# Matching for Credit: Testing Market Rules Across Models of Joint-Liability Lending*

Thilo Klein†

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**Abstract**

I analyse an environment where limited liable agents are exposed to similar economic shocks and have some information about each other's projects that principals do not. In this setting, joint-liability contracts are optimal because they induce endogenous peer selection that acts as a screening device to exploit agents' local information. I show that imposing rules on permissible group constellations, similar to those used by group-lending programmes, can improve welfare. A structural matching model for data from Thai borrowing groups suggests that the diversification of risks within groups has a welfare effect equivalent to a 25 percent reduction in interest.

Keywords: microcredit; joint liability; diversification; market design; stable matching; endogeneity; selection model; agriculture; Thailand

JEL Codes: C11, C31, C34, C36, C78, C57, D02, D47, D82, G21, O16, Q14

This paper analyses the effect of imposing rules on permissible group constellations for agents in joint-liability contracts. I show that by using rules that prevent the grouping together of agents who are exposed to the same economic shocks, a principal can mitigate market failures caused by asymmetric information. Group formation creates an endogeneity problem but a novel structural matching model is able to exploit the characteristics of other agents to separately identify and estimate the effects of the rules on agents' participation decision (adverse selection) and direct effects (including moral hazard).

This work is motivated by contracts successfully used by real-world lending institutions, such as group-lending schemes and credit co-operatives. Joint-liability

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†Centre for European Economic Research (ZEW), L7 1, 68161 Mannheim, Germany.

contracts have pushed out financial frontiers in developing countries by expanding access to credit for low-income households that lack seizable collateral and are now reaching over 200 million borrowers (Reed, 2015). These contracts, however, have less bite in rural settings, where financial exclusion is most pronounced. Microfinance institutions have questioned the use of group lending in agriculture because the bank loses its bails when group members' projects fail concurrently.[1] Ahlin (2009) even shows that borrowers select group members who are exposed to similar shocks, in order to avoid joint-liability payments. Still, joint-liability contracts remain optimal in this setting.[2] This paper therefore takes interest and joint-liability rates as given and instead takes a market design perspective to microcredit (see Rai and Sjöström, 2013, for an overview) to identify rules for group formation that improve aggregate welfare.

The theoretical literature has long considered the positive project covariation of agricultural loans as an impediment to the expansion of lending programmes in rural markets (refer to Mosley, 1986). Ghatak (2000), for example, demonstrates that under perfect project correlation, joint-liability contracts are equivalent to individual contracts. Contrary to this widely held view, Ahlin and Townsend (2007) extend two well-established models of joint-liability lending to show that positive project covariation raises repayment. In the Ghatak (1999) adverse selection setting with underinvestment (Stiglitz and Weiss, 1981), correlated returns make borrowing attractive again for safe borrowers. In the Stiglitz (1990) ex-ante moral hazard model, correlation mutes incentives to choose risky projects. In this paper, I develop the key trade-off of the conflicting effects suggested separately in the literature. The negative repayment effect in Ghatak (2000), is found to be dominant for most parameter constellations in both models (compare Table 1, columns 1-i and 2-i). In the adverse selection setting, the intuition is as follows. While higher project correlation draws safer types into the market, the expected repayment of these new types is the same as that of the previously safest types because the increase in correlation makes them avoid liability payments. Furthermore, the previously safest types, and all others, now have a worse expected repayment. Thus, repayment is found to decline on average and this suggests that a diversification strategy is useful.

[1] This offers an explanation for the recent move towards individual-liability lending by large microfinance institutions such as BancoSol and Grameen Bank (Attanasio *et al.*, 2015) and for the industry trend to lend to non-poor clients in urban areas (de Quidt *et al.*, 2012; Reed, 2015).

[2] In an ex-ante moral hazard context, Che and Yoo (2001) find that joint liability is the optimal collusion-proof contract, even under almost perfect project correlation. Similarly, in the Stiglitz and Weiss (1981) adverse selection setting, Laffont (2003) finds that joint-liability lending is still the optimal contract when returns are correlated.

An empirical test of the theoretical predictions is complicated by three, possibly counteracting effects, which this paper distinguishes empirically using credible exclusion restrictions. To illustrate, take the decision of a firm's management on rules for the intercultural composition of the firm's units. First, there is the *direct effect* of intercultural team composition on team outcomes for a given pool of workers. This may concern whether communication problems outweigh the synergies within mixed teams. Second, this direct effect is net of *sorting bias*. This bias arises for a given pool of workers, if open-minded workers are more likely to sort into mixed teams and open-mindedness is unobserved by the econometrician and results in better team outcomes. In this case, the direct effect of mixed teams would be overstated because it picks up the positive effect of open-mindedness. Third, a management decision on rules stipulating mixed teams would have a *participation effect*, in that it may result in a smaller pool of workers because of fewer applicants and workers resigning if they dislike working in mixed teams.

The empirical findings of previous studies are subject to *sorting bias*, which is well recognised in the literature (see Hermes and Lensink, 2007).[3] To overcome this issue, experimental methods have become popular means of testing theories of joint-liability lending.[4] A limitation of these experiments is that they do not test the effects of sorting on specific, design-relevant variables. Furthermore, field experiments suffer from a participation problem if agents cannot be committed to take a loan before knowing their group members (see the *Ideal Experiment 1* in Section 3). To estimate the *direct effect*, this paper instead contributes to structural empirical work on matching markets that has a wide range of beneficial applications[5] and contrasts with the related networks literature from a methodological point of view.[6] The structural matching model developed in this paper corrects for *sorting bias* by generalising the Heckman (1979) selection correction to

[3]Three empirical studies (Wydick, 1999; Zeller, 1998; Sharma and Zeller, 1997) find significant negative repayment effects and Ahlin and Townsend (2007) find the reverse (see Table 1, 1-ii).

[4]Karlan (2007) makes use of the quasi-random group assignment of microlender FINCA in Peru to estimate the *direct effect* of social connections. In framed field experiments, Giné *et al.* (2010) implement a 'partner choice' treatment to estimate the *direct effect* of endogenous group formation compared to random assignment. Similarly, *participation* and *direct effects* combined can be tested with 'group recruitment' (Abbink *et al.*, 2006) or 'self-selection' (Cassar and Wydick, 2010) treatments that require participants to register for lab experiments in groups.

[5]In one-sided matching markets, applications range from US school district mergers (Gordon and Knight, 2009) to Japanese municipal amalgamations (Weese, 2015). These models use more restrictive assumptions on agent's preferences than this paper, requiring either pairwise symmetric preferences or a restriction of the analysis to geographically permissible coalitions.

[6]Models of network formation such as Fafchamps and Gubert (2007) have no restriction on group size, which results in competition for places and thereby complicates the empirical analysis in this paper. Klonner (2006) and Eeckhout and Munshi (2010) study a different problem of two-sided matching of borrowers and lenders into chit fund groups of fixed size.

allow for the selection process being the equilibrium outcome of a group formation game. The identifying exclusion restriction is that the characteristics of all agents in the market affect who matches with whom, but the performance of a matched group is determined only by its own members (see the example in Section 1).

Table 1: Summary of theoretical and empirical results

| Upward arrows indicate a positive repayment effect of project covariation. | | | | | | |
|---|---|---|---|---|---|---|
| | Ahlin/Townsend | | This paper | | | |
| | Theory | Empirics | Theory | Empirics | | |
| | | Logit | | Probit | Structural | Simulation |
| | (1-i) | (1-ii) | (2-i) | (2-ii) | (2-iii) | (2-iv) |
| A. Direct effect | | | | | | |
| - Stiglitz (1990) | ↑ | | ↓[a)] | | ↓ | ↓[c)] |
| B. Participation | | | | | | |
| - Ghatak (1999) | ↑ | | ↓[b)] | | | ↓ |
| *subtotal* (A+B) | ↑ | | ↓ | | | ↓ |
| C. Sorting bias | | | ↑ | | ↑ | |
| *total* (A+B+C) | | ↑ | | ↑ | ↑ | |

[a)] Negative for low risk aversion *or* low return differential of risky and safe projects.
[b)] Negative for low marginal risk types *or* high liability payment.
[c)] Coefficients for simulations are taken from the estimates of the structural model.

The structural model is applied to a resurvey of the data used in Ahlin and Townsend (2007), allowing me to model the endogenous group formation explicitly. The *direct effect* is a test of the revised predictions in the moral hazard model of Stiglitz (1990). In line with the predictions, I find a significantly negative *direct effect* of project covariation on repayment. This negative *direct effect* is net of an even larger, positive *sorting bias* which is the result of groups with higher project correlation having better observable and unobservable characteristics (Table 1, 2-iii). The *participation effect* from matching on risk exposure is tested in agent-based simulations using parameter estimates from the structural model. Varying the rules to either allow or prohibit matching on risk exposure – but keeping the model fixed to predict the repayment outcome – allows me to separate the *participation effect* in my revision of Ghatak (1999). I find that anti-diversification draws borrowers into the programme who would not have taken a loan otherwise. However, as predicted by the model, this positive effect is more than offset by the negative effect of the bank losing joint-liability payments when projects fail concurrently (see Table 1, 2-iv).

The empirical work most closely related to this paper is the analysis of microfinance group formation in Ahlin (2009). The value added by my paper is twofold. First, Ahlin's theoretical matching model assumes a market with an infinite number of borrowers and transferable utility. His "onion-style" equilibrium matching does not hold in finite markets with non-transferable utility, where the existence and uniqueness of equilibria are not generally guaranteed.[7] I derive uniqueness conditions in this context, where matching takes place on several characteristics.[8] Second, from Ahlin's analysis it is unclear what the implications of anti-diversification are for borrowers' repayment to the bank and aggregate welfare of both borrowers and the bank. As for the repayment effect, I analyse the implications of endogenous group formation for repayment. I thereby add to pioneering work on selection models in matching markets, which simultaneously estimate a matching model that parametrically selection-corrects an outcome equation.[9] As for the effects on aggregate welfare, Ahlin concludes that "borrower surplus" is higher with anti-diversification. However, the models of Ghatak and Stiglitz are both based on zero-profit constraints as is the operation of the Thai borrowing groups studied in this paper. In this setting, a benevolent lender will pass on the additional revenue from better repayment by lowering interest rates. I show that diversification can lower interest rates by 25 percent and thereby improve the welfare of borrowers – a finding that is at odds with the interpretation in Ahlin.

In practice, there is some evidence that banks operating on the Grameen model explicitly rule out the grouping of relatives in order to avoid collusion against the lender (see Alam and Getubig, 2010, p. 17). Given the findings of this paper, lenders are well-advised to extend these rules and also prevent the grouping together of borrowers who are exposed to similar income shocks.

[7]While the non-transferable-utility assumption is less common in the microfinance literature, there is no empirical evidence for the existence of such transfers. Furthermore, the assumption of non-transferable utility is particularly well placed in the context of group lending, where ex-ante transfers are not possible due to limited initial wealth and Holmström and Tirole (1997) show that incentives are muted if a borrower initially pledges too much of her future income.

[8]A unique equilibrium is necessary for the likelihood of empirical models to be well-defined (Bresnahan and Reiss, 1991; de Paula, 2013). Uniqueness is guaranteed if and only if preferences are aligned (Pycia, 2012). I derive uniqueness conditions when preferences are not generally aligned in that they are "vertical" in borrowers' risk type (safer partners are better) and "horizontal" in risk exposure (partners exposed to the same economic shocks are better). Such preference profiles are common in several other contexts. In marriage markets, partners have been shown to marry up within the same caste (Banerjee *et al.*, 2013). Similarly, in study groups, pupils match with more academically able peers within the same gender.

[9]Such models have been proposed for two-sided markets in Sørensen (2007), who examines whether firms are more likely go public when matched with more experienced venture capitalists, and applied in Chen (2013) and Park (2013). The model developed here is the first to implement this strategy in a one-sided matching market.

This paper is organised as follows. Section 1 clearly motivates the sorting bias and illustrates the correction method. Section 2 develops the key trade-off between the conflicting effects suggested in the literature and establishes uniqueness conditions for equilibrium matching. Section 3 presents the empirical strategy. Section 4 describes the data and presents the results. Section 5 concludes.

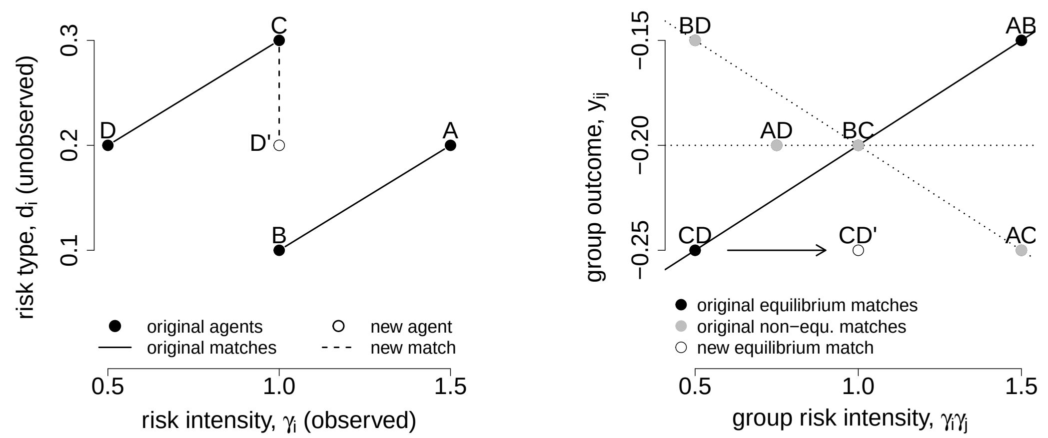
# 1 Example of sorting bias and identification

This section clearly motivates the importance of the bias that arises from sorting into groups and illustrates a simple correction method. The focus is on the omitted variable bias that results when variables influencing both group formation and outcomes are unobserved. This is a special case of the measurement error problem that is controlled for in the model developed in Section 3.

