

# How does Micro-credit Work? Risk-Matching, Diversification, and Borrower Selection

## Preliminary Draft

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### Abstract

The micro-credit movement has used innovative lending techniques to push financial frontiers. Many micro-lenders operate in an environment with no collateral and limited information about borrowers. If borrowers vary in unobservable risk, individual lending contracts may involve safe borrowers cross-subsidizing risky ones, and thus may drive safe borrowers from the market. Ghatak (1999, 2000) shows that group-based, joint liability contracts embed an effective discount for safe borrowers, given that borrowers match homogeneously by risk-type. This discount can attract safe borrowers and revive a relatively dormant lending market. We extend borrower heterogeneity to a second dimension, correlated risk. We show that borrowers will anti-diversify risk within groups, in order to lower chances of facing liability for group members. We directly test homogeneous sorting by risk and intra-group diversification of risk using data on Thai micro-credit borrowing groups. Univariate tests involve calculating the between-group contributions of borrower differences in a village as well as rank correlations between borrower characteristics and group identity. Non-parametric tests show evidence of both homogeneous sorting by risk and risk anti-diversification within groups. Multivariate analysis based on Fox's (2006) maximum score estimator gives some support to the univariate results by suggesting that homogeneous matching along both dimensions is profitable. We also quantify the degree to which theoretically predicted matching discounts are being realized in practice, and give some indication of the barriers to their realization.

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# 1 Introduction

The “micro-credit” movement is viewed as one of the most promising recent advances in economic development. Its goal being to extend financial markets to the world’s poor, it has received considerable focus from international institutions. The UN, for example, declared 2005 the “International Year of Microcredit”. Economists have also praised it, for example as “one of the most significant innovations in development policy of the past twenty-five years.”<sup>1</sup> The idea and implementation of micro-credit won the 2006 Nobel Peace Prize for Bangladesh’s Muhammad Yunus and the Grameen Bank – a Prize not generally given for work in economic development. The sheer scope of the movement testifies to the amount of confidence placed in micro-credit. It is reported that more than 100 million customers worldwide are borrowing small loans from around 10,000 microfinance institutions.<sup>2</sup>

Despite its advances, many questions about micro-credit remain unanswered. An obvious and important one – does it work? – still seems to elude a definitive answer.<sup>3</sup> Another important question – *how* does it work? – has seen some progress and is the focus of this paper. One might argue that this second question is as important as the first. After all, widespread micro-credit is the current reality, and its momentum is unlikely to be reversed in the near future. Further, there is substantial *prima facie* evidence for its success. The large number of micro-credit institutions lending to poor borrowers but achieving robust repayment rates, financial sustainability, and repeat relationships is historically unprecedented.

How have micro-lenders managed to operate healthy banks among the world’s poor? The small size of the loans and the fact that they are often not backed by collateral have given rise to experimental lending techniques. One such technique is group lending, also called joint liability lending (pioneered by the Grameen Bank among others). Borrowers are required to form groups, and to bear some liability for the loans of fellow group members. As several economists have shown theoretically, joint liability lending can partially or completely overcome the informational and enforcement limitations that make uncollateralized lending hard – in the context of moral hazard (e.g., Stiglitz, 1990, Banerjee et al., 1994), adverse selection (e.g., Ghatak, 1999, 2000), and strategic default (e.g., Besley and Coate, 1995).

Our goal is to understand how well the theory explains the practice of group lending. Specifically, we focus on a well-known adverse selection context<sup>4</sup> in which there is no collateral and borrowers’ distributions of returns have identical means but vary in riskiness. In this environment, a lender that cannot observe risk will offer all borrowers the same terms, but effectively will charge less to risky borrowers, who fail more often, than to safe borrowers. Thus there is cross-subsidization from safe to risky borrowers, and this may cause safe borrowers to exit the market (Stiglitz and Weiss, 1981).

Add to this context a communal tightness, that is, that borrowers know each other well,

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<sup>1</sup>Timothy Besley, quoted in Armendariz de Aghion and Morduch (2005). This book, Ghatak and Guinane (1999), and Morduch (1999) provide broad introductions to the topic.

<sup>2</sup>See Bellman (2006).

<sup>3</sup>Of course, there is probably no single answer. See Armendariz de Aghion and Morduch (2005) for a discussion of impact studies. The non-random placement and take-up of micro-credit opportunities is one obstacle to identifying impacts. Ahlin and Jiang (2005) explore the impact issue theoretically.

<sup>4</sup>This focus is justified by the direct and indirect evidence for adverse selection in these lending contexts found in Ahlin and Townsend (2004, 2006).

including each other's riskiness. Ghatak (1999, 2000) shows that group lending contracts can be used in this context to overcome the bank's lack of information, partially or fully. Here a group lending contract means that the lender requires borrowers to sort into pairs and makes each borrower liable for his partner's loan. The foundational result is that groups match homogeneously in risk. Every borrower prefers a safer partner, to reduce expected liability; but safe borrowers prefer them more, since they succeed more often and liability is only operative when one succeeds.

Given homogeneous risk-matching, group lending mitigates the adverse selection problem. The lender now can screen borrowers, since safe borrowers have safe partners and so are more willing to accept joint liability (Ghatak, 2000).<sup>5</sup> The lender can also pool borrowers, simply offering all groups the same standard contract with joint liability (Ghatak, 1999). Even though contract terms are uniform, there is effectively a built-in discount for safe borrowers: their partners are safer and thus the joint liability clause is less costly for them in expectation. This discount can draw into the market some or all safe borrowers who would have been excluded under individual loans.

The pooling result is appealing in practical terms. It implies that even a very passive or unsophisticated lender that offers a single, standard joint liability contract is giving implicit discounts to safe borrowers, relative to the case of using individual liability contracts. This may help explain the popularity of group lending in micro-credit – lenders that use it may be invigorating an otherwise anemic market (even unwittingly).

However, the lynchpin in this analysis is the homogeneous risk-matching of the borrowing groups. Without it, there is no discount for safe borrowers operating through joint liability. A main contribution of this paper is to test directly for homogeneous risk-matching among borrowing groups in Thailand<sup>6</sup> and to quantify the size of the discounts relative to theoretically predicted ones. We are unaware of other direct tests of this result.

A second main point of this paper points to a potentially more ambiguous side of voluntary group formation. In particular, we add the potential for *correlated* risk to the model and examine whether borrowers will form groups so as to diversify or anti-diversify. The main theoretical result is that groups sort homogeneously in both dimensions: they match with similar risk-types, and among those, with partners exposed to the same risk. The rationale for anti-diversification is straightforward. A borrower wants to maximize correlation with his partner because this raises the odds that when his partner fails, he also fails and will not be held liable. Groups anti-diversify in order to lower liability for their partners.

Correlated risk restricts the lender's ability to use joint liability. Consider the extreme case where returns are perfectly correlated within a group. Joint liability is then never executed and group lending reduces to individual lending. A full analysis of contracting in this environment of correlated risk is beyond the scope of this paper, but the analysis here suggests that this aspect of voluntary group formation can work against efficiency.

We test empirically whether groups are diversified or not, in terms of risk. The data for these and the risk-matching tests come from the Townsend Thai dataset, which includes information on borrowing groups from the Bank for Agriculture and Agricultural Cooperatives

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<sup>5</sup>Gangopadhyay et al. (2005) refine the earlier results of Ghatak (2000).

<sup>6</sup>This is the first question on the microfinance empirical research agenda Morduch (1999, p. 1586) lays out: "Is there evidence of assortative matching through group lending as postulated by Ghatak (1999)?"

(BAAC). The BAAC is the predominant rural lender in Thailand and offers group lending contracts to borrowers with little or no collateral. Borrowers form groups autonomously, though the BAAC may veto one or more proposed members.

One feature of the data is that where possible, and indeed often, two groups from the same village are surveyed. Considering the village as the relevant universe for group formation, we can assess whether groups appear homogeneous by comparing across two groups in the same village. Specifically, for each village and ordered variable, we calculate rank correlations and inequality (e.g. variance) decompositions into between- and within-group components. For each village and non-ordered variable, we calculate fractionalization<sup>7</sup> decompositions into between- and within-group components. We put these calculations in perspective by repeating them for all possible combinations of the village borrowers into groups of the size observed. The results from the actually observed groups are then mapped into a *sorting percentile* reflecting how homogeneous or heterogeneous group formation is relative to all possibilities (holding group size and borrowing pool fixed).

For any given variable, villages can be found at both ends of the spectrum – homogeneous sorting (high sorting percentile) and heterogeneous sorting (low sorting percentile). Sorting percentile means and medians (across villages) suggest predominant tendencies. Using the fact that if matching is completely random over a certain variable, then village sorting percentiles are drawn from a uniform distribution, we test for matching patterns using Kolmogorov-Smirnov (KS) tests of the sample cdf of village percentiles against the uniform distribution.

We find direct evidence for homogeneous matching by risk, statistically significant but quantitatively moderate. The KS tests reject heterogeneous sorting at the 5% level. Median sorting percentiles range from 59% to 62%,<sup>8</sup> suggesting that risk homogeneity is an important, but not overwhelming, consideration in group formation. It therefore appears that group lending gives a moderate effective discount to safe borrowers.

We also find evidence for anti-diversification within groups. This is seen in three ways: occupational homogeneity within groups, greater coincidence of bad years for income within groups than across groups, and clustering of similar income shocks within groups. Of these, the occupation homogeneity is most striking. The median village has a sorting percentile of 84-91%. For coincidence of worst years for income, the median sorting percentiles are 64-66%; for clustering of income shocks, 66%. Statistical significance in the KS tests holds for each measure but worst-year coincidence. The evidence suggests that groups are responding to incentives to avoid diversifying intra-group risk.

Multivariate analysis would alleviate concerns that sorting appears homogeneous along one dimension merely due to correlation with another more important dimension. Hence we turn to Fox's (2006) maximum score estimator, which allows direct estimation of certain pay-off function parameters up to scale. This estimator chooses parameter values that maximize the frequency with which observed groupings yield higher payoffs than feasible, unobserved groupings – all groupings that result from swapping  $k$  borrowers across two groups in the same village, in our implementation.

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<sup>7</sup>Fractionalization is a measure of dissimilarity with respect to a non-ordered variable; see section 4.

<sup>8</sup>That is, the median village has groups that are more homogeneously sorted than about 60% of all possible combinations.

Results are supportive of homogeneous matching along both risk-type and correlated risk dimensions. The coefficient on risk-type interaction is positive and statistically significant at 1% (using subsampling for hypothesis tests), showing that the payoff to homogeneous matching by risk-type is positive. The coefficient for within-group similarity in timing of bad income shocks is positive and significant at 15%, adding a bit of evidence that anti-diversification raises payoffs. Both results support the theory.

Using the structural estimates, we can directly calculate the “discounts” that borrowers obtain due to purposeful matching along both dimensions. These discounts can be compared against quantities theory would predict with and without an infinite population. We estimate that at least 8% of the pure homogeneous risk-matching matching discount (applicable in an infinite population) and 16% of the rank-ordered risk-matching discount (applicable in a finite population) are being realized in practice. These point estimates suggest that the finiteness of the borrowing pool lowers the realizable discount by half. The analogous results for the anti-diversification discount at 0% and 10%, respectively.

