiple bank lending relationships than risk-loving ones, because loan size has a negative impact on their utility from lending. We summarize the above elements into a series of testable propositions:

Proposition 1: *In the ID treatment and for high levels of the borrower's trustworthiness ($\beta > \beta^*$), the relative preference of lenders towards single lending should be inversely related to their level of risk aversion.*

Proposition 2: *In the RL treatment and for high levels of the borrower's trustworthiness ($\beta > \beta^*$), the relative preference of lenders towards single lending should be more pronounced than in the ID treatment, but still inversely related to their level of risk aversion.*

Safe versus Risky treatments

As previously mentioned, we run two separate sessions per treatment, one with a low-risk (α_{high}) project, the other with a high-risk (α_{low}) project.[24]

In a setting with asymmetric information about the project riskiness α, only known to the borrowers, it's only through repeated interactions that lenders should adapt their beliefs over

[24] Note that α enters in the computation of β^*. In particular, and given our parametrization, for $\alpha = \alpha_{low} = 0.55$, $\beta^* = 1.51$: only risk-loving lenders would agree to lend (Case 2). Conversely, for $\alpha = \alpha_{high} = 0.95$, $\beta^* = 0.87$, and both Case 1 and Case 2 can be observed.

the combination of the borrowers' riskiness and trustworthiness. As a consequence, the share of accepted requests should increase over periods in the case of safe sessions and decrease in the case of risky ones, with a significant difference between the two. Thus we expect the following:

Proposition 3: *Lenders are more likely to grant credit in low-risk than high-risk sessions.*

First versus Second Lender

Because lenders enter the game sequentially, our experiment also allows to exploit variations across lenders' order. As mentioned earlier, lenders' decisions to grant credit can also be driven by information spillovers about past rejections. In particular, a lender may decide to withdraw his funds if he observes the other lender doing so in the same round of play. Indeed, by the design of the game, in the single-lending case, second lenders know that they enter the game only if the first lender rejected the borrower's request. Such information spillover therefore inherently reduces the perception of creditworthiness.[25] In the multiple lending case instead, the second lender has no such information on the other lender's decision, as for first lenders.

Proposition 4: *The negative information spillover obtained by second lenders in the single lending case should reduce their lending with respect to the multiple lending case.*

4 Empirical methodology and results

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

4.1 Descriptive Statistics

We start investigating our data with descriptive statistics in order to get a first intuition about players' behaviours and their differences across treatments. The main variables considered in the empirical analysis include decisions about single versus multiple funding strategies and repayment by borrowers, and lending. More precisely, *Full*, is a dummy variable taking value of 1 if the borrower chooses single lending, and 0 if she chooses to split the loan request. The variable *Repay* takes value of 1 if, conditional on project success, the borrower repays, and 0 if

[25] Information spillovers have been analysed by Albertazzi et al. (2014) using data from the Italian Credit Register.

she free-rides. This variable is not observed if the project is unsuccessful. Finally, the variable *Lend* takes value of 1 if the lender agrees to the loan request, and 0 if he refuses. The variable is not observed if the lender does not enter the game.[26] Summary statistics across the whole sample are reported in Panel A of Table 2. Table 2 also reports the mean difference tests between sessions according to project riskiness (Panel B) or treatment (Panel C), and according to loan type (single versus multiple lending requests, Panel D), or lenders' risk aversion (Panel E).[27] We use two-sided Wilcoxon-Mann-Whitney tests to verify whether differences are significant, using means per group (of two borrowers and one lender) as independent observations.[28] Between seven and eight groups of three players participated to each of the four sessions, for a total of 32 groups, allowing for variability in the data.

4.1.1 Borrowers' behaviour

Average repayment rates across sessions appear to be very high (81%, cf. Table 2, Panel A). Similarly, we obtain that borrowers have strong preferences towards single bank lending relationships, with a 76% chance of choosing single loan requests (cf. Table 2, Panel A). Panel B of Table 2 reveals that borrowers' behaviour (as shown by statistics over *Full* and *Repay*) is impacted by the projects' failure probability. More precisely, the share of single lending requests is higher in the safe sessions (81% against 70%). In addition, repayment after project success is significantly more frequent in the safe sessions (89% in safe sessions versus 71% in risky sessions).

Figure 3 below provides information on the evolution of the average repayment (β_j in the model) over periods for different project failure probabilities. Borrowers in the safe sessions are constantly trustworthy, while free-riding behaviour increases over periods in the risky case.

4.1.2 Lenders' behaviour

On average, lenders have accepted to give credit a bit more than half of the times (54%, cf. Table 2, Panel A). We find that lenders lend significantly more in safe sessions (72% in the safe sessions versus 36% in risky ones), as predicted by **Proposition 3**. We plot the mean value of *Lend* for each period and category of α in Figure 4 below (this variable corresponds to γ_i in the model). While in the safe sessions the average lending acceptance rate is stable over time, we

[26] For a more detailed description of the variables used in the regressions, see Table 3 in Appendix A3.

[27] At this stage, only one dimension is studied at the time, while interaction effects between several of these factors will be studied in section 4.2.

