Using Repayment Data to Test Across Models of Joint Liability Lending

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Abstract

Theories rationalizing joint liability lending are rich in implications for repayment rates. We exploit this fact to test four diverse models. We show that the models' repayment implications do not always coincide. For example, higher correlation of output and borrowers' ability to act cooperatively can raise or lower repayment, depending on the model. Data from Thai borrowing groups suggest that repayment is affected negatively by the joint liability rate (ceteris paribus) and social ties, and positively by the strength of local sanctions and correlated returns. Further, the relative fit of the adverse selection versus informal sanctions models varies by region.

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A number of theoretical papers explore the key mechanism that gives group loans an advantage over individual loans. But these models take different stands on the underlying economic environment and the problem which groups are imagined to try to overcome. Specifically, we use as springboards to the data four widely cited papers representative of the literature. Two of these papers highlight moral hazard problems which joint liability lending and monitoring can mitigate: Stiglitz (l990) and Banerjee, Besley, and Guinnane (l994). One focuses on an environment of limited contract enforcement and the remedy of village sanctions: Besley and Coate (l995). The fourth shows how adverse selection of borrowers can be partially overcome by joint liability contracts: Ghatak (l999).[1] We take these models as emphasizing the problems of moral hazard, limited commitment, and adverse selection typically thought of as obstacles to trade and the cause of limited (or non-existent) lending by formal financial intermediaries.

The empirical side of research in joint liability lending has lagged relatively far behind. There is little empirical work that views the data through the lens of theory.[2] The point of our paper is to attempt to bridge the gap between theoretical and empirical work.

All four models are found to be rich in predictions regarding the determinants of the group repayment rate. We examine the predictions both of variables already included in the models as published, and especially of new variables we can introduce in a general way. See Table 1 of Section 1 for a summary of theoretical predictions. All predictions are derived holding all else constant; in particular, we discard the lender's zero-profit condition imposed in some of the models. The reason has to do with the lending institution in our data, discussed in more detail in section 2.2.

Some of the more interesting theoretical predictions overturn conventional wisdom and expose conflict between the models. Take cooperation, modeled in this paper as the ability costlessly to commit to a set of actions that is Pareto optimal within the borrowing group. In one moral hazard model, this ability to act cooperatively leads to less risk-taking by eliminating a borrower's ability to free-ride on his partner's safe behavior. Cooperation thus raises the repayment rate. However, in the other moral hazard model and in the limited enforcement model, both of which introduce informal penalties, cooperation can lower repayment by making possible binding agreements not to use excessively harsh penalties. Social capital can thus lower repayment and promote collusion.

Consider next correlation between borrower returns, which none of the original models addresses. We find that under plausible assumptions higher correlation lowers repayment in the limited enforcement model. In that environment, default happens when both borrowers realize low returns; this event is more likely when returns are more correlated. On the other hand, two models illustrate that correlation can raise repayment, for different reasons. In one moral hazard model, higher correlation raises the safe project payoff more than the risky project payoff, because saving the joint liability fee (which correlation raises the odds of) is

[1] Ghatak (2000), Gangopadhyay et al. (2005), and Armendariz de Aghion and Gollier (2000) also examine joint liability lending in the context of adverse selection. We focus on Ghatak (1999) because its focus on pooling contracts (as opposed to the screening contracts of the first two) and strong informational flows among villagers (as opposed to the weak information flows of the third) best fits the setting of our data.

[2] Wydick (1999) provides an exception. Using self-collected data from urban and rural borrowing groups Guatemala, he tests the relative importance of social ties, group pressure, and monitoring in explaining repayment performance. He concludes that measures of monitoring are the strongest positive predictors.

more valuable to risk-averse borrowers when realized returns are moderate, as they are with the safe project. In the adverse selection model, higher correlation similarly raises borrowing payoffs by making execution of joint liability rarer; the effect is to draw in marginal borrowers, who are safer than the average, and raise the expected repayment rate. Correlation may thus have counter-intuitive, positive effects on repayment.

We also find that a higher degree of joint liability can lower repayment, ceteris paribus. One might expect a higher degree of joint liability to increase incentives for repayment-promoting group behavior, whether it be monitoring, penalizing, or screening. This is indeed the result that emerges in one of the moral hazard models. But another moral hazard model shows that joint liability is itself an additional repayment burden and thus may skew incentives toward risky projects; and the adverse selection model shows that higher joint liability pushes marginal, safer borrowers out of the market and lowers the expected repayment rate. These results may seem to counter the original papers' results on the efficiency of group lending; however, they hold with the interest rate fixed, while previous results incorporate joint liability with a simultaneous decline in the interest rate.