The paper is organized as follows. The model setup and results on homogeneous sorting are in section 2. Data are described and key variables defined in section 3. Section 4 presents the methodology behind the nonparametric univariate tests, as well as the results. Section 5 presents the multivariate estimation. Section 6 quantifies the discounts borrowers obtain due to sorting and compares them to theoretically predicted amounts. Section 7 concludes.

## 2 Theory: Group Formation with Correlated Risk

### 2.1 Model Setup

There is a measure one continuum of risk-neutral potential borrowers, each endowed with a project requiring one unit of capital. Every project has expected value  $E$ . However, agents and their projects differ in risk. Agent  $i$ 's project yields gross returns of  $Y_i$  (i.e. “succeeds”) with probability  $p_i$  and yields zero gross returns (i.e. “fails”) with probability  $1 - p_i$ . The higher  $p_i$ , the lower agent  $i$ 's risk, in the sense of second-order stochastic dominance. Population risk-types are distributed over  $(\underline{p}, \bar{p})$  according to density function  $g(p)$  and cdf  $G(p)$ , where  $0 < \underline{p} < \bar{p} < 1$ .

A lender requires potential borrowers to form groups of size two, each member of which is jointly liable for the other. Specifically, contracts are assumed to take the following form (as in Ghatak, 1999, 2000). A borrower who fails pays the lender nothing, since loans are uncollateralized. A borrower who succeeds pays the lender gross interest rate  $r$ . A borrower who succeeds and whose partner fails pays an additional joint liability payment  $q$ . Thus, a borrower of type  $p_i$  who matches with a borrower of type  $p_j$  has expected payoff

$$\Pi_{ij} = E - p_i r - p_i(1 - p_j)q, \quad (1)$$

assuming the borrowers' returns are uncorrelated. Note that

$$\frac{\partial^2 \Pi_{ij}}{\partial p_i \partial p_j} = q > 0. \quad (2)$$

That is, risk-types are complements in the joint payoff function and homogeneous matching by risk is the equilibrium outcome, as Ghatak has shown.

To this environment we add the potential for correlated returns. Given a group  $(i, j)$  with unconditional probabilities of success  $(p_i, p_j)$ , there is a unique, one-parameter class of joint output distributions (see Ahlin and Townsend, 2004 and 2006):

	$j$ Succeeds ( $p_j$ )	$j$ Fails ( $1 - p_j$ )
$i$ Succeeds ( $p_i$ )	$p_i p_j + \epsilon_{ij}$	$p_i(1 - p_j) - \epsilon_{ij}$
$i$ Fails ( $1 - p_i$ )	$(1 - p_i)p_j - \epsilon_{ij}$	$(1 - p_i)(1 - p_j) + \epsilon_{ij}$

The case of  $\epsilon_{ij} \equiv 0$  is the case of independent returns considered by Ghatak. A positive (negative)  $\epsilon_{ij}$  induces positive (negative) correlation between borrower returns. Borrower  $i$ 's payoff to borrowing with borrower  $j$  under this generalized joint distribution is

$$\Pi_{ij} = E - p_i r - [p_i(1 - p_j) - \epsilon_{ij}]q = E - p_i r - p_i(1 - p_j)q + \epsilon_{ij} q. \quad (3)$$

This is similar to payoff 1. The one addition is that higher correlation (higher  $\epsilon_{ij}$ ) raises payoffs by directly lowering the probability of asymmetric outcomes and, thus, of paying  $q$ .

Correlation parameter  $\epsilon_{ij}$  may differ arbitrarily across  $(i, j)$  groupings. We proceed by placing a simple structure on the population's correlatedness. The structure is grounded in two aggregate shocks,  $A$  and  $B$ .  $A$  and  $B$  are assumed to be distributed identically and independently; they equal  $+1$  or  $-1$ , each with probability one half.

Each agent is assumed to be exposed to risk from either shock  $A$  or shock  $B$ , or neither. The probability of success of an "A-risk" agent depends on the realization of  $A$  in the following way:  $p_i|A = p_i + \gamma A$ , for some  $\gamma > 0$ . That is, if there is a good shock ( $A = 1$ ), an A-risk agent's success probability gets a boost, equal to  $\gamma$ ; and vice versa if there is a bad shock ( $A = -1$ ). Note that exposure to shock  $A$  does not change an agent's unconditional probability of success, since this probability has an equal chance of being raised or lowered by  $\gamma$ :

$$(p_i|A = 1) * Prob(A = 1) + (p_i|A = -1) * Prob(A = -1) = (p_i + \gamma)/2 + (p_i - \gamma)/2 = p_i.$$

"B-risk" agents' success depends on the realization of shock  $B$  in the exactly analogous way:  $p_i|B = p_i + \gamma B$ . Fractions  $\alpha$  and  $\beta$  of the population are exposed to shocks  $A$  and  $B$ , respectively, with  $\alpha, \beta > 0$  and  $\alpha + \beta \leq 1$ . The remaining  $1 - \alpha - \beta$  agents are exposed to neither aggregate shock: that is, their probabilities of success are unaffected by the outcomes of  $A$  and  $B$ . Aggregate shock affiliation is assumed uncorrelated with unconditional probabilities of success, the  $p_i$ 's.

Potential groups fit into one of two categories. The first category of groups contains borrowers both exposed to the same shock, i.e. both A-risk or both B-risk. One can show that for groups in this category,<sup>9</sup>

$$\epsilon_{ij} = \epsilon \equiv \gamma^2. \quad (4)$$

That is, borrower returns are positively correlated in these groups. Two borrowers exposed to a common shock are more likely to succeed and fail together because their probabilities of success are pushed in the same direction by the shock. The second category includes

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<sup>9</sup>To see this, assume that borrowers  $(i, j)$  are both A-risk. With probability  $1/2$ , the shock is good and the probability of both succeeding is  $(p_i + \gamma)(p_j + \gamma)$ ; similarly, with probability  $1/2$  the probability of both succeeding is  $(p_i - \gamma)(p_j - \gamma)$ . The unconditional probability of both succeeding is thus  $p_i p_j + \gamma^2$ .

all other combinations. It is clear that for groups in the second category,  $\epsilon_{ij} = 0$ . This is because the shocks each borrower is exposed to – idiosyncratic and perhaps also aggregate – are independent. Returns are thus uncorrelated.

In summary, the correlation structure boils down to  $\epsilon_{ij} = 0$  for pairs not exposed to the same shock and  $\epsilon_{ij} = \epsilon$  for pairs exposed to the same shock. Let  $\kappa_{ij}$  equal one if borrowers  $i$  and  $j$  are similarly exposed, and zero otherwise. The payoff of borrower  $i$  matching with borrower  $j$  can thus be written, modifying equation 3,

$$\Pi_{ij} = E - rp_i - qp_i(1 - p_j) + q\epsilon\kappa_{ij}. \quad (5)$$

The payoff can also be written exactly analogously to the no-correlation payoff 3:  $E - rp_i - q'_{ij}p_i(1 - p_j)$ , where the *effective* joint liability rate  $q'_{ij}$  is

$$q'_{ij} = q \left( 1 - \frac{\epsilon\kappa_{ij}}{p_i(1 - p_j)} \right). \quad (6)$$

That is, higher correlation between borrowers  $i, j$  lowers the effective rate of joint liability that borrower  $i$  faces. It does this by making partner bailouts less likely.

## 2.2 Equilibrium Matching

Our interest is in whether groups form homogeneously in unconditional risk, as in Ghatak (1999, 2000), *and* whether they diversify or amplify risk within the group. For example, do  $A$ -risks match with  $B$ -risks or with fellow  $A$ -risks? This question need not directly bear on risk-sharing: households may share risk with other households regardless of whether they are in the same joint liability borrowing group. The issue instead is how groups form in response to joint liability contracts, which directly bears on the efficiency gains of group lending.

We follow Ghatak in assuming that agents fully observe each other's unconditional risk and risk exposure, and that there are no search frictions. Lack of frictions and full observability among agents is an appropriate benchmark for matching within relatively tight-knit villages.

Consider a set of equilibrium groups. There are six sets into which all groups can be partitioned: AA, BB, NN, AB, AN, BN, where the set names denote the risks faced by the two borrowers, with “N” for neither. For example, set AA contains all groups with two  $A$ -risks and set BN contains all groups with one  $B$ -risk and one borrower exposed to neither shock.

Examination of payoff equation 5 makes clear that risk-types continue to be complements in this environment; the cross-partial is still given by expression 2. This implies that in any positive-measure set of groups within which  $\kappa_{ij}$  is fixed – in particular, AA, BB, and NN – almost every group is homogeneous in risk-type. Within these sets, matching is essentially one-dimensional so standard results apply.

In the sets where  $\kappa_{ij}$  is not fixed – AB, AN, BN – switching partners based on risk-type may also affect correlation. Still, it can be shown that none of these sets have positive measure in equilibrium. Consider AB, for example. Risk-type complementarity implies rank-ordering within risk exposure type. That is, if  $(i, j)$  and  $(i', j')$  are groups and borrowers  $i, i'$  ( $j, j'$ ) are  $A$ -risk ( $B$ -risk), then  $p_i \geq p_{i'} \rightarrow p_j \geq p_{j'}$ ; otherwise, the grouping  $(i, j')$  and  $(i', j)$

would raise surplus. Given this fact and if set AB has positive measure, then for any  $\delta > 0$ , there must exist two groups  $(i, j)$  and  $(i', j')$  with  $|p_i - p_{i'}| < \delta$  and  $|p_j - p_{j'}| < \delta$ . Then the grouping  $(i, i')$  and  $(j, j')$  would strictly raise surplus if  $\delta$  is small enough. First, the maximum loss in surplus due to risk-type complementarities (from the case where  $p_i = p_j$ ) would be  $\delta^2$ . Second, surplus would rise due to the increase in within-group correlatedness, which would add  $q\epsilon$  to each borrowers' payoff. So for any  $\epsilon > 0$ , a small enough  $\delta$  can be chosen such that this switch raises surplus:  $4q\epsilon > \delta^2$ . Thus AB cannot have positive measure in equilibrium. Similarly, AN and BN cannot. The only difference in the argument is that the borrower swap outlined above would add  $q\epsilon$  to the payoffs of two out of four borrowers – this still raises total surplus.

Thus, in equilibrium all groups are homogeneous in risk-type and risk-exposure; they contain either both  $A$ -risk, both  $B$ -risk, or both unexposed borrowers. The intuition for the latter result is simple: borrowers anti-diversify within groups to lower their chances of facing liability for their partners.

Recall that higher within-group correlation lowers the effective joint liability rate (see equation 6). While a complete analysis of contracting in this environment is beyond the scope of this paper, it appears that borrower sorting along the correlated risk dimension limits the lender's ability to use joint liability effectively. At the least, it represents a lump-sum transfer to certain borrowers (see equation 5); with bank profits fixed, this must be compensated for by higher and potentially more distortionary  $r$  and/or  $q$ .