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

Table 2: Descriptive Statistics and Mean difference tests between treatments

Panel A

	All sample	se	N
Full	0.76	0.23	32
Repay	0.81	0.23	31
Lend	0.54	0.32	32

Panel B

	Safe	se	N	**Risky**	se	N	W-M-W test
Full	0.81	0.24	16	0.70	0.22	16	$Safe > Risky$ *
Repay	0.89	0.21	16	0.71	0.23	15	$Safe > Risky$ ***
Lend	0.72	0.33	16	0.36	0.17	16	$Safe > Risky$ ***

Panel C

	ID	se	N	**RL**	se	N	W-M-W test
Full	0.75	0.23	18	0.77	0.25	14	$ID = RL$
Repay	0.82	0.20	18	0.78	0.27	14	$ID = RL$
Lend	0.53	0.32	18	0.55	0.32	14	$ID = RL$

Panel D

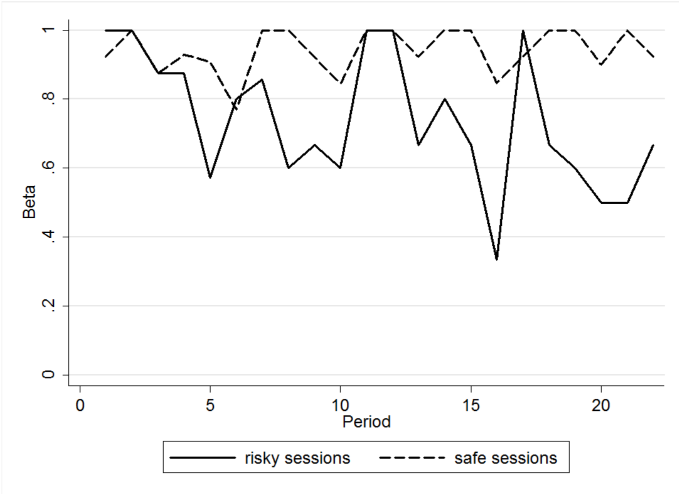
	Full ($\phi = 1$)	se	N	**Partial** ($\phi = 0$)	se	N	W-M-W test
Repay	0.85	0.23	29	0.71	0.37	19	$Full = Partial$
Lend	0.53	0.33	32	0.47	0.33	26	$Full = Partial$
$Lend\ first$	0.571	0.055	32	0.432	0.078	26	$Full = Partial$
Lend second	0.370	0.070	28	0.498	0.068	26	$Full = Partial$

Panel E

	Risk-averse	se	N	**Risk-lover**	se	N	W-M-W test
Lend	0.47	0.093	15	0.51	0.066	26	$Risk - averse = Risk - lover$

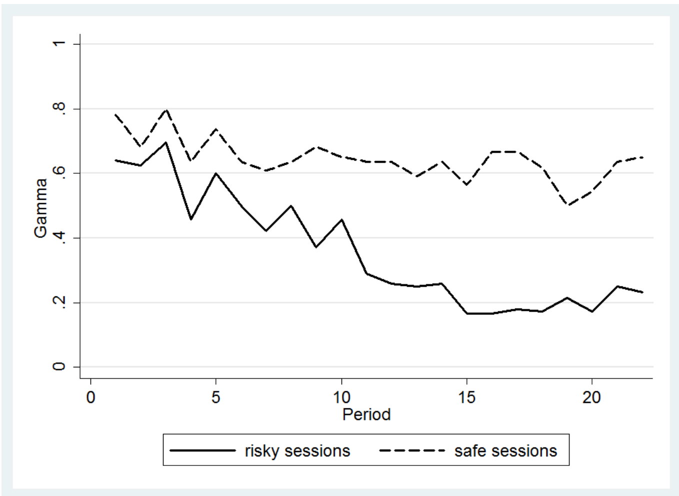
Note: We compute means at the group level, over N groups. There are 32 groups in total, however we get some missing observations for the following reasons. For the *Repay* variable, we only observe 31 groups because one of the borrowers never got to make a decision in the entire game (she was denied a loan by both lenders in all periods). For what concerns the *Lend second* variable, the missing observations are cases for which the second lender never got to make a decision; the first lender always agreeing to lend. Finally, Panel E reports the lending behaviour depending on lenders' risk aversion at the individual level. We report the significance of the Wilcoxon-Mann-Whitney equality tests as follows: $*p < 0.10, **p < 0.05, ***p < 0.01$. Risk-averse lenders report a risk measure below the 33rd percentile; risk-loving ones above or equal the 66th percentile.

Figure 3: Repayment decisions over time, risky versus safe sessions.



observe a decreasing trend in the risky sessions. This result suggests that, when default events accumulate in the risky case, lenders revise their proxy on the probability of default and reduce their lending.

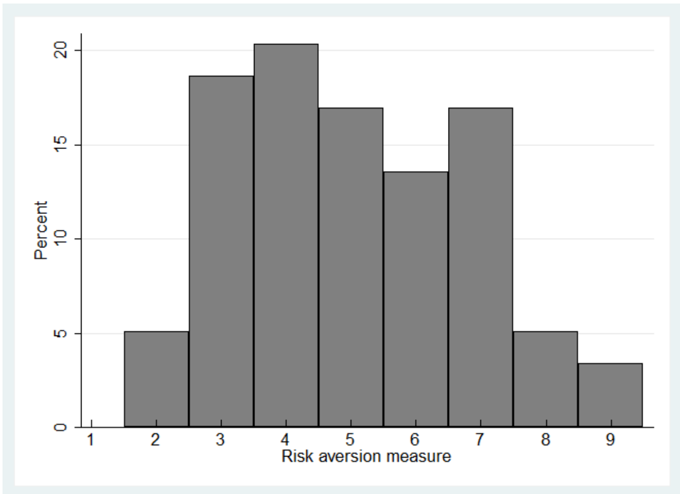
Figure 4: Lending decisions over time, risky versus safe sessions.