Empirical results confirm some of these and other theoretical predictions. We find that cooperation, measured by the degree of intra-group sharing, is negatively associated with repayment. A relatively direct measure of covariance of income shocks is positively associated with repayment. Joint liability within the group, measured by the percent of the group that is landless, is a negative predictor of repayment. We also find that the strength of social sanctions, measured by the likelihood of a village-wide lending shutdown to a defaulter, positively predicts repayment.

The theoretical and empirical results here should also serve to challenge, or refine, the notion that groups succeed because of their ability to access and make use of social collateral. They point to the fact that strong social cohesion may lead to weak incentives to repay, and lack of social cohesion may lead to excessive penalties that actually promote high repayment rates. Evidently, care must be taken in interpreting the interaction between borrower welfare and high repayment rates. Wydick (1999) and Ghatak and Guinnane (1999) make similar points about the ambiguous relationship between social ties and repayment, the latter in the context of several historical and contemporary examples; Rahman (1999) is also related. Here we formalize the theory and provide empirical tests.

We do find that no model matches all the full-sample empirical findings, though each contributes substantially to explaining some of them. Breaking the sample up by region causes some better overall fits to emerge. The limited enforcement model of Besley and Coate does best in the poorer, low-infrastructure Northeast in its prediction that village penalties go with higher repayment. The screening model of Ghatak does best in the wealthier, central region in its predictions that the degree of joint liability payment will decrease repayment and that the loan size has a positive, then negative effect on repayment. Interestingly, follow-up results indicate the regional divergence in results is due less to wealth per se than to whatever factors make commercial banks rarer, perhaps physical and legal infrastructure. The patterns we find suggest that strategic default may be more prevalent problem in low-infrastructure areas, while information problems (in particular adverse selection) may be more prevalent in more developed areas.[3]

[3]The evidence is not direct evidence of a given impediment to trade. Rather, it is evidence about how

Most of the theoretical literature focuses on conditions under which joint liability contracts are optimal relative to individual liability contracts, typically with an endogenous, market-clearing interest rate. For example, in Stiglitz (1990) and in Ghatak (1999), an increase in the degree of joint liability allows profit-maximizing lenders to lower the interest rate and induce safer project choice or draw in safer borrowers. In a competitive equilibrium, lenders still make zero profits but borrower welfare is enhanced through joint liability. Direct tests involve relating the prevalence of joint liability versus individual liability contracts or other outside options against the covariates suggested by the models. In a companion paper, Ahlin and Townsend (forthcoming), we use this direct approach to test predictions of Holmström and Milgrom (1990), the related Prescott and Townsend (2002), and Ghatak (1999). We find, consistent with the theory, that intra-village wealth heterogeneity predicts group, joint liability contracts, and further that there is a U-shaped relationship of group borrowing with household wealth. We also find strong evidence for adverse selection, and distinguish this finding from one for moral hazard.

In this paper we adopt an indirect, but equally telling, approach. Specifically, we test the models' implications for borrower repayment rates, *given* the joint liability contract is in use. We are thus not attempting to assess directly the effect of group lending on repayment.[4] Instead, we are finding determinants of repayment in a group lending context and using this as evidence for or against group lending models. The probability of repayment plays a fundamental role in each model's setup and results, and is therefore a useful key for unlocking and examining the mechanics of each of the models. We therefore turn our attention from contract choice per se to those internal mechanics. The exception in this paper is our addition to the model of Ghatak, in which both loan size (borrow less than offered) and whether to enter into a group (borrow at all under joint liability) are two individual selections which determine how observed repayment should vary with observed loan amounts.

1 Theories and Implications

We discuss next the specific setups of the four models, focusing on the mechanics and intuition behind their *repayment implications.* That is, if p is the group probability of repayment and X is a key determinant of p, we attempt to sign $\partial p/\partial X$ is as general a way as possible. These are not, for the most part, the theoretical results of the published papers, which focus on comparing the efficiency of joint liability and individual liability; we are therefore in uncharted territory. All repayment results are essentially partial derivatives, i.e. are derived without imposing a zero-profit condition on the bank, a decision we discuss in section 2.2.

