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Microcredit Contracts, Risk Diversification and Loan Take-Up*

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Abstract

We study theoretically and empirically the demand for microcredit under different liability arrangements and risk environments. A simple theoretical model shows that the demand for joint-liability loans can exceed that for individual-liability loans when risk-averse borrowers value their long-term relationship with the lender. Joint liability then offers a way to diversify risk and to reduce the chance of losing access to future loans. We also show that the demand for loans depends negatively on the riskiness of projects. Using data from a randomized controlled trial in Mongolia we find that these model predictions hold true empirically. In particular, we use innovative data on subjective risk perceptions to show that expected project risk negatively affects the demand for loans. In line with an insurance role of joint-liability contracts, this effect is muted in villages where joint-liability loans are available.

JEL: D14, D81, D86, G21, O16

Key words: Microcredit, joint liability, loan take-up, risk diversification

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1 Introduction

The past few years have witnessed an intense debate on whether microcredit can lift people out of poverty. Advocates have long painted a picture in which many households escape poverty once they get access to small loans. However, more recently, doubts have emerged about whether microcredit systematically improves living standards. This scepticism has been fuelled by rigorous evidence from across seven countries which shows that when poor households get access to microloans this typically does not lead to meaningful increases in either income or consumption (Banerjee et al. (2015)).

One explanation for these insignificant average impacts is that relatively few people take up microcredit when it is offered to them. Low take-up rates may to some extent reflect a lack of creditworthy borrowers and profitable projects. Low-quality potential borrowers tend to rationally self-select out of the credit market or are screened out by loan officers. Yet, even among entrepreneurs that in principle could service debt there may be limited appetite to borrow (Johnston and Morduch (2008)). Low take-up may for instance reflect borrowers' dissatisfaction with the contractual structure of microcredit itself. That is, entrepreneurs that in principle would like to borrow may be dissuaded from doing so because of certain unattractive features of microcredit contracts.

Microfinance is very heterogeneous and microcredit contracts differ in many dimensions. An important question is therefore how microcredit can be turned into a more attractive and hence more effective tool to increase entrepreneurship and living standards. Recent evidence suggests that small design changes – such as introducing grace periods (Field et al. (2013)) or tailoring repayment schedules to the needs of individual borrowers (Beaman et al. (2015)) – may affect how people use microcredit. This paper focuses on a quintessential feature of microcredit contracts: their liability structure.

In the early days of its existence, much attention was given to microcredit contracts in which borrowers form groups that are jointly liable.[1] Such a feature, possibly exploiting

[1] Under joint liability, small groups of borrowers are responsible for the repayment of each other's loans. All group members are treated as being in default when at least one of them does not repay and all

informational advantages of clients relative to loan officers, was supposed to improve loan performance and raise repayment rates. The fact that joint-liability loans can also have a risk-sharing aspect received less attention in the literature. In this paper we focus on this aspect as it can possibly increase loan take-up in situations where projects are risky and where uncertainty is a salient component of the decision process.

The main idea, which we explore both theoretically and empirically, is that joint-liability encourages risk sharing among group members and, therefore, reduces the risk involved in any given project. This may in turn lead to an increase in the proportion of borrowers that start a business (as compared with individual-liability credit). To formalize this simple point, we develop a concise theoretical model where individuals choose whether to take up a loan for a risky project or to pursue a safe project.[2] Risk-averse investors will therefore be less willing to take up a loan to finance a risky project the higher is the risk of such projects. The model produces two main testable predictions. First, individuals will be more likely to take up a loan when offered a joint-liability contract instead of an individual liability one. Second, while in both contractual frameworks take-up rates go down with the risk of the project, this effect is muted for joint-liability contracts.

We provide empirical evidence on the relationship between risk and loan take-up that supports both these theoretical predictions. To do so, we exploit the data used in Attanasio et al. (2015), which contains detailed survey data from a randomized controlled trial (RCT) in Mongolia. As part of this RCT individual-liability and joint-liability credit was randomly introduced across villages (while no credit was introduced in a set of control villages). This unique set up allows for a clean comparison of both types of liability structure while keeping other product features constant.

The Mongolian survey data is unique in that it contains, for each respondent, crucial information about the subjective probability distribution of the returns on the investment projects that could be financed by the newly available microcredit. Having elicited such

members are then denied subsequent loans.

[2] While the model is static, we consider future welfare by assuming that default implies the loss of access to future loans from the lender.

subjective probability distributions through a number of questions we describe below, we can compute the riskiness of investment projects at the individual and (by averaging) at the village level. We can therefore relate differences in loan take up between individual and joint-liability schemes to the (perceived) riskiness of the projects available in different villages. These results can then be compared with the two model predictions mentioned above. This comparison shows that the subjective riskiness of projects negatively affects the demand for loans but that this effect is muted in villages where joint-liability loans are available. This confirms the insurance role of joint-liability loans.

Our findings contribute to a rich literature on joint-liability lending that has emerged over the last two decades.[3] Theoretical work has explored how joint liability may reduce adverse selection (Ghatak (1999, 2000) and Gangopadhyay et al. (2005)); ex ante moral hazard by preventing excessively risky projects and shirking (Stiglitz (1990), Banerjee et al. (1994) and Laffont and Rey (2003)); and ex post moral hazard by preventing non-repayment in case of successful projects (Bohle and Ogden (2010)). In models such as those developed by Besley and Coate (1995) and Ghatak and Guinnane (1999), joint liability fosters mutual insurance among group members and consequently leads to better repayment performance. More recently, De Quidt et al. (2014) compare joint-liability lending with two types of individual-liability lending: with and without group meetings (which facilitate informal mutual insurance). They show that in a context of high social capital, individual-liability lending where borrowers are able to sustain informal mutual insurance (implicit joint liability) can improve upon explicit joint-liability lending in terms of borrower welfare and repayment.

On the empirical side, a small number of papers assess the impact of liability structure on repayment performance. Ahlin and Townsend (2007) test empirically the implications of different models with joint liability in the context of Thailand and find a negative relationship between the degree of joint liability, as proxied by the fraction of the group that is landless, and repayment. Giné and Karlan (2014) examine the impact of joint liabil-

[3] See Ghatak and Guinnane (1999) for a comprehensive early summary.

ity on repayment through two experiments in the Philippines. They find that removing group liability, or introducing individual liability from scratch, did not affect repayment rates over the ensuing three years. In a related study, Carpena et al. (2013) exploit a quasi-experiment in which an Indian lender switched from individual to joint-liability, the reverse of the switch in Giné and Karlan (2014). They find that joint liability significantly improved repayment rates.

Unlike this earlier theoretical and empirical work, our main focus is not so much on repayments but on the take-up of productive investments. Whilst we do not discuss the specific credit-market frictions, such as moral hazard and adverse selection, that prevent the financing of these projects in the absence of a micro-lender, we consider the impact of joint liability relative to individual liability on risk taking and investment behavior. This issue has been explored to a lesser extent in the literature and remains ambiguous.[4] On the one hand, joint liability may encourage risk taking if clients expect to be bailed out by co-borrowers as part of the mutual insurance mechanism inherent to joint-liability contracts. On the other hand, joint liability may reduce moral hazard if borrowers monitor each other and if there is a credible threat of punishment, for instance through social sanctions, in case a co-borrower defaults. Giné et al. (2010) find, based on laboratory-style experiments in a Peruvian market, that contrary to much of the theoretical literature, joint liability stimulates risk taking - at least when borrowers know the investment strategies of co-borrowers. When borrowers could self-select into groups there was a strong negative effect on risk taking due to assortative matching. Fischer (2013) undertakes similar laboratory-style experiments and also finds that under limited information, group liability stimulates risk taking as borrowers free-ride on the insurance provided by co-borrowers.[5] When co-borrowers have to give upfront approval for each others' projects ex ante moral hazard is mitigated.[6]

[4] Early seminal contributions on informal insurance arrangements are Coate and Ravallion (1993) and Ligon et al. (2002). In these models, risk-averse individuals agree on an informal risk-sharing arrangement that, while legally not enforceable, is credible due to expected future reciprocity.