Instead, behaviours across treatments (*ID* versus *RL*, Panel C) and loan type (*Full* versus *Partial* choice, Panel D) do not statistically differ. Note however that lenders positively react to the single lending decision, since *Lend* is higher in *Full* (53%) than *Partial* (47%), which would hint at a dominance of the commitment effect relative to the risk aversion lending motive. This is also true when we look at the behaviour of lenders who played first. Conversely, we find that lenders who enter second in the game are more likely to lend in a group loan than in a single bank lending relationship, opposite to what is found for the first lender. Although not significant, these results suggest that there are different mechanisms at place when determining the lenders' choices of granting credit. Possibly, such differential behaviour across lenders can be partly explained by the presence of information spillovers (as stated in **Proposition 4**).

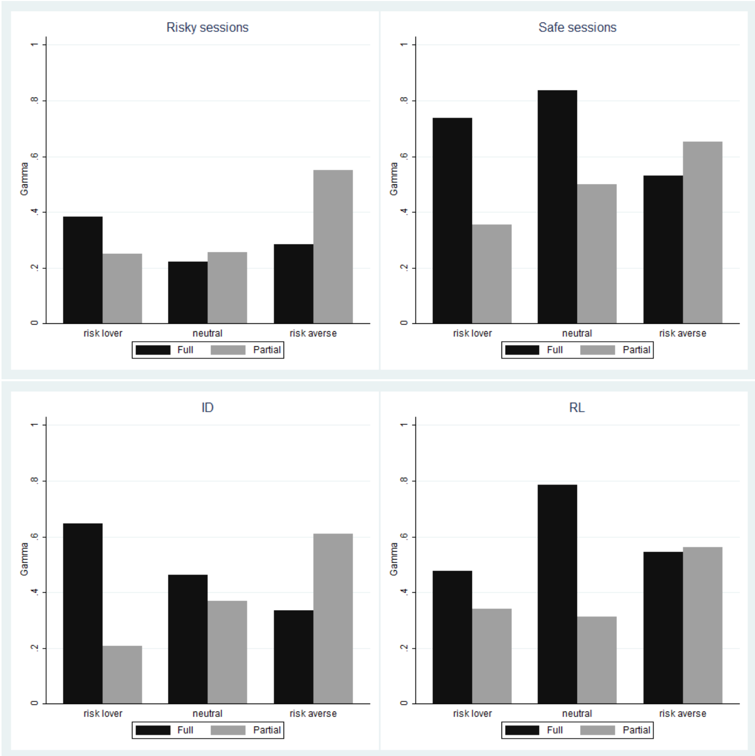
Figure 5 below presents the distribution of risk aversion in our sample of lenders. The median (and mean) of this self-assessed risk aversion measure is 5 on a scale from 1 (not risk-averse) to 9 (very risk-averse). For instance, in Brown and Serra-Garcia (2014), players displayed an average of 5.9 on a scale from 0 to 11, where higher values refer to a higher propensity to choose the certain outcome in a risk preference elicitation task.

Figure 5: Distribution of risk aversion self-assessed measure.



A simple comparison between risk-averse and risk-loving lenders' behaviour doesn't allow to detect any impact of risk on *Lend* (cf. Table 2, Panel E). To this end, Figure 6 shows lending propensities across sessions, risk aversion levels, and loan size categories.

Figure 6: Lending decisions across categories.



Beyond reflecting the higher rejection rate in the risky sessions (Fig. 6, top left), we note that the probability to lend differs across risk aversion and loan size groups. We do not observe a negative relation between risk aversion and lending propensity in general, however risk-averse lenders seem to prefer *Partial* loan requests in both risky and safe sessions, in accordance with the predictions of our model. Instead, neutral and risk-loving lenders choose to lend under single lending more often than under multiple lending, especially in the safe sessions. Performing the same exercise across treatments (Fig. 6, bottom) helps us understand better the relation between loan size and risk aversion. In the ID treatment, where information on borrowers' repayment behaviour is made more precise, risk-averse borrowers clearly lend more under multiple lending, in accordance with **Proposition 1**. On the contrary, preference towards single lending is evident in the RL treatment where this information is not disclosed, and inversely related to lenders' level of risk aversion, as expected from **Proposition 2**. In that case, single lending acts as a commitment device and increases borrowers' probability to be funded. In this second treatment, risk-averse lenders appear indifferent between *Partial* and *Full* requests because of the trade-off they face between the commitment and the risk aversion motives. We further investigate the determinants of borrowers' and lenders' behaviour in the following section.

4.2 Determinants of players' decisions

If **Proposition 3** on the role of project failure probability on players' behaviour is already confirmed by our W-M-W test, the other conjectures on the role of risk aversion and loan size are suggested by the descriptive statistics but not yet proven.

Given that all dependent variables are binary, we estimate our main equations using a dynamic logit model on our panel throughout 22 periods.[29] We compare how subjects' behaviour changes across treatments using alternatively sub-samples and treatment dummy variables. We also control for the effect of time and for unobserved static differences across groups by clustering the standard errors at the group level. Finally, the results are robust to the inclusion of a gender variable.