## 2.3 Extension to n-person Groups

In reality, two-person joint liability groups are rare. Here we extend the notation to  $n$ -person groups. Following Ghatak (1999), we assume that a borrower owes  $\tilde{q}$  for each fellow group member that fails. Letting  $M$  denote the set of borrowers in the group to which borrower  $i$  belongs, borrower  $i$ 's payoff (in the absence of correlated risk) can be written

$$\Pi_{iM} = E - rp_i - \tilde{q}p_i \sum_{j \in M \setminus i} (1 - p_j).$$

Defining  $q \equiv \tilde{q}(n - 1)$  and  $\bar{p}_{M \setminus i}$  as the average  $p_j$  in  $M \setminus i$ , the payoff can be written

$$\Pi_{iM} = E - rp_i - qp_i(1 - \bar{p}_{M \setminus i}), \quad (7)$$

directly analogous to payoff 3.

With the correlation structure outlined in section 2.1, payoffs can be written

$$\Pi_{iM} = E - rp_i - qp_i(1 - \bar{p}_{M \setminus i}) + q\epsilon \bar{\kappa}_{i, M \setminus i}, \quad (8)$$

where  $\bar{\kappa}_{i, M \setminus i}$  is the average  $\kappa_{ij}$  in  $M \setminus i$ , i.e., the percent of group  $M$  exposed to the same risk as borrower  $i$ . This is directly analogous to equation 5. Finally, the joint surplus of group  $M$ , i.e. the sum of payoffs of group- $M$  borrowers, can be written

$$JS_M = nE - \sum_{i \in M} p_i(r + q) + \tilde{q} \sum_{i \in M} \sum_{j \in M \setminus i} p_i p_j + \tilde{q} \sum_{i \in M} \sum_{j \in M \setminus i} \epsilon \kappa_{ij}. \quad (9)$$

An argument analogous to that of section 2.2 shows that equilibrium matching will be homogeneous both by unconditional risk-type and by risk exposure.

### 3 Data and Variable Descriptions

**Data description and environment.** The data come from the Townsend Thai data base, in particular from a large cross section of 192 villages, conducted in May 1997, and a smaller re-survey conducted in April and May 2000. The larger, “baseline” survey covers four provinces from two contrasting regions of Thailand. The central region is relatively close to Bangkok and enjoys a degree of industrialization, as in the province of Chachoengsao, and also fertile land for farming, as in the province of Lopburi. The Northeast region is poorer and semi-arid, with the province of Srisaket regarded as one of the poorest in the entire country and the province of Buriram offering a transition as one moves back west toward Bangkok. Within each province, twelve subcounties, or tambons, were chosen. Within each tambon, a cluster of four villages was selected. In each village as many borrowing groups of the Bank for Agriculture and Agricultural Cooperatives (BAAC) as possible were interviewed, up to two. In all we have data on 262 groups, 200 of which are one of two groups representing their village. Each group designates an official leader, and the leader responded to questions on behalf of the group.

The “resurvey” data were collected from a subset of the same tambons. Included are data on 87 groups, 14 of which are the only groups in their village, 70 of which are one of two groups interviewed from the same village, and 3 of which are one of three groups interviewed from the same village. Besides sample size, there are two key differences between the resurvey data and the baseline survey data. First, in the resurvey individual group members respond to questions on their own behalf, up to five per group and on average 4.5; in the baseline survey, the group leader responds for all members. Second, several resurvey questions were designed explicitly to measure income risk and correlatedness, while the baseline survey captures mainly general information on the individual-member level.<sup>10</sup>

The BAAC is a government-operated development bank in Thailand. It was established in 1966 and is the primary formal financial institution serving rural households. It has estimated that it serves 4.88 million farm families, in a country with between sixty and seventy million inhabitants, about eighty percent of which live in rural areas. In the Townsend Thai baseline household survey covering the same villages, BAAC loans constitute 34.3% of the total number of loans, as compared with 3.4% for commercial banks, 12.8% for village-level financial institutions, and 39.4% for informal loans and reciprocal gifts (see Kaboski and Townsend, 1998).

The BAAC allows smaller loans<sup>11</sup> to be backed only with social collateral in the form of joint liability. To borrow in this way, a borrower must belong to an official BAAC borrowing group and choose the group-guarantee option on the loan application, and the group then faces explicit liability for the loan. That is, in the event of a group member’s default on a loan, the BAAC may opt to follow up with the delinquent borrower *or* other group members in search of repayment. This kind of borrowing is widespread: of the nearly 3000 households in the household survey, just over 20% had a group-guaranteed loan from the BAAC

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<sup>10</sup>One limitation in this paper is that there is no fruitful way to merge the two datasets, either because the groups are different or because identification numbers are inconsistent. Consequently, multivariate analysis (discussed in section 5) must be survey-specific.

<sup>11</sup>The cap on group loans at the time of the survey was 50,000 Thai baht, about \$2000. The median group loan was closer to \$1000.

outstanding in the previous year.

Groups typically have between five and fifteen members; about 15% are larger. Of critical importance to this paper on sorting, group formation is primarily at the discretion of the borrowers themselves. Typically, groups are born when borrowers propose a list of members to the BAAC, and the BAAC then approves some or all members. The BAAC seems to use its veto power sparingly: only about 12% of groups in the baseline survey report that the BAAC struck members from the list.<sup>12</sup> We know of no case where the BAAC adds members to a list or forms a group unilaterally. Thus, while the BAAC has some say about group formation, it is largely left to the borrowers themselves.

**Variable descriptions.** Our basic empirical strategy involves comparing across groups within villages to determine whether homogeneity is greater within groups than across groups. To do so, measures of risk and of correlatedness are necessary. Our measure of risk takes the model quite literally, and has been used in other tests of the adverse selection environment (see Ahlin and Townsend, 2004). Group members were asked in the resurvey what their income would be in the coming year if it were a good year ( $Hi$ ), what their income would be if it were a bad year ( $Lo$ ), and what they expected their income to be ( $Ex$ ). Assuming that income can take only one of two values,  $Hi$  and  $Lo$ , the probability of success, **prob** or prob-high, works out to be

$$prob = \frac{Ex - Lo}{Hi - Lo},$$

using the fact that  $prob * Hi + (1 - prob) * Lo = Ex$ . Another measure of risk, less directly related to the model, is the **coefficient of variation** of income.<sup>13</sup> Based on the same projected income distribution, this works out to be

$$\sigma/Ex = \sqrt{Hi/Ex - 1} \sqrt{1 - Lo/Ex}.$$

Since data on explicit risk exposure are lacking, correlatedness is measured in three indirect ways. First, we use information on **occupation** from the baseline survey, since exposure to aggregate shocks is likely to be relatively similar within occupations. Occupation is coded in one of twenty categories, including “rice farmer”, “corn farmer”, “construction worker in village”, “mechanic”, etc. Since the BAAC targets agricultural workers exclusively (at the time of the survey), there is less variation in occupation than would be ideal: only 46 out of 100 villages with two groups have *any* occupational heterogeneity among the two groups’ borrowers. Nonetheless, we can analyze tendencies to diversify in the 46 villages where heterogeneity exists.

Second, we use timing of bad income years, **worst-year**. Specifically, the resurvey asks borrowers which year of the past two was worse for household income: “one year ago”, “two years ago”, or “neither”. If borrowers are exposed to the same aggregate shocks, bad income years are more likely to coincide; thus coincidence of bad years can proxy anti-diversification. One drawback of this measure is its coarseness, as it maps past performance into one of three categories.

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<sup>12</sup>This is in response to a free-form question about how original members were determined when the group was founded.

<sup>13</sup>The coefficient of variation equals the standard deviation normalized by the mean.

Third, we calculate a direct measure of a household income **shock**, from the resurvey. It is designed to capture the percent deviation of this year’s income from its expected value. The household’s current income comes from a very detailed compilation of realized business and farm income for the just-completed year, *Inc*. Its expected income is proxied by next year’s expected income, *Ex*, mentioned above. The income shock is then  $Shock = (Inc - Ex)/Ex$ . This measure cleanly captures the income shock if households’ income draws are i.i.d. over time. Then *Ex* is exactly mean income, and *Shock* is this year’s realized random component of income (as a percent of mean income). If incomes are not stagnant over time but growing at the same expected rate across households, the measure would merely have to be adjusted by a constant to continue to capture the income shock. However, if household incomes are growing at different rates, then *Shock* captures not only the income shock but differential growth rates of income. We view this as the main drawback of this measure: within-group homogeneity may imply sorting aimed at anti-diversifying risk, or it may imply sorting based on income growth rates.

Flaws notwithstanding, the three measures of correlatedness should combine to give a suggestive picture of group propensities to diversify or anti-diversify.

## 4 Univariate Methodology and Results

### 4.1 Univariate Methodology

**Decompositions and rank correlations.** Homogeneous sorting can be detected by comparing across groups within villages. Two general approaches are used. One is a decomposition of differences between village borrowers into within-group and between-group components. A dominant between-group component suggests homogeneous sorting. The second approach is to calculate rank correlations between a focal variable and an arbitrary group index. A high absolute-value rank correlation suggests homogeneous sorting.

More specifically, consider data on ordered variable  $x$  from two groups in village  $v$ ,  $M$  and  $N$ , of respective sizes  $m$  and  $n$ :  $M = (x_1, \dots, x_m)$  and  $N = (x_{m+1}, \dots, x_{m+n})$ . We calculate a variance decomposition of  $X = (x_1, \dots, x_{m+n})$  into between-group and within-group components. The same can be done for a number of decomposable inequality measures – we also use Theil’s second measure, i.e. the mean log deviation.<sup>14</sup> The disadvantage of this measure is that it fails to work with non-positive values. To illustrate the approach, consider a village with group data  $M = (2, 5, 6, 8)$  and  $N = (1, 4, 7, 9)$ . Both variance and mean log deviation would register zero-percent between-group inequality, since the group means are the same. However,  $M' = (1, 2, 5, 6)$  and  $N' = (4, 7, 8, 9)$  would attribute 44% of overall variance to between-group differences and 30% of the overall mean log deviation to between-group differences, reflecting the fact that groups appear to sort somewhat homogeneously by variable  $x$ .

One can also calculate rank correlations between the data  $X$  and a group index variable,  $y$ , where for example  $y_1 = \dots = y_m = 1$  and  $y_{m+1} = \dots = y_{m+n} = 2$ . Rank correlations are useful in the context of sorting because they use only the ordinality (rankings) of the data

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<sup>14</sup>The mean log deviation equals the log of (the arithmetic mean divided by the geometric mean). For a decomposition, see Foster and Shneyerov (2000).

and not the cardinality. That is, they are invariant with respect to any data transformation that leaves the relative rankings unchanged.<sup>15</sup>

Two rank correlation measures are used, Spearman’s rho and Kendall’s tau<sub>b</sub>.<sup>16</sup> For example, consider groups  $M = (2, 5, 6, 8)$  and  $N = (1, 4, 7, 9)$ . Both rank-correlation measures give zero correlation between  $(2, 5, 6, 8, 1, 4, 7, 9)$  and group index  $(1, 1, 1, 1, 2, 2, 2, 2)$ , indicating no evidence of homogeneous sorting. However, groups  $M' = (1, 2, 5, 6)$  and  $N' = (4, 7, 8, 9)$  register correlations of 57% under Kendall’s tau<sub>b</sub> and 65% under Spearman’s rho, reflecting somewhat homogeneous sorting. The correlations would be the same but negative if group  $M'$  were indexed by 2 and  $N'$  by 1. Since the group index is arbitrary, we take the absolute value of the rank correlation. This restricts the value to be in  $[0, 1]$ , as is the case in the inequality decompositions.