[5] Wydick (1999) provides empirical evidence from Guatemala on intra-group insurance against idiosyncratic risks.

[6] A related empirical literature investigates the introduction of formal insurance products on risk taking

The results of our theoretical model are consistent with those of Fischer (2013) and Giné et al. (2010). Our contribution is to focus on the interaction between the liability structure of microcredit and borrowers' own perception of the local risk environment. In particular, we show that joint-liability can substantially reduce the negative effect of expected project risk on loan take up.

The remainder of this paper is structured as follows. We start by presenting our theoretical model (Section 2) and then describe the data we use to check whether our model predictions hold true in the given context (Section 3). Section 4 presents our findings, after which we conclude in Section 5.

2 Risk sharing in a model of microcredit with different liability contracts

Unlike earlier papers in the microfinance literature, our emphasis is not so much on repayments but on the take-up of productive investments. The main idea that we want to outline is that joint liability might encourage (or provide an institutional setting that allows) risk sharing among group members as, de facto, it reduces the amount of risk involved in a given project. Joint liability may therefore lead to an increase in the proportion of borrowers that start a business.

2.1 General set up

To make this simple point we use a model where individuals choose whether to take up a loan for a risky project or pursue a safe project. While the model is static, we also consider a term that represents future welfare as we assume that default implies the loss of future loans from the lender. As in Giné et al. (2010), the risky project is socially desirable since

in settings where (imperfect) informal insurance is available. Mobarak and Rosenzweig (2013) find that the introduction of formal (rainfall) insurance, which complemented informal insurance networks among households, increased risk taking among Indian farmers by incentivizing them to switch to higher-risk, higher yield crop varieties.

it has an expected return that is (considerably) higher than the return on the safe project. Whether the excess return compensates for the additional return variability depends on individual risk aversion. Moreover, the availability of joint-liability loans institutionalizes a risk-sharing mechanism that may not be available in the absence of this type of credit. We then test the predictions of our simple model, and give an empirical characterization of results that are ambiguous from a theoretical point of view, with data we collected as part of a randomized controlled trial.

Let's consider individuals who can either invest in a productive but risky project or in a safe project. Each individual is endowed with a quantity D, which may be different across individuals. If invested in the safe project, D provides a certain return of DR^s. We can think of this as financing consumption or some very simple activity that is not particularly risky or productive.

All individuals also have access to a risky project. This risky project requires an investment of $D + B$, where $D \ll B$. We assume that investing in the risky project earns a return R^H with probability q and R^L with probability $1 - q$. There is a lender that supplies loans of size B to finance the project at a rate R^b. We assume the following set of inequalities between the various rates:

$$\begin{aligned} R^H &> R^s; \\ R^b &> R^L \geq 0; \\ R^H &> 2R^b; \\ qR^H + (1-q)R^L &> R^k,\ k = s,\ b. \end{aligned}$$

The first inequality simply says that the return on the risky project, when successful, is greater than the return on the safe project. The second inequality indicates that the borrowing rate is greater than the return on the risky project when it is unsuccessful, while the third inequality says that the return on the risky project is potentially very high. This inequality guarantees that in the joint-liability case, a successful partner can bail out an unsuccessful one. Finally, the fourth inequality conveys that the expected value of the risky project is higher than both the return on the safe project and the borrowing rate.

We now discuss what happens when an individual has a loan with the lender and defaults. Although the model is static (we consider only one period) in reality the relationship between the borrower and the lender may be of a long-term nature. Default may jeopardize this long-term lending relationship and thus involve a cost. We assume that this relationship is valued at some exogenous amount of K utils. One could develop a more complete model but for the main point we want to make this is not necessary.

At the end of the period, individuals enjoy utility that depends on whether they chose the safe or risky project and, in the latter case, on whether the project was successful or not. If they do not default on the loan (either because they simply did not borrow or because they borrowed and repaid on time) they also obtain K utils. K represents the reputation with the lender and the associated availability of future loans (which may moreover come at a lower interest rate if the lender rewards repeat borrowing). To the extent that default is publicly observable in the local community, K may also include the preservation of social collateral. K is measured in utils.[7]

The individuals in our economy are heterogeneous in R^s, i.e. there are differences in the returns on the safe project, such as home production. We nevertheless assume that all R^s satisfy inequality (4). We need this heterogeneity to allow some individuals to borrow while others do not. For expositional simplicity we assume that there are two groups of individuals of the same size in the economy and that within each group the product DR^s is uniformly distributed over the same support. All individuals share the same utility function, which is increasing and concave, as well as the utils that they derive from the long-term relationship with the lender. Finally, all individuals consume an amount y which is exogenous and cannot be recovered by the lender.

We now consider two types of contracts: individual liability and joint liability. For simplicity we assume that joint-liability groups include only two individuals and that

[7] For simplicity, we assume that the K utils from not defaulting on a loan are the same under joint and individual liability.

individuals form groups with individuals with similar R^s.[8]

2.1.1 The individual-liability contract

When an individual does not take up a loan, she will retain the long-term relationship with the lender. When an individual-liability loan is taken and the project turns out to be successful, the borrower will repay BR^b and preserve her long-term lending relationship. However, if the project is unsuccessful, she repays only $(D + B)R^L$, which is assumed to be below BR^b. She also loses the long-term relationship with the lender and consumes the exogenous amount y.

2.1.2 The joint-liability contract

In the case of joint liability, we assume that the two borrowers are identical in the product DR^s. That is, we assume that individuals are matched in groups with similar individuals in the one dimension of heterogeneity that we are considering. This assumption simplifies the analysis and it is not crucial for the point we want to make. We assume that the outcomes of the two projects are independent. Hence both projects will be successful with probability q^2, they will both be unsuccessful with probability $(1 - q)^2$, and only one will be successful with probability $2q(1 - q)$.

The two individuals in a group are jointly liable for their loans. As they are identical, they will make the same choices. If they choose the safe project and do not take up a loan, they will both receive DR^s and preserve the long-term relationship with the lender. If they take up a loan and both their projects are successful they will both repay their loan and interest and preserve the lending relationship. If the first individual's project is successful and that of the second one is not, the first individual will bail out the second and pay the lender $2R^bD$ to cover both loans. However, we assume that she will get the proceedings of the investment from the second individual ($(D + B)R^L$) as a partial

[8] When we consider different degrees of risk aversion we obtain very similar results. Note that in our experiment matching was endogenous and take-up was high, suggesting that assortative matching took place. Appendix A provides evidence that individuals within a group are indeed characterized by similar risk attitudes.

compensation. Symmetrically, if the first individual's project fails while the second's is successful, she will consume only y but preserve the long-term relationship with the lender as she will be bailed out by her partner.