Figure 1: Illustration of sorting bias and identification

(a) Individual borrower characteristics, stable matches and exogenous variation from borrower $D'$ in a second market

(b) Regression bias from matching and identification by comparison of groups $CD$ and $CD'$ across markets




## 1.1 Sorting bias

Consider a credit market with four entrepreneurs $A$, $B$, $C$ and $D$ who can take loans in groups of two and let the matches $AB$ and $CD$ be observed. The group repayment is based on the model in Ghatak (1999) with two modifications for ease of exposition in this example. First, denote borrower $i$'s probability of default as $d_i$ and assume that $d_i d_j$ is close to zero and therefore negligible. Second, assume that all borrowers are exposed to the same external shocks but differ in the intensity $\gamma$ with which external shocks affect their probability of repayment. A group of agents $i$ and $j$ then has an expected repayment to the bank of

$$Y_{ij} = \beta_0 + \beta_1 \cdot \gamma_i \gamma_j + \delta \cdot (d_i + d_j). \tag{1}$$

Let the observable component in the linear outcome equation be the group correlation $\gamma_i \gamma_j$ and let group risk $(d_i + d_j)$ be unobserved. Now consider estimating the parameter $\beta_1$ assuming, for simplicity, that the true coefficients are $\beta_0 = 0$, $\beta_1 = 0$ and $\delta = -1/2$. That is, the group outcome only depends on the unobservable group risk: $Y_{ij} = -1/2 \cdot (d_i + d_j)$. For the observed matches $AB$ and $CD$, Figure 1b shows that a simple OLS yields an upwards-biased coefficient of $\hat{\beta}_1 = 0.1$. It further illustrates that the source of the bias is the systematic matching of borrowers into groups that results in the observed match $AB$ having both safer group risk and higher group correlation than $CD$. The bias resolves when groups are assigned randomly. Then, the slope estimate can be seen as the equally weighted average of the OLS estimates for the three equiprobable, feasible group constellations $AB$-$CD$, $AC$-$BD$ and $AD$-$BC$, i.e. $\hat{\beta}_1^* = \frac{1}{3}(0.1 - 0.1 + 0) = 0$.

## 1.2 Empirical strategy

The endogenous matching that complicates the inference can be a useful source of exogenous variation that helps to identify $\beta_1$. To see this, first denote the individual match valuation of borrower $i$ over $j$ as $u_{i,j} = \frac{\alpha}{2} \cdot \gamma_i \gamma_j - d_j$. Further, define by $V_{ij} = u_{i,j} + u_{j,i}$ the sum of the mutual valuations. Assuming that observed groups are in equilibrium, a match is observed if its valuation is in the set $\Gamma_\mu$ (defined below) of feasible equilibrium valuations, i.e. the equilibrium indicator is $D_{ij} = 1[V_{ij} \in \Gamma_\mu]$ with

$$V_{ij} = \alpha \cdot \gamma_i \gamma_j - (d_i + d_j). \tag{2}$$

This equation captures the unobserved group risk $(d_i + d_j)$ as a residual and the empirical model in Section 3 allows this term to enter Eqn 1 as a control. The estimation of this matching equation requires a unique equilibrium in the market. In Figure 1a, the levels of both variables are chosen such that agents $A$ and $B$ always form a top coalition (for any coefficient $\alpha > 0$). This guarantees the unique equilibrium matching $\mu = \{AB, CD\}$. The estimation proceeds by imposing a set of inequalities $\Gamma_\mu$ on match valuations to guarantee that they satisfy the equilibrium condition of no *blocking coalitions*.[10] These inequalities impose an upper limit on the match valuation of non-equilibrium matches and a lower limit for equilibrium matches. These match-specific limits have a simple economic interpretation as agents' opportunity costs of leaving (or maintaining) their equilibrium matches (see Section 2 for the mathematical derivation).

## 1.3 Identification

The identification of the parameters in the outcome equation requires exogenous variation in the form of an instrumental variable that affects the matching but not the match outcome. In this paper, it is the variation in borrower types across markets that serves this role. To illustrate, consider a second market with similar borrowers $A$, $B$, $C$, $D$ but with an additional borrower $D'$. The presence of $D'$ changes the relative ranking in the market and results in the new stable matching $\mu^* = \{AB, CD'\}$ (see Figure 1a). Implicitly, this change in the ranking induces exogenous variation in groups' project correlation and, in turn, changes the equilibrium limits from $\Gamma_\mu$ to $\Gamma_{\mu^*}$ for purely exogenous reasons. These limits determine the matching (i.e. who matches with whom) but the outcome of a matched group is determined only by its members.

In very concrete terms, note that for the second market, the estimate of $\beta_1$ for the observed matching $\mu^* = \{AB, CD'\}$ is again biased upwards. However, a direct comparison of the two markets shows that the repayment of borrower $C$'s group remains the same when the risk intensity of his group member changes (from $\gamma_D = 0.5$ to $\gamma_{D'} = 1$ in Figure 1b). A natural estimate of $\beta_1$ is therefore $\hat{\beta}_1 = 0$. For the empirical application, it remains to determine which borrower groups are comparable across markets (i.e. have similar unobserved risk types). This requires a matching model similar to Eqn 2.

## 1.4 Model validation

Monte Carlo experiments designed to test for the validity of the estimator are presented in a companion paper (Klein, 2015). The paper uses simulated data from a one-sided matching market. The data generating process is based on the parameters from the Thai group lending programme used in this paper. The results for three experiments, each representing a different market setting and sampling strategy, show that the estimator is consistent and unbiased, even for

[10] A blocking coalition is a coalition of players that would prefer to leave their current matches and form a new match together.

the small sample studied in this paper with 40 markets and two groups of five borrowers each.

# 2 Theoretical framework

This section is divided into two subsections. The first derives the repayment implications of correlated project returns for the two most widely cited theoretical models of joint-liability lending. The second (i) establishes uniqueness conditions for the equilibrium matching used in the empirical model and (ii) derives the sign of the sorting bias that results when matching is on both risk and exposure type.

## 2.1 Revised theories and implications

For both theoretical models I present the model and the positive repayment effects derived in the model extensions by Ahlin and Townsend (2007). I then introduce the negative effect of anti-diversification in Ghatak (2000) and develop the key trade-off.

### 2.1.1 Adverse selection: Participation effect

The Ghatak (1999) model uses the Stiglitz and Weiss (1981) setting of credit rationing. There is a continuum of risk-neutral borrowers who are endowed with one unit of labour and no pledgeable collateral. Agents can either sell their labour and earn an outside option $\bar{u}$ or borrow and invest one monetary unit in an uncertain project. Agent $i$'s project yields an actual outcome of $y_i$ with success probability $p_i$ and 0 otherwise. The distribution of risk types is given by the density $g(p)$, with support over $[\underline{p}, 1]$ for some $\underline{p} \in (0, 1)$. The expected return $E$ is the same for all risk types. Under asymmetric information, the lender cannot discriminate between borrower risk types and therefore offers a pooling contract with gross interest rate $r$.

In this setting, Ghatak (1999) shows how the lender can harness joint-liability contracts in groups of two borrowers to mitigate credit rationing. Under this type of contract, a joint-liability payment $q \leq r$ is due in the asymmetric event where borrower $i$ succeeds and partner $j$ fails. Ahlin and Townsend (2007) extend this setting to allow for project returns that are positively correlated. This is implemented in the form of a constant $\bar{\epsilon}$ that adds probability mass to the symmetric events (where both borrowers succeed or fail) and subtracts it from the asymmetric events (where one group member fails and the other succeeds). In this model, the expected utility of borrower $i$ forming a group with borrower $j$ can be written as

$$u_{i,j} = E - rp_i - q[p_i(1 - p_j) - \bar{\epsilon}]. \tag{3}$$

Here, the expected utility is given by the expected project return $E$ less the expected payable interest $rp_i$ and expected joint-liability payment $q[p_i(1 - p_j) - \bar{\epsilon}]$. Because agents have no pledgeable collateral, borrower $i$ only pays $q$ in the asymmetric case where her project is successful and partner $j$ defaults.

Agents face two decisions: (i) with whom and (ii) whether to take a loan. For the first decision, Ghatak (1999) shows that agents form groups that are homogeneous in risk type such that $p_i = p_j$. This follows from risk type complementary in Eqn 3, which exhibits a positive cross-partial derivative with respect to agents' risk types. For the second decision, agents take a loan when the expected utility $u_{i,j}$ exceeds that of the outside option $\bar{u}$. Because the cost of borrowing, i.e. the expected repayment, is strictly increasing in risk type, there is a marginal type $\hat{p}$ that solves the participation equation

$$E - r\hat{p} - q[\hat{p}(1 - \hat{p}) - \bar{\epsilon}] = \bar{u} \tag{4}$$

with equality. Credit is rationed as borrowers with projects safer than $\hat{p}$ do not find it profitable to borrow. Ahlin and Townsend (2007) argue here that increasing the project correlation mitigates credit rationing and thereby has a positive effect on the repayment to the bank. The intuition for this result is that higher $\bar{\epsilon}$ increases borrowers' utility by avoiding liability payments more often. This is because project correlation shifts probability mass from asymmetric to symmetric events. An increase in $\bar{\epsilon}$ therefore draws safer types into the market. This results in a new marginal type $\hat{p}' > \hat{p}$ and a safer borrower pool with types $p \in [\underline{p}, \hat{p}']$.

### *Developing the key trade-off*

Contrary to the conclusions drawn in Ahlin and Townsend (2007), this safer borrower pool does not generally improve group repayment. To illustrate, note that after an increase in $\bar{\epsilon}$, the new marginal type $\hat{p}'$ now has the same expected repayment $(E-\bar{u})$ as the previous marginal type $\hat{p}$. However, the previous marginal type and all others now have worse expected repayment (by the term $q \cdot d\bar{\epsilon}$) because the increase in correlation allows them to avoid liability payments more often. Proposition 2.1 provides conditions for project covariation to reduce repayment when the distribution of risk types is uniform.

**Proposition 2.1.** *Under a uniform distribution of risk types, the marginal effect of project covariation on expected repayment is strictly negative if either (i) the marginal type $\hat{p}$ is smaller than 3/4 or (ii) the joint-liability payment $q$ does not exceed 3/5 of the gross interest rate $r$.*

*Proof:* See Appendix A.

The intuition for the thresholds is that for correlation to improve repayment (i) the marginal types $\hat{p}$ that are drawn into the market must be sufficiently safe to offset the negative effect of increased joint defaults *and* (ii) joint-liability payment $q$ must be sufficiently high to lure the marginal types into the market in the first place. Proposition 2.1 is limited to uniform distributions of risk types. Corollary 2.1 below shows that these thresholds are even higher for distributions with lower probability mass in the area of the marginal type.

**Corollary 2.1.** *The lower the density of the risk-type distribution $g(\hat{p})$ at the marginal risk type $\hat{p}$, the more an increase in project covariation will impair expected group repayment.*

*Proof:* See Appendix A.

The reasoning behind this corollary is that for an increase in project correlation to improve repayment, it must draw in considerably more safe types to offset the negative effect from borrowers avoiding joint-liability payments. For this to be the case, the distribution of types has to have considerable probability mass in the upper tail of the distribution.

*Prediction for the context of the Bank for Agriculture and Agricultural Cooperatives*

In the context of the Bank for Agriculture and Agricultural Cooperatives (BAAC), the model would predict a strictly negative repayment effect of correlation. The BAAC charges a fixed gross interest rate of 109% for small loans and joint-liability payments $q$ are implemented in the form of a temporary increase in the payable interest rate. The maximum interest rate in the 1997 BAAC survey was 117%, which translates as a maximum joint-liability rate of $q = 8\%$ $(= 117\% - 109\%)$. The ratio $q/r = 8\%/109\% \approx 0.07$ is well below the 3/5 threshold. In addition, the actual distribution of types in the 2000 BAAC resurvey is Normal;[11] therefore, the predictions derived in Ahlin and Townsend (2007) cannot explain their empirical finding that repayment is better in markets with higher project correlation.

### 2.1.2 Ex-ante moral hazard: Direct effect

The Stiglitz (1990) model takes the homogeneous groups in Ghatak (1999) as given. The moral hazard problem relates to the following cooperative project choice after loan disbursement. Borrowers choose cooperatively between projects with different probabilities of success $p_k$ with $k \in \{B, H\}$. Here $B$ is the baseline project that was tied to the borrower in the previous subsection and $H$ is the hazardous project with $p_H < p_B$. The hazardous project $H$ has a higher *actual* outcome when successful, i.e. $y_H > y_B$, but a lower *expected* outcome, $p_H y_H < p_B y_B$. Information is asymmetric in that the lender does not observe which project is chosen but the group members do: Stiglitz assumes costless peer monitoring and enforcement. Group members make symmetric project choices that maximise their joint utility $U_{kk}$, resulting in individual project success probability

$$p \;=\; p_H \cdot 1[U_{BB} < U_{HH}] \;+\; p_B \cdot 1[U_{BB} \geq U_{HH}], \qquad (5)$$

where $1[\cdot]$ is the Iverson bracket. In this context, the influence of project covariation $\bar{\epsilon}$ on the probability of repayment $p$ depends on whether changes in $\bar{\epsilon}$ shift incentives towards the hazardous project. Using the project correlation structure introduced in the previous subsection, Ahlin and Townsend (2007) write the expected group pay-offs, given project choice $k \in \{B, H\}$, as

$$U_{kk} \;=\; U(y_k - r) \cdot [p_k^2 + \bar{\epsilon}] + U(y_k - r - q) \cdot [p_k(1 - p_k) - \bar{\epsilon}]. \qquad (6)$$

Ahlin and Townsend (2007) now argue that the utility gain from avoiding joint-liability payment (of size $2q \cdot d\bar{\epsilon}$) due to an increase in $\bar{\epsilon}$ is comparatively higher for the baseline project, tilting incentives towards choosing the safer project. This is because (i) the baseline project has lower returns when successful and (ii) borrowers' utility is concave.