A separate technique is needed for *non-ordered* categorical variables, such as occupation. We employ a decomposition approach, where the measure to be decomposed is analogous to an inequality measure in non-ordered space: fractionalization.<sup>17</sup> It is the probability that two randomly selected members of a population differ with respect to the (categorical) variable in question.<sup>18</sup> If the share of a population that fits into category  $j$  is denoted  $s_j$ , fractionalization  $F$  can be calculated as

$$F = 1 - \sum_j s_j^2.$$

For example, if in village  $v$  group  $M$  has occupations (Corn,Rice,Corn,Corn) and group  $N$  has occupations (Rice,Rice,Rice,Corn), then occupational fractionalization among borrowers village  $v$  is 50%.

Ahlin (2005) provides a decomposition of fractionalization into between-group and within-group components. Specifically, he shows that total fractionalization is a convex combination of within-group and between-group fractionalization, where between-group (within-group) fractionalization is defined as the probability two randomly selected members of a population differ, conditional on being from different groups (from the same group). In the example of  $M = (\text{Corn,Rice,Corn,Corn})$  and  $N = (\text{Rice,Rice,Rice,Corn})$ , 62.5% of total fractionalization is attributable to the between-group component. If instead  $M' = (\text{Corn,Rice,Rice,Corn})$  and  $N' = (\text{Corn,Rice,Rice,Corn})$ , this number would be 50%.

**Sorting percentiles.** To move toward a statistical test for homogeneous sorting, the results from each technique are next placed in context. As above, consider data  $X = (x_1, \dots, x_{m+n})$  from two groups in village  $v$ ,  $M$  and  $N$ , of respective sizes  $m$  and  $n$ . We form all possible combinations of the  $m + n$  borrowers into two groups of respective sizes

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<sup>15</sup>Perfectly homogeneous sorting applies with an infinite population of borrowers. In a finite population, payoff complementarity would not generally lead to homogeneous sorting, but would lead to rank-ordering of groups.

<sup>16</sup>Formulas can be found in Gibbons and Chakraborti (2003, pp. 419-420, 422-423). Kendall’s tau<sub>b</sub> allows for ties; for Spearman’s rho, we use the same rank for tied observations, the midrank.

<sup>17</sup>Fractionalization along ethno-linguistic and other dimensions has been used by a number of authors in analyses of economic growth. See Mauro (1995), Easterly and Levine (1997), and Alesina et al. (2003).

<sup>18</sup>Thus it is closely related to the gini coefficient, which is (half) the expected difference in incomes (relative to mean income) between two randomly selected members of a population. In both cases, the sampling is with replacement. It is also closely related to measures of concentration; in fact, it equals (one minus) the Herfindahl index.

$m$  and  $n$  and perform the same calculation – inequality decomposition, rank correlation, or fractionalization decomposition – on each one. The observed village grouping can then be assigned a “sorting percentile” (or sorting percentile range, given ties and a finite population) based on where its calculated value falls relative to this universe of possibilities. In this way, every village, variable, and technique is assigned a value (or range) in  $[0, 1]$ , with higher numbers representing greater homogeneity in sorting and lower numbers representing more heterogeneous sorting.

To illustrate, consider again a village with groups  $M = (2, 5, 6, 8)$  and  $N = (1, 4, 7, 9)$ . There are  $\binom{8}{4} = 70$  ways to sort eight borrowers into two groups of size four. Of these seventy combinations, sixty four register higher between-group inequality while six (including the observed combination) register exactly the same, i.e. zero between-group inequality, using either variance or mean log deviation. Thus this village is somewhere between the 0th and 8.6th percentiles in terms of group homogeneity; its sorting percentile range is  $[0, 8.6]$ . The somewhat wide range reflects the fact that there are ties and that the population is relatively small. Consider groups  $M' = (1, 2, 5, 6)$  and  $N' = (4, 7, 8, 9)$ . There are four combinations of borrowers higher, sixty two combinations lower, and four combinations tied, both in terms of between-group variance and mean log deviation. The village’s sorting percentile range is thus  $[88.6, 94.3]$ . Recall that 30% of mean log deviation but 44% of the variance across village borrowers in this village is attributable to between-group differences. Translating these numbers in percentile ranges shows both that this may be considered a large amount of between-group differences, relative to the distribution of characteristics, though the decomposition numbers may seem more moderate; and that the variance and mean log deviation paint a more comparable picture than the raw decompositions might have indicated.<sup>19</sup>

Similar analysis produces sorting percentiles based on the rank correlation measures. The village with  $M = (2, 5, 6, 8)$  and  $N = (1, 4, 7, 9)$  gets a sorting percentile range of  $[0, 11.4]$ , based on either rank correlation measure. The village with  $M' = (1, 2, 5, 6)$  and  $N' = (4, 7, 8, 9)$  gets a sorting percentile range of  $[88.6, 94.3]$ , just as with the inequality decompositions. In general, however, the percentile ranges are often wider with rank correlations than with variance decompositions since they use less information and consequently result in ties more frequently.

The same approach can be used with fractionalization decomposition of categorical variables. If  $M = (\text{Corn}, \text{Rice}, \text{Corn}, \text{Corn})$  and  $N = (\text{Rice}, \text{Rice}, \text{Rice}, \text{Corn})$ , thirty six combinations have less, two combinations have greater, and thirty two combinations have the same between-group contribution to overall fractionalization. Thus the village’s sorting percentile range would be  $[51.4, 97.1]$ . A village with  $M' = (\text{Corn}, \text{Rice}, \text{Rice}, \text{Corn})$  and  $N' = (\text{Corn}, \text{Rice}, \text{Rice}, \text{Corn})$  would have thirty six combinations greater and thirty four combinations tied in terms of between-group fractionalization. Its percentile range would be  $[0, 51.4]$ . These percentile ranges are admittedly wide, and heterogeneous matching is likely to occur even by chance. More data and a greater number of categories would tend to shrink the ranges.

Thus for a given technique and variable, each village is assigned a sorting percentile range. A higher sorting percentile range reflects more homogeneous sorting, as measured

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<sup>19</sup>However, the measures do not always give rise to the same sorting percentiles.

by the given technique, while a lower sorting percentile reflects more heterogeneous sorting. One can then interpret villages with percentiles above the 95th as exhibiting homogeneous sorting at the 5% confidence level, for example.

**A nonparametric test.** Rather than test sorting village by village, however, we combine villages in a single test (per variable and technique) of the overall tendency to sort homogeneously. Each village's sorting percentile is treated as a draw from the same distribution, and this distribution is compared using the Kolmogorov-Smirnov (KS) test to a benchmark distribution. An advantage of this approach is that it is non-parametric and requires no distributional assumptions.

The benchmark comparison distribution is the one that would obtain if sorting with respect to the given variable were completely random in all villages: the uniform distribution on  $[0, 1]$ . To see that the uniform is the appropriate comparison, consider the case of a large number of borrowers in a village, no two combinations of which (into two groups of the given sizes) result in a tie using the given technique. If each of the  $N$ , say, possible combinations is equally likely, then each  $1/N$ -percentile is equally likely to be observed. That is, the sorting percentile is drawn from the uniform distribution (approximately, with the difference getting arbitrarily small as  $N$  increases).

With smaller numbers of borrowers and, especially, with ties, the uniform distribution is a less accurate approximation. This is because the appropriate distribution is a step function approximation of the uniform, and the steps are larger the lower is the number of combinations  $N$  (a number which varies by village) and the more ties there are. For robustness to this, we focus on the percentile ranges rather than the percentiles themselves. We assign the village not a single percentile (e.g. the midpoint of the range), but an equal chance of equaling any percentile in the percentile range, i.e. a random variable distributed uniformly over the percentile range. For example, if a village's sorting percentile is between the 92nd and 96th percentiles, we consider it to be uniformly distributed between the 92nd and 96th percentiles.

With this interpretation, the correct benchmark distribution is *exactly* the uniform regardless of the number of combinations  $N$  and the number of ties. To see this, let there be  $K \leq N$  different values arising when the given technique is performed on the  $N$  combinations, with values  $v_1 < v_2 < \dots < v_K$ . (Ties involve  $K < N$ .) Also, let  $n_i$  be the number of combinations that give rise to value  $v_i$  and  $N_i$  be the number of combinations that give rise to any value  $v \leq v_i$ , with  $N_0 \equiv 0$ ; then  $N_i = \sum_{k=1}^i n_k$  and  $N_K = N$ . If sorting is completely random, then each of the  $N$  combinations of borrowers is equally likely to obtain. With probability  $p_i \equiv n_i/N$  the realized combination will result in value  $v_i$ , with percentile distributed uniformly over range  $[\frac{N_{i-1}}{N}, \frac{N_i}{N}]$ . The distribution of percentiles  $z$  is then

$$f(z) = \sum_{i=1}^K p_i \int_{\frac{N_{i-1}}{N}}^{\frac{N_i}{N}} \frac{1}{\frac{N_i - N_{i-1}}{N}} dz = \sum_{i=1}^K \frac{n_i}{N} \int_{\frac{N_{i-1}}{N}}^{\frac{N_i}{N}} \frac{N}{n_i} dz = \sum_{i=1}^K \int_{\frac{N_{i-1}}{N}}^{\frac{N_i}{N}} dz = \int_0^1 dz.$$

Thus, as long as the distribution function across villages is constructed not using exact percentiles, but rather uniform distributions over percentile ranges, the correct comparison regardless of population size and number of ties is the uniform. This is the approach we take. Weighting each village equally, we construct the sample cdf from the percentile ranges. For example, consider two villages, with respective sorting percentile ranges  $[25, 30]$  and

[80, 90]. The sample cdf using percentile ranges would be flat at zero until (0.25, 0), then travel linearly upward from (0.25, 0) to (0.3, 0.5), then be flat at one half until (0.8, 0.5), then travel linearly upward from (0.8, 0.5) to (0.9, 1), and finally remain flat at one.<sup>20</sup>

One final issue has to do with village weighting in the KS tests. Note that if all borrowers in a village have the same value for a given variable, then there is no inequality (or fractionalization), so the between-group component is not defined and the village must be dropped. This village borrower homogeneity happens not infrequently for categorical variables, such as occupation. Thus in our baseline approach, all villages with any differences are given equal and positive weights, while villages with no differences are implicitly given zero weight. A more continuous approach would be to weight each village in proportion to the amount of overall heterogeneity that exists within it. Hence, we also report results for categorical variables from weighting each village’s observation in proportion to the total fractionalization in the village.<sup>21</sup>

## 4.2 Univariate Results

**Sorting by risk-type.** The probability of achieving the high income realization, **prob**, is a close analog to the risk-type variable in the theory and is thus the focus of our empirical tests for homogeneous risk-matching.<sup>22</sup> The sample cdfs of village sorting percentile ranges for *prob* based on inequality decompositions, constructed as described in the previous section, are graphed in Figure 1. Based on these percentile ranges and the variance measure, the mean (median) village is more homogeneously sorted than 57% (62%) of all possible combinations of borrowers into groups of the observed sizes. The random-matching benchmark, the uniform, is graphed as a dotted line. Using a one-sided KS test, we reject at the 5% level the hypothesis of heterogeneous sorting, that is, that the true distribution is first-order stochastically dominated by the uniform.