For purposes of comparing the models and fully using our data to address key questions, we introduce new variables when this is possible in a relatively general way and with a minimum of assumptions. The implications of the various models, some of which we derive

well a model that features a given impediment to trade does in explaining repayment data. In this context, lack of evidence for a given model may be due to its featured impediment to trade being less important *or* to its auxiliary assumptions failing to hold.

[4]Using cross-institution, cross-country regressions, Cull et al. (this issue) find that higher interest rates and less direct monitoring are associated with greater portfolio at risk for lenders using individual contracts, but not for lenders using group contracts. They argue this suggests that group lending mitigates information problems directly, lessening the need to rely on lower interest rates or direct monitoring.

in this section and the rest of which can be found in Ahlin and Townsend (2002), but all of which will be tested empirically, are summarized in Table 1. The models' predictions agree along some dimensions and disagree along others. We do not claim that a prediction by a model here is general to all models in its genre (moral hazard, adverse selection, etc.), nor that our way of modeling a particular phenomenon is the only way (except when generality is claimed). Further, we do not claim these models are the best possible choices among all alternatives to fit the data. Still, we view the results as indicative about how leading representatives of each genre work.

[Table 1 about here]

In the following analysis, we omit some details and adopt common notation wherever possible. All the models analyze groups of size two in a static setting of limited liability. Both members of a group face the same contract terms.[5] Three of the models restrict attention to binomial output distributions, while the fourth allows for more general distributions. Omitted proof details can be found in Ahlin and Townsend (2002).

1.1 Moral Hazard: Stiglitz 1990

When liability is limited, borrowers may prefer project outcome distributions with greater probability weight in the tails. This is because the lower tail outcomes are effectively subsidized by the lender. In essence, limited liability raises the incentives to gamble. Stiglitz addresses this kind of moral hazard and shows how joint liability decreases group incentives to gamble by giving each borrower a stake in the success of his partner.

Each borrower receives a loan L and chooses a risky or safe project, producing output $Y(p_R, L)$ with probability p_R or $Y(p_S, L)$ with probability $p_S > p_R$, respectively. The complementary probabilities result in zero output. The safe project gives higher expected output, but lower output when successful:[6]

$$p_S Y(p_S, L) > p_R Y(p_R, L) \quad \textit{and} \quad Y(p_S, L) < Y(p_R, L). \tag{A1}$$

Limited liability can skew incentives toward the less efficient, risky project.

Joint liability contracts take the following form. The lender gets nothing from a borrower who fails (due to limited liability), rL from a borrower who succeeds, and an additional payment qL from a borrower who succeeds and whose partner fails. Expected utility of a borrower who chooses technology i and whose partner chooses technology j, call it V_{ij}, can be written, under independent returns and standard utility function $U(\cdot)$,

$$V_{ij}(r, L, q) = p_i p_j U[Y(p_i, L) - rL] + p_i(1 - p_j)U[Y(p_i, L) - rL - qL], \; i, j \in \{R, S\}. \tag{1}$$

The first term represents the expected payoff from both borrowers succeeding, the second from borrower i succeeding and borrower j failing.

[5]In general, the theory we examine does not take into account intra-group heterogeneity, though this clearly exists in the data. The exception is Ghatak, who allows for intra-group heterogeneity in risk-type but shows that it does not exist in equilibrium.

[6]This latter assumption is not explicit in the paper, but if not true, a risky project would have no redeeming feature in comparison with a safe one and would never be chosen.

The paper assumes cooperative behavior and restricts attention to symmetric choices. Thus a group makes whichever symmetric project choice gives each member higher utility:

$$p = p_R \cdot 1\{V_{SS}(r, L, q) < V_{RR}(r, L, q)\} + p_S \cdot 1\{V_{SS}(r, L, q) \geq V_{RR}(r, L, q)\}, \tag{2}$$

where $1\{\cdot\}$ represents the indicator function. In this context, *the impact of some variable X on the repayment rate p is determined by whether a change in X tilts incentives more toward the safe or risky project.* For example, if $\partial V_{SS}/\partial X > \partial V_{RR}/\partial X$, then the repayment rate p is increasing in X, in the sense that there may exist a cutoff value in the range of X values above (below) which safe (risky) projects are chosen.

Stiglitz shows that in this sense the repayment rate is declining in r and L. An increase in r makes success more onerous and raises the implicit, relative subsidy to failure, encouraging gambling. An increase in L raises the risky payoff relative to the safe one, by a direct assumption Stiglitz makes. These results are represented graphically in Fig. 1. The "**Switch Line**" gives combinations of (r, L) that leave the borrowers indifferent between projects: $V_{SS} = V_{RR}$. Above it (higher r) or to the right (higher L), risky projects are preferred; below it, safe projects.