We first study the determinants of single lending requests from the borrower's perspective, as reported in Table 4. Columns 1-2 describes our results from the sub-samples by treatment, and column 3 reports estimates for the whole sample, where we include the treatment effect, identified by the ID variable, along with the interactions between ID and the other regressors. Our model only explains borrowers' decisions in the RL treatment, in which single lending requests are positively associated with projects' probability of success ($Safe$) and negatively correlated with time (the variable $Period$). This is confirmed by the fact that the variable $ID * Period$ (column 3) is positive and significant, showing that, with respect to the RL treatment, borrowers are more likely to ask for single bank lending contracts as the rounds of the session increase. In line with the results by Farinha and Santos (2002), multiple lending is associated with poor creditworthiness and increases over time. In the RL treatment, borrowers use the choice of single lending in the early rounds as a signal for their inherent trustworthiness, however their riskiness becomes apparent from their default history. In the ID treatment instead, the signalling is more directly exercised through repayment behaviour observed by lenders, limiting the use of single lending choice as a signalling tool. These results confirm our theoretical predictions about borrowers' behaviour in terms of loan size choice: the need to signal their trustworthiness through a borrowing decision appears in weak enforcement environments.

We thus summarize results from Table 4 in the following:

Result 1: *Borrowers opt for single loans as a way to communicate their creditworthiness when*

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

it is not directly observable.

As a next step, we consider lenders' behaviour (*Lend*). We add to the previous set of regressors the *Full* variable, and, in order to control for coordination effects arising between lenders, the dummy variable *PlayFirst* which takes the value of 1 if the lender is the first to enter the game. Results are displayed in Table 5: not surprisingly, we observe that the effect of project riskiness, expressed by the *Safe* variable, is always positive and significant. Moreover, the impact of time is negative and significant, as anticipated by the graphical evidence (Fig. 4).[30] These results are confirmed in column 3 displaying a negative and significant interaction effect of $ID * Safe$: lenders' reaction to project riskiness differs in both treatments. Specifically, lenders are more likely to grant credit to safer projects, but to a lower extent in the ID treatment than in the RL treatment. This can be explained by the different information borne by the default event in both treatments: in the RL treatment, lenders overreact because they can't disentangle free-riding from project failure. This particular issue will be studied further below, see Table 8. We summarize results from Table 5 in the following:

Result 2: *Lenders are more likely to grant credit to low-risk than high-risk projects. Project riskiness matters to a higher extent when information upon borrowers' trustworthiness is not available.*

We further investigate lenders' behaviour by taking into account their degree of risk aversion, testing predictions 1 and 2. When information about borrowers' quality is disclosed (in the ID treatment), we should be able to detect the impact of risk aversion on lenders' decisions, that is, risk-averse lenders' preference towards multiple lending (**Proposition 1**). Conversely, in opaque informational environments (in the RL treatment), lenders would interpret single bank lending relationships as a signal of commitment from more trustworthy borrowers, and lend more under single lending requests than in the ID treatment (**Proposition 2**). Our last set of regressions tests these predictions and estimates the impact of risk aversion on lenders' propensity to lend. Results from Table 6 show that, in the ID treatment, conditional on receiving a request for a

[30] As a robustness check, we also estimated the determinants of lending behaviour including $Period^2$ and the interaction effects between project risk (Safe) and time. In accordance with figure 4, but only in the case of the RL treatment, the linear effect is positive and significant; the non-linear effect is also significant, but negative. The coefficient of Safe alone becomes unsignificant in all models, but the impact of the other independent variables on lending behaviour are not significantly altered. In tables 5 and 6, we choose to display the model specifications without such interaction variables, but the alternative results are available upon request.

single loan, risk-averse lenders are less likely to lend than risk-loving ones: the interaction effect $Full * Riskaverse$ presents a negative sign. Our analysis thus provides empirical evidence to support **Proposition 1**. In the RL treatment, the interacted variable presents a negative coefficient too, but it is not significant. This may suggest that, in the RL treatment, there are other mechanisms in place that neutralise the effect of this variable as expected from **Proposition 2**. The first reason relates to the role of single lending as a way to identify trustworthy borrowers. Another possible explanation could relate to the use of relationship length as a proxy for the quality of borrowers. The difference between the two treatments is however not captured by the interactions of these terms with the ID variable. In our view, this is because the mechanism is similar in both treatments, but more salient in the ID case, where single lending does not act as a commitment device. We summarize our last result as follows:

Result 3: *In strong enforcement environments, risk-averse lenders are more likely to grant group loans than single loans.*

As a robustness check, we investigate whether differences in lenders' behaviours depending on their order of play emerge throughout the game. Empirical contributions to this line of research have shown that banks may be less willing to grant credit if they observe other lenders having denied the borrower's request in the past (Albertazzi et al., 2014). To this end, we replicate results from Table 6 (column 3)[31] by distinguishing between the first and the second lenders. Results are displayed in Table 7. Interestingly, only first lenders are more likely to lend when they receive a request for a larger loan, while this effect is not significant for second lenders. Similarly, we find that the coefficient of $Full * Riskaverse$ presents a negative sign and is statistically different from zero only for first lenders. All in all, these results suggest that findings from Table 6 are mainly driven by first lenders. Results are instead less clear-cut for second lenders. A potential explanation for these heterogeneous behaviours is that of information spillovers: when borrowers opt for single bank lending relationships, second lenders are informed that first lenders have rejected the borrower's request, through the information content embedded in the loan application itself. Therefore, besides risk aversion, this makes an additional reason for second lenders to prefer multiple lending to single lending. This result

[31] Because splitting the sample by lender reduces the number of observations quite much, especially for second lenders, we perform the analysis over both ID and RL treatments jointly. Still, our main results are robust to the analysis by treatment as well.

thus partly confirms **Proposition 4**: second lenders' decisions can be also accounted for by information spillovers.