The distribution, including means and medians, looks similar when using mean log deviation instead of variance decompositions. However, the KS test p-value is significantly larger. The reason is due to the much smaller sample size, 15 instead of 32. This comes from the breakdown of the mean log deviation measure when there are zeros, a feature of the data from at least one respondent in 17 of the villages.

The sample cdf of village sorting percentile ranges for *prob* based on rank correlations is shown in Figure 2. Both Spearman’s rho and Kendall’s tau<sub>b</sub> give mean (median) sorting percentiles of 58% (59%), and reject heterogeneous sorting at a 5% confidence level based on the KS test. Overall, the data point to statistically significant but not quantitatively overwhelming homogeneous risk-matching.

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<sup>20</sup>The sample cdf using the midpoints of the percentile ranges would be flat at zero until a spike from (0.275, 0) to (0.275, 0.5), then be flat at one half before spiking from (0.85, 0.5) to (0.85, 1), and finally remain flat at one. This sample cdf has greater deviations on both sides of the uniform than the one we construct.

<sup>21</sup>For example, consider again two villages with respective sorting percentile ranges [25, 30] and [80, 90]. Further imagine the two villages register fractionalization numbers of 0.75 and 0.25, respectively. Then the *weighted* sample cdf using percentile ranges would be flat at zero until (0.25, 0), then travel linearly upward from (0.25, 0) to (0.3, 0.75), then be flat at one half until (0.8, 0.75), then travel linearly upward from (0.8, 0.75) to (0.9, 1), and finally remain flat at one. That is, the first village would receive three times as much weight as the second since its overall fractionalization is three times as high.

<sup>22</sup>Ahlin and Townsend (2004) find direct evidence for adverse selection using this measure.

A second measure of risk, though in a way not as closely related to the theory, is the **coefficient of variation** of projected income, described in section 3. Sorting tendencies based on this variable and inequality decompositions are graphed in Figure 3. According to variance decomposition, the mean (median) village is more homogeneously sorted than 63% (72%) of all possible combinations. The KS test rejects heterogeneous sorting at the 5% level. Mean log deviation decompositions give similar results, though the small sample size lowers statistical significance of the KS test (due to reasons discussed above).

However, when judged by the rank correlations there is less evidence for homogeneous sorting by coefficient of variation; see Figure 4. The means and medians drop to 59% and 55-56%, respectively, and the KS tests come somewhat close but fail to reject heterogeneous sorting. While the coefficient of variation measure gives weaker results, we view it as auxiliary to the *prob* measure, and somewhat supportive. Overall, the data give solid evidence for a degree of homogeneous risk-matching.

**Sorting by correlated risk.** We next examine diversification within groups. **Occupational** diversification, based on decomposition of occupational fractionalization, is graphed in Figure 5. The results overwhelmingly reject occupational diversification. The mean (median) village is more homogeneously sorted by occupation than 75% (84%) of all group formations. These numbers increase to 79% and 91% when villages are weighted by the overall amount of occupational heterogeneity (measured by fractionalization) in the village. Admittedly, only 46 out of the 100 villages with two groups have *any* occupational heterogeneity; but where heterogeneity exists, it clearly does not appear to be used to diversify groups. Using weighted and unweighted cdfs, the KS tests reject occupational diversification at the 1% level.

Next, consider the **worst-year** measure. This is a categorical variable which can be treated either as non-ordered or as ordered, with both “one year ago” and “two years ago” considered closer to “neither” than they are to each other. Fractionalization decompositions from the non-ordered case are reported in Figure 6 and rank correlation results from the ordered case in Figure 7.<sup>23</sup> The approaches give similar results, yielding unweighted and weighted means (medians) of 59-60% (65-66%) in the case of the decompositions and slightly lower means (medians) of 58% (64%) in the case of the rank correlations. Both come fairly close but fail to reject diversification reflected in non-coincidence of bad income years.

Finally, we consider coincidence of income **shocks**, measured by the percent deviation of this year’s realized income from next year’s expected income. Rank correlations are presented in Figure 8.<sup>24</sup> The rank correlation measures yield means (medians) of 59-60% (66%) and reject diversification at the 10% level. That is, income shocks are relatively coincident within groups, consistent with the view that groups anti-diversify so as to increase correlated risk.

Overall, the univariate tests paint a picture of homogeneous group composition along dimensions of unconditional risk and of correlated risk exposure, just as the theory predicts.

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<sup>23</sup>Results from Spearman’s rho are nearly identical to those from Kendall’s tau<sub>b</sub>, so are not reported.

<sup>24</sup>Variance decomposition yielded similar results: mean 58%, median 65%, KS p-value 0.067. Mean log deviation decomposition is omitted because this measure is undefined if there is one zero or negative number and nearly all villages have at least one such response.

## 5 Multivariate Methodology and Results

Univariate analysis may suggest one variable to be a key sorting dimension when in reality this variable is merely correlated with a second variable that is the true key sorting dimension. For example, one could interpret the evidence for homogeneous risk matching as driven by 1) borrowers' desires to match based on correlated risk, not unconditional risk per se, and 2) a correlation between unconditional risk and correlated risk. The latter could arise if some aggregate shocks are more volatile than others, in which case matching based on similar shock exposure would induce homogeneous matching based on unconditional risk also.

The maximum score estimator of Fox (2006) provides a multivariate approach capable of isolating the partial effects of the two risk dimensions. Simultaneously, it allows us to take the model literally and estimate key parameters in the borrowing payoff function, up to scale. This will facilitate quantification of the effective reduction in liability due to anti-diversification.

The estimator works by choosing parameters that most frequently give observed agent groupings higher joint surplus (sum of payoffs) than feasible, unobserved agent groupings. Thus the estimator exploits the idea that in an environment with no search frictions and transferable utility, like ours, observed groupings maximize total surplus.

Consider observed groups  $M$  and  $N$  in village  $v$ . Let  $M'$  and  $N'$  denote an alternative arrangement of the borrowers from  $M$  and  $N$  into two groups. Since villages are relatively small and geographically concentrated, we assume that borrowers can match with any others in their village; thus  $M'$  and  $N'$  represent a feasible, unobserved grouping. If  $JS_G(\phi)$  gives the joint surplus of any group  $G$  as a function of parameters  $\phi$ , theory predicts that

$$JS_M(\phi) + JS_N(\phi) \geq JS_{M'}(\phi) + JS_{N'}(\phi). \quad (10)$$

The estimator chooses parameters  $\phi$  that maximize the score, the number of inequalities of the form 10 that are true, where each inequality corresponds to a different unobserved grouping  $M', N'$ .

Our set of unobserved groupings, and thus inequalities, comes from all  $k$ -for- $k$  borrower swaps across groups in the same village.<sup>25</sup> For example, if we have data on five borrowers in each of two groups in the same village, there are  $5 \times 5 = 25$  one-for-one swaps,  $10 \times 10 = 100$  two-for-two swaps, and so on. Theory would also justify other kinds of inequalities, for example those arising from a  $k$ -borrower transfer. We choose not to use transfers because they change group size, which was held fixed in the theory. At any rate, Fox (2006) shows consistency of the estimator when using a only subset of implied inequalities.

Using the model's exact joint surplus function, reproduced from equation 9 here:

$$JS_M = nE - \sum_{i \in M} p_i(r + q) + \tilde{q} \sum_{i \in M} \sum_{j \in M \setminus i} p_i p_j + \tilde{q} \sum_{i \in M} \sum_{j \in M \setminus i} \epsilon \kappa_{ij},$$

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<sup>25</sup>If the larger group in a village has size  $m$  and the smaller group has size  $n$ ,  $k$  is capped at  $\min\{n, m - 1\}$ .

inequality 10 simplifies to

$$\begin{aligned} & \sum_{i \in M} \sum_{j \in M \setminus i} \tilde{\beta}_a p_i p_j + \sum_{i \in M} \sum_{j \in M \setminus i} \tilde{\beta}_b \kappa_{ij} + \sum_{i \in N} \sum_{j \in N \setminus i} \tilde{\beta}_a p_i p_j + \sum_{i \in N} \sum_{j \in N \setminus i} \tilde{\beta}_b \kappa_{ij} \geq \\ & \sum_{i \in M'} \sum_{j \in M' \setminus i} \tilde{\beta}_a p_i p_j + \sum_{i \in M'} \sum_{j \in M' \setminus i} \tilde{\beta}_b \kappa_{ij} + \sum_{i \in N'} \sum_{j \in N' \setminus i} \tilde{\beta}_a p_i p_j + \sum_{i \in N'} \sum_{j \in N' \setminus i} \tilde{\beta}_b \kappa_{ij}, \end{aligned}$$

where  $\tilde{\beta}_a = \tilde{q}$  and  $\tilde{\beta}_b = \tilde{q}\epsilon$ . Note that in this example and generally, all terms in the joint surplus function that do not involve interactions between borrower characteristics drop out of the inequality, since they appear identically on both sides. Thus coefficients on non-interaction payoff function terms (e.g.  $E$ ,  $r$ ) cannot be estimated.

Given data on borrower probabilities of success ( $p_i$ 's) and correlatedness ( $\kappa_{ij}$ 's), parameters  $\tilde{\beta}_a$  and  $\tilde{\beta}_b$  can be estimated, but only up to scale, since multiplication by any positive scalar would preserve the inequality. Note that  $\epsilon$  would still be identified as  $\tilde{\beta}_b/\tilde{\beta}_a$ . This approach, however, requires data that can capture the existence of correlation ( $\kappa_{ij}$ ) as distinct from the intensiveness ( $\epsilon$ ) of correlation. That is, to identify  $\epsilon$ ,  $\kappa_{ij}$  should reflect the similarity of shocks to which borrowers are exposed, but not the degree of exposure to those shocks. Our (re-survey) measures of correlatedness – both of which reflect similarity of income shocks – cannot be assumed to distinguish existence and intensiveness of correlatedness.

However, identifying  $\epsilon$  separately from  $\kappa_{ij}$  is not critical for our purposes. We proceed as follows. Let  $C_{ij} \equiv \epsilon \kappa_{ij}$  reflect the overall correlation between borrowers  $i$  and  $j$ . We proxy  $C_{ij}$  by

$$C_{ij} = \phi_{wst} 1\{worst\_year_i = worst\_year_j\} - \phi_{shk} |g(shock_i) - g(shock_j)|, \quad (11)$$

where  $g(\cdot)$  is a monotonic transformation function designed to reduce the influence of outliers.<sup>26</sup> Coincident bad-income years and similarly-valued income shocks are thus taken to indicate the degree of correlation between borrowers.