2.2 Theoretical results

The last two columns of Table 1 summarize the contractual arrangements described in Section 2.1. Each row reports the utilities obtained by individual 1 in a given scenario.

Table 1: **Utility of individual 1 when the risky project is chosen**

	Probability	Individual liability	Joint liability
Both succeed	q^2	$U(y+Y^H)+K$	$U(y+Y^H)+K$
1 succeeds, 2 fails	$q(1-q)$	$U(y+Y^H)+K$	$U(y+Y^H-Y^P)+K$
1 fails, 2 succeeds	$q(1-q)$	$U(y)$	$U(y)+K$
Both fail	$(1-q)^2$	$U(y)$	$U(y)$
where $Y^H = DR^H + B(R^H - R^b)$; $Y^P = BR^b - (D+B)R^L$.			

Expected utility under individual liability, U^I, and group liability, U^G, are, respectively:

$$U^I = q^2\left(U\left(y+Y^H\right)+K\right) + q(1-q)\left(U\left(y+Y^H\right)+K\right) + q(1-q)U(y) + (1-q)^2\,U(y)$$

$$U^G = q^2\left(U\left(y+Y^H\right)+K\right) + q(1-q)\left(U\left(y+Y^H-Y^P\right)+K\right) + q(1-q)(U(y)+K) \\ + (1-q)^2\,U(y).$$

Each individual computes the expected utility of the risky project and compares it to the utility that she can get by investing in the safe project. Which of the two is chosen depends obviously on all the parameters of the model. However, defining U^I and U^G as

$U^I == U(y + R^{s*}D)$ and $U^G == U(y + R^{s**}D)$, the following proposition is immediate.

Proposition 1. Under individual liability, there exists a level of returns to the safe project R^s, R^{s*}, such that individuals with $R^s > R^{s*}$ will invest in the safe projects and individuals with $R^s \leq R^{s*}$ will get a loan from the lender. Analogously, under joint liability, there is a level of returns to the safe project R^s, R^{s**}, such that individuals with $R^s > R^{s**}$ will invest in the safe projects and individuals with $R^s \leq R^{s**}$ will form groups that take a loan from the lender.

The proof of the proposition follows from the consideration of the expected utility under the two alternatives and from the fact that the excess return on the risky project is monotonic and decreasing in R^s.□

In this context, for a given utility function, investment choices are determined by the entire return distribution and not just by its variance. Participation in a joint-liability scheme, for instance, might reduce risk but also change the mean of the distribution because the successful individual has to bail out a potentially unsuccessful partner and, in return, is bailed out by her partner in certain states of the world. The overall effect depends on how much individuals value the long-term relationship with the lender. If K is large enough, the mean will increase and the proportion of individuals that will take a joint-liability loan increases too.

An interesting case to consider, and one that delivers a sufficient condition for an increase in the proportion of borrowers under joint liability, is the case in which K is such that the 'mean expected return' does not decrease when moving to a joint-liability contract. We can show that this holds when the relationship with the lender is valued more than the difference in utility when successful with and without having to bail out the joint-liability partner.

Assumption 1. Suppose that K is such that:

$$K \geq U(y + Y^H) - U(y + Y^H - Y^P)$$

This assumption easily delivers the following proposition:

Proposition 2. If Assumption 1 holds, the fraction of individuals that take the loan under joint liability is higher than the one under individual liability.

Proof. Assumption 1 implies that:

$$q^2\left(U\left(y+Y^H\right)+K\right)+q(1-q)\left(U\left(y+Y^H\right)+K\right)+q(1-q)U(y)$$
$$+(1-q)^2U(y)\leq q^2\left(U\left(y+Y^H\right)+K\right)+q(1-q)\left(U\left(y+Y^H-Y^P\right)+K\right)$$
$$+q(1-q)(U(y)+K)+(1-q)^2U(y)$$

Where the left-hand side of this expression is the expected return under individual liability, while the right-hand side is the expected return under joint liability. This can be more easily seen by simplifying the expression to $U(y+Y^H)-U(y+Y^H-Y^P)\leq K$. Proposition 2 then follows directly from the concavity of the utility function.□

The intuition behind the proposition is quite simple. A joint-liability contract does two things. On the one hand it offers some insurance as the two borrowers share risk. On the other hand, there is a change in the mean return as a result of two considerations. First, if the individual risky project is unsuccessful, the individual will be able to retain the relationship with the bank. This is valued at K. Second, she has to bail-out her partner in the event she is successful and the partner is unsuccessful. This is valued at $Y^P=BR^b-(D+B)R^L$. Thus, only when K is relatively high or Y^P is relatively low, is an individual more likely to value joint liability and the assumption of the proposition holds. In this case the insurance effect prevails.

Given our definitions in Table 1, the expected income from the risky project under individual liability is qY^H+y while the variance of this income is $q(1-q)(Y^H)^2$. To the return on the risky asset, one should add the value of not defaulting and preserving the long run relationship with the bank, valued at K. We now want to assess what happens with the fraction of individuals taking up a loan when the riskiness of the project increases. To do so, we consider mean preserving spreads of the return distribution. One way of doing this is to increase $q(1-q)$, but changing y so that $q(Y^H)+y$ stays constant. When $q \in [0, 0.5)$, $q(1-q)$ is increasing in q while when $q \in (0.5, 1]$ it is decreasing. We will consider the latter case, so that to increase the variance we will consider decreases in q.[9] To keep the mean of the return on the risky project at some value $\omega = q(Y^H) + y > R^k, k = s, b$; we will have that as we change q, Y^H will have to change along $Y^H = \frac{\omega}{q}$. The variance, along this set of parameters, will be given by $\frac{\omega^2(1-q)}{q}$, which is decreasing in q. Analogously, in the case of joint liability, one would have to adjust the parameters of the relevant distribution to keep the mean constant as the variance changes.

Proposition 3. Both under individual liability and joint liability, the fraction of individuals that take up a loan is decreasing in the variance of the risky project, for a given mean of the risky project or, more formally, if $q \in (0.5, 1]$*:*

$$\frac{\partial R^{s*}}{\partial q}_{|Y^H = \frac{\varpi}{q}.} > 0;$$

$$\frac{\partial R^{s**}}{\partial q}_{|Y^H = \frac{\varpi}{q}.} > 0.$$

Proof. The proof of this proposition follows from the definition of R^{s*} and R^{s**}. Take first R^{s*}, which we defined implicitly through $U^I == U(y + R^{s*}D) = q[U(y + Y^H) + K] + (1 - q)U(y)$. As the mean of the income prospect does not change but the variance decreases (which happens as q increases over the interval $q \in (0.5, 1]$), the right-hand side of this expression will increase, by concavity of the utility function. Therefore, under individual liability, R^{s*} will increase and, as a consequence, the proportion of individuals that take up a loan will increase for a reduction in the variance. Under joint liability, Assumption 1 guarantees that, as we change Y^H to keep the mean of the underlying distribution

[9] An analogous argument can be made for the other case.