In a final exercise, we study the role of the type of information about borrowers' default. We replace the $Safe$ variable with other proxies of borrowers' riskiness. $DefaultHist$ is a dummy variable which takes the value of 1 if the borrower has ever defaulted, as also displayed in the Credit Register. Instead, $FreerideHist$ is a dummy variable which takes the value of 1 if the borrower has ever free-ridden. Such event is only observed by the lending players in the ID treatment. Results are shown in Table 8. If in the RL treatment lenders cannot identify the type of default (thus $DefaultHist$ and $FreerideHist$ have the same predictive power), in the ID treatment only the measure related to trustworthiness ($FreerideHist$) has a significant impact on the probability to lend. In the regressions including both treatments (columns 5-6), such results are confirmed by a positive interaction effect $ID * DefaultHist$ and no significant difference in the case of the free-riding variable, $ID * FreerideHist$. This further gives evidence that in this case lenders react differently to default events depending on their exogenous or behavioural cause. Indeed, they punish free-riding but are lenient towards risky borrowers. We can thus conclude that borrowers having a good reputation towards a lender (a stable relationship based on the borrowers' trustworthy behaviour) can mitigate their risky profile and benefit from relatively good credit terms.

5 Conclusion

This paper aims at shedding new light on the conditions under which banks prefer to enter in single versus multiple bank lending relationships. Despite the extensive empirical and theoretical literatures that explore the motives and benefits for firms to engage in one or several bank lending relationships, it is still unclear what determines banks' preference towards one of the two strategies. Given the difficulties to disentangle risk aversion and relationship lending in a pure observational setting, we explore the respective roles of (imperfect) information and lenders' risk aversion on their preference towards single or multiple lending by means of a laboratory experiment, testing the theoretical predictions from a simple static model. In particular, we exogenously vary the quality of information lenders observe upon borrowers' behaviour, and exploit this variation to study how lenders' modify their lending behaviour when asked to engage in a single versus a multiple bank lending relationship. Our results suggest that lenders' decisions are significantly driven by both the type of information context they operate in and their degree of risk aversion. We do find that lenders are more likely to grant credit to low-risk than high-risk projects, especially in more opaque settings. In such weak enforcement environments, where information upon the borrowers' trustworthiness cannot be easily acquired, our model suggests that there is a trade-off between risk aversion and signalling effects of loan size on lenders' willingness to lend. This is evident in our empirical results where we do not catch a significant interaction effect between the choice of single lending and risk aversion.

Conversely, when borrowers' repayment behaviour can be better monitored (in strong enforcement environments), risk-averse lenders are more likely to grant group than single loans. In that case, lenders react to borrowers' *behaviour*, rather than exogenous determinants of default such as risk. They increase lending to those borrowers that have clearly signaled their willingness to cooperate, by being trustworthy, concentrating their credit and choosing repeatedly the same lender.

Although with some limitations, especially related to the size of our sample, our findings may contribute to explain why multiple lending is not only observed in weak enforcement contexts, as shown by Ongena and Smith (2000), but also in strong enforcement contexts, as for example in Italy (De Masi and Gallegati, 2012) or Japan (Amiti and Weinstein, 2013).

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A1. Modelling

Figure 7: The game tree. This figure shows the extensive form of the game. We report, at each node, which player makes the action (b borrower; $l1$ the first lender; $l2$ the second lender). The borrower makes the first move and decides whether to opt for a single bank lending strategy ($Full$ decision, here indicated with F) or a multiple one ($Partial$ decision, indicated with P). Lenders, in turn, must decide whether to lend credit (Y in the figure) or not (N). The last node of each branch of the game tree shows a number. These are used to identify the final payoff of each player based on the adopted strategy as reported in Figure 8.

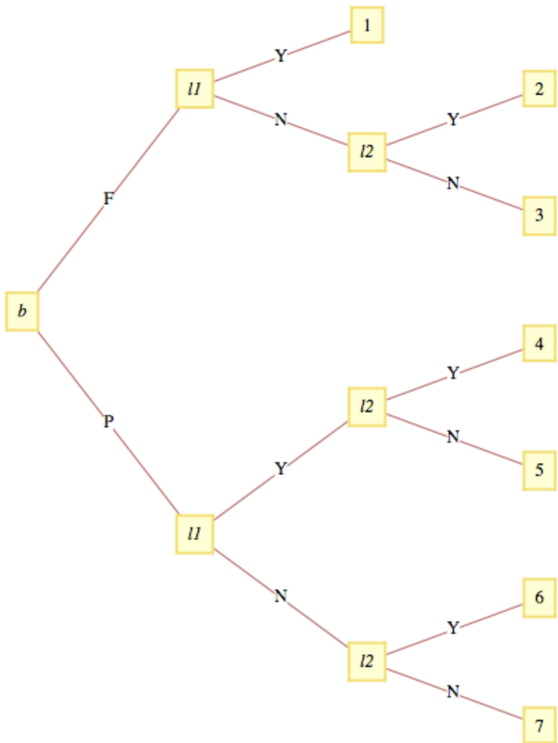


Figure 8: Agents' payoffs. This figure shows the agents' payoffs based on the strategy adopted in the game. The final number in brackets is used to relate the payoff with the corresponding strategy as per Figure 7.