Rewriting the joint surplus function using  $C_{ij}$  and excluding non-interaction terms:

$$\begin{aligned} JS_M &= \tilde{q} \sum_{i \in M} \sum_{j \in M \setminus i} p_i p_j + \tilde{q} \sum_{i \in M} \sum_{j \in M \setminus i} C_{ij} \\ &= \sum_{i \in M} \sum_{j \in M \setminus i} (\beta_1 p_i p_j + \beta_2 1\{worst\_year_i = worst\_year_j\} - \beta_3 |g(shock_i) - g(shock_j)|), \end{aligned} \quad (12)$$

where  $\beta_1 = \tilde{q}$ ,  $\beta_2 = \tilde{q}\phi_{wst}$ , and  $\beta_3 = \tilde{q}\phi_{shk}$ . The sign but not the magnitude of parameter  $\tilde{q}$  is thus identified. In estimation, then,  $\beta_1$  is normalized to +1 or -1. However, both  $\phi_{wst}(= \beta_2/\beta_1)$  and  $\phi_{shk}(= \beta_3/\beta_1)$ , and thus the correlation function  $C_{ij}$ , are identified.

A positive estimate of  $\beta_1$  would support the theory. This would directly establish that risk-types are complements in the payoff function (since the cross-partial is directly proportional to  $\tilde{q}$ ) and thus that payoffs are higher for homogeneously sorted groupings than

<sup>26</sup>Specifically,  $g(x) = sgn(x) * [|x|/(1 + |x|)]^{1/2}$ . This function is symmetric about zero and has a range of  $(-1, 1)$ . The exponent 1/2 was chosen so that the interquartile range of  $shock$  spans half the range of the transformed variable.

heterogeneously sorted groupings as the theory predicts. Positive estimates of  $\beta_2$  and  $\beta_3$  would also support the theory, indicating that payoffs increase in the degree of correlation between borrowers, exactly as the theory predicts. Finally, it should be noted that this approach estimates partial effects on the payoff of matching along one dimension holding the other fixed.

Risk types  $p_i, p_j$  are measured by *prob*, discussed in section 3. If there are  $V$  villages indexed by  $v$ , and each village  $v$  has two groups,  $M_v$  and  $N_v$ , the estimator comes from

$$\max_{\beta_1 \in \{-1, 1\}, \beta_2, \beta_3} \sum_{v=1}^V \sum_{M'_v, N'_v} 1\{JS_{M_v} + JS_{N_v} > JS_{M'_v} + JS_{N'_v}\},$$

where<sup>27</sup> the alternate groupings  $M'_v$  and  $N'_v$  come from all  $k$ -for- $k$  borrower swaps, as discussed above.

Maximization is carried out using the genetic algorithm routine in Matlab. Results from this estimation give  $\hat{\beta}_1 = 1$ ,  $\hat{\beta}_2 = 1.05 = \hat{\phi}_{wst}$  and  $\hat{\beta}_3 = 0.00 = \hat{\phi}_{shk}$ . Thus, risk-types are complementary in the payoff function; in addition, risk anti-diversification as measured by coincidence of bad income years increases payoffs. This supports the theoretical result of homogeneous matching by both risk-type and risk exposure.

As suggested by Fox (2006), hypothesis tests are carried out by subsampling. That is, we create 100 datasets each containing 24 villages, by randomly sampling (without replacement) from the 32 villages in the dataset. The coefficients are estimated for each dataset. The hypothesis that a given coefficient is negative is rejected at the 10% level, say, if 10 or less estimates of the coefficient are negative. We find that all 100 estimates of the unconditional risk coefficient  $\beta_1$  are positive. A negative cross-partial with respect to risk-types can thus be rejected at the 1% level. This offers strong support of the theory of homogeneous risk-matching. The coefficient on worst-year coincidence,  $\beta_2$ , is estimated as positive in 88 of the subsamples; thus, negativity can be rejected at the (slightly unconventional) 15% level. The coefficient  $\beta_3$  is nowhere close to significantly different from zero. A simple interpretation for this result is that worst-year coincidence is a strictly dominant proxy for correlated risk.

Overall, the evidence from these tests is consistent with the idea that both dimensions of risk heterogeneity create their own incentives for homogeneity.

## 6 Quantifying Effects of Matching

In this section, we use previous theory and estimation to quantify 1) how closely the implicit risk premia (or safety discounts) that arise from homogeneous matching mimic the theoretically predicted amounts, and 2) the payoff boosts due to anti-diversification with groups.

**Risk-matching discounts.** First, compare the borrowing payoff, reproduced here from equation 8:

$$\Pi_{iM} = E - rp_i - qp_i(1 - \bar{p}_{M \setminus i}) + q \in \bar{K}_{i, M \setminus i},$$

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<sup>27</sup>The estimator uses a strict inequality though theory requires only a weak one. Given a continuous distribution of match-specific error terms introduced to support the estimator, equalities can be ignored with probability one.

to the benchmark of random matching by risk-type (and matching by risk-exposure held fixed). Under random matching,  $\bar{p}_{M \setminus i}$  would be replaced in the payoff by  $\bar{p}_{V \setminus i}$ , defined as the average success probability of other borrowers in the same village  $V$  as  $i$ . This is because each would have the same probability of being grouped with  $i$ . Borrower  $i$ 's gain in payoffs due to non-random matching, call it  $D_{actual}$  for actual discount, is then calculated to be

$$D_{actual} = qp_i(\bar{p}_{M \setminus i} - \bar{p}_{V \setminus i}).$$

The theoretically predicted payoff comes from replacing  $\bar{p}_{M \setminus i}$  in the borrowing payoff with  $p_i$ , which corresponds to perfectly homogeneous matching. The discount in this case is

$$D_{homogeneous} = qp_i(p_i - \bar{p}_{V \setminus i}).$$

Of course, discounts can be negative (i.e. risk premia); under homogeneous matching, they are for high-risk types ( $p_i < \bar{p}_{V \setminus i}$ ). This variation in discount by risk is exactly what underpins group lending's efficiency gains.

Homogeneous matching relies on risk-type complementarity *and* on there being a continuum of borrowers. If instead the number of borrowers is finite, as is obviously the case in our data, perfect homogeneity generally does not hold. However, even with a finite borrowing pool groups are still rank-ordered by risk-type in equilibrium.<sup>28</sup> Let  $M^{RO}$  be the group to which  $i$  would belong if borrowing groups in village  $V$  were rank-ordered by risk-type. The predicted discount under rank-ordering is

$$D_{rank-ordered} = qp_i(\bar{p}_{M^{RO} \setminus i} - \bar{p}_{V \setminus i}).$$

We thus have two theoretically predicted discounts, one of which makes a greater concession to reality. Assume the actual discount is some convex combination of the random-matching discount and a theoretically predicted discount:

$$D_{actual} = \alpha D_{theoretical} + (1 - \alpha) D_{random},$$

for some  $\alpha \in [0, 1]$ . Since we define discounts against the benchmark of random matching,  $D_{random} = 0$ . Incorporating this and dividing the equation by  $qp_i$  gives

$$\bar{p}_{M \setminus i} - \bar{p}_{V \setminus i} = \alpha(p_{theoretical} - \bar{p}_{V \setminus i}), \tag{13}$$

where  $p_{theoretical}$  is one of the theoretically predicted benchmarks of the previous paragraphs,  $p_i$  or  $\bar{p}_{M^{RO} \setminus i}$ . All quantities can be measured, again using *prob* as the measure of  $p_i$ . To measure  $\bar{p}_{M^{RO} \setminus i}$ , we form two rank-ordered groups from the village borrowers, preserving group sizes;  $\bar{p}_{M^{RO} \setminus i}$  is then the average  $p_j$  in the group to which borrower  $i$  would belong, excluding  $p_i$ .<sup>29</sup> A linear regression can be thus be used to estimate  $\alpha$ , the percent of the theoretically predicted discounts/premia that are being realized in practice.

We estimate  $\alpha$  using median regression and standard errors calculated via bootstrapping, with 10,000 repetitions and sampling clustered at the village level. We find  $\hat{\alpha} = 7.9\%$  for

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<sup>28</sup>This is true if risk-type is the only matching dimension. If there are two dimensions along with matching occurs, even rank-ordering may not hold as borrowers trade off matching gains along the two dimensions.

<sup>29</sup>If the two groups in the village vary in size, there are two potential  $M^{RO}$ 's; we average the two resulting discounts.

homogeneous matching and  $\hat{\alpha} = 15.9\%$  for rank-ordered matching; both are significant at the 5% level. That is, about 8% of the homogeneous-matching discount and 16% of the rank-ordered matching discount is being realized in practice. Using the point estimates for the discounts, the realizable discounts/premia drop in half due to the finiteness of the borrowing pool. Given attenuation bias due to measurement error, these can be considered lower bounds. Overall, it appears that group lending is delivering a modest but non-negligible discount to safe borrowers.

**Anti-diversification discounts.** Similar analysis can be carried out for the correlated risk dimension. The analog to equation 13 is<sup>30</sup>

$$\overline{C}_{i,M\setminus i} - \overline{C}_{i,V\setminus i} = \alpha(C_{theoretical} - \overline{C}_{i,V\setminus i}),$$

where  $C_{theoretical}$  is one of the theoretically predicted benchmarks,  $C_{ii}$  or  $\overline{C}_{i,MRO\setminus i}$ . All measurements of  $C$  come from equation 11 using the previous section's estimates of the  $\phi$ 's. The most stringent theoretical prediction is perfect homogeneity in risk exposure,  $C_{ii}$ , which corresponds here to all group members having the exact same worst-year and income shock. Less stringent is matching within a finite population solely based on correlated risk, the analog to rank-ordering by risk-type. This corresponds to  $\overline{C}_{i,MRO\setminus i}$ , which we calculate by finding the grouping in borrower  $i$ 's village that maximizes the correlated-risk part *only* of the sum of payoffs (see equation 12), then averaging the  $C_{ij}$ 's,  $j \neq i$ , across all borrowers  $j$  in the group to which  $i$  would belong. Of course,  $\overline{C}_{i,M\setminus i}$  and  $\overline{C}_{i,V\setminus i}$  are calculated as the average  $C_{ij}$ 's,  $j \neq i$ , across all borrowers  $j$  in, respectively, the group to which  $i$  belongs and the village to which  $i$  belongs.

We find  $\hat{\alpha} = 0.00\%$  for homogeneous matching and  $\hat{\alpha} = 10.0\%$  for rank-ordered matching; the latter is significantly non-negative at the 10% level. The results suggest that at least 10% of the actual discounts available from anti-diversification are being realized in practice. We expect measurement error to be an even bigger issue in these estimates, since the discounts are calculated using both proxy variables *and* estimated coefficients (the  $\hat{\phi}$ 's). Actual anti-diversification discounts may be significantly larger.

## 7 Conclusion

In the context of limited liability lending and unobserved risk type, theory suggests that borrowers will sort homogeneously by risk; this embeds an effective discount for safe borrowers and improves efficiency. However, theory also suggests that borrowers will sort so as to anti-diversify risk and thereby to minimize potential liability for their fellow group members. While the first kind of sorting works in favor of efficiency, the second kind may work against it by limiting the lender's ability to use group lending effectively.