[11] Shapiro-Wilk, Jarque-Bera and Kolmogorov-Smirnov tests of the risk-type variable (demeaned at the village level) cannot reject the null of Normality (N=, p-values of 0.60, 0.65 and 0.81, respectively).

*Developing the key trade-off*

Again, the modelling in Ahlin and Townsend (2007) does not consider the negative effect that correlation has through borrowers avoiding joint-liability payments to the bank. The key trade-off is developed in Proposition 2.2 below.

**Proposition 2.2.** *The marginal effect of project covariation on repayment is strictly negative if either (i) borrowers are not extremely risk averse or (ii) the returns of the hazardous project are not substantially larger than those of the baseline project.*

*Proof:* See Appendix A.

The intuition for the negative repayment effect for risk-neutral borrowers is straightforward: with either (i) a linear utility function or (ii) $y_H \approx y_B$, the marginal increase in utility from higher project covariation is the same for both the baseline and the hazardous project, $\partial U_{BB}/\partial\bar{\epsilon} = \partial U_{HH}/\partial\bar{\epsilon} = 2q$. For (i), this is because the slope of the utility function is constant. For (ii), this results from the gain in utility being evaluated at the same wealth level. Therefore, a change in $\bar{\epsilon}$ has no effect on project choice. However, it has a strictly negative effect of $-2q \cdot d\bar{\epsilon}$ from a diversification point of view because it reduces the probability that at least one borrower is successful.

## 2.2 Characterisation of stable matchings

This subsection extends the analysis of Ghatak (1999) by endogenising project correlation and allowing for a group size larger than two. Restricting this model to the empirical context, with two groups per market, I establish uniqueness conditions for stable matchings when utility is non-transferable. Equilibrium matching is shown to result in an endogeneity problem if borrowers' risk types are not fully captured by exogenous variables. I derive equilibrium conditions that impose simple inequalities on the latent group valuations and give traction to the empirical matching model that corrects for this bias.

### 2.2.1 Endogenous project correlation

The model used in the empirical application extends Ghatak (1999) to groups of size $n > 2$ and allows for project correlation that is determined endogenously. The latter is implemented by introducing three exposure types, $A$, $B$ and $N$, which constitute the proportions $\theta_A$, $\theta_B$ and $\theta_N$ of the agent population (as in Ahlin, 2009). $N$-types are not affected by external shocks. For $A$- and $B$-types, the independent shocks $A$ and $B$ equiprobably add or subtract, respectively, a shock term $\gamma$ from the project success probability. Extending the model in Eqn 3 in this way, borrower $i$'s utility from taking a loan with group $G$ can be written as

$$u_{i,G} = E - rp_i - qp_i \sum_{j \in G \setminus i} (1 - p_j) + q\epsilon \sum_{s \in \{A,B\}} 1[i \in s] \cdot (n_s^G - 1), \tag{7}$$

where $1[\cdot]$ is the Iverson bracket, which is 1 if borrower $i$ is of exposure type $s \in \{A, B\}$ and 0 otherwise, $n_s^G$ is the number of borrowers of exposure type $s$ in group $G$ and the constant $\epsilon := \gamma^2$ gives the intensity of the projects' exposure to shocks.

### 2.2.2 Assumptions

The analysis below makes four assumptions. First, reflecting the nature of the Thai group-lending data (see Section 4), the analysis is restricted to two groups per market. Second, I treat the distribution of risk types $p \in [\underline{p}, 1)$ and exposure types $s \in \{N, A, B\}$ as independent: $p \perp s$ (Assumption H1). Third, I assume that utility is not linearly transferable between borrowers. In models with non-transferable utility, agents always prefer matches with higher valuations. That is, agents cannot negotiate binding contracts to compensate for committing to match with less attractive partners. Lastly, for the likelihood of the empirical model to be well defined, the observed equilibrium in the data must be a unique stable matching (Bresnahan and Reiss, 1991). The existence and uniqueness of an equilibrium can be guaranteed by imposing suitable restrictions on agents' preferences. This is common practice in the empirical analysis of matching markets (see Footnotes 5 and 8 in the Introduction). I build on results in Pycia (2012), who shows that pairwise-aligned preferences are both necessary and sufficient for the existence of a unique equilibrium matching. Pairwise-aligned preferences imply that any two borrowers that belong to the same two groups prefer the same group over the other. That is, for an equilibrium group $HIJ$, aligned preferences would imply that borrowers $H$ and $I$ agree on the relative ranks of $J$ and $K$, i.e. $HIJ \succsim_H HIK \Leftrightarrow HIJ \succsim_I HIK$, where $\succsim_i$ represents agent $i$'s preference relation over groups that contain $i$.

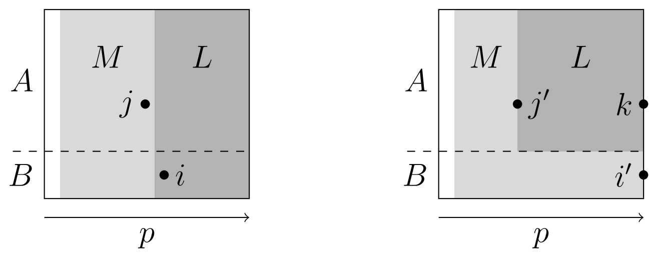
### 2.2.3 Equilibrium characterisation

Figure 2a illustrates pairwise-aligned preferences for two groups, $M$ and $L$. Here, matching is on risk type $p$ only. This is equivalent to assuming that the measure of risk exposure intensity $\epsilon$ is 0. In this case, preferences are aligned in that the groups are strictly rank-ordered by risk type (because of risk-type complementarity). In the following, I refer to the group with the highest risk-ordering of types as the *dominant* group $L$ (dark shading) and the other group as the *residual* group $M$ (light shading).

Figure 2: Matching on risk type (horizontal axis) and exposure type (vertical axis) in two-group markets.

(a) Matching on risk-type, $p$, only

(b) Matching on risk $p$ and exposure $s$




For $\epsilon > 0$, sorting takes place along two dimensions, where preferences are *vertical* in risk type $p$, in that borrowers always prefer a safer partner (irrespective of their own type), but also *horizontal* in exposure type $s$, in that borrowers only value partners of their own type. In two-group markets, the existence of a unique equilibrium is guaranteed if preferences are aligned in the dominant group $L$. This is because no member of this group will find it attractive to switch to residual group $M$ and therefore the matching is stable. Proposition 2.3 derives the necessary conditions.

**Proposition 2.3.** *In two-group markets, preferences are aligned in the dominant group $L$ if either (i) $\epsilon$ is zero – or, equivalently, all agents are of the same exposure type – or (ii) $\epsilon$ and the proportion of the leading exposure type $A$ are sufficiently large.*

*Proof:* See Appendix A.

The conditions in Proposition 2.3 are reasonable in an agricultural context where rice farmers are the dominant group (as in the Townsend Thai project, see Section

4) and their projects are arguably subject to intense common shocks. The intuition here is that in agricultural lending, there is one dominant exposure type: exposure to weather shocks. If these shocks are sufficiently strong, then matching is first on exposure type and then aligned in risk type within exposure type (as Figure 2b illustrates). In villages with two borrower groups, this results in a dominant group, which is composed of the 'weather shock' exposure types with the safest projects (here, group $L$). This group is stable (or in equilibrium) when utility is non-transferable, because no borrower would prefer to match with a different exposure type or a higher risk type. The remaining borrowers form a residual group, which is composed of 'weather shock' exposure types with riskier projects and those with other exposure types (here, Group $M$). At the same time, this equilibrium matching (i) creates an endogeneity problem that results in sorting bias and (ii) provides an elegant solution to the problem. Both results are discussed in turn.

*Sorting bias*

The valuation $V_G$ of group $G$ is the sum over all group members' utilities from matching with this group, i.e. the sum over the interaction terms in Eqn 7.[12]

$$V_G = -q \sum_{i \in G} \sum_{j \in G \setminus i} [p_i(1-p_j) + p_j(1-p_i)] + q\epsilon \sum_{s \in \{A,B\}} n_s^G(n_s^G - 1) \quad (8)$$

The group valuation in Eqn 8 is increasing in risk type (for $p > 0.5$), exposure intensity $\epsilon$ and the coincidence of same exposure types. Equilibrium matching, as illustrated in Figure 2b, results in a positive correlation between the groups' risk type (first term of Eqn 8) and project covariation (second term). Figure 2b shows the equilibrium matching, where the dominant group is homogeneous in exposure type (all $A$ types). We can see that the group with higher project covariation (group $L$) has safer risk types on average. Corollary 2.2 states this formally.

**Corollary 2.2.** *In two-group markets with project correlation, equilibrium matching exhibits positive correlation between the groups' average risk type and project covariation.*

*Proof:* See Appendix A.

In the resulting matching, the dominant group has, on average, projects that are both safer and more highly correlated than the residual group. Now, if risk

[12]Note that the group valuation $V_G$ does not contain borrower $i$'s expected return $E$ and interest payment $rp_i$, because these realisations are independent of group members.

type is partially unobservable and captured in the error term, then the coefficient pertaining to project correlation will be biased. I refer to this as sorting bias throughout the paper.

*Equilibrium characterisation*

The equilibrium conditions can be expressed as simple inequalities that impose lower and upper bounds on the match valuations of the observed and unobserved (or counterfactual) matches. I impose these bounds in the empirical matching model in Section 3 to guarantee that a unique equilibrium is estimated. Proposition 2.4 summarises the stability conditions based on bounds $\overline{V_G}$ and $\underline{V_G}$, derived in Appendix A. The proof is for aligned preferences in the general case with arbitrary group and market size. The conditions for observed equilibrium groups $G \in \mu$ and unobserved non-equilibrium groups $G \notin \mu$ are equivalent, but they impose different bounds on the latent valuation variables that guarantee the estimation of the unique market equilibrium.

**Proposition 2.4.** *The matching $\mu$ is stable iff $V_G < \overline{V_G} \quad \forall G \notin \mu$. Equivalently, the matching $\mu$ is stable iff $V_G > \underline{V_G} \quad \forall G \in \mu$.*

*Proof:* See Appendix A.

The upper bounds $\overline{V_G}$ have a natural economic interpretation; they are the maximum of the opportunity costs for group $G$'s members of leaving their respective equilibrium groups and joining non-equilibrium group $G$. Similarly, the lower bounds $\underline{V_G}$ give the maximum of the opportunity costs of group $G$'s members maintaining their equilibrium match $G$.

# 3 Empirical strategy

This section outlines the empirical strategy used to identify the direct and participation effects separately. I describe what is being tested in the following and how these tests relate back to the theoretical models.

## 3.1 Direct effect

Subsection 3.1.1 develops a structural empirical model to estimate the direct repayment effect of project correlation net of sorting bias. The estimation strategy replicates the following ideal experiment with standard cross-sectional survey data.

*Ideal Experiment 1: Direct effect net of sorting bias*

1. Announce in each village that loan applicants will be assigned to groups randomly and make applicants sign up to a waiting list.
2. For half of the villages (chosen at random), surprise applicants by allowing groups to form endogenously. For the other half, assign groups randomly.
3. Obtain the parameter estimates of randomly and endogenously formed groups. Call the first estimates the *direct* effect of project covariation and the difference between the two groups the *bias from sorting*.

### 3.1.1 Estimation strategy

Technically, the equilibrium groups constitute a self-selected sample. The selection problem differs substantially from the classical Heckman (1979) two-stage correction. Here, the first-stage selection mechanism that determines which borrower groups are observed (and which are not) is a one-sided matching game and not a simple discrete choice, as in the Heckman model. A discrete choice model assumes that an observed match reveals group partners' preferences concerning each other. An observed matching, however, is the outcome of complex interactions and conflicts of interest between agents. In particular, borrowers can only choose from the set of partners who would be willing to form a match with them, but we do not observe their relevant choice sets. This makes direct inference based on a discrete choice model impossible, even if it accounts for social interactions such as the models in Brock and Durlauf (2007) and Ciliberto and Tamer (2009).