Borrowers' payoffs:

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

First lenders' payoffs:

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

Second lenders' payoffs:

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

A2. Computations

A2.1. Equation (2).

The payoff from not lending is given by the sure payoff

$$E(y_{notlend,single}) = E(y_{notlend,multiple}) = s,$$

which implies that their associated variances are null ($\sigma^2_{y_{notlend,single}} = \sigma^2_{y_{notlend,single}} = 0$). When agreeing to lend under a full request, the payoff and variance are $E(y_{lend,single}) = \alpha\beta D(1+r) - D + s$ and $\sigma^2_{y_{lend,single}} = \alpha\beta D(1+r)(1-\beta)[\alpha D(1+r) + 4(s-D)^2]$. In the case of multiple lending they are $E(y_{lend,multiple}) = \alpha\beta\frac{D}{2}(1+r) - \frac{D}{2} + s$ and $\sigma^2(\beta_j)_{y_{lend,multiple}} = \alpha\beta\frac{D}{2}(1+r)(1-\beta)[\alpha\frac{D}{2}(1+r) + 4(s-\frac{D}{2})^2]$.

A2.2. $\bar{V}_{single}$ and $\bar{V}_{multiple}$

We now study the relationship between $\bar{V}_{single}$ and $\bar{V}_{multiple}$.

$$\bar{V}_{single} < \bar{V}_{multiple} \iff \frac{2(\alpha\beta D(1+r) - D)}{\sigma^2_{y_{lend,single}}} < \frac{(\alpha\beta D(1+r) - D)}{\sigma^2_{y_{lend,multiple}}} \tag{11}$$

where

$$\sigma^2_{y_{lend,single}} = \alpha\beta D(1+r)(1-\beta)[\alpha D(1+r) + 4(s-D)^2]$$

$$\sigma^2_{y_{lend,multiple}} = \alpha\beta\frac{D}{2}(1+r)(1-\beta)[\alpha\frac{D}{2}(1+r) + 4(s-\frac{D}{2})^2]$$

We multiply both sides by $\frac{1}{2}\alpha\beta D(1+r)(1-\beta)$ which is always positive for $\beta \in (0,1)$. Inequality (11) thus becomes:

$$\frac{\alpha\beta D(1+r) - D}{\alpha D(1+r) + 4(s-D)^2} < \frac{\alpha\beta D(1+r) - D}{\alpha\frac{D}{2}(1+r) + 4(s-\frac{D}{2})^2} \tag{12}$$

Assuming $\alpha\beta D(1+r) - D > 0$, which happens for $\beta > \beta^*$, we can simplify both sides of the inequality and get:

$$\frac{1}{\alpha D(1+r) + 4(s-D)^2} < \frac{1}{\alpha\frac{D}{2}(1+r) + 4(s-\frac{D}{2})^2} \tag{13}$$

This is equivalent to:

$$\alpha D(1+r) + 4(s-D)^2 > \alpha\frac{D}{2}(1+r) + 4(s-\frac{D}{2})^2$$

which, simplified, gives:

$$\alpha \frac{D}{2}(1+r) > 4[(s-\frac{D}{2})^2-(s-D)^2]$$

It is immediate to see that the above inequality always holds, being the LHS always positive and the RHS always negative. Therefore, we can conclude that, for $\beta > \beta^* \Rightarrow \bar{V}_{single} < \bar{V}_{multiple}$. Following the previous demonstration, we can easily prove from (13) that if $\beta < \beta^* \Rightarrow \bar{V}_{single} > \bar{V}_{multiple}$.

A2.3. Associating expected loan size to Full and Partial decisions

We associate expected loan size to each choice (Full or Partial) as follows.

If the borrower opts for Full, the expected value of this strategy is $E(\phi_j = 1) = \gamma_1(D-s) + (1-\gamma_1)\gamma_2(D-2s) + (1-\gamma_1)(1-\gamma_2)(-2s)$, where γ_1 and γ_2 are the probabilities that the first and the second lender would lend, respectively. If, instead, the borrower opts for Partial, the expected value of the strategy will be: $E(\phi_j = 0) = \gamma_1\gamma_2(D-2s) + (1-\gamma_1)\gamma_2(D/2-2s) + (1-\gamma_2)\gamma_1(D/2-2s) + (1-\gamma_1)(1-\gamma_2)(-2s)$.