(relevant for the individual-liability case) constant when the variance changes, the level of R^{s**} will have to move in the same direction of R^{s*}.□

Proposition 4. Suppose Assumption 1 holds. Then the negative effect of the variance of the project on loan take up is larger under individual liability than under joint liability. That is:

$$\frac{\partial R^{s*}}{\partial q}_{|Y^H=\frac{\varpi}{q}.} > \frac{\partial R^{s**}}{\partial q}_{|Y^H=\frac{\varpi}{q}.} > 0;$$

To prove Proposition 4, we consider how $U^G - U^I$ varies when q increases over the interval $(0.5, 1]$ and Y^H decreases (such that ω remains constant). The rationale for considering $U^G - U^I$ is that the difference in the proportion of borrowers between group and individual liability is an increasing function of $U^G - U^I$, which is given by the following expression.

$$\begin{aligned} U^G - U^I &= q(1-q)(U(y+Y^H-Y^P) - U(y+Y^H) + K) \\ &= g(q)[U(y+\frac{\omega}{q} - Y^P) - U(y+\frac{\omega}{q}) + K \end{aligned}$$

Notice that $g(q)$ is decreasing in q, while the term in square brackets is positive under Assumption 1. Furthermore, the term in square brackets is decreasing in q because of the concavity of the utility function. Therefore we have:

$$\begin{aligned} \frac{\partial U^G - U^I}{\partial q} &= (1-2q)[U(y+\frac{\omega}{q} - Y^P) - U(y+\frac{\omega}{q}) + K] \\ &- \frac{1-q}{q}\omega[U'(y+\frac{\omega}{q} - Y^P) - U'(y+\frac{\omega}{q})] < 0 \end{aligned}$$

where the inequality holds under Assumption 1. This proves the statement.□

3 Data

In this section, we describe the experimental data we use to test whether our model predictions hold true empirically.

3.1 The experiment

To test our model's predictions, we need a setting that provides substantial cross-sectional heterogeneity in investment risk, empirical measures to gauge potential borrowers' own perceptions of this risk, and exogenous variation in the liability structure of the microcredit contracts on offer. We use data collected as part of the impact evaluation of a microfinance initiative that satisfy these three requirements. The evaluation implemented a randomized field experiment among 1,148 relatively poor women in 40 villages across five rural provinces in Mongolia. The aim of the experiment was to measure and compare the impact of individual versus joint-liability microcredit on various poverty outcomes. The findings are discussed in Attanasio et al. (2015), who also provide a detailed description of the experimental set-up and data collection. We provide a brief summary here.

The 40 villages were randomized into three groups: 10 villages did not receive loans from the implementing partner; in 15 villages individual-liability loans were offered; and in a further 15 villages joint-liability loans were offered. Before randomization, extensive baseline data were collected from women who were interested in taking up a microloan. These women were identified during information sessions that were held in February 2008. The data used in this paper therefore refer to respondents that had expressed an interest in borrowing before they knew whether they would be offered a loan as part of the experiment and, if so, whether this would be an individual or a joint-liability loan.

Table 2: Descriptive statistics and treatment-control balance

		Control Group			Indiv - Control		Group - Control	
	Obs	Obs	Mean	St. Dev.	Coeff.	*p-value*	Coeff.	*p-value*
Respondent age	961	260	40.881	9.360	-1.521	*0.179*	-0.506	*0.337*
Respondent education(<=VII)	961	260	0.150	0.358	-0.013	*0.754*	-0.021	*0.289*
Respondent religion(1=Buddhist)	961	260	0.758	0.429	-0.058	*0.375*	0.000	*0.998*
Household composition								
# members	961	260	4.888	1.828	-0.048	*0.851*	0.047	*0.712*
# adults (>=16 years old)	961	260	1.754	1.255	0.009	*0.958*	0.005	*0.950*
# children (<16 years old)	961	260	3.158	1.530	-0.069	*0.720*	0.032	*0.746*
Self-employment activities								
Any type of enterprise	961	260	0.60	0.490	-0.012	*0.849*	0.000	*0.998*
Respondent has own enterprise	961	260	0.396	0.490	-0.005	*0.937*	-0.016	*0.566*
Other employment activities								
# of non self-empl. income sources	961	260	0.546	0.742	0.042	*0.646*	0.062	*0.227*
Wages from agricultural work	961	260	0.088	0.285	0.037	*0.361*	0.021	*0.227*
Wages from private business	961	260	0.119	0.325	0.006	*0.834*	0.023	*0.175*
Wages from mining	961	260	0.023	0.150	-0.012	*0.517*	0.011	*0.332*
Wages from teaching	961	260	0.112	0.315	-0.009	*0.786*	-0.014	*0.369*
Wages from government	961	260	0.100	0.301	0.014	*0.737*	0.003	*0.882*
Income from benefits	961	260	0.850	0.358	-0.027	*0.457*	0.000	*0.976*
Any other income	961	260	0.073	0.261	0.030	*0.412*	0.010	*0.517*
Household asset index	961	260	0.06	0.95	-0.115	*0.414*	0.00	*0.973*

Notes: Household (business) asset index: Calculated for a list of home electrical appliances (business assets). Each asset is given a weight using the coefficients of the first factor of a principal-component analysis. Each index, for a household i, is calculated as the weighted sum of standardized dummies equal to 1 if the household owns the durable good. '000s MNT: Thousands of Mongolian tögrög. The exchange rate at baseline was USD 1 to MNT 1,150. Source: Baseline household survey and author calculations.

Table 2 provides a brief overview of the respondents in the sample. On average, the women were 41 years of age and 85% of them had received formal schooling for more than seven years. The respondents lived in households of on average five members, three of which were children below the age of 16. 60% of the women interested in a loan lived in a household that had a business and in 40% of cases the women owned a business themselves. The business was typically the only source of income. As mentioned above, the lender explicitly focused on relatively poor women. This is reflected in the fact that the average household in our sample earned MNT 1,100,000 ($955) per year[10], which compares to an average rural household income of MNT 3,005,000 ($2,610) in 2007 (Mongolian statistical office). The last four columns of Table 2 also show that randomization was successful. None of the presented variables shows any imbalances between the intervention arms.[11]

After completion of the baseline survey, villages were randomized into the intervention arms and lending groups were formed in the villages that were allocated to the joint-

[10]We define earnings as entrepreneurial profits plus wages from formal employment by all household members. Social benefits are excluded.

[11]Attanasio et al. (2015) provide a more detailed discussion of the treatment-control balance at baseline.

liability treatment. The treatment period during which the lender provided loans in the individual and joint-liability villages lasted 1.5 years: from March 2008 to September 2009. During this period, participating women in treatment villages could apply for (repeat) loans[12], while the lender refrained from lending in the control villages. At the end of the period a detailed follow-up survey was conducted among the respondents in all 40 villages.

3.2 Measuring investment risk

To test our model predictions we need information on the investment risks that potential borrowers perceive. Our baseline survey data contain information on the subjective probability distribution of the returns on the investment projects that could be financed by the newly available microcredit.

The baseline survey asked all participants that intended to use the loan for a business investment (83% of all participants) about the expected maximum and minimum values that future returns could take.[13] After getting an answer, the interval defined by the minimum and maximum was partitioned into subintervals and respondents were asked to assess the probability that future returns would be below the value that defined these subintervals. In other words, we elicited a few points of the cumulative distribution function (CDF) of future returns. By making assumptions on the functional form of the distribution, this data can be used to construct different moments of the expected return distribution, including mean and standard deviations.

Whilst the questions on the minimum and maximum were relatively easy to ask, the questions involving a probability statement were more challenging. As an alternative to using these data and making strong distributional assumptions that allow one to estimate mean and standard deviation based on a few points of the CDF, one can use the average of the minimum and maximum as a measure of location and their difference as a measure

[12] Of all borrowers 47 per cent received at least one repeat loan during the experiment.