The empirical strategy, therefore, is to simultaneously estimate the outcome equation of repayment performance with the matching game. The matching game is given by the following match equation

$$V_G = W_G\alpha + \eta_G. \tag{9}$$

There are $|\Omega|$ equations, where $\Omega$ is the set of feasible groups in the market.[13] $V \in \mathbb{R}^{|\Omega|}$ is a vector of latents and $W \in \mathbb{R}^{|\Omega|\times k}$, a matrix of $k$ characteristics for all feasible groups. $\alpha \in \mathbb{R}^k$ is a parameter vector, and $\eta \in \mathbb{R}^{|\Omega|}$ is a vector of random errors. A group – and therefore its repayment outcome $Y_G$ – is observed if it is part of the equilibrium matching $\mu$, i.e. its group valuation is in the set of valuations $\Gamma_\mu$

[13] The set of feasible groups in two-group markets with group size $n$ comprises all $\binom{2n}{n}$ possible $k$-for-$k$ borrower swaps for $k \in \{1, ..., n-1\}$ across the two groups.

that satisfy the equilibrium condition.[14] This set of valuations is the link between the structural empirical model and the equilibrium characterisations derived in Proposition 2.4, Subsection 2.2. With $V \in \mathbb{R}^{|\Omega|}$, the vector of all valuations in the market, the equilibrium condition can be written as a collection of inequalities that give upper and lower bounds on the match valuations

$$V \in \Gamma_\mu \Leftrightarrow \left[V_G < \overline{V_G} \; \forall G \notin \mu\right] \Leftrightarrow \left[V_G > \underline{V_G} \; \forall G \in \mu\right]. \tag{10}$$

For the outcome equation, the binary dependent variable is given as $Y_G = 1[Y_G^* > 0]$, where the latent group outcome variable $Y_G^*$ is

$$Y_G^* \quad = \quad X_G\beta + \varepsilon_G, \tag{11}$$

with $\varepsilon_G := \delta\eta_G + \zeta_G$, where $\zeta_G$ is a random error. This specification allows for a linear relationship between the error terms in the selection and outcome equations with covariance $\delta$. The design matrices $X \in \mathbb{R}^{|\mu|}$ and $W \in \mathbb{R}^{|\Omega|}$ do not necessarily contain distinct explanatory variables.

*Distribution of error terms*

The joint distribution of $\varepsilon_G$ and $\eta_G$ is assumed bivariate normal with mean zero and constant covariance $\delta$.

$$\begin{pmatrix} \varepsilon_G \\ \eta_G \end{pmatrix} \sim N\left(0, \begin{bmatrix} \sigma_\xi^2 + \delta^2 & \delta \\ \delta & 1 \end{bmatrix}\right) \tag{12}$$

Here, the variance of the error term of the outcome equation $\sigma_\varepsilon^2$ is $var(\delta\eta + \xi) = \delta^2 + \sigma_\xi^2$. To normalise the parameter scale, the variance of $\eta$ and $\zeta$ is set to 1, which simplifies $\sigma_\varepsilon^2$ to $1 + \delta^2$ in the estimation. If the covariance $\delta$ were zero, the marginal distributions of $\varepsilon_G$ and $\eta_G$ would be independent and the selection problem would vanish.

*Identification*

Interaction in the market makes estimation computationally involved but also overcomes the identification problem. Identification requires exogenous variation. In this model, this is provided for every group by the characteristics of agents who are in the same market but not in the same group. To illustrate, take a market

[14] The Heckman (1979) model is a special case where the set of feasible valuations is $\Gamma = [0, +\infty)$.

with four agents $A$, $B$, $C$ and $D$. The characteristics in the outcome equation of group $AB$ are simply $X = (X_{AB})$. The characteristics in the matching equation are $W = (X_{AB}, X_{CD}, X_{AC}, X_{AD}, X_{BC}, X_{BD})$, and the independent elements of $W$ are then $W' = (X_{CD}, X_{AC}, X_{AD}, X_{BC}, X_{BD})$. The identifying assumption is thus that the characteristics of agents outside the match (those comprised in $W'$) are exogenous. Put differently, the identifying exclusion restriction is that the characteristics of all agents in the market affect who matches with whom, but the outcome of an equilibrium group is determined exclusively by its own members. Note that other agents' characteristics are not used as instruments in a traditional sense. Rather than entering the selection equation directly, they pose restrictions on the match valuations by determining the bounds in the estimation.

*Estimation*

For the estimation, I use Bayesian inference with a Gibbs sampling algorithm that performs Markov Chain Monte Carlo (MCMC) simulations from truncated normal distributions. The latent outcome and valuation variables $Y^*$ and $V$ are treated as nuisance parameters and sampled from truncated Normal distributions that enforce sufficient conditions for the draws to come from the equilibrium of the group formation game. For the posterior distributions, see Appendix B. The conjugate prior distributions of parameters $\alpha$, $\beta$ and $\delta$ are Normal and denoted by $N(\bar{\alpha}, \Sigma_\alpha)$, $N(\bar{\beta}, \Sigma_\beta)$ and $N(\bar{\delta}, \sigma_\delta^2)$, respectively. In the estimation, the prior distributions of $\alpha$ and $\beta$ have mean zero and variance-covariance matrix $\Sigma_\beta = (\frac{1}{|\mu|}X'X)^{-1}$ and $\Sigma_\alpha = (\frac{1}{|\Omega|}W'W)^{-1}$, respectively. This is the widely used g-prior (Zellner, 1986). For $\delta$, the prior distribution has mean zero and variance 10. For this parameter, the prior variance is at least 40 times larger than the posterior variance in all estimated models. This confirms that the prior is fairly uninformative.

### 3.1.2 Testable effects and links to theory

By linking the structural empirical model to the variables defined in the theory, the empirical specification of the matching and outcome equations can be written as

$$V_G = -q \sum_{i \in G} \sum_{j \in G \setminus i} [p_i + p_j - 2p_i p_j] + q\epsilon \sum_{s \in \{A,B\}} n_s^G (n_s^G - 1) + \eta_G \tag{13}$$

$$Y_G^* = r \sum_{i \in G} p_i + q \sum_{i \in G} \sum_{j \in G \setminus i} [p_i + p_j - 2p_i p_j] - q\epsilon \sum_{s \in \{A,B\}} n_s^G (n_s^G - 1) + \delta \eta_G + \zeta_G. \tag{14}$$

The matching equation is the empirical equivalent of Eqn 8. Eqn 14 gives the expected repayment $Y_G^*$ of group $G$. In words, the expected repayment equals the expected interest payment plus the expected liability payment (if projects are independent) and minus the liability payment that the group avoids due to correlated returns. The final term $\delta\eta_G$ controls for unobservable group characteristics through the error term of the matching equation $\eta_G$. The error term $\zeta_G$ captures realised individual or aggregate shocks such as health or market demand effects.

For the parameters, the gross interest rate $r$ is known to be fixed at 1.09 in the BAAC lending programme and is therefore fixed at this level here. The parameters $q$, $q\epsilon$ and $\delta$ are estimated in the model. The expected signs of the parameters are as given in Eqns 13 and 14. Of particular interest is the sign of $q\epsilon$, which pertains to the project correlation variable in the outcome equation. From a diversification point of view, project correlation has a strictly negative effect. However, this effect can be (i) outweighed by a positive effect from mitigating moral hazard (see Proposition 2.2) or (ii) confounded by a positive sorting bias from endogenous group formation (see Corollary 2.2.). Controlling for unobservable group valuation $\eta_G$ allows me to estimate the direct repayment effect net of sorting bias. The extent and sign of the sorting bias are captured by parameter $\delta$.

## 3.2 Participation effect

In a second step, I test for the participation effect of restricting matching on risk exposure. This effect is estimated in agent-based simulations using the coefficient estimates from the structural model as parameters. Varying the matching process but keeping the model fixed to predict the repayment outcome allows me to separate the participation effect from the direct effect. The agent-based simulations can be thought of as replicating the following ideal experiment.

*Ideal Experiment 2: Participation effect*

1. Randomly assign villages to one of two regimes. Dependent on the regime, have groups apply under either (i) matching on risk type only – i.e. groups must be balanced in exposure type – or (ii) matching on both risk and exposure type.

2. For all villages, surprise loan applicants by disbursing individual-liability loans instead of joint-liability loans.

3. Compare the average repayment rates under the two regimes. Call the difference in repayment the participation effect of matching on risk exposure.

### 3.2.1 Estimation strategy

To estimate the size of the participation effect, I work with the full sample of borrowers in the 2000 BAAC data and run agent-based simulations to see how many and what sorts of groups will borrow at the current contract terms under different matching regimes. The characteristics of these self-selected groups are then used to predict the expected repayment using the parameter estimates from Eqn 14. The protocol for the agent-based simulation is described in Appendix C.

### 3.2.2 Testable effects and links to theory

The Ghatak (1999) adverse selection model makes two testable predictions for our data. First, it predicts that an increase in project correlation draws additional borrowers into the market who would not have taken a loan otherwise. Second, this positive effect should be more than offset by the negative effect of the bank losing joint-liability payments when projects fail concurrently.

# 4 Empirical results

The empirical strategy in Section 3 is applied to data from the Townsend Thai project. The analysis here uses data from both the 1997 baseline survey and a smaller resurvey conducted in 2000. Replication code and datasets are available in R package `matchingMarkets` (Klein, 2018), the corresponding vignette (Klein, 2015) and in Appendix E. The empirical robustness of the results is examined in Appendix D.

## 4.1 Data

The survey project is a panel that focuses on villages in four provinces (*changwat*) of Thailand: two in the North-east region and two in the Central region. The baseline data used in the Ahlin and Townsend (2007) paper was collected in 1997. For this study, 12 subdistricts (*tambons*) were selected at random within each of the four provinces. Within each *tambon*, four villages were selected at random. This resulted in a sample of 192 villages, in which two survey instruments were applied. In the initial household survey (Townsend, 1997b), 15 households in each village were selected at random, yielding a total sample of $192 \times 15 = 2,880$ households. The second survey instrument was the initial Bank for Agriculture and Agricultural Cooperatives (BAAC) survey (Townsend, 1997a) or BAAC 1997. The BAAC is a government-owned development bank and the largest lender to this population. In the BAAC 1997 survey, for every village as many borrower groups as possible were identified and a maximum of two groups were randomly selected for interviews. In total, 262 BAAC groups were identified and their group leaders interviewed.

For the main part of the analysis, I use data from a smaller resurvey that was conducted in 2000 and comprises variables that were specifically designed to test the theory in Ghatak (1999). In the resurvey, for each of the four original provinces, four *tambons* were selected randomly from the 12 *tambons* in the baseline survey. This resurvey again consisted of two instruments: a household resurvey (Townsend, 2000b) and a BAAC resurvey (Townsend, 2000a), referred to as BAAC 2000 in the following. BAAC 2000 consists of a group-leader survey, in which the heads of BAAC groups were interviewed, as well as a group survey, in which up to five group members were interviewed. The final sample of the BAAC 2000 used for analysis comprises the characteristics of 68 lending groups.

## 4.2 Variables

The variables used in the empirical analysis are directly related to the extension of Ghatak's (1999) theoretical model of borrower group formation in Subsection 2.2. The average *risk type* and *project covariation* are measured as below, and the remaining variables are summarised in Table 2.

*Risk type*: Group members were asked for their expected income for the following year, which is denoted as $E_i$. They were also asked for their expected income if the following year was a good year $H_i$ or a bad year $L_i$. The measure $p_i = \frac{E_i - L_i}{H_i - L_i}$ serves as a proxy for borrower $i$'s probability of success, using the property that

Table 2: Summary of group-level variables.

| Variable | Description | mean (sd) |
|---|---|---|
| *Dependent variable* | | |
| - repayment_outcome[a)] | BAAC *never* raised interest rates as a penalty for late repayment | 0.46 (0.50) |
| *Exposure* | | |
| - ln(group_age)[b)] | Log of number of years group had existed | 4.31 (1.01) |
| *Risk type* | | |
| - success_prob $p_i^{c)}$ | Group members' project success prob. | 0.70 (0.07) |
| - success_prob_int $p_i p_j^{c)}$ | Two-way interactions of success prob. | 0.21 (0.03) |
| *Project covariation* | | |
| - worst_year $wst^{c)}$ | Measure of coincidence of economically bad years across group members | 0.57 (0.37) |
| *Contract terms* | | |
| - interest_rate | Gross interest rate is fixed at 109% for loans below 60,000 Thai baht | 1.09 (–) |
| - loan_size[a)] | Average loan size borrowed by the group (thousand Thai baht, currency value in 2000) | 1.59 (1.01) |

[a)] from 2000 BAAC group-leader survey
[b)] random regression imputation based on 1997 and 2000 BAAC surveys (see Appendix E)
[c)] from 2000 BAAC group survey

$p_i H_i + (1 - p_i) L_i = E_i$.

*Project covariation*: A group's project covariation is proxied by the variable *worst_year*, which is a vector indicating which of the previous two years was worse for a borrower economically. The group-level variable gives the average coincidence of worst years based on all possible borrower-by-borrower comparisons. This measure establishes a direct link with the different exposure types in Ahlin (2009) in that each year can then be interpreted as exposing agents to a different shock. The measure of project covariation then gives the probability that two randomly drawn group members have the same exposure type.