[Fig. 1 about here]

1.1.1 Checking q

To examine the effect of q on repayment we use a substantive assumption:

$$p_S(1 - p_S) \geq p_R(1 - p_R). \tag{A2}$$

This ensures that asymmetric borrower outcomes, which involve a payment of the joint liability fee, occur more often with safe than with risky projects.

Proposition 1. *Under assumptions A1 and A2, the group repayment rate is lower for groups with higher q.*

Proof. We compare $\partial V_{SS}/\partial q$ with $\partial V_{RR}/\partial q$. ■

Higher joint liability lowers the payoff of either project (importantly, with r fixed). Which payoff it hurts *more* depends on two factors: 1) in which project is qL paid more often and 2) under which project is the utility loss of paying qL greater, conditional on paying it. Assumption A2 guarantees that the safe project involves paying qL more often. Assumption A1 guarantees that the payment costs more in utility terms with a safe project, since output is lower there (and utility is concave); in other words, after gambling and winning, it is less painful to make an extra payment. In short, the joint liability payment is paid more often and during times of lower income under the safe project choice, so an increase in q tilts incentives toward risky projects.[7] Graphically, the result on q would be represented by shifting the Switch Line left as q increases.

[7] If assumption A2 did not hold and risky projects involved asymmetric outcomes more often, then the result would depend on how big this difference in frequency of outcomes were, how risk-averse the borrowers are, and how large risky output is relative to safe output.

1.1.2 Subtracting cooperation

In a departure from the Stiglitz model, assume borrowers play non-cooperatively: both choose safe projects only if neither can gain by deviation to a risky project. The condition for both to choose safe projects is $V_{SS} \geq V_{RS}$, which is stronger than $V_{SS} \geq V_{RR}$ of the cooperative case, since (using equation 1)

$$V_{RS} - V_{RR} = p_R(p_S - p_R)\left\{U[Y(p_R, L) - rL] - U[Y(p_R, L) - (r+q)L]\right\} > 0. \quad (3)$$

Proposition 2. *The group repayment rate is higher for groups acting cooperatively.*

With non-cooperative behavior, the temptation to free-ride on one's partner's safe behavior sometimes derails the symmetric safe-project equilibrium. Non-cooperative groups choose risky projects more often. Graphically, the Switch Line for non-cooperative groups is shifted down as compared to the cooperative Switch Line, as in Fig. 1.

1.1.3 Adding correlation

A final modification to the model introduces correlation in borrower output realizations.[8] Let the joint probability distribution for the returns of a borrowing group choosing projects that succeed with probability p_i and p_j be

	j Succeeds (p_j)	j Fails ($1-p_j$)
i Succeeds (p_i)	$p_i p_j + \epsilon$	$p_i(1-p_j) - \epsilon$
i Fails ($1-p_i$)	$(1-p_i)p_j - \epsilon$	$(1-p_i)(1-p_j) + \epsilon$

A positive ϵ adds probability to the symmetric events (both-succeed and both-fail) and subtracts it from the asymmetric events; and vice versa for a negative ϵ. The zero-correlation case assumed above has $\epsilon = 0$, while $\epsilon > 0$ ($\epsilon < 0$) implies positive (negative) correlation.

Any joint distribution that preserves p_i and p_j as the unconditional probabilities of success must take this form.[9] However, for each (p_i, p_j) combination, ϵ could in theory be different. Restricting attention to symmetric project choices as before, there are two potentially different correlation structures: $\epsilon_R \equiv \epsilon(p_R, p_R)$ and $\epsilon_S \equiv \epsilon(p_S, p_S)$. These capture the degrees of covariance across safe and risky projects, respectively.

We focus on two cases in which covariance structure is in some sense independent of project risk. The first variation on this assumption is

$$\epsilon(p, p) = \epsilon. \quad \text{(A3)}$$

The second variation ensures that both the safe and risky project distributions have the same *correlation coefficient*, equal to ρ, as straightforward calculation verifies:

$$\epsilon(p, p) = \rho * p(1-p). \quad \text{(A4)}$$

Under either assumption, the probability of success is as in equation 2, with payoffs equal to

$$V_{kk} = (p_k^2 + \epsilon_k)U[Y(p_k, L) - rL] + [p_k(1-p_k) - \epsilon_k]U[Y(p_k, L) - (r+q)L], \quad k \in \{R, S\}. \quad (4)$$

[8] A similar modification to a model of strategic default is analyzed by Armendariz de Aghion (1999).