[13] The specific wording of the questions was: "*If the enterprise were to be extremely successful, how much total gross revenue/total sales would you expect to make over the next 12 months (in togrog)?*" and "*If the enterprise turned out to be extremely unsuccessful, how much total gross revenue/total sales would you expect to make over the next 12 months (in togrog)?*".

of uncertainty. These measures are independent of any distributional assumptions on the CDF and are exclusively based on the minimum and maximum questions.

The results that we present below hold independently of whether we use the range of variation (calculated without any functional form assumptions) or use variables based on additional assumptions. We present results using the first, simpler measure and provide robustness tests based on the more complicated measures in Table 7.[14] The fact that results are very comparable is in line with other studies that show that the range of variation for a variable correlates well with the variance of this variable as obtained on the basis of additional assumptions about the functional form of the CDF and collecting additional information on this function (Attanasio et al. (2005); Attanasio and di Mario (2008); Delavande et al. (2011)).

In a next step, we take the range of variation of expected investment returns at the individual level and then aggregate up to the village level. We do so for two reasons. First, the survey only asked about expected investment returns for those women who intended to invest the loan into a business. The information is therefore missing for the 17% of the sample that planned to use the loan for consumption expenditures (including education and health). Second, our measure may be affected by some measurement error. Using village-level averages is equivalent to applying village dummies as an instrument for the individual-level variable. Our aggregate measure therefore also partially addresses the possibility that our risk proxy may be endogenous in that it refers to specific projects that individuals choose. To summarize, our village-level measure of risk, R_j^V, for individual k in village j is constructed as follows:

$$R_j^V = \frac{1}{N_j} \sum_{k=1}^{N_j} (E^{max}[return]_{k,j} - E^{min}[return]_{k,j}]$$

[14]The functional form assumption we make is that of a piece-wise uniform distribution and as a measure of risk we use the coefficient of variation for this distribution.

where N_j is the number of respondents in village j, and $E^{max}[return]_{k,j}$ ($E^{min}[return]_{k,j}$) is the log maximum (minimum) expected investment return for individual k in village j.

Table 3 gives basic descriptive statistics for village risk in our experimental sample. The first column shows the village-level average of the range between the log of expected minimum and maximum investment returns. The second column shows our risk measure as just explained. Columns 3 and 4 then show these measures without taking the natural logarithm of the minimum and maximum expected investment returns. We can see that in the average village, the range between minimum and maximum expected investment returns is USD 768 with a standard deviation of USD 489.

Table 3: Village risk – Descriptive statistics

	Logs		Levels (USD)	
	Mean(max-min)	R_j^V	Mean(max-min)	R_j^V
Mean	12.728	0.762	768	1,537
Sd	0.471	0.157	489	978
Min	12.003	0.482	213	426
Max	13.734	1.153	2,036	4,073
Obs.	30	30	30	30

Notes: This table provides descriptive statistics of our village-level risk measure. The first two columns show logs whereas the last two columns show USD levels. Exchange rate at baseline: USD 1 to MNT 1,150.

In Table B.1 in Appendix B, we regress village risk on various village characteristics. Perceived investment uncertainty is higher in villages that recently experienced a crop disaster; where more people lost their job over the last year; where households have more dependents (childen younger then 16 and elderly); where dairy or felt production is a key local industry (vulnerable to weather shocks); where fewer people are Buddhist (indicating a heterogeneous ethnic composition as Buddhism is the main religion in Mongolia); and that are further away from the province center (a measure of access to services).

3.3 The loan products

As in the model, which assumes that loans are taken up to invest in a productive project, the purpose of both the individual and the joint-liability loans was to finance small-scale entrepreneurial activities.[15] Table 4 provides an overview of the main loan features.

Table 4: The loan products

Monthly interest rate	1.5 to 2%	
Grace period	One or two months depending on loan maturity	
Repayment frequency	Monthly, no public repayment meetings. In case of joint-liability loans, the group leader collects and hands over repayments to the loan officer	
Progressive traits	Larger loans, lower interest rate and longer maturity after each repaid loan	
In case of default	Loss of access to future loans (for the whole group in case of joint-liability loans)	
	Individual-liability loans	Joint-liability loans
Liability structure	Individual	Joint
Average maturity 1st loan	224 days	199 days
Average maturity 2nd loan	234 days	243 days
Average size 1st loan	USD 411	USD 279
Average size 2nd loan	USD 472	USD 386
Collateral	Flexible approach	Joint savings (20% of loan) sometimes supplemented by assets

Notes: This table describes the main characteristics of the individual and joint-liability loans. Average loan size is conditional on having a loan. Average loan size of joint-liability loans refers to loans per borrower not per group. Loans were disbursed in tögrög not USD.

Given the focus on business creation and expansion, loans had a grace period of either two months (loans exceeding six months) or one month (shorter loans). The average maturity and loan size differed by liability structure. Most joint-liability loans were composed of individually approved sub-loans with a maturity of between 3 and 12 months depending on the loan cycle (within a group all sub-loans had the same maturity). The average maturity of individual-liability loans was slightly longer. The average size of the first

[15] Besides agriculture - both animal husbandry and crop growing - the main village industries are baking, wood-processing, retail activities and felt making.

joint-liability loan was USD 279 (as compared to USD 411 for individual loans).

The interest rate of both types of loans varied between 1.5% and 2% per month and was reduced by 0.1% after each successful loan cycle. Other dynamic incentives included the possibility to increase the loan amount and/or maturity after each repaid loan. In our model these dynamic incentives are reflected in K, the amount at which borrowers value the relationship with the lender.

Group members had to agree among themselves who would apply for a loan and for what purpose. The lender then screened each application and if a project was deemed too risky, the lender would exclude that applicant while the other members could still get a loan. Group leaders were responsible for monitoring and collecting monthly repayments and handing them over to the loan officer. In line with our model, borrowers would lose access to future loans from the institution in case of default. Joint-liability contracts stated explicitly that the lender would terminate lending to the whole group if a group member did not fully repay a loan.

There were no public repayment meetings.[16] Groups decided themselves on the modalities of their cooperation, including whether to meet regularly or not, and if so, how frequently (typically once per month). The joint-liability loan was therefore more flexible than "traditional" group lending, which borrowers often consider burdensome due to the frequent and lengthy repayment meetings (Wydick (1999)).[17]

4 Empirical findings

We organize our empirical results around the predictions of our simple theoretical model, which is a useful tool to interpret findings on how the take up of microcredit depends on whether a lender offers joint or individual-liability contracts and on the perceived

[16] Field and Pande (2008) randomly assign weekly or monthly repayment meetings (for individual-liability loans) and find that a lower-frequency schedule can significantly reduce transaction costs without increasing defaults. However, building on the same experiment, Feigenberg et al. (2013) show that more frequent meetings have a positive impact on borrowers' social capital and pro-social behavior. In the longer term this resulted in lower default rates on borrowers' second loans (even though all borrowers had by that time reverted to the same repayment frequency).

[17] In Giné and Karlan (2014) weekly meetings were held in both individual and joint-liability villages.

riskiness of prospective investment projects. Although our sample was pre-screened and included only women that had expressed an initial interest in taking a loan, we do observe substantial heterogeneity in loan take-up. Overall, 53.5% of all interviewed women ended up taking a loan from the lender whereas the remainder abstained from borrowing.