$$E(Full) = \gamma_1(D-s) + (1-\gamma_1)\gamma_2(D-2s) + (1-\gamma_1)(1-\gamma_2)(-2s) \tag{14}$$

$$E(Partial) = \gamma_1\gamma_2(D-2s)+(1-\gamma_1)\gamma_2(D/2-2s)+(1-\gamma_2)\gamma_1(D/2-2s)+(1-\gamma_1)(1-\gamma_2)(-2s) \tag{15}$$

$$E(Full) > E(Partial) \iff$$
$$\gamma_1(D-s) + (1-\gamma_1)\gamma_2(D-2s) + (1-\gamma_1)(1-\gamma_2)(-2s) >$$
$$\gamma_1\gamma_2(D-2s) + (1-\gamma_1)\gamma_2(D/2-2s) + (1-\gamma_2)\gamma_1(D/2-2s) + (1-\gamma_1)(1-\gamma_2)(-2s)$$

$$\gamma_1 D + (1-\gamma_1)\gamma_2 D - \gamma_1\gamma_2 D - \gamma_1 s > \gamma_1\gamma_2(-2s) + (1-\gamma_1)\gamma_2\frac{D}{2} + (1-\gamma_2)\gamma_1\frac{D}{2} + (1-\gamma_2)\gamma_1(-2s)$$

$$\gamma_1 D + (1-\gamma_1)\gamma_2 D - \gamma_1\gamma_2 D - (1-\gamma_1)\gamma_2\frac{D}{2} - (1-\gamma_2)\gamma_1\frac{D}{2} > \gamma_1 s - \gamma_1\gamma_2(2s) - (1-\gamma_2)\gamma_1(2s)$$

$$\gamma_1(1-\gamma_2)\frac{D}{2} + (1-\gamma_1)\gamma_2\frac{D}{2} > \gamma_1 s - \gamma_1\gamma_2(2s) - (\gamma_1-\gamma_1\gamma_2)(2s)$$

$$\frac{D}{2}(\gamma_2 + \gamma_2 - 2\gamma_1\gamma_2) > -\gamma_1 s$$

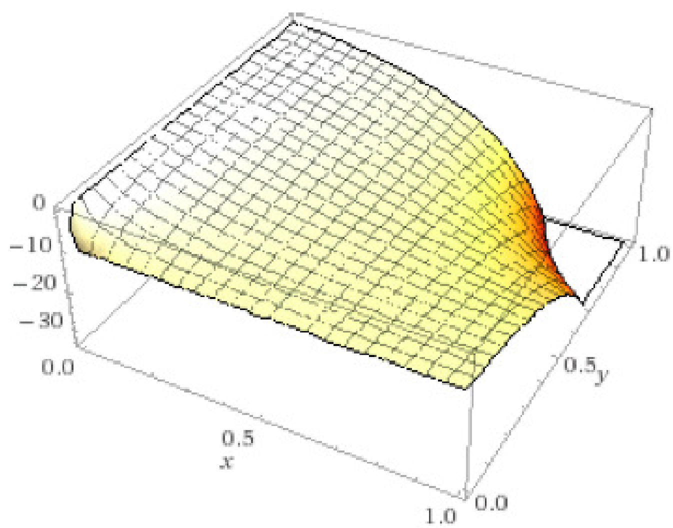
$$E(Full) > E(Partial) \iff D > \frac{-\gamma_1(2s)}{\gamma_1 + \gamma_2 - 2\gamma_1\gamma_2} = \underline{D} \tag{16}$$

We compare the expected values of both strategies and get the following relation:

$$E(\phi_j = 1) > E(\phi_j = 0) \iff D > \frac{-\gamma_1(2s)}{\gamma_1 + \gamma_2 - 2\gamma_1\gamma_2} = \underline{D} \tag{17}$$

Because $\underline{D} < 0$ as can be seen from figure 9, we can conclude that the above inequality is always satisfied, and the expected value of opting for the Full strategy is always higher than the one of the Partial strategy.

Figure 9: $\underline{D}$ as a function of γ_1 and γ_2.



A3. Empirics

Table 3: Variables used in the regressions

Variable	Description
$Full_{j,t}$	= 1 if the borrower chooses single lending in period t = 0 if the borrower chooses multiple lending (split the lending request)
$\gamma_{i,t}$	= 1 if the lender accepts the loan request in period t = 0 if he denies it *(First and second lender choices are pooled)*
$Safe$	= 1 for sessions with a high value of α = 0 otherwise
$Riskaverse_i$[32]	= 1 if the lender answered 6,7,8; = 2 if answered 4,5; =3 if answered 1,2,3.
$DefaultHist_{j,t}$	= 1 if the borrower has defaulted at least once in previous periods = 0 otherwise
$FreerideHist_{j,t}$	= 1 if the borrower has refused to repay at least once in previous periods = 0 otherwise
$Period_t$	the period of play, ranging from 1 to 22
$PlayFirst_{i,t}$	= 1 if the lender is chosen to play first in the round of play = 0 otherwise

[32]We construct the $Riskaverse$ variable from question 9 of the final survey: *How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? (1=you totally try to avoid risks.....9=you are fully prepared to take risks).*

Table 4: Determinants of single lending requests

dep var: Full	ID	RL	All
	(1)	(2)	(3)
Safe	0.103	0.190*	0.218*
	(0.112)	(0.131)	(0.132)
Period	0.002	-0.010***	-0.012***
	(0.003)	(0.005)	(0.004)
ID			-0.139
			(0.115)
ID*Safe			-0.138
			(0.208)
ID*Period			0.013***
			(0.005)
Nb of observations	396	308	704
Nb borrowers	17	14	31