[9] This follows from the fact that the entries in row one (column one) must add to p_i (p_j), and the entries in row two (column two) must add to $1 - p_i$ ($1 - p_j$).

Proposition 3. *Under assumptions A1 and A3, or under assumptions A1, A2, and A4, the group repayment rate is higher for groups with higher project return correlation.*

Correlation shifts probability weight from the state in which a borrower is successful and his partner fails to the state in which both borrowers are successful. This shift is more valuable with the safe project, since output is lower and thus the utility gain from not paying qL is higher there. This somewhat surprising result contrasts with the common assumption of the empirical literature that positive correlation is bad for repayment. This model makes clear it can differentially raise payoffs of safe projects, lowering the temptation to gamble.

1.2 Moral Hazard: Banerjee, Besley, Guinnane 1994

BBG focus on the same moral hazard problem as Stiglitz: the temptation of limited liability borrowers to gamble with riskier projects. The key differences are in agents' risk neutrality, role asymmetry, and in the introduction of monitoring backed by punishment capability.[10] Combined with joint liability, threatened punishments can reduce incentives for risk-taking.

Groups are asymmetric: they consist of one member who borrows and a cosigner who monitors.[11] The borrower receives one unit of capital and chooses a project indexed by $p \in [\underline{p}, 1]$, where $\underline{p} > 0$. As in Stiglitz, the project return is $Y(p)$ with probability p and zero otherwise. The lender collects r from the borrower when his project is successful and q from the cosigner otherwise (loan size is normalized to one).

The risk-neutral borrower's payoff (gross of any penalties) is thus $p[Y(p)-r] = E(p)-pr$, where $E(p) \equiv pY(p)$ is expected output. By assumption, expected output is increasing in p, as in Stiglitz; $p = 1$ is thus socially optimal. Also assumed is that the interest rate and loan size are such that given limited liability, the borrower prefers riskier projects to safer ones, and left alone will gamble with $p = \underline{p}$. Specifically:

$$0 < E'(p) < r \quad \textit{and} \quad E''(p) \leq 0, \tag{A5}$$

implying that expected output is decreasing in risk but the borrower's expected payoff is increasing in risk.

The monitor can penalize the borrower based on his project choice. A penalty that costs the borrower c to bear costs the monitor $M(c)$ to impose, with M increasing and convex. The minimum penalty needed to enforce project p exactly outweighs the borrower's gain from deviating to the riskiest project $p = \underline{p}$. It is

$$c(p, r) = E(\underline{p}) - \underline{p}r - [E(p) - pr]. \tag{5}$$

The monitor then chooses p to maximize payoff

$$(1-p)(-q) - M[c(p, r)],$$

[10]We modify their model by shutting down lending within the group. As BBG show, this departure is appropriate assuming the outside lender has a lower cost of funds.

[11]This is not an a priori unreasonable description of our data, since not all group members take loans every year.

which includes the joint liability fee q, paid with probability $(1-p)$, and the monitoring cost of implementing p. The first-order condition is

$$q = M'[c(p,r)]c_p(p,r) = M'[c(p,r)]\,[r - E'(p)]. \tag{6}$$

We call this the **Monitoring Equation**. The benefit of more monitoring (left-hand side) is saving the joint liability fee q more often. The cost of more monitoring (right-hand side) is proportional to the marginal cost of penalizing, $M'(c)$, and the size of the additional penalty needed to lower risk, $c_p(p,r)$, which captures the severity of the moral hazard problem. Costs and benefits are graphed against p in Fig. 2.

[Fig. 2 about here]

Repayment effects of some variable X, say, come through the effects of X on the costs and benefits of monitoring. They can be derived by totally differentiating the Monitoring Equation with respect to p and X to obtain $\partial p/\partial X$.

1.2.1 Checking q

An increase in joint liability q raises the benefit of monitoring without affecting the cost. The unambiguous result is more monitoring and less risk-taking by the borrower.

Proposition 4. *Under assumption A5, the group repayment rate p is higher for groups with higher joint liability payment q.*

Interestingly, the prediction for q is opposite that of the Stiglitz model. In BBG, greater liability creates incentives for more intense group pressure to perform well. Stiglitz incorporates not only this effect, but also the idea that the joint liability payment acts like an additional tax on success, since only a successful borrower pays it.