4.1 Liability structure and loan take-up

Proposition 2 states that, under some mild and plausible conditions on the value of access to future loans, loan take-up will be higher under joint liability than under individual liability. In Table 5 we test this proposition on the basis of a sample of all women that were interviewed both at baseline and at endline and that had access to either individual or to joint-liability loans (depending on which of these two treatments had been randomly assigned to their village). Due to the village-level randomization, the potential borrowers in the joint and individual-liability villages are very similar along a large number of observable characteristics (Table 2). They also do not differ in terms of their risk aversion (p-value: 0.33) or our subjective measure of investment risk (p-value: 0.21) (see also Appendix A on assortative matching).

We estimate a probit model for the probability that a respondent took a loan with the lender. We are interested in the coefficient for *Joint liability*, an indicator of whether the potential borrower was based in a joint-liability rather than an individual-liability treatment village. The first column of Table 5 presents a parsimonious specification while the second column also includes household-level covariates. The third column adds province fixed effects. Standard errors are clustered at the village level and since we have 30 villages in total (15 individual-liability and 15 joint-liability treatment villages), we use the conservative wild cluster bootstrap-t procedure to take into account the relatively small number of clusters (Cameron et al. (2008)). This does not affect the significance level of any of our results.

Across all three specifications, and in line with our Proposition 2, loan take-up is about 13 percentage points higher in joint-liability villages (this difference is significant at

Table 5: Liability structure and loan take up

	Loan take-up		
	(1)	(2)	(3)
Joint liability	0.132*	0.130*	0.125*
	(1.91)+	(1.79)+	(1.84)+
Household covariates	No	Yes	Yes
Province fixed effects	No	No	Yes
Obs.	836	830	829

Notes: This table shows probit regressions to estimate the relationship between the microcredit liability structure offered to potential borrowers and loan take-up. Coefficients are marginal effects. t statistics in parentheses, standard errors clustered at the village level. Covariates included in columns (2) and (3) are: indicator variables whether the household head has high education and is married, his/her age and age squared, whether the household includes at least one member above the age of 60 and below the age of 16, and whether the household is buddhist and hahl. We also include information on the household's economic status (whether the dwelling is owned, whether they own a fence, well, vehicle, tools, animals, the value of assets) and indicators whether certain shocks were experienced in the last year (crop disaster, illness, jobloss, death). We finally account for whether the household had debt outstanding and the number of loans. The loss in observations in these two columns is due to missing covariate information. * indicates significance at $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. + indicates significance using the wild cluster bootstrap-t procedure at $p < 0.10$, ++ $p < 0.05$, and +++ $p < 0.01$).

the 10% level). Most household-level covariates are not strongly correlated with take-up (results available on request). Households that at baseline owned a well, fence or tools and machinery had a higher probability of getting a loan, either because they are less poor or because they could use these items as collateral. Importantly, these household-level determinants are very similar across both types of treatment villages. In Table C.1 in Appendix C we show that there are virtually no differences across both village types in terms of various observable characteristics of those that decide to take up loans.

4.2 Investment risk, liability structure and loan take-up

When risk-averse individuals make investment choices, they consider not only the mean expected return of a project but also the associated investment risk. Indeed, in the context of our model, Proposition 3 focuses on how changes in the riskiness of a project, as measured by the variance of its expected returns, affect loan take-up under the two different lending contracts.

To test Propositions 3 and 4, we use our measure of perceived project risk: the individually reported range of variation of expected investment returns aggregated up to the village level (see the relevant equation for R_j^V in Section 3.2). We exploit the variability of this measure across villages to identify the relationship between contractual arrangements, risk and loan take-up. To model this relationship, we estimate a probit regression where the probability of taking up a loan is a function of the (average) subjective risk measure and the interaction of this variable with the contractual structure. As in Table 5, we control for various household covariates, include province fixed effects, and cluster standard errors at the village level. The results, reported in Table 6, line up nicely with the theoretical predictions of our model.

Table 6: Investment risk, liability structure and loan take up

	Loan take-up	
	(1)	(2)
Joint liability	-0.472**	0.604
	(-2.54)++	(0.42)
Village risk	-0.888***	-0.950***
	(-3.30)+++	(-2.96)+++
Joint liability*Village risk	0.781**	0.887**
	(2.48)++	(2.49)++
Average expected returns		0.091
		(0.60)
Joint liability*Av. expected returns		-0.100
		(-0.58)
Household covariates	Yes	Yes
Province fixed effects	Yes	Yes
Obs.	829	829

Notes: This table shows probit regressions to estimate the relationship between the microcredit liability structure offered to potential borrowers, village risk and loan take-up. Coefficients are marginal effects. t statistics in parentheses, standard errors clustered at the village level. * indicates significance at $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. + indicates significance using the wild cluster bootstrap-t procedure at $p < 0.10$, ++ $p < 0.05$, and +++ $p < 0.01$.

In particular, we find that in riskier villages – as measured by a high average variance of subjective risk perceptions – the probability of taking up a loan (and presumably engaging in a productive activity) is significantly lower. Potential borrowers that are more uncertain about their future returns appear less willing to commit to the fixed repayment schedule of a loan. This also holds true when we control for expected returns and their interaction with village risk as well (column 2).

While the coefficient on the joint-liability dummy is negative and significant, the interaction term between joint-liability and village risk is significantly positive. That is, as predicted by Proposition 4, the effect of project risk on loan take up is much reduced in villages where joint-liability contracts are offered. Indeed, the average effect of joint liability is positive for all values of risk observed across our sample. This is in line with our hypothesis that the higher take up in joint-liability villages can be explained by the insurance role that such contracts play.

4.3 Robustness

Table 7 provides various robustness tests of our core results. In columns 1 and 2, we run a linear probability model instead of a probit regression. The estimated marginal effects change only slightly and the significance levels remain the same, which is reassuring. Second, in columns 3 and 4 we add information on whether the respondent had a loan outstanding at baseline or not. We do so because some borrowers already had a small loan outstanding at the start of the experiment (typically some form of consumer credit) and this variable turned out not to be balanced at baseline. The results show that participants that already had some credit were also more likely to borrow for business purposes during the experiment. Importantly, adding these covariates does not impact any of the previously described results.

Next, in columns 5 and 6, we replace the village-level average of the range of variation (our risk measure) with the village-level average of the coefficient of variation. The construction of the latter variable requires an additional functional-form assumption (piecewise uniform distribution). The results again remain qualitatively unchanged.

Lastly, one might be concerned that loan take-up does not only reflect decisions by potential borrowers (i.e. credit demand) but also loan-officer behavior (credit supply). The model itself suggests that default is less costly for the lender under joint-liability since group members aim to bail each other out if K is valued high enough. This implies that loan officers might be slightly more lenient in granting loans to riskier clients in joint-liability villages. To assess to what extent such supply-side considerations may influence our results, we use additional information collected as part of the follow-up household survey. Respondents were asked whether they had applied for a loan with the lender during the experiment and, if so, whether this loan was granted or not. In case the loan was granted, the respondent was asked whether she accepted the loan offer or not.

We use this information to create two alternative loan take-up indicators (our dependent variable). First, we create a dummy variable that indicates whether the respondent *applied* for a loan with the lender (independent of whether the loan was subsequently granted or taken in the end). This is a pure measure of the initial demand for micro-credit. Second, we create a similar variable but set it to zero for those respondents who applied for a loan, were granted one, but nevertheless decided not to take it. Our data show that there were 42 respondents who declined a loan offer from our lender. Half of these respondents rejected the offer because they thought the loan amount was too small. Others considered the interest rate too high or did not agree with the repayment schedule. Finally, two respondents mentioned that the collateral requirements were too high.