We test these matching predictions using data from Thai borrowing groups. Both predictions are upheld to some degree. Direct comparisons to completely random matching using Kolmogorov-Smirnov tests give evidence that groups are somewhat homogeneous in unconditional risk and in types of risk exposure. Multivariate tests using Fox's maximum score estimator confirm that the payoff to similarity is positive, in both dimensions. Thus

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<sup>30</sup>Recall that  $C_{ij} \equiv \epsilon\kappa_{ij}$ .

sorting appears to be giving at least a moderate discount to safe borrowers, but also appears to be limiting effective liability via anti-diversification.

These results provide direct evidence of a specific mechanism by which group lending can improve efficiency in micro-lending markets. They add to our understanding of how innovations in lending have been able to extend finance to the world's poor and why group lending has been such a popular lending mechanism in the micro-credit movement.

From a policy standpoint they show that voluntary sorting by borrowers may also have its downside. Sorting to anti-diversify can work against the lender's interests and, in equilibrium, the borrowers'. Applying the results narrowly, lenders may want to intervene to promote risk diversification within groups – for example, requiring occupational diversity – provided their intervention will not prevent homogeneous risk matching. More generally, lenders may wish to step in with respect to group composition on certain dimensions while leaving other dimensions completely at the borrowers' discretion. Accomplishing this in a precise fashion may be impossible; however, attempts to do so may be some of the profitable next steps of lender experimentation in extending credit markets to the poor.

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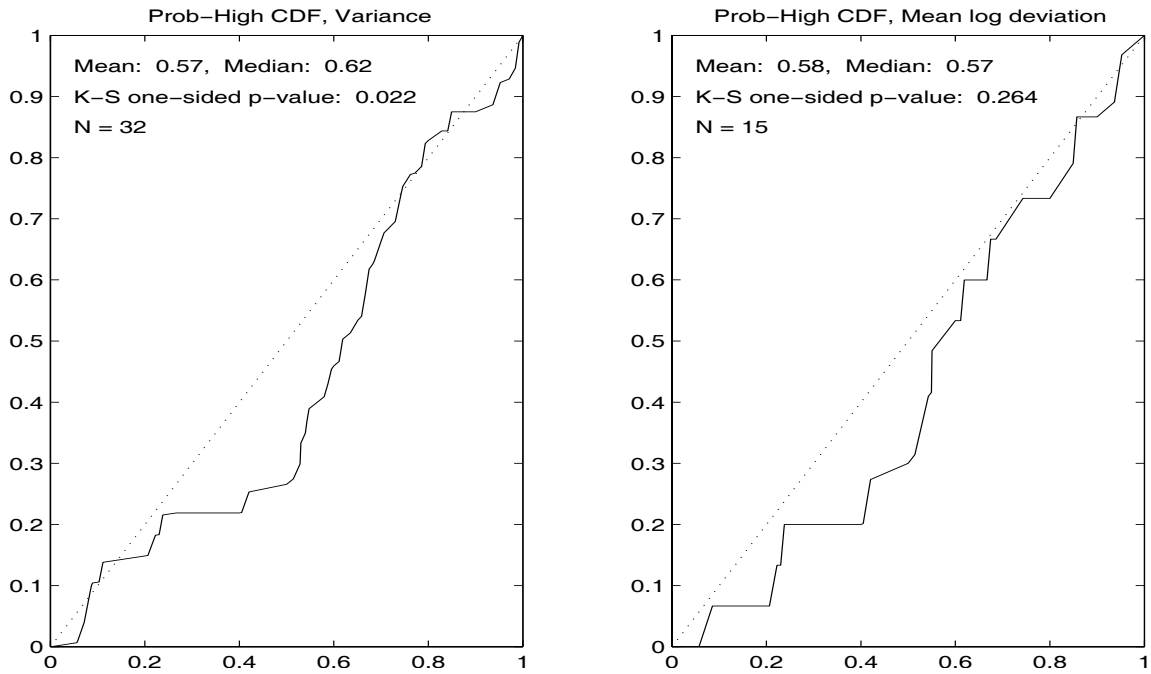


Figure 1: Sample cdf of villages based on decomposition of variance (left panel) and of mean log deviation (right panel) of *prob*, the probability of realizing high income.

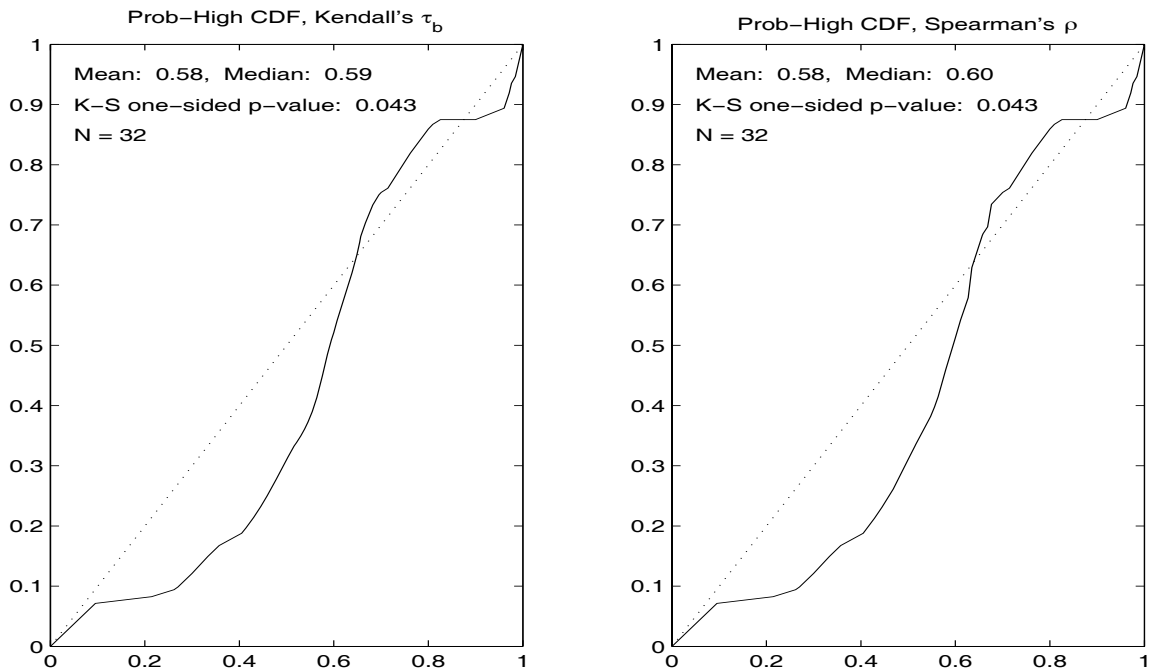


Figure 2: Sample cdf of villages based on rank correlations of *prob* and group identity.

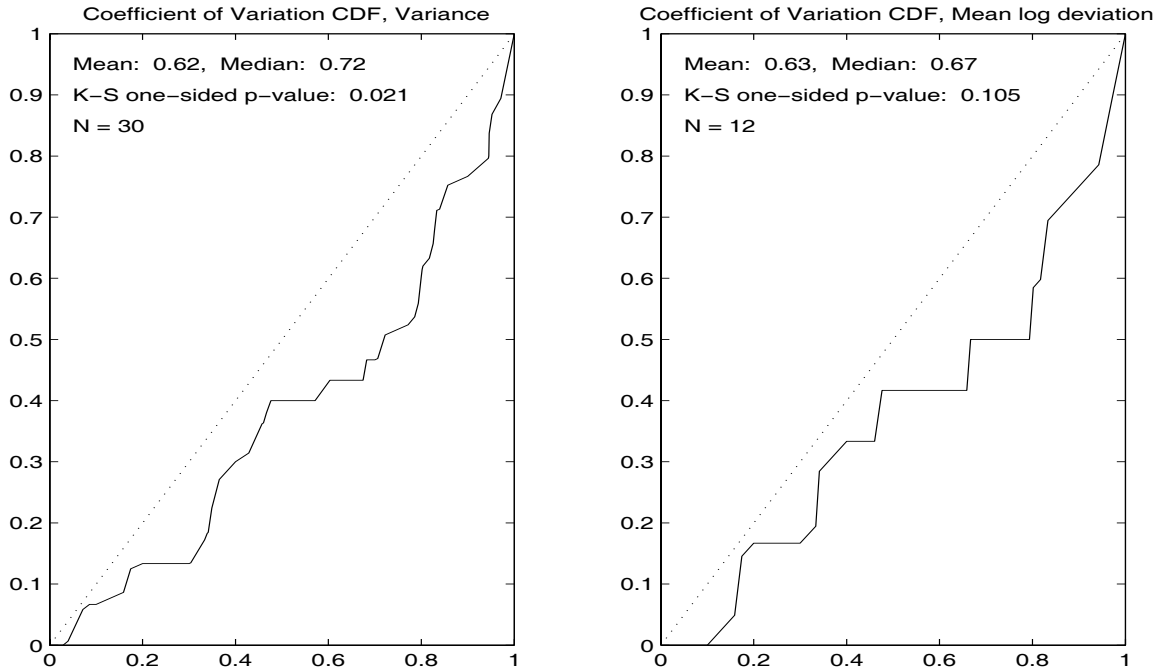


Figure 3: Sample cdf of villages based on decompositions of variance (left panel) and mean log deviation (right panel) of coefficient of variation of future income realizations.

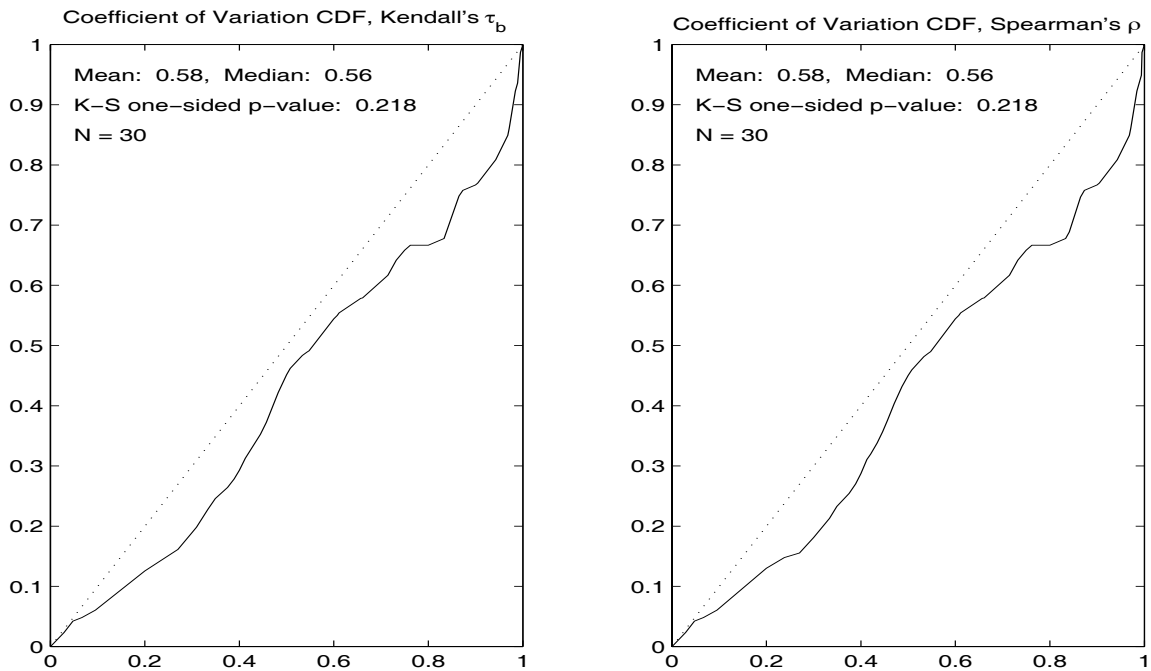


Figure 4: Sample cdf of villages based on rank correlations of future income coefficient of variation and group identity.