1.2.2 Adding L

Here we let loan size L vary, as in Stiglitz. Assuming separability, we write

$$Y(p,L) = Y(p,1)F(L). \tag{A6}$$

Usual assumptions are made on F, including (weak) concavity. We let $E(p) \equiv pY(p,1)$, so that expected output equals $E(p)F(L)$. The amounts due from the borrower upon success and the monitor upon failure, respectively, are rL and qL. The analog to assumption A5, ensuring a moral hazard problem, is

$$0 < E'(p)F(L) < rL \quad \textit{and} \quad E''(p) \leq 0. \tag{A7}$$

Proposition 5. *Under assumptions A6 and A7, the group repayment rate is lower for groups with higher L.*

Proof: see Appendix A.

A larger loan from the lender raises the cost of monitoring for two reasons. First, under diminishing returns it increases the interest payment (rL) relatively faster than the gross returns ($F(L)$);[12] since risky projects avoid repaying the loan more often, they become relatively more attractive to the borrower, and the monitor must threaten stiffer penalties. Second, even under constant returns, a larger loan scales up required penalties and therefore makes the marginal penalty more costly, since the cost of imposing penalties is convex.

1.2.3 Adding cooperation

Assume the monitor and borrower can enforce any joint agreement on project choice *costlessly*, as in Stiglitz. They will thus maximize the sum of payoffs. The problem becomes to choose p in order to maximize

$$E(p) - pr - (1-p)q,$$

the sum of net payoffs of the borrower and monitor. The first order condition can be written

$$q = r - E'(p). \tag{7}$$

Comparison with non-cooperative Monitoring Equation 6 reveals as the critical condition whether $M'(c)$ is greater or less than one. If less, the non-cooperative sloped line in Fig. 2 is lower than the cooperative one, and the resulting p is lower under cooperation.

Proposition 6. *Under assumption A5, the group repayment rate is lower for groups that can cooperate and enforce side-contracts if $M'(c) < 1$ and higher if $M'(c) > 1$.*

The cooperative setup is isomorphic to the non-cooperative case where $M(c) = c$, where the monitor can apply penalties that affect the borrower's payoff at a one-for-one cost to the monitor's own payoff (or equivalently, pay a bonus contingent on project choice). If the marginal cost of penalizing is less than (greater than) one, then the monitor enforces a safer project (riskier project) than in the group-surplus maximizing case, and non-cooperation results in a higher (lower) repayment rate.

This prediction (when $M'(c) < 1$) is counter to that of the Stiglitz model, where cooperation enables the group to circumvent free-riding. Here, non-cooperative behavior facilitates the monitor's use of cheap penalties to enforce a higher probability of repayment than is optimal from the group's perspective. The common idea that social capital leads to better-behaving groups may thus be turned on its head. Lenders may even prefer groups with less social capital if this translates into less ability to collude.

1.3 Strategic Default: Besley, Coate 1995

In BC, project choice is fixed; the game begins after project outcomes have been realized as borrowers decide whether or not to repay. The cost of repayment is the gross interest rate r (loan size is normalized to one). The benefit of repayment is avoiding penalties imposed

[12] This holds true in the parameter space governed by assumption A7, that is, where there is a moral hazard problem.

by the lender and, under joint liability, penalties imposed by the group or community. Joint liability is found to raise repayment rates if these informal sanctions are strong enough.

The two borrowers' returns are drawn independently from distribution $F(Y)$, with support $[0, Y_{max}]$. Repayment decisions are then made non-cooperatively.[13] Joint liability here implies that if the lender does not receive the full repayment amount from the group, $2r$, he imposes an *official penalty* on each borrower. The penalty on borrower i depends on borrower i's output, so we write it as $c^o(Y_i)$. It is increasing in Y_i but always less than Y_i, by assumption. In other words, the lender penalizes more severely when output is higher, but never as severely as outright confiscation. Since penalties depend positively on output, borrowers who realize high returns (low returns) will choose to repay (default). One can define a cutoff function

$$\underline{Y}(r) \equiv (c^o)^{-1}(r). \tag{8}$$

By construction, when weighing repaying r against incurring penalties $c^o(Y)$, repayment is more attractive if $Y \geq \underline{Y}(r)$ and default is more attractive if $Y < \underline{Y}(r)$. Above $\underline{Y}(r)$, official penalties are greater than r, and vice versa.