We use these alternative dependent variables in the last four columns of Table 7. Two interesting observations stand out. First, we do not find village risk to be a significant predictor of loan demand when the average expected return in the village is not held constant. Second, once the average return is controlled for, village risk is a significant predictor. The coefficient sizes are somewhat smaller than those in Table 6, but not by a large margin, and the main result remains statistically significant at the 5% level.

Table 7: Robustness tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Outcome: Loan take-up						Outcome: Household applied for loan			
	Linear probability model		Adding information on baseline loans (probit model)		Alternative risk measure (based on coeff. of variation)		Application independent of uptake		Application conditional on uptake	
Group liability (GL)	-0.338*	0.606	-0.466**	0.507	-0.657***	-0.463	-0.256	0.665	-0.256	0.689
	(-1.67)	-0.42	(-2.21)++	-0.29	(-4.21)+++	(-0.29)	((-0.82)	(0.61)	(-0.86)	(0.68)
Village risk (VR)	-0.874***	-0.931***	-0.805***	-0.851***	-50.94***	-51.51***	-0.187	-0.747***	-0.176	-0.702**
	(-3.40)+++	(-3.03) +++	(-3.59)+++	(-3.29)+++	(-3.42)+++	(-3.50)+++	(-1.13)	(-2.64)++	(-1.12)	(-2.54)++
Interaction: GL*VR	0.681**	0.772**	0.722**	0.811**	61.90***	62.26***	0.500	0.879**	0.463	0.816**
	(2.27)++	(2.44)++	(2.47)++	(2.47)++	(3.24)+++	(2.99)+++	(1.08)	(2.47)	(1.05)	(2.45)+
Average expected return (ER)	0.085		0.068		0.003			0.166		0.179
	(0.58)		(0.53)		(0.02)			(1.20)		(1.37)
Interaction: GL*ER	-0.087		-0.0823		-0.0211			-0.110		-0.112
	(-0.52)		(-0.57)		(-0.13)			(-0.76)		(-0.80)
Loan outstanding (LO) at BL			0.110**	0.109**						
			(2.29)++	(2.27)++						
Interaction: LO*GL*VR			0.0896	0.0923						
			(0.30)	(0.30)						
Interaction: LO*GL			-0.209	-0.208						
			(-1.02)	(-1.00)						
N	829	829	829	829	829	829	829	829	829	829

Notes: This table provides various robustness tests of our main results on the relationship between microcredit liability structure, village risk and loan take-up. Columns 1 and 2 show a linear probability model. Columns 3 and 4 control for credit at baseline. Columns 5 and 6 use an alternative measure of village risk. Columns 7-10 report regressions with different dependent variables in order to correct for supply-side effects. Coefficients are marginal effects. t statistics in parentheses, standard errors clustered at the village level. * indicates significance at $p<0.10$, ** at $p<0.05$, and *** at $p<0.01$; + indicates significance using the wild cluster bootstrap-t procedure at $p<0.1$, ++ at $p<0.05$ and +++ at $p<0.01$.

5 Conclusions

We have analyzed the demand for microcredit under different liability arrangements and risk environments. We started out with a simple theoretical model to show that the demand for joint-liability loans can exceed that for individual-liability loans when risk-averse borrowers value their long-term relationship with the lender. Joint liability then offer a way to diversify risk and to reduce the chance of losing access to future loans.

To test these model predictions, we need a setting with significant cross-sectional variation in investment risk as well as a good measure of individuals' subjective perceptions of this risk. Moreover, we need exogenous variation in the liability structure that is offered to borrowers. We exploit data from a randomized controlled trial in Mongolia that fulfill these requirements. Using these data, we find that our model predictions hold true empirically in our setting. We first of all observe that individuals that are offered a joint-liability loan are more likely to take up credit than individuals that are offered individual-liability credit. Using novel measures of subjective risk perceptions, we find that – in line with the predictions of the model – the probability of loan take-up is lower in villages where risk is higher. In line with an insurance role of joint-liability contracts, this effect is muted in villages where joint-liability loans are available.

An important policy implication of our findings is that product design can be a key determinant of loan take-up and that this may hold true in particular in high-risk environments, which are prevalent in many emerging and developing countries. More specifically, our results suggest that in such environments especially relatively risk-averse borrowers may value the insurance aspect of joint-liability microcredit contracts as it provides them with a form of insurance. While a continuation of the trend towards liability individualization may therefore be beneficial to less risk averse (e.g. relatively wealthy) borrowers, this trend may at the same time gradually exclude poorer and more risk-averse borrowers from the market for formal financial services.

Appendix

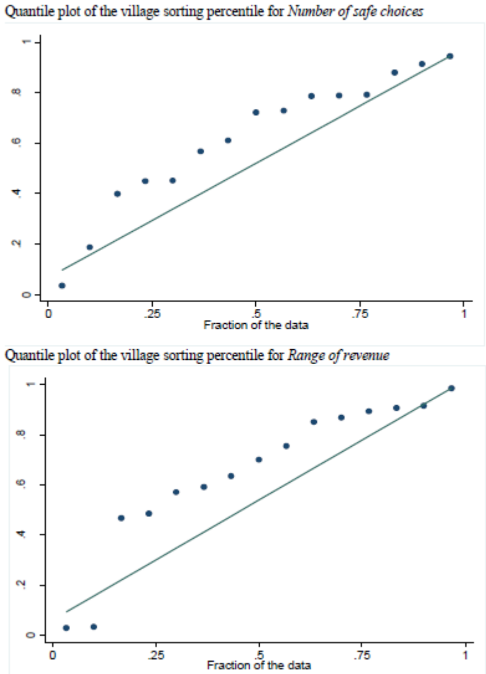
Appendix A - Assortative matching

We would like to assess whether group formation in the joint-liability villages was characterized by assortative matching. In these villages an average of fifteen women borrowed as part of a joint-liability group and the question at hand is whether they self-selected into relatively homogeneous risk groups. To analyze this issue we first create borrower-level measures of both risk aversion and subjective project risk. To measure risk aversion, we count the number of 'safe' choices that a borrower picked when going through a set of five paired lottery choices (cf. Holt and Laury (2002)). To measure project risk, we elicited information on the distribution of subjective income expectations by asking women about the maximum (minimum) amount of entrepreneurial revenues that they expected to earn in case the next 12 months would be extremely successful (unsuccessful). We then define project risk as the log difference between the respondent's highest and lowest income estimate for the next year (cf. Section 3.2).

Next, we use these two risk measures to assess whether the observed borrower groups were more homogeneous in terms of risk aversion and borrower risk when compared to all hypothetical borrower configurations (of the same group sizes) that could have been possible in a village but did not materialize in reality (see Figure A.1). To compare the observed configuration with this universe of hypothetical group configurations, we calculate for each configuration the village-level summary measure *Between.* We do this for both the risk aversion measure and the project risk measure. *Between* is the ratio of the between-group to the overall variance in a village. As a measure of group homogeneity, high values of *Between* indicate that within-group variance is low.