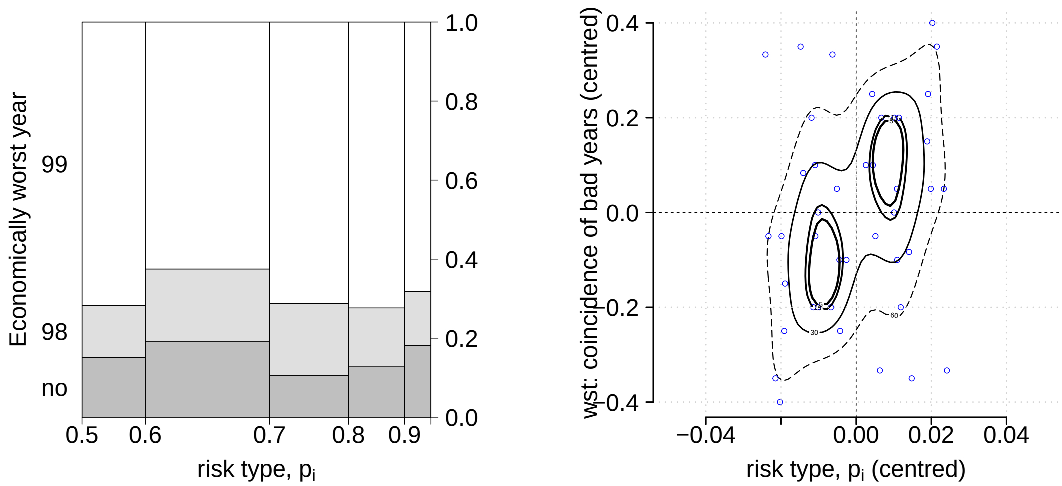
## 4.3 Assumptions

The credibility of the model relies on the validity of the two assumptions made in Subsection 2.2.2. The first was that the distribution of risk types $p \in [\underline{p}, 1)$ is the same for all levels of exposure types $s \in \{N, A, B\}$. The spine plot in Figure 3a plots these two variables against each other based on the 2000 BAAC survey used in the empirical analysis. The exposure types on the vertical axis are categorised based on which of the previous two years was worse for the borrower economically. The data exhibits no systematic relationship between risk type $p$ on the horizontal axis and exposure type $s$ on the vertical axis. The second assumption was that agents' preferences are non-transferable and aligned. A necessary condition for this assumption to hold in two-group markets is a positive correlation between the groups' average risk type and project covariation (see Corollary 2.2). For each of the 29 markets, the contour plot in Figure 3b maps these two variables; centred by market averages to allow for comparability between groups from different markets. Each point represents one group and the contour lines connect points with same estimated density. The bimodal density shows that the group that is safer on average (higher $p$) also has higher positive project correlation (and vice versa).

Figure 3: Validation of assumptions underlying the empirical matching model.

(a) Spine plot of borrower-level risk exposure vs. risk type in BAAC data

(b) Contour plot of group-level project correlatedness vs. risk type




## 4.4 Direct effect

The first Probit model in Table 3 gives the marginal effect of project covariation on repayment. The dependent variable is 1 if there were no arrears during the group's lifetime and 0 otherwise. To compare the riskiness of groups with different ages and, therefore, different exposure to risk, I control for the natural logarithm of group age. I also add village-level dummies to control for between-village heterogeneity. The resulting positive coefficient suggests that a high level of project covariation is associated with less arrears. This replicates the surprising result in Ahlin and Townsend (2007) using data from the 2000 resurvey. This positive repayment effect can be explained by either correlation mitigating moral hazard for extremely risk-averse borrowers (see the Stiglitz model, Proposition 2.2) or the endogenous matching that biases $\hat{\beta}_{wst}$ upwards because it picks up the effect of the omitted risk-type variable (see Corollary 2.2). To explore this bias from sorting, the second Probit model controls for contract terms and the positive repayment effect of risk type. This control mitigates the sorting bias for $\hat{\beta}_{wst}$ and results in a switch in sign, which is consistent with the negative effect from anti-diversification, as predicted in the Stiglitz model for moderately risk-averse agents (see Eqn 14).

Table 3: Probit and structural models with village dummies

*S.E. in parentheses; one-sided significance at 0.1, 1, 5, 10% denoted by ***, **, *, and .*

| | ***Probit model (1)*** | ***Probit model (2)*** | ***Structural*** |
|---|---|---|---|
| ***Outcome equation*** | | | |
| *Dependent variable: repayment_outcome[a) ] = 1 if the BAAC has never raised interest as a penalty for late repayment; 0 otherwise.* | | | |
| *Risk type* | | | |
| - success_prob $p_i$ | – | +1 | +1 |
| - success_prob_int $p_i p_j$ | – | 0.238 (1.607) | 1.571 (1.811) |
| *Project covariation* | | | |
| - same_worst_year $wst^{a)}$ | 0.170 (0.289) | -0.015 (0.219) | -0.586 (0.244)** |
| *Contract terms* | | | |
| - loan_size | – | 0.263 (0.421) | 0.970 (0.359)*** |
| - loan_size_sqrd | – | -0.050 (0.088) | -0.187 (0.078)** |
| *Exposure* | | | |
| - ln(group_age) | -0.040 (0.054) | -0.116 (0.161) | -0.395 (0.110)*** |
| *Village dummies* | YES | YES | YES |
| Observations | 68 | 68 | 68 |
| ***Matching equation*** | | | |
| *Dependent variable: group observability indicator = 1 if group is observed; 0 otherwise.* | | | |
| *Risk type* | | | |
| - success_prob_int $p_i p_j$ | – | – | -0.778 (0.928) |
| *Project covariation* | | | |
| - same_worst_year $wst$ | – | – | 0.356 (0.121) *** |
| *Controls* | – | – | YES |
| Observations[b)] | – | – | 5,342 |
| ***Variance*** | | | |
| Covariance $\delta$ | – | – | 0.512 (0.128)*** |

[a)] Karlson *et al.* (2012) one-sided test for difference of *Probit(2)* and *Structural*, p-value 0.048.
[b)] 5,284 counterfactual groups and 58 factual groups.

### 4.4.1 Matching on observables

The above switch in sign implies a positive correlation between risk type and exposure type, which results from endogenous matching on both covariates as derived in Corollary 2.2. To confirm that this is the mechanism at work, the matching on observables is tested in the matching equation of the structural model in Table 3. In this equation, the independent variables are constructed from individual borrowers' characteristics for 58 factual (or equilibrium) groups and 5,284 counterfactual (or non-equilibrium) groups in all 29 two-group villages. The dependent variable is 1 for the 58 equilibrium groups and 0 otherwise. The latent group valuations are simulated for equilibrium and non-equilibrium groups using the Gibbs sampler presented in Subsection 3.1.1. Turning to the results, the signs of the marginal effects[15] are consistent with the predictions from the theory in Eqn 13.[16] The negative sign on the risk-type variable means that borrowers value group members with safer projects. (Note: the negative sign on the coefficient results in a positive cross-partial derivative with respect to agents' risk types in Eqn 13.) While this effect is non-significant, the positive sign on the exposure-type variable is significant at the 0.1%-level and indicates that borrowers value peers of the same exposure type. This finding is in line with the matching mechanism derived in Corollary 2.2. This is interesting in that it suggests that exposure type may play an even more significant role in group formation than risk type, which has been the primary focus of the microfinance literature to date.

### 4.4.2 Matching on unobservables

If matching is also on unobservables that affect group repayment – such as local information on risk types – then $\hat{\beta}_{wst}$ is still biased upwards in the second Probit model. To correct for this bias, the structural model in Table 3 estimates the matching and outcome equations jointly and allows local information to enter the outcome equation in form of the error term $\eta$ of the matching equation. The

[15]The marginal effects for the selection equation are obtained as $\frac{\partial P}{\partial W} = \phi(0)\alpha/\sqrt{2}$, with the probability $P$ that group $G$ has a higher valuation than group $G'$ equal to $Pr(W_G\alpha + \eta_G > W_{G'}\alpha + \eta_{G'}) = \Phi((W_G - W_{G'})\alpha/\sigma_{\eta_G - \eta_{G'}}) = \Phi((W_G - W_{G'})\alpha/\sqrt{2})$. The standard error of the marginal effect is given by $\phi(0)\sigma_\alpha/\sqrt{2}$. To see this, consider a linear transformation of $X \sim N(\mu, \sigma)$ as $Y = aX$. It then follows that $Y \sim N(a\mu, a\sigma)$.

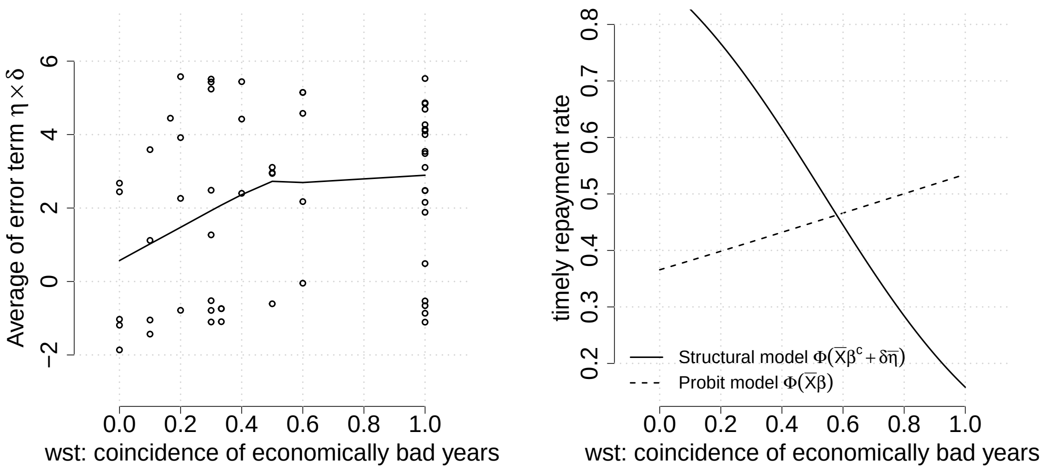
[16]Note that coefficient magnitudes on risk type and correlatedness need not be the same in both equations of the structural model. This is mainly for two reasons: first, the response of the outcome equation is the probability of timely repayment rather than the expected repayment; and second, the parameters in the outcome equation are based on the adverse selection model and do not reflect the moral hazard effects through which correlated projects can tilt incentives towards safer projects.

variance section in Table 3 shows considerable matching on unobservables: the covariance between the error terms of the matching and outcome equations is $\hat{\delta} = 0.512$, which is equivalent to a correlation of $+0.41$ $(= \frac{\sigma_{\varepsilon,\eta}}{\sigma_\varepsilon \sigma_\eta} = \frac{0.512}{(1+0.512^2)\cdot 1})$. A direct comparison between the second Probit model and the sorting-corrected structural model yields an upwards bias in the Probit model of $+0.57$ $(= -0.015 - [-0.586])$ for $\hat{\beta}_{wst}$ that is significant at the 5%-level. This bias results from the positive correlation of project covariation and unobservables $\eta$ in the outcome equation (see Figure 4a). In the case of group lending, this means that groups with higher project covariation also have better unobserved characteristics. In the structural model, the error term $\eta$ in the matching equation enters the outcome equation as $\delta\bar{\eta} > 0$. The omission of this sorting-correction term in the Probit regression leads to a positive correlation $cor(wst, \varepsilon)$ because $\varepsilon$ is proportional to $\delta\eta$ (i.e. $\varepsilon = \delta\eta + \xi$, where $\xi$ is a random error). Matching on both observables ($wst$) and unobservables ($\eta$) thus explains the sorting bias in the second Probit model.

Figure 4: Matching on unobservables. Relative magnitudes of sorting bias and the direct effect of project covariation on repayment outcomes.

(a) Error terms of observed groups against covariation measure $wst$

(b) Decomposition of sorting bias and direct effects




### 4.4.3 Decomposition of sorting bias and direct effect

Figure 4b illustrates the decomposition of sorting bias and direct effects. The decomposition is done by comparing the estimated regression lines for the first Probit model with the outcome equation of the structural model. The models are evaluated conditional on the value of $wst$ on the horizontal axis with all other variables at their means. The solid regression line of the structural model gives the expected repayment – conditional on $wst$ – when all borrowers are randomly assigned to groups. This is because the estimates are conditional on all feasible groups (observed and unobserved) in the market. The dashed Probit regression line depicts the estimates for observed groups only and therefore also captures the sorting bias. To emphasise, if borrowers were assigned at random, as in Ideal Experiment 1 in Section 3, the two lines would overlap perfectly.

In Figure 4b, we see that allowing groups to match endogenously (dashed line) results in more timely repayment for groups with higher project covariation. This is the result in Ahlin and Townsend (2007). However, it does not imply a causal relationship. To quantify this effect, note that an increase in project covariation by one standard deviation at the sample mean results in an expected improvement in the probability of timely repayments of +6.3 percentage points ($= 0.170 \cdot 0.37 = \hat{\beta}_{wst}^{probit} \cdot \hat{\sigma}_{wst}$). This improvement follows from two opposing effects. First, from the structural model we find a significantly negative *direct effect* of $-22$ percentage points ($-0.586 \cdot 0.37 = \hat{\beta}_{wst}^{str} \cdot \hat{\sigma}_{wst}$) because the bank loses joint-liability payments when projects fail simultaneously. This is consistent with the revised predictions from the moral hazard model of Stiglitz (1990) when borrowers are not extremely risk averse. Second, from the difference between the Probit and structural models we find an even larger but positive *sorting bias* of +28 percentage points ($[\hat{\beta}_{wst}^{probit} - \hat{\beta}_{wst}^{str}] \cdot \hat{\sigma}_{wst}$). This is because the highly correlated groups have unobservables that make them +28 percentage points safer.

## 4.5 Participation effect

For the direct effect, the empirical model does not allow for an outside option leaving in or excluding some potential borrower groups. The participation effect tests whether allowing for matching on exposure type can draw sufficiently safe types – that would not have taken a loan otherwise – into the market in order to offset the negative effect from avoiding liability payments. This is an indirect test of the model extension of Ghatak (1999) in Subsection 2.1, which predicts a negative repayment effect.

Table 4 presents the results of the simulations for (1) matching on risk type only versus (2) matching on both risk type and exposure type. The first row gives the number of borrowers whose utility from taking a loan with their equilibrium groups exceeds the outside option of wage labour. Contrary to the predictions of the theories, matching on exposure type (anti-diversification) does not draw more

Table 4: Agent-based simulation of expected repayment under different matching regimes.

| Simulation based on 250 individuals in 29 two-group markets. | | |
|---|---|---|
| *Matching process:* | matching on $p$ only (1) | matching on $p$ and $s$ (2) |
| *Participation* | | |
| 1. No. of borrowers | 161 | 161 |
| 2. No. of groups | 16 | 15 |
| *Group characteristics* | | |
| 3. $\bar{p}$ | 0.75 | 0.73 |
| 4. $\bar{wst}$ | 0.54 | 0.65 |
| *Predicted repayment* | | |
| 5. $\hat{\bar{Y}}$ | 0.45 | 0.37 |
| 6. 85% CI [a)] | (0.48, 0.41) | (0.41, 0.33) |

[a)] Confidence intervals based on endpoint transformation.

borrowers into the programme (161) than matching on risk type alone (161). This result carries through from the individual to the group level: the restriction on minimum group size makes borrowing infeasible for groups where the participation condition is satisfied for fewer borrowers than the minimum group size. The number of remaining groups is given in the second row.