It is now possible to classify most outcomes by whether the group will repay or not. First, if both borrowers realize returns $Y_i, Y_j < \underline{Y}(r)$, the group will default. Official penalties are not strong enough to give incentives for either borrower to pay r. This outcome corresponds to box A in Fig. 3. Second, if both borrowers realize returns $\underline{Y}(r) \leq Y_i, Y_j < \underline{Y}(2r)$, the group will repay. Both borrowers prefer repaying r to incurring official penalties.[14] This outcome corresponds to box B in Fig. 3. Third, if either borrower realizes return $Y \geq \underline{Y}(2r)$, the group will repay. This is because the more successful borrower will bail out the group if he has to, since paying $2r$ is better than incurring official penalties when returns are this high. This corresponds to the unlabelled part of the unit square in Fig. 3.

[Fig. 3 about here]

The remaining case is the one in which there is disagreement, but neither borrower is willing to bail out the group: $Y_i < \underline{Y}(r)$ and $\underline{Y}(r) \leq Y_j < \underline{Y}(2r)$, say. This corresponds to boxes AB in Fig. 3. Here, borrower i prefers to default while borrower j prefers to repay, his own share at least, but not pay for both. With no further assumption, the group defaults. However, BC introduce informal penalties that are imposed on a borrower i, say, who decides to default when his partner j would want to repay. The effect of the *unofficial penalty* is to increase the willingness to repay of the low-output borrower in these situations of disagreement. If informal penalties are arbitrarily severe, nearly all of these situations result in group repayment, and vice versa if they are arbitrarily weak.

By assumption, the unofficial penalty, $c^u(Y_i, \Lambda_j)$, depends on two things. One is the delinquent borrower i's ability to repay, Y_i. The second is his partner j's desire to repay, proportional to his gain from repayment relative to default, $\Lambda_j \equiv c^o(Y_j) - r$. More generally, one can define a new cutoff output level above which repayment is optimal, accounting for

[13] For the details of the game, see BC. In short, the borrowers decide simultaneously whether or not to repay r in a first stage. If the decision is not unanimous, the borrower who decided in the first stage to repay can revise his decision in a second stage, paying 0 or $2r$.

[14] In this case there can also be a default equilibrium due to group coordination failure. We assume along with BC that the borrowers' preferred equilibrium (repayment) is played.

both official and unofficial penalties. Call this cutoff $\hat{\underline{Y}}(r, Y_j)$ for borrower i, say.[15] It depends on the partner's output Y_j in the following way: the higher Y_j, the stronger are the partner's desire to repay and thus the higher unofficial penalties, so the lower is $\hat{\underline{Y}}$.

In summary, default occurs in two circumstances only: when both borrowers' realizations are below $\underline{Y}(r)$, and when one realizes output $\underline{Y}(r) \leq Y_j < \underline{Y}(2r)$ and the other $Y_i < \hat{\underline{Y}}(r, Y_j)$. The repayment rate p is thus

$$p = 1 - [F(\underline{Y}(r))]^2 - 2 \int_{\underline{Y}(r)}^{\underline{Y}(2r)} F(\hat{\underline{Y}}(r, Y)) dF(Y). \tag{10}$$

In Fig. 3, the set of joint output realizations leading to default, the **Default Region**, consists of box A and some parts of the AB boxes. In particular, there is a curve running through the AB boxes and the point (a, a), below which repayment does not happen (the dashed curve here). This curve represents $\hat{\underline{Y}}(r, Y)$, and is thus lower when unofficial penalties are stronger.

In this context, *the effect of any variable on repayment will come either as it changes the boundaries of the Default Region, via a change in costs or benefits of repayment, or as it changes the probability of falling into the Default Region.*

1.3.1 Checking official and unofficial penalties

Stiffer penalties raise the cost of default and do not affect the cost of repayment. Interestingly, stiffer official penalties also can raise unofficial penalties, since they raise the non-delinquent borrower's desire to repay. Graphically, stronger penalties shrink the Default Region in Fig. 3 via a lowering of a, b, and the $\hat{\underline{Y}}$ curves.