We then compare how homogeneous the observed grouping of borrowers in a specific village is compared to the possible groupings of the same borrowers in that village. Due to the limited number of hypothetical groupings in a village it is not possible to calculate

Figure A.1: Assortative matching in joint-liability villages



Notes: These two graphs plot the default order values of the village sorting percentiles (y-axis) against their cumulative probabilities (x-axis). The sorting percentile is the percentage of all possible groupings of borrowers in the village that result in a lower value of the variable *Between* than the one observed. *Between* is a measure of group homogeneity and higher values indicate more homogenous groups within a village. In the first graph individual risk aversion is measured as the number of safe choices the respondent made in a lottery game. In the graph below individual risk is measured as the difference between the revenue expected in an extremely successful year and the revenue expected in an extremely unsuccessful year. The diagonal represents the random uniform distribution.

the exact percentage of possible groupings that would have resulted in a lower *Between* measure. Instead we calculate a sorting percentile range and report its mean.

For the risk aversion measure, the average village has a mean sorting percentile of 0.62. This means that, on average, 62 per cent of all the possible groupings in the joint-liability villages would have resulted in a lower *Between* value than the one observed. That is, the average village is more homogeneous than 62 per cent of all possible groupings. The median village is more homogeneous than 72 per cent of all possible groupings. For the income risk measure, we find similar results. Here the mean (median) sorting percentile is 65 (70) per cent. We conclude that it is likely that the endogenous group formation in the fifteen joint-liability villages was to some extent characterized by assortative matching.

Appendix B - Determinants of village-level risk

Table B.1: Determinants of village-level risk

	Village risk
Crop disaster %	0.385**
	(0.048)
Job loss %	2.644*
	(0.279)
Robbery %	0.158
	(0.124)
Death %	0.070
	(0.140)
Illness %	-0.022
	(0.61)
Money transfers %	0.051
	(0.039)
Under 16	0.196***
	(0.014)
Over 60	0.776***
	(0.193)
Industry: Dairy	0.108***
	(0.020)
Industry: Felt	0.266***
	(0.026)
Buddhist %	-0.283***
	(0.033)
Distance to province center	0.001***
	(0.000)
Constant	0.308**
	(0.060)
Observations	30
R-squared	0.839

Notes: Data source: Village and household survey. This table shows a regression to link village risk to various village-level characteristics. The first five variables are village averages of households reported to have experienced the mentioned shock within the last year (crop disaster, job loss, robbery, death, illness). The variable "Money transfers %" is the average of households that reported to have received or given a monetary transfer from friends or family within the last year. "Under 16" and "Over 60" are village level averages of households that include at least one member below the age of 16 or above the age of 60. Variables "Industry: Dairy" and "Industry: Felt" indicate whether one of the top three industries in the village is dairy or felt, respectively. "Buddhist %" is the percentage of buddhists in the village. "Distance to province center" is a continuous variable, indicating the number of kilometers between the village and the province center. Robust standard errors in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level.

Appendix C - Who takes up loans?

One might expect that the joint-liability contract perhaps attracted a different group of people who took up loans as compared to those who took up individual-liability loans. Table C.1 presents a statistical comparison between the women that took up a loan in the joint-liability and those in the individual-liability villages. For each variable we present the baseline mean for the individual-lending treatment group (in the post-attrition sample) as well as the difference in means between the individual and the joint-liability borrowers (with a p-value for a t-test of equality of these means).

The table shows very few significant differences between individual-liability and joint-liability borrowers along a large number of observable characteristics. For instance, we find no significant differences in terms of household composition; borrower characteristics such as age, education, and religion); the types of self-employment activities; consumption expenditures; and location (distance to province center). The only difference we observe is one in terms of initial credit access. Women taking loans in joint-liability villages are slightly less likely to have a loan with a bank at baseline (significant at 5% level). However, this does not translate in a statistically significant difference in terms of the amount of total outstanding debt at baseline. When we control for initial debt (Table 7) all our results continue to go through.

Table C.1: Comparison of borrowers in individual versus joint-liability villages

		Individual			Group - Indiv	
	Obs	Obs	Mean	St. Dev.	Coeff.	*p-value*
Panel A. Post-attrition household sample						
Household composition						
# members	422	192	4.797	1.677	0.225	*0.336*
# adults (>=16 years old)	422	192	1.661	1.344	0.130	*0.551*
# children (<16 years old)	422	192	3.151	1.378	0.084	*0.548*
Age of respondent	422	192	39.844	8.374	-0.148	*0.891*
Education of respondent (1=at most grade VII)	422	192	0.099	0.299	0.018	*0.520*
Religion of respondent (1=Buddhist)	422	192	0.724	0.448	0.024	*0.738*
Self-employment activities						
Any type of enterprise	422	192	0.63	0.485	-0.003	*0.959*
Respondent has own enterprise	422	192	0.391	0.489	0.009	*0.869*
Revenue of respondent's enterprise	422	192	450.1	1,210	112.5	*0.427*
Expenses of respondent's enterprise	422	192	310.1	963.9	61.4	*0.544*
Profit of respondent's enterprise	422	192	140.0	819.6	51.1	*0.590*
Employment activities (except self-employment)						
# of income sources	422	192	0.599	0.717	-0.038	*0.733*
Wages from agricultural work	422	192	0.115	0.319	-0.028	*0.529*
Wages from private business	422	192	0.089	0.285	0.016	*0.602*
Wages from mining	422	192	0.010	0.102	0.033	*0.083*
Wages from teaching	422	192	0.089	0.285	-0.010	*0.716*
Wages from government	422	192	0.146	0.354	-0.041	*0.338*
Income from benefits	422	192	0.932	0.252	0.024	*0.385*
Any other income	422	192	0.214	0.411	-0.079	*0.078*
Consumption (1,000s MNT)						
Total consumption expenditures (yearly)	405	186	2,916	2,068	-67.75	*0.901*
Durable consumption (yearly)	419	191	930	1,019	-62.79	*0.655*
Non-durables consumption (monthly)	415	189	89.62	95	-10.43	*0.492*
Food consumption (weekly)	414	190	17.70	19.68	3.27	*0.594*
Household asset index	422	192	-0.12	1.03	0.02	*0.871*
Distance to province center (in km)	413	192	129	37.32	-19.75	*0.346*
Access to credit:						
Loan from bank	422	192	0.635	0.483	-0.157	*0.037*
Loan from relatives	422	192	0.031	0.174	-0.010	*0.566*
Loan from friends	422	192	0.026	0.160	0.000	*0.998*
Any other loan	422	192	0.083	0.277	0.017	*0.750*
Any type of loan	422	192	0.714	0.453	-0.127	*0.060*
Amount borrowed from (1,000s MNT):						
Bank	415	187	510	785	-106	*0.290*
Relatives	414	188	0.5	6	-0.1	*0.901*
Friends	414	189	0.4	4	-0.2	*0.625*
Other	414	190	7.1	27	-1.1	*0.768*
Total	414	186	558	820	-121.8	*0.205*
Panel B. Attrition						
Not surveyed at endline	422	192	0.125	0.332	-0.021	*0.612*

Notes: Data source: baseline household survey. Unit of observation: household. Panel A: sample includes only households of respondents who took up a loan and who were surveyed at endline. Panel B: sample includes all households surveyed at baseline. In case of household characteristics, the standard errors are clustered at the village level. Wages from private business includes wages from working in a shop, market, bank, finance company, or other private business. 1,000s MNT: Thousands of Mongolian tögrög. The exchange rate at baseline was USD 1 to MNT 1,150.

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