While anti-diversification does not draw in more borrowing groups (15 vs 16), these groups are riskier ($\bar{p}$ in row 3) and have considerably higher project correlation ($\bar{w}st$ in row 4). The predicted probability of timely repayment of 0.37 for these groups is consequently lower than when matching on risk type only (0.45). This is because under high project correlation, the bank receives fewer joint-liability payments, consistent with the model predictions from Ghatak (1999). The effect is statistically significant at the 15%-level and of economic importance: diversification results in a 22 percent increase in timely repayment equivalent to a ceteris paribus reduction in the interest rate by 25 percent.[17] The results suggest that

[17]The calculation of the welfare effect is based on the total differential of the bank's payoff function in Eqn A14 with respect to $y$, $r$, $p$ and $\epsilon$. Solving for $dr$ results in $dr = (dy + q \cdot d\epsilon - (r + q \cdot (1 - 2 \cdot p)) \cdot dp)/(p + dp)$. Using parameters from Table 2 ($r = 1.09$), Table 3 ($q = 0.778$) and Table 4 ($p = 0.745$, $dy = -0.073$, $dp = -0.015$, $d\epsilon = 0.109$), we find that the bank can offset the reduced repayment of $dy = -7.3$ percentage points that results from moving from a diversified group composition in matching process (1) in Table 4 towards matching process (2) by increasing interest rates by $dr = 3.1$ percentage points. That is, under matching process (2), the bank would charge a gross interest rate of 109% plus 3.1% to compensate for worse repayment rates. The diversification in matching process (1) would therefore allow for a reduction of interest rates by 0.031/(0.09+0.031) = 25.62 percent.

lenders would benefit from preventing the grouping together of borrowers exposed to similar income shocks.

### 4.6 Implications for market design

The results concerning the direct and participation effects imply that banks should prevent the matching of borrowers who are exposed to similar income shocks. A policy recommendation, however, would depend on whether imposing such rules would also prevent borrowers from matching on dimensions that may be desirable from the lender's perspective, such as social connections. If borrowers match with those that they know best, then project covariation is naturally tied to social connectedness because friends or relatives will often have the same income sources and therefore be exposed to similar income shocks. Taken together, endogenous matching will result in groups with both correlated returns and social ties.

In terms of optimal market design, there are three cases to distinguish. First, if the project correlation measure captures social connectedness fully, then group diversification can be implemented by restricting the grouping together of relatives, as suggested in the Grameen Replication Guidelines (Alam and Getubig, 2010). The remaining two cases are relevant when social connectedness is (partly) captured in the error term. The implications of the findings in this section then also depend on the expected repayment effect of social connectedness. If social connectedness improves repayment, pushing for diversification may have either no effect or even a negative on repayment. If, on the other hand, social connections have a negative effect on repayment, then there is a clear case for diversifying groups. In the theoretical and empirical literature, there is no clear consensus on the effect of social connections on repayment. For the Thai village context used in this paper, Ahlin and Townsend (2007) find that cooperative behaviour in groups has a negative effect on repayment. This is consistent with the models of Banerjee *et al.* (1994) and Besley and Coate (1995), who predict that cooperation prevents a group from exerting repayment pressure on its members. The result from the survey that most closely matches the context of this paper thus suggests a positive repayment effect from diversification.

## 5 Conclusion

I analyse the optimal design of rules for group formation in matching markets with an application to group lending in microfinance. The particular focus is on microlenders' decisions on rules to diversify borrower groups with respect to their exposure to common income shocks. Such rules affect group outcomes by influencing who matches with whom (direct effect) and who participates in the market (participation effect). A distinction between these effects allows a direct test of ex-ante and ex-post mechanisms through which the variable of interest affects group outcomes. This distinction is particularly useful in the field of (micro)finance, where the evaluation of adverse selection models requires that moral hazard effects are not in force, and vice versa.

I develop the trade-off for conflicting predictions of extant asymmetric information models and estimate both effects separately. The empirical analysis is complicated by an endogeneity problem that occurs whenever agents match on both (i) the independent variable of interest and (ii) characteristics unobserved to the researcher but correlated with the outcome of interest. To correct for the resulting sorting bias, I develop a generalised Heckman selection model with credible exclusion restrictions that exploits agents' local information to control for unobserved group characteristics. These unobservables are inferred in a matching model that captures the strategic interactions of agents who can only choose from the set of partners that would be willing to match with them.

This paper has implications for empirical and theoretical work on matching markets as well as for microfinance practice, and three main outcomes can be identified. First, empirical studies on group outcomes can correct for the bias that results from sorting using R package `matchingMarkets` (Klein, 2018). Alternatively, empirical findings should be interpreted with this bias in mind, noting that direction and size are often unclear. In the Thai group-lending context in this paper, the positive sorting bias even exceeds the negative direct effect of borrowers' correlated returns on repayment, which has led previous research – using the same dataset – to make incorrect policy recommendations. Second, most theoretical work on microfinance builds on the result that endogenous group formation is socially optimal when matching is on risk type. Future modelling should take into account that matching also takes place on other dimensions – such as exposure to common shocks – with adverse effects on group repayment. Third, for microfinance practice, this finding suggests that lenders would benefit from ensuring that borrowing groups are sufficiently diversified in their exposure to income shocks. This may be achieved by placing suitable restrictions on the composition of borrower groups.

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# A Proofs

*Proof of Proposition 2.1.* Denote by $\tilde{p}$ the *average* success probability of borrowers with risk type $p \in [\underline{p}, \hat{p}]$ who would take a loan at contract terms $(r, q)$ and form groups with project covariation $\epsilon$.

$$\tilde{p} \; = \; \frac{\int_{\underline{p}}^{\hat{p}} s \; g(s) \; ds}{G(\hat{p})} \tag{A1}$$

This is the expression for the expectation of a truncated distribution with probability density function $g(\cdot)$ and cumulative distribution function $G(\cdot)$. Making use of the selection equation Eqn 4, the expected repayment $\tilde{y}$ of this borrower pool can be written as

$$\tilde{y} \; = \; r\frac{\int_{\underline{p}}^{\hat{p}} s \; g(s) \; ds}{G(\hat{p})} + q\frac{\int_{\underline{p}}^{\hat{p}} s(1-s) \; g(s) \; ds}{G(\hat{p})} - q\epsilon \tag{A2}$$

$$= \; (r+q)\frac{\int_{\underline{p}}^{\hat{p}} s \; g(s) \; ds}{G(\hat{p})} - q\frac{\int_{\underline{p}}^{\hat{p}} s^2 \; g(s) \; ds}{G(\hat{p})} - q\epsilon. \tag{A3}$$

Using Leibniz integral rule, quotient rule and the fact that $\int_{\underline{p}}^{\hat{p}} s^2 g(s) ds = (\tilde{p}^2 + \tilde{\sigma}_p^2)G(\hat{p})$, where $\tilde{\sigma}_p^2$ is the variance of the success probability in the borrower pool, we can write the marginal effect of project covariation on expected repayment as

$$\frac{\partial \tilde{y}}{\partial \epsilon} \; = \; (r+q)\frac{\hat{p}g(\hat{p})}{G(\hat{p})}\left(1 - \frac{\tilde{p}}{\hat{p}}\right)\frac{\partial \hat{p}}{\partial \epsilon} - q\frac{\hat{p}^2 g(\hat{p})}{G(\hat{p})}\left(1 - \frac{\tilde{p}^2 + \tilde{\sigma}_p^2}{\hat{p}^2}\right)\frac{\partial \hat{p}}{\partial \epsilon} - q. \tag{A4}$$

From Eqn 4 we know that $\partial \hat{p}/\partial \epsilon = q/[r + q(1-2\hat{p})]$. Substituting, setting $\underline{p} = 0$ (without loss of generality) and assuming $p$ to be from a uniform distribution[18] yields

$$\frac{\partial \tilde{y}}{\partial \epsilon} \; = \; \frac{1}{2}(r+q)\frac{q}{r + q(1-2\hat{p})} - \frac{2}{3}q\hat{p}\frac{q}{r+q(1-2\hat{p})} - q \tag{A5}$$

$$= \; \frac{1}{6}q\left[\frac{2q\hat{p}}{r+q(1-2\hat{p})} - 3\right] < 0 \; \Leftrightarrow \; \hat{p} < \frac{3}{8}\frac{q+r}{q}. \tag{A6}$$

This implies that project covariation strictly *reduces* expected repayment if either (i) $\hat{p} < 3/4$ or (ii) $q/r < 3/5$. Consider these results one at a time. For (i), note that, for $q > 0$, $\partial \tilde{y}/\partial \epsilon$ is strictly increasing in joint liability payment $q$ which is

[18] This implies that $\tilde{p} = \frac{1}{2}(\hat{p} + \underline{p}) = \frac{1}{2}\hat{p}$, $\tilde{\sigma}_p^2 = \frac{1}{12}(\hat{p}^2 - \underline{p})^2 = \frac{1}{12}\hat{p}^2$, $g(\hat{p}) = 1/[1-\underline{p}] = 1$, and $G(\hat{p}) = \frac{\hat{p}-\underline{p}}{1-\underline{p}} = \hat{p}$.

bounded from above at $r$. It therefore suffices to analyse the case where $q = r$ for which straightforward calculation (using Eqn A6) results in $\partial\tilde{y}/\partial\epsilon < 0 \Leftrightarrow \hat{p} < 3/4$. Similarly, for (ii), since $\partial\tilde{y}/\partial\epsilon$ is increasing in $\hat{p}$ it suffices to state the condition for $\hat{p}$ close to 1.[19] In this case, we have $\partial\tilde{y}/\partial\epsilon < 0 \Leftrightarrow q/r < 3/5$. □

*Proof of Corollary 2.1.* The proof of this corollary follows directly from Eqn A4 in the proof of Proposition 2.1. The cross partial derivative $\frac{\partial}{\partial g(\hat{p})}\left(\frac{\partial\tilde{y}}{\partial\epsilon}\right) = \frac{\partial^2\tilde{y}}{\partial g(\hat{p})\partial\epsilon}$ is positive if

$$(r+q)\frac{\hat{p}}{\frac{\partial G(\hat{p})}{\partial g(\hat{p})}}\left(1-\frac{\tilde{p}}{\hat{p}}\right)\frac{\partial\hat{p}}{\partial\epsilon} > q\frac{\hat{p}^2}{\frac{\partial G(\hat{p})}{\partial g(\hat{p})}}\left(1-\frac{\tilde{p}^2+\tilde{\sigma}_p^2}{\hat{p}^2}\right)\frac{\partial\hat{p}}{\partial\epsilon} \quad \text{(A7)}$$

$$(r+q)\left(1-\frac{\tilde{p}}{\hat{p}}\right) > q\hat{p}\left(1-\frac{\tilde{p}^2+\tilde{\sigma}_p^2}{\hat{p}^2}\right) \quad \text{(A8)}$$

$$(r+q)(\hat{p}-\tilde{p}) > q(\hat{p}^2-\tilde{p}^2)-q\tilde{\sigma}_p^2. \quad \text{(A9)}$$

It can be checked that, for $q \le r$ and $\hat{p} > \tilde{p}$, it holds that $(r+q)(\hat{p}-\tilde{p}) > q(\hat{p}^2-\tilde{p}^2)$ and therefore the above inequality is satisfied for all parameter constellation in Ghatak (1999). The condition $q \le r$ is an incentive compatibility constraint. The rationale behind this constraint is that if joint-liability $q$ were to exceed interest payment $r$, the borrower with the successful project would prefer to announce success and pay interest $r < q$ instead of the full joint-liability payment (Gangopadhyay *et al.*, 2005). □

*Proof of Proposition 2.2.* The starting point of the proof are two identical, hazardous projects $L$ and $M$ between which borrowers are indifferent.

$$V_{L-M} = V_L - V_M \quad \text{(A10)}$$

$$= [p_H^2+\epsilon]\cdot U_H + [p_H(1-p_H)-\epsilon]\cdot U_{Hq} \quad \text{(A11)}$$
$$-[p_H^2+\epsilon]\cdot U_H - [p_H(1-p_H)-\epsilon]\cdot U_{Hq} = 0.$$

Now consider an increase in $\epsilon$ for both projects. How much safer can the first project be made in response when (i) the risk-return ratio is fixed at $dy/dp$ and (ii) the borrowers are to be held indifferent between the safer and the risky project? Taking the total differential with respect to $\epsilon$ for both projects and allowing a

[19] Note that for $\hat{p} = 1$ we have $\partial\hat{p}/\partial\epsilon = 0$ because $p \in [\underline{p}, 1]$ and thus $\partial\tilde{y}/\partial\epsilon = -q < 0$ from Eqn A4.