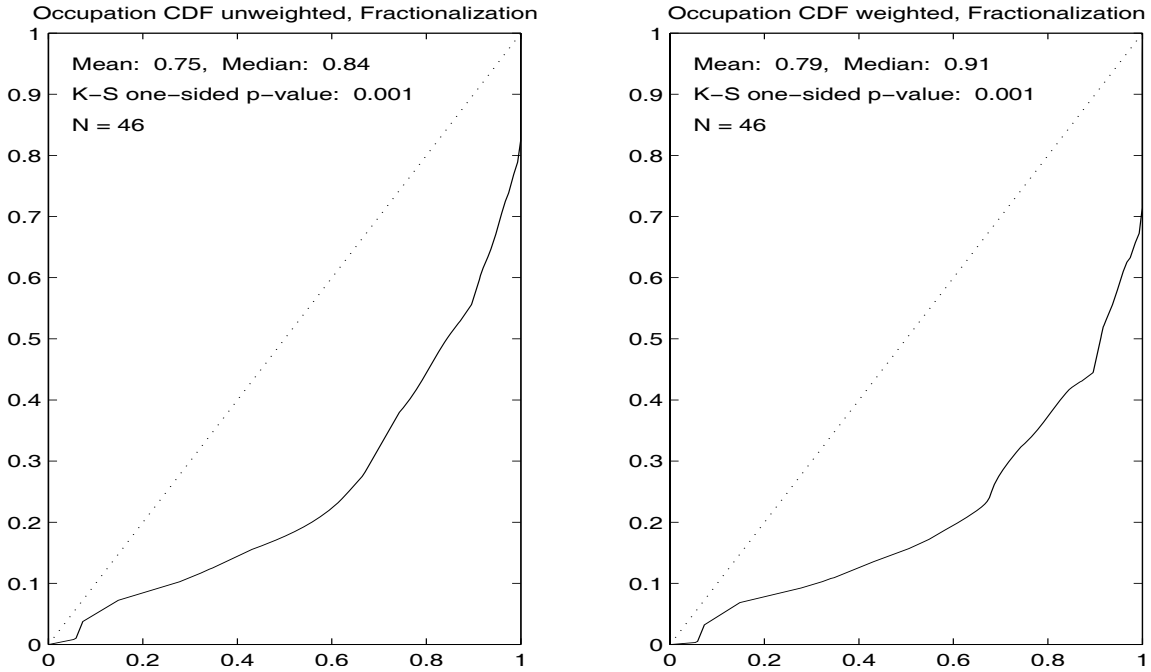


Figure 5: Sample cdf of villages based on decomposition of occupational fractionalization, unweighted (left panel) and weighted by fractionalization (right panel).

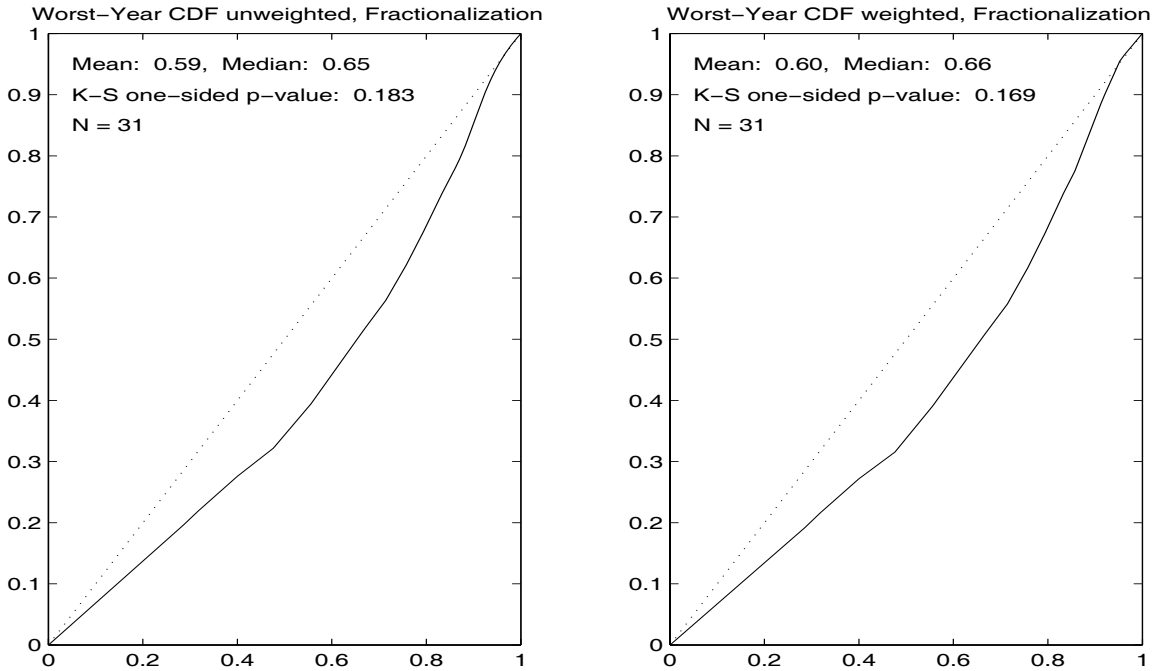


Figure 6: Sample cdf of villages based on decomposition of worst-year fractionalization, unweighted (left panel) and weighted by fractionalization (right panel).

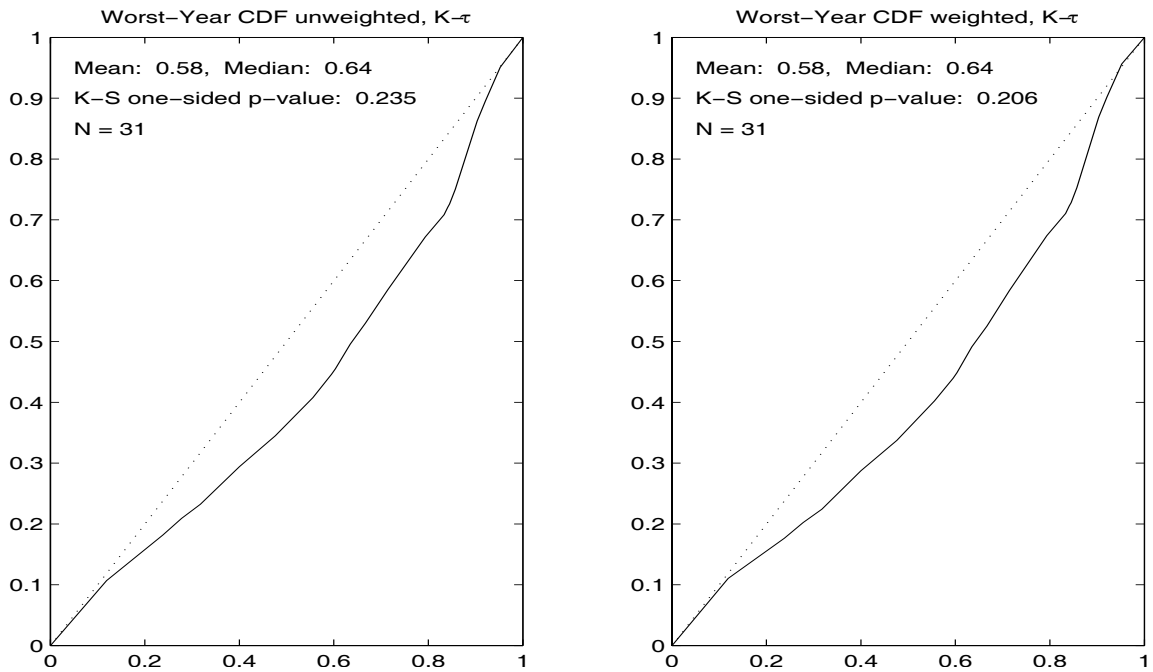


Figure 7: Sample cdf of villages based on Kendall's  $\tau_b$  rank correlations of worst-year and group identity.

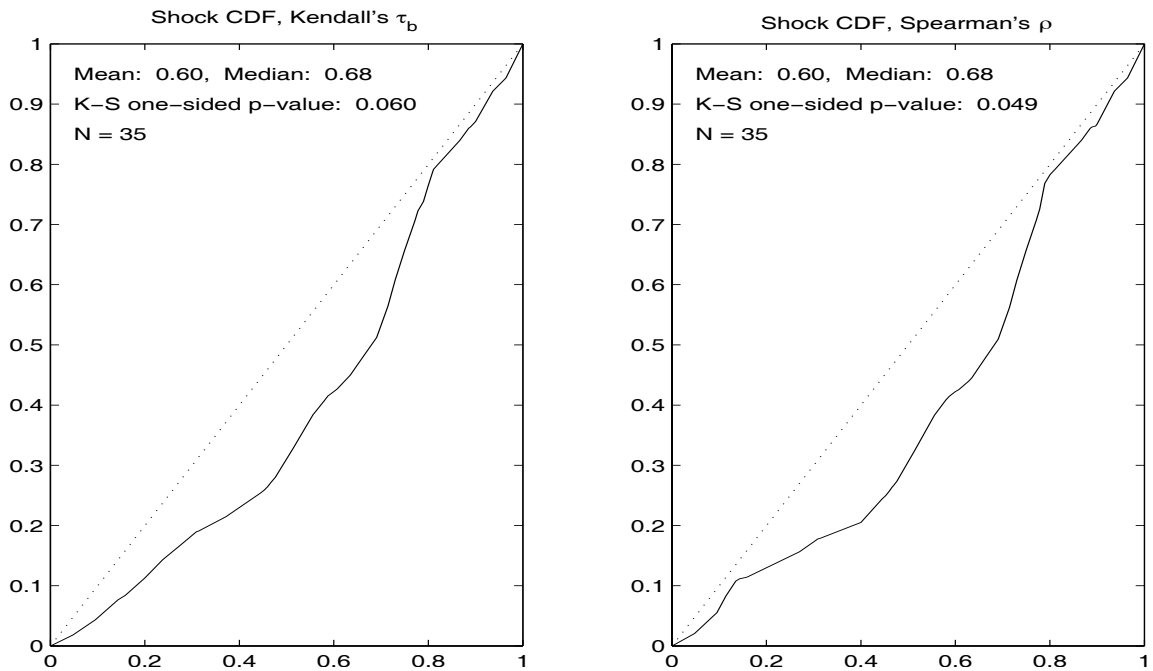


Figure 8: Sample cdf of villages based on rank correlations of income shock and group identity.