Proposition 7. *The repayment rate is higher for groups with stronger official or unofficial penalties.*

1.3.2 Adding cooperation

Assume borrowers can costlessly enforce agreements among themselves. Since utility is transferable, they will maximize the sum of payoffs and repay if and only if the sum of official penalties is greater than the group's total debt:

$$c^o(Y_i) + c^o(Y_j) \geq 2r. \tag{11}$$

An indifference curve in joint output space can be defined, below which the group defaults. Note that every point of indifference occurs in exactly the situations of disagreement discussed above (the AB boxes in Fig. 3), where one borrower realizes low output, $Y < \underline{Y}(r)$, and the other moderate output, $\underline{Y}(r) \leq Y < \underline{Y}(2r)$. If both realize low output (box A),

[15] $\hat{\underline{Y}}(r, Y_j)$ is defined implicitly, to satisfy

$$r = c^o(\hat{\underline{Y}}) + c^u[\hat{\underline{Y}}, c^o(Y_j) - r]. \tag{9}$$

At $\hat{\underline{Y}}$, it is equally costly to pay r and to suffer default penalties. Above $\hat{\underline{Y}}$, official and possibly unofficial penalties increase, making it strictly better to pay r; below $\hat{\underline{Y}}$, the reverse is true.

penalties are clearly too low to encourage repayment; if both realize moderate output (box B) or one realizes high output (the unlabelled region), penalties are sufficient.

The repayment condition 11 at equality, using the definition of $\underline{Y}$ as $(c^o)^{-1}$, is $Y_i = \underline{Y}[2r - c^o(Y_j)]$. Thus the indifference curve is decreasing and goes through $(0, \underline{Y}(2r))$, $(\underline{Y}(r), \underline{Y}(r))$, and $(\underline{Y}(2r), 0)$ (respectively, $(0, b)$, (a, a), and $(b, 0)$ in Fig. 3). An example (under linear official penalties) is the dash-dotted line in Fig. 3. Below this line is the *cooperative* Default Region. The cooperative repayment rate can be written

$$p = 1 - [F(\underline{Y}(r))]^2 - 2 \int_{\underline{Y}(r)}^{\underline{Y}(2r)} F[\underline{Y}(2r - c^o(Y))] dF(Y). \tag{12}$$

Comparison with equation 10 reveals that the severity of unofficial penalties, which cooperation renders unused, determines the effect on the repayment rate. If unofficial penalties are severe, the cutoff $\hat{\underline{Y}}(r, Y)$ is low and the non-cooperative repayment rate is higher; and vice versa. Graphically, *non-cooperative* Default Regions under weak and strong unofficial penalties are demarcated, respectively, by the dashed and dotted curves in Fig. 3.

Proposition 8. *The repayment rate is lower (respectively, higher) for groups acting cooperatively if unofficial penalties are greater than (respectively, less than) the non-defaulting borrower's loss from default.*[16]

The cooperative setup is isomorphic to the non-cooperative case where $c^u(Y, \Lambda) = \Lambda$, under which the unofficial punishment exactly fits the "crime", i.e. the cost to the partner of default. If unofficial penalties are more severe, there are output realizations where *official* penalties on the group would be less than $2r$, yet the low-output partner repays to avoid the *unofficial* penalties. If acting cooperatively, the low-output borrower could instead compensate his partner directly for his loss Λ, leaving some surplus to be split as the group defaults. As with BBG and for similar reasons, the common idea that social capital leads to better-behaving groups may thus be turned on its head.

1.3.3 Adding correlation

Here we introduce correlation between project returns. Unlike the previous two exercises, this leaves the Default Region unchanged but alters the probability of falling into it. No perfectly general results are available; it is clearly possible to increase overall correlation while lowering the chance of falling into the Default Region, and the reverse. Our aim is to analyze a symmetric, parametric yet general correlation structure, as in the earlier section 1.1.3.

The basic idea in our parameterization is to raise the probability of similar outcomes (Y_i near Y_j) and lower the probability of dissimilar outcomes (Y_i far from Y_j). Accordingly, we add or subtract probability mass relative to (a transformation of) an arbitrary monotonic polynomial function of the absolute difference $|Y_i - Y_j|$. For details, see the discussion leading up to Assumption A9 in the appendix as well as Ahlin and Townsend (2002).

[16]Specifically, $c^u(Y_i, \Lambda_j) > \Lambda_j$ for all $Y_i \geq 0$ and $\Lambda_j > 0$ implies the cooperative repayment rate is lower and $c^u(Y_i, \Lambda_j) < \Lambda_j$ for all $Y_i \geq 0$ and $\Lambda_j > 0$ implies the cooperative repayment rate is higher. To see this, note that setting $c^u(Y_i, \Lambda_j) = \Lambda_j = c^o(Y_j) - r$ in equation 9 of the previous footnote gives that $\underline{Y}[2r - c^o(Y_j)