simultaneous change in $p$ and $y$ for the first project yields:

$$\begin{aligned} dV_{L-M} &= (U_H - U_{Hq}) \cdot d\epsilon + [(U_H - U_{Hq}) \cdot 2p_H + U_{Hq}] \cdot dp \\ &+[(p_H^2 + \epsilon) \cdot U'_H + (p_H(1-p_H) - \epsilon) \cdot U'_{Hq}] \cdot \frac{dy}{dp} \cdot dp \\ &+(U'_H - U'_{Hq}) \cdot dy \cdot d\epsilon + [(U'_H - U'_{Hq}) \cdot 2p_H + U'_{Hq}] \cdot dy \cdot dp \\ &-(U_H - U_{Hq}) \cdot d\epsilon, \end{aligned} \tag{A12}$$

where $U'_k = \partial U_k / \partial y$. Setting $dV_{L-M} = 0$ holds the borrower indifferent between the two projects and yields the rate by which an increase in correlation results in a safer project choice, for given level of $dy$ and risk-return ratio $dy/dp$.

$$\begin{aligned} dp/d\epsilon &= \Big\{ -(U'_H - U'_{Hq})dy \Big\} / \Big\{ (U_H - U_{Hq})2p_H + U_{Hq} + [(U'_H - U'_{Hq})2p_H \\ &\quad + U'_{Hq}]dy + [(U'_H - U'_{Hq})(p_H^2 + \epsilon) + U'_{Hq}p_H]\frac{dy}{dp} \Big\}. \end{aligned} \tag{A13}$$

The expected repayment to the bank is

$$Y = r \cdot p_H + q \cdot [p_H(1-p_H) - \epsilon]. \tag{A14}$$

Taking the total differential w.r.t. $p$ and $\epsilon$ yields

$$dY = (r + q(1-2p_H)) \cdot dp - q \cdot d\epsilon \tag{A15}$$

$$\frac{dY}{d\epsilon} = (r + q(1-2p_H)) \cdot \frac{dp}{d\epsilon} - q. \tag{A16}$$

Substituting $dp/d\epsilon$ from Eqn A13 above into Eqn A16 gives the marginal repayment effect of correlated returns as

$$\begin{aligned} dY/d\epsilon &= \Big\{ (r + q(1-2p_H))(U'_{Hq} - U'_H)dy \Big\} / \Big\{ (U_H - U_{Hq})2p_H + U_{Hq} \\ &\quad + [(U'_H - U'_{Hq})2p_H + U'_{Hq}]dy + [(U'_H - U'_{Hq})(p_H^2 + \epsilon) + U'_{Hq}p_H]\frac{dy}{dp} \Big\} - q. \end{aligned}$$

Observe that there are two situations in which the marginal repayment effect is strictly negative. First, if borrowers are risk neutral or moderately risk averse such that $U'_{Hq} \approx U'_H$ then $dY/d\epsilon = -q < 0$. In this case, utility is close to linear and correlation has no effect on decision between projects but a strictly negative effect from anti-diversification. The second case is when $dy$ goes towards zero. Then $dY/d\epsilon = -q < 0$ because the income level at which the utility gain from avoiding liability payment (due to increased project correlation) is evaluated – and thus the slope of the utility – is similar for safe and risky projects. □

*Proof of Proposition 2.3.* Part (i) of the proposition is trivial. For part (ii), note that the matching pattern in Figure 2b is an equilibrium under aligned preferences if the safest risk type in group $L$, denoted by $k$, prefers to remain matched with group member $j'$ over a swap of $j'$ for borrower $i'$ from group $M$, i.e. if $u_{k,j'} > u_{k,i'}$. This is the case for $\epsilon > p_k(p_{i'} - p_{j'})$. If this inequality holds for marginal type $k$, then any borrower $x$ in $L$ prefers $j'$ over $i'$ (because $p_x < p_k$ and net utility in Eqn 7 is decreasing in $p$). Thus, preferences are aligned within the leading exposure type $A$ for the dominant group $L$ and the matching is stable.

The condition for aligned preferences is satisfied if exposure intensity $\epsilon$ is sufficiently large and the difference $p_{i'} - p_{j'}$ is sufficiently small. The latter term is decreasing in the proportion of the leading exposure type. To see this, note that the integral over the probability density function of risk type $p$ below must equal 1/2 in the case with two groups per market.

$$\theta_A \int_{p_{i'}}^{p_{j'}} f_p(t)\ dt \quad = \quad \frac{1}{2} \tag{A17}$$

Here, the integral is pre-multiplied with the proportion of $A$-types, $\theta_A$, because, by Assumption H1, the proportion is constant for any point in the distribution of $p$. Now, fix any distribution of risk types, $f_p$, and note that the higher the proportion of $A$-types, $\theta_A$, in the market the higher the value of $p_{j'}$, the lowest risk type in group $L$. Thus the smaller is the difference $p_{i'} - p_{j'}$. Graphically, in Figure 2a, for any distribution of risk types, the more $A$-type borrowers, the smaller the term $p_{i'} - p_{j'}$. □

*Proof of Corollary 2.2.* To begin with, under Assumption H1 both groups $M$ and $L$ have the same group project correlation and $L$ has safer risk types than $M$ (see Figure 2a). An $i$-for-$j$ swap has two effects.

First, it results in an increase in project covariation for group $L$ and a decrease for group $M$. To see this, note that the total differential of Eqn 8 with respect to $n_s$ is $q\epsilon \sum_{s\in\{A,B\}}(2n_s - 1)dn_s$. For an $i$-for-$j$ swap in group $L$ we have $dn_A = +1$ and $dn_B = -1$, which results in an *increase* in group project correlation of $2q\epsilon(n_A - n_B) > 0$, where the sign of the inequality results from the fact that $n_A > n_B$. Conversely, for group $M$, setting $dn_A = -1$ and $dn_B = +1$ we observe a *decrease* in group project correlation by $2q\epsilon(n_B - n_A) < 0$.[20]

[20] After several $A$-for-$B$ swaps, group $M$ may eventually have more $B$-types than $A$-types, i.e. $n_B^M > n_A^M$ (see Figure 2b) and project correlation increases. However, the correlation of $L$ still

Second, such a swap increases the average riskiness of types in group $L$ but never makes $L$ riskier than $M$ on average. It follows that sorting induces a positive correlation between the two dimensions. □

*Proof of Proposition 2.4.* A matching is stable if deviation is unattractive. Alternative matches are therefore bound to have a lower valuation than observed ones. Specifically, the valuation of an *unmatched* group $G$ must be smaller than the maximum valuation of the equilibrium matches $\mu(i)$ that its members $i$ belong to. If $G$'s valuation was larger, then its members would block their equilibrium matches to form the new coalition $G$. We thus have an *upper bound* $\overline{V_G}$ for the valuation of $G \notin \tilde{\mu}$.

$$G \notin \tilde{\mu} \quad \Leftrightarrow \quad V_G < \max_{i \in G} V_{\mu(i)} =: \overline{V_G} \tag{A18}$$

For the *if* direction ($\Rightarrow$) assume for contradiction that $G$ is a *blocking coalition* for $\mu$. Per the definition of blocking coalitions, this implies that all agents in this coalition prefer being matched to each other over being matched to their current partners in $\mu$, i.e., $G \succ_i \mu(i)\ \forall i \in G$. Given aligned preferences, the condition implies that $V_G > V_{\mu(i)}\ \forall i \in G$. Together this implies that $V_G > \max_{i \in G} V_{\mu(i)}$, which contradicts the assumption in the proposition.

For the *only if* direction ($\Leftarrow$) assume $\mu$ to be a stable matching with $G \notin \mu$. Since by stability $G$ is not a blocking coalition, it must hold that there is at least one individual $i$ that prefers its equilibrium group $\mu(i)$ over group $G$, i.e. $\exists\ i \in G : \mu(i) \succ_i G$. Given aligned preferences, this condition implies that $\exists\ i \in G : V_{\mu(i)} > V_G$. Together these conditions imply that $V_G < \max_{i \in G} V_{\mu(i)}$, which is the upper bound condition from the proposition.

Following the same logic as above, the valuation of a *matched* group $G$ must be larger than the maximum valuation of the feasible deviations of its group members. Feasible deviations of $G$'s group members are such that they are attractive to those borrowers outside of group $G$ that are necessary to form these new matches. That is, feasible deviations are such that their value is larger than the maximum valuation of the equilibrium groups that the non-group-$G$ members of that deviating group belong to.

$$G \in \tilde{\mu} \quad \Leftrightarrow \quad V_G > \max_{G'' \in S} V_{G''} =: \underline{V_G} \tag{A19}$$

Here, $S$ is the set of feasible deviations from $G$, defined as $S(G) := \{G' \in$

grows at a faster rate.

$\mathcal{G}|G' \cap G \notin \{\emptyset, G\}, V_{G'} > max_{i \in G' \setminus G} V_{\mu(i)}\}$. That is, a deviation from $G$ to $G'$ is feasible for all new non-$G$ borrowers in $G'$ if the valuation of $G'$ is larger than the maximum that new borrowers would receive in their equilibrium match, i.e. if $V_{G'} > max_{i \in G' \setminus G} V_{\mu(i)}$. The set of new borrowers are those borrowers in $G'$ that do not belong to the original equilibrium match $G$, i.e. those in $G' \setminus G$.

For the *only if* direction ($\Leftarrow$) assume $\mu$ to be a stable matching with $G \in \mu$. Since $\mu$ is stable, no member of $G$ can benefit from deviating. Given aligned preferences, for any member $i \in G$ this implies that $V_G > V_{G'}\ \forall G' \in S$, where $S$ is the set of feasible deviations for group members of $G$. Together this implies the inequality $V_G > \max_{G' \in S} V_{G'}$ in the proposition.

For the *if* direction ($\Rightarrow$) assume that the inequalities in the proposition hold. Let $G$ be a match in $\mu$. It follows from the inequalities in the proposition that no member of $G$ can be part of a blocking coalition. $\square$

# B Simulation of posterior distribution

The Bayesian estimator uses the data augmentation approach (proposed by Albert and Chib, 1993) that treats the latent outcome and valuation variables as nuissance parameters.

## Conditional posterior distribution of outcome variables

The outcome equation is defined (and observed) for realised matches, $G \in \mu$, only. For binary outcome variables, when the observed outcome $Y_G$ equals one, the conditional distribution of the latent outcome variable $Y_G^*$ is truncated from below at zero as $N\left(X_G\beta + (V_G - W_G\alpha)\delta, 1\right)$ with density

$$\begin{aligned}\mathbb{P}(Y_G^*|V, Y_{-G}^*, \theta, Y, \mu, W, X) &= C \cdot \mathbb{1}\left[Y_G^* \geq 0\right] \\ &\quad \cdot \exp\left\{-0.5\left(Y_G^* - X_G\beta - (V_G - W_G\alpha)\delta\right)^2\right\}.\end{aligned}$$

When $Y_G$ equals zero, the distribution is the same but now truncated from *above* at zero. In markets with one group only, the term $(V_G - W_G\alpha)\delta$ is dropped because $V_G$, $\alpha$ and $\delta$ need not be estimated in this case. When an offset is used in the estimation, the distributions are truncated at minus the group-specific offset value instead of zero.

## Conditional posterior distribution of valuation variables

For unobserved matches, $G \notin \mu$, the distribution of the latent valuation variable is $N\left(W_G\alpha, 1\right)$, truncated from above at $\overline{V_G}$ with density

$$\begin{aligned}\mathbb{P}(V_G|V_{-G}, Y^*, \theta, Y, \mu, X, W) &= C \cdot \mathbb{1}\left[V_G \leq \overline{V_G}\right] \\ &\quad \cdot \exp\left\{-0.5(V_G - W_G\alpha)^2\right\}.\end{aligned}$$

For observed matches, $G \in \mu$, the conditional distribution of the latent valuation variable is truncated from below at $\underline{V_G}$ as $N\left(W_G\alpha + (Y_G^* - X_G\beta)\delta/(\sigma_\xi^2 + \delta^2), \sigma_\xi^2/(\sigma_\xi^2 + \delta^2)\right)$ with density

$$\begin{aligned}\mathbb{P}(V_G|V_{-G}, Y^*, \theta, Y, \mu, X, W) &= C \cdot \mathbb{1}\left[V_G \geq \underline{V_G}\right] \cdot \exp\Bigg\{-0.5\Bigg(V_G \\ &\quad -W_G\alpha - \frac{(Y_G^* - X_G\beta)\delta}{\sigma_\xi^2 + \delta^2}\Bigg)^2 \cdot \frac{\sigma_\xi^2 + \delta^2}{\sigma_\xi^2}\Bigg\}.\end{aligned}$$

The variance of $\sigma_\xi^2/(\sigma_\xi^2+\delta^2)$ for the valuation variables is chosen such that the variance of the error term in the selection equation, $\sigma_\eta^2$, equals one.[21]

## Conditional posterior distribution of parameters

### Alpha

The coefficient vector $\alpha$ in the selection equation is only estimated for the subset of markets with two borrower groups. This subset is denoted by $T_2$ and, together with the set of one-group markets $T_1$, makes the total set of markets $T$. The conditional posterior of $\alpha$ is $N\left(\hat{\alpha},\hat{\Sigma}_\alpha\right)$, where

$$\hat{\Sigma}_\alpha = \left[\Sigma_\alpha^{-1}+\sum_{t\in T_2}\left[\sum_{G\in M_t}W_G'W_G+\sum_{G\in\mu_t}\frac{\delta^2}{\sigma_\xi^2}W_G'W_G\right]\right]^{-1} \tag{A20}$$

and

$$\hat{\alpha} = -\hat{\Sigma}_\alpha\left[-\Sigma_\alpha^{-1}\bar{\alpha}+\sum_{t\in T_2}\left[\sum_{G\in M_t}-W_G'V_G \right.\right.$$
$$\left.\left.+\sum_{G\in\mu_t}\frac{\delta}{\sigma_\xi^2}W_G'\left(Y_G^*-X_G\beta-V_G\delta\right)\right]\right]. \tag{A21}$$

The variables $\Sigma_\alpha^{-1}$ and $\Sigma_\alpha^{-1}\bar{\alpha}$ are constants given the priors. In the estimation, I chose the priors $\bar{\alpha}=0_{|\alpha|,1}$ and $\Sigma_\alpha=10\cdot I_{|\alpha|}$, where $0_{n_1,n_2}$ is the zero matrix of dimension $n_1\times n_2$ and $I_n$ is the identity matrix of dimension $n$. The values of the two constants are therefore $\Sigma_\alpha^{-1}=(10\cdot I_{|\alpha|})^{-1}$ and $\Sigma_\alpha^{-1}\bar{\alpha}=0_{|\alpha|,|\alpha|}$ respectively.