Note: We only observe 31 groups because one of the borrowers never got to make a decision in the entire game. Standard errors in parentheses. Dynamic random effects (Logit RE), displaying marginal effects at variable means. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Determinants of lending behaviour (full vs partial requests)

dep var: Lend	ID	RL	All
	(1)	(2)	(3)
Play First	0.126*	0.094	0.112**
	(0.064)	(0.070)	(0.047)
Safe	0.372*	0.624***	0.687***
	(0.201)	(0.092)	(0.115)
Full	-0.175**	-0.060	-0.098
	(0.069)	(0.080)	(0.080)
Period	-0.028***	-0.029***	-0.032***
	(0.005)	(0.006)	(0.006)
ID			0.111
			(0.223)
ID*Safe			-0.445**
			(0.206)
ID*Full			-0.058
			(0.104)
ID*Period			0.005
			(0.007)
Nb of observations	613	464	1077
Nb lenders	36	28	64

Note: Standard errors in parentheses. Dynamic random effects (Logit RE), displaying marginal effects at variable means. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Determinants of lending behaviour (risk aversion)

dep var: Lend	ID	RL	All
	(1)	(2)	(3)
Play First	0.163**	0.096	0.129**
	(0.075)	(0.070)	(0.052)
Safe	0.450**	0.623***	0.696***
	(0.216)	(0.093)	(0.119)
Full	0.310	0.181	0.214
	(0.213)	(0.169)	(0.133)
Riskaverse	-0.015	0.212*	0.281*
	(0.191)	(0.119)	(0.147)
Full*Riskaverse	-0.237**	-0.162	-0.211***
	(0.109)	(0.010)	(0.074)
Period	-0.035***	-0.029***	-0.032***
	(0.006)	(0.006)	(0.006)
ID			0.459
			(0.334)
ID*Safe			-0.374
			(0.257)
ID*Full			0.090
			(0.122)
ID*Riskaverse			-0.293
			(0.193)
ID*Period			-0.002
			(0.008)
Nb of observations	518	464	966
Nb lenders	31	28	59

Note: We only observe 59 groups because for a few groups, we weren't able to retrieve the answers to the questionnaire, which contained the questions uncovering their risk aversion. Standard errors in parentheses. Dynamic random effects (Logit RE), displaying marginal effects at variable means. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Determinants of lending behaviour (coordination)

dep var: $Lend_i$	Lend first	Lend second
	(1)	(2)
Safe	0.698***	0.426**
	(0.126)	(0.207)
Full	0.598***	-0.187
	(0.125)	(0.201)
Riskaverse	0.380**	0.084
	(0.158)	(0.128)
Full*Riskaverse	-0.352***	-0.067
	(0.100)	(0.102)
Period	-0.031***	-0.035***
	(0.008)	(0.010)
ID	0.319	0.149
	(0.392)	(0.359)
ID*Safe	-0.366	-0.253
	(0.293)	(0.167)
ID*Full	0.028	0.182
	(0.158)	(0.179)
ID*Riskaverse	-0.240	-0.133
	(0.190)	(0.166)
ID*period	0.007	-0.004
	(0.010)	(0.012)
Nb of observations	638	328
Nb lenders	58	48

Note: The lower number of groups refers to the missing information regarding the risk aversion measure, and, for the second lenders only, the fact that they never got to enter the game (first lenders agreeing to lend in full). Standard errors in parentheses. Dynamic random effects (Logit RE), displaying marginal effects at variable means. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Determinants of lending behaviour (default vs. free ride)

dep var: Lend	ID		RL		All	
	(1)	(2)	(3)	(4)	(5)	(6)
Play First	0.226***	0.213***	0.054	0.073	0.136**	0.141**
	(0.077)	(0.078)	(0.074)	(0.077)	(0.055)	(0.056)
Full	0.427**	0.485***	0.084	0.015	0.209	0.198
	(0.185)	(0.173)	(0.183)	(0.187)	(0.140)	(0.141)
Riskaverse	0.049	0.081	0.206	0.159	0.312**	0.294*
	(0.196)	(0.187)	(0.139)	(0.141)	(0.159)	(0.155)
Full*Riskaverse	-0.302***	-0.330***	-0.121	-0.073	-0.227***	-0.217***
	(0.114)	(0.116)	(0.105)	(0.108)	(0.078)	(0.079)
DefaultHist	-0.220		-0.564***		-0.601***	
	(0.158)		(0.088)		(0.090)	
FreerideHist		-0.358***		-0.532***		-0.513***
		(0.102)		(0.082)		(0.088)
Period	0.031***	-0.018**	-0.015**	-0.009	-0.018***	-0.012*
	(0.007)	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)
ID					0.025	0.179
					(0.463)	(0.415)
ID* DefaultHist					0.435**	
					(0.186)	
ID* FreerideHist						0.164
						(0.163)
ID*Full					0.171	0.180
					(0.127)	(0.130)
ID*Riskaverse					-0.293	-0.283
					(0.210)	(0.203)
ID*period					-0.012	-0.006
					(0.009)	(0.010)
Nb of observations	495	495	444	444	924	924
Nb lenders	31	31	28	28	59	59

Note: We only observe 59 groups because for a few groups, we weren't able to retrieve the answers to the questionnaire, which contained the questions uncovering their risk aversion. Standard errors in parentheses. Dynamic random effects, displaying marginal effects at variable means. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.