### Beta

Similarly, the conditional posterior distribution of $\beta$ is $N\left(\hat{\beta},\hat{\Sigma}_\beta\right)$, where

$$\hat{\Sigma}_\beta = \left[\Sigma_\beta^{-1}+\sum_{t\in T_1}\sum_{G\in\mu_t}\frac{1}{\sigma_\xi^2}X_G'X_G+\sum_{t\in T_2}\sum_{G\in\mu_t}\frac{1}{\sigma_\xi^2}X_G'X_G\right]^{-1} \tag{A22}$$

[21] $\sigma_\eta^2=var(\frac{\varepsilon\delta}{\sigma_\xi^2+\delta^2}+x)=\frac{(\sigma_\xi^2+\delta^2)\delta^2}{(\sigma_\xi^2+\delta^2)^2}+\sigma_x^2=\frac{\delta^2}{(\sigma_\xi^2+\delta^2)}+\sigma_x^2$. So $\sigma_\eta^2=1$ iff $\sigma_x^2=\sigma_\xi^2/(\sigma_\xi^2+\delta^2)$.

and

$$\hat{\beta} = -\hat{\Sigma}_\beta \left[ -\Sigma_\beta^{-1}\bar{\beta} - \sum_{t\in T_1}\sum_{G\in\mu_t} \frac{1}{\sigma_\xi^2} X_G' Y_G^* \right.$$
$$\left. - \sum_{t\in T_2}\sum_{G\in\mu_t} \frac{1}{\sigma_\xi^2} X_G' (Y_G^* - \delta(V_G - W_G\alpha)) \right]. \tag{A23}$$

Here, the values of the two constants are $\Sigma_\beta^{-1} = (10 \cdot I_{|\beta|})^{-1}$ and $\Sigma_\beta^{-1}\bar{\beta} = 0_{|\beta|,|\beta|}$ respectively.

**Delta**

Finally, for $\delta$ the posterior is $N(\hat{\delta}, \hat{\sigma}_\delta^2)$, with

$$\hat{\sigma}_\delta^2 = \left[ \frac{1}{\sigma_\delta^2} + \sum_{t\in T_2}\sum_{G\in\mu_t} \frac{1}{\sigma_\xi^2} (V_G - W_G\alpha)^2 \right]^{-1} \tag{A24}$$

and

$$\hat{\delta} = -\hat{\sigma}_\delta^2 \left[ -\frac{\bar{\delta}}{\sigma_\delta^2} - \sum_{t\in T_2}\sum_{G\in\mu_t} \frac{1}{\sigma_\xi^2} (Y_G^* - X_G\beta)(V_G - W_G\alpha) \right]. \tag{A25}$$

Analogously, the values of the two constants are $\frac{1}{\sigma_\delta^2} = \frac{1}{10}$ and $\frac{\bar{\delta}}{\sigma_\delta^2} = 0$.

# C Protocol for agent-based simulations

The agent-based simulation follows the protocol below.

1. Obtain the equilibrium groups in the 29 two-group markets for different matching regimes: (i) matching on risk type only and (ii) matching on both risk and exposure type. Equilibrium groups are determined using the group valuation in Eqn 13 (with $\eta_G$ set to zero) and equilibrium conditions derived in Proposition 2.4.

2. Calculate borrower $i$'s expected pay-off $\tilde{u}_{i,G}$ from taking a loan with equilibrium group $G$ based on the empirical specification of Eqn 7 as follows

$$\tilde{u}_{i,G} \quad = \quad E_i + \bar{l}_t \left[ -rp_i - \hat{q}p_i \sum_{j \in G \setminus i} (1 - p_j) + \hat{q\epsilon} \sum_{s \in \{A,B\}} 1[i \in s] \cdot (n_s^G - 1) \right], \tag{A26}$$

   where $\bar{l}_t$ is the median loan size in market $t$ and $\hat{q}$ and $\hat{q\epsilon}$ are the parameter estimates from Eqn 13.

3. Evaluate each borrower's participation condition $\tilde{u}_{i,G} > \bar{u}_t$, where $\bar{u}_t$ is the value of a borrower's outside option, measured as the median wage rate for agricultural labour in that market.

4. Exclude a group from the sample if the participation condition is satisfied for fewer members than the minimum group size in the market.

5. For the remaining groups, predict the expected repayment using Eqn 14 and the parameter estimates from the structural empirical model.

# D Robustness of the results

This appendix examines whether the primary result – the decomposition into a negative direct effect and a positive sorting bias – is robust to various empirical issues.

I first examine a potential reverse causation problem, in that all group members may report their worst year as that in which their group faced repayment problems. This would provide an alternative explanation as to why groups with correlated returns have worse repayment outcomes. To rule out this explanation, first note that when borrowers were asked why they perceived one year as worse than another, only five out of a total of 390 borrowers gave the reason 'unable to repay debt' in their response. In addition, repayment was surveyed retrospectively over the full lifetime of groups. The average group age was 11 years, but project correlation is calculated based on just two years.

A second concern is survivorship bias. Groups with safer types are more likely to survive, particularly when returns are highly correlated. This 'survival of the safest' would result in groups with more correlated returns being safer and provide an alternative to my endogenous matching explanation. To disprove this explanation, it is enough to show that older groups are not safer on average. In fact, the correlation between risk type and group age is negative, at -0.055, p-value 0.653, meaning that survivorship bias is not an issue.

Third, the equilibrium conditions are derived based on the assumption that the matching data represent the complete market. In the paper, the model is estimated using a random sample of five borrowers from groups with 11 borrowers on average. This is a shortcoming in the empirical analysis. However, Klein (2015) presents Monte Carlo evidence of the robustness of the estimator in small samples, which confirms that the resulting attenuation bias even underrates the sorting bias that this paper corrects for.

Finally, the surveys of the Townsend Thai project sample up to two groups per village. This number concurs with the average number of groups per village. In the 1997 household survey, 22% households indicate having obtained a BAAC group-guaranteed loan in the past year. With an average of 121 households per village and an average group size of 11.5 borrowers, there are an average of $121 \cdot 0.22/11.5 = 2.3$ groups per village.

# E Replication guide[22]

The results reported herein are fully replicable using the `knitr` literate programming engine in the `R` open-source software environment for statistical computing. `R` packages used are: `foreign`, `knitr`, `matchingMarkets`, `reshape`, `survival`, `tseries`.

## E.1 Data sources and preparation

All files for replication are in the `inputs/` folder. Documentation and original data used in the paper are in `inputs/rawdata/` and can be directly downloaded in zip format from the Harvard Dataverse:

- 1997 BAAC survey (study_10676) at http://hdl.handle.net/1902.1/10676
- 1997 Household survey (study_10672) at http://hdl.handle.net/1902.1/10672
- 2000 BAAC survey (study_12057) at http://hdl.handle.net/1902.1/12057
- 2000 Household survey (study_10935) at http://hdl.handle.net/1902.1/10935

These files are preprocessed using the script in `code/1-0-data-preparation.R` and the cleaned and transformed data is written to the `inputs/data/` folder for analysis.

### E.1.1 Group-level variables

I start the preprocessing with the 1997 group-level data in Ahlin and Townsend (2007). This data is not used in the analysis because it lacks individual-level information. It serves two purposes: First, it allows me to verify the correct implementation of the variable transformations in Ahlin and Townsend (2007) which are subsequently applied to the 2000 group-level data in this paper. Second, information on the borrower group age in the 1997 data is used to impute this missing variable in the 2000 data.

### E.1.2 Regression imputation of group age

The imputation proceeds in three steps. In the first step, a regression model that explains group age is estimated. This model combines data from the BAAC 1997 and 2000 surveys in an interval regression. While the group age is not observed in

[22] This section of the Appendix is not intended for publication.

the BAAC 2000 data, the quasi-panel still allows me to find bounds for a group's age (see Table A1 for a summary). Note first that groups from villages that only had a single group in the BAAC 1997 can be no older than this group's age in the BAAC 1997 survey plus three. Furthermore, for all other villages we know that the log-age of groups in the BAAC 2000 survey can be no larger than 34 ($= 2000 - 1966$) because the BAAC started its group lending operations in 1966. Finally the BAAC 2000 contains a group history of events such as the admission of new members or the assistance members provided to their peers. The first event documented in this history sets a lower bound on a group's age, which is otherwise bounded from below at 1.

Table A1: Definition of bounds for interval regression of the missing group_age variable

| Groups from | lower bound | upper bound |
|---|---|---|
| *BAAC 1997 survey* | $\text{group\_age}_{97}$ | $\text{group\_age}_{97}$ |
| *BAAC 2000 survey* | | |
| - in villages with single group in '97 | $\max\{\text{group\_hist}_{00}, 1\}$ | $\text{max\_age}_{97}$+3 |
| - in all other villages | $\max\{\text{group\_hist}_{00}, 1\}$ | 2000-1966 |

The results of the interval regression are presented in Table A2 below. The independent variables are explained in Table 2. PCG_membership is a village-level variable that gives the percentage of the village population that is a member of a production credit group. Intuitively, we would expect to find less mature groups in a village were PCG membership is prevalent because this may indicate that BAAC operations in that village started more recently. The expected effect of other variables follows similar reasoning. For example, both group size and loan size are expected to be associated with higher group age simply because groups tend to attract new members as they mature and the loan size typically increases for more mature borrowers.

In the second step, the model above is used to predict the group age for groups in the BAAC 2000 data. In the final step, the uncertainty is reintroduced into the imputations by adding the prediction error into the regression. This is done by adding the working residuals of the interval regression model to the predicted values. The result is plotted in Figures A1a and A1b below where the predicted values are on the straight line; dots represent the original BAAC 1997 data and circles depict the imputed data.

The validity of the imputations is tested by comparing the imputed group_age to the upper and lower bounds in Table A1. The fact that the predictions remain well within the bounds for *all* 68 groups in the BAAC 2000 data gives us some confidence in the model.

### E.1.3 Borrower-level variables

Borrower-level variables are constructed based on the 2000 BAAC survey and the combined borrower and group level data is in `data/borrower-level.RData`.

### E.1.4 Matching data

The core part of the data preparation is the generation of group characteristics based on borrower-level variables for both factual and counterfactual groups. This is implemented and documented in function `stabit` in `R` package `matchingMarkets` (Klein, 2018). The resulting group-level data is in `data/group-level.RData`.

## E.2 Descriptive statistics, models and simulations

The `R` code in `inputs/code/` for descriptive statistics, econometrics and simulation results is commented and can be run independently to obtain all results in figures, tables and text in the paper. The code is annotated with tags of the form `## ---- label:`, which allow the identification of the section in `sections/` that a code chunk is called from in the LaTeX document. To see how results from the `R` code are embedded in the paper, see the `.Rnw` files whose file names correspond directly to the tag of the code chunk in the `R` script.

The estimator developed in this paper is implemented in the `R` package and the source code available on the Comprehensive R Archive Network. To test the functionality of the software implementation in this package, Klein (2015) provides simulation evidence of the correct implementation of both design matrix generation and estimators.

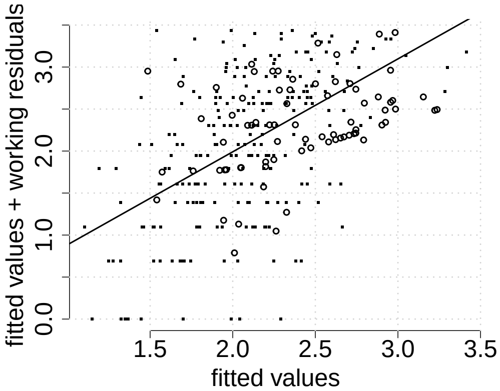
Table A2: Interval regression imputation of the missing group_age variable

*S.E. in parentheses; significance at 0.1, 1, 5, 10% denoted by ***, **, *, and . respectively.*

| ***Interval regression*** | | |
|---|---|---|
| *Dependent variable as defined in Table A1.* | | |
| Intercept | 1.451 (0.497) | ** |
| ln(group_size) | 0.871 (0.118) | *** |
| loan_size | 0.005 (0.006) | . |
| loan_size_sqrd | -0.000 (0.000) | . |
| average_land | 0.007 (0.002) | ** |
| average_education | -0.548 (0.135) | *** |
| PCG_membership | -0.631 (0.276) | * |
| BAAC 2000 (ref: 1997) | 0.371 (0.125) | ** |
| ln(scale) | -0.332 (0.043) | *** |
| Observations | 306 | |
| $R^2$ | 0.245 | |
| LR-test, $Pr(> \chi^2_7)$ | 1e–14 | |

Figure A1: Comparison of distributions of original group_age variable in BAAC 1997 (dots) and random regression imputation of missing BAAC 2000 group_age variable (circles)

(a) Actual observations (dots) and regression imputations (circles) plotted against fitted values




(b) Actual residuals (dots) and imputed residuals (circles) plotted against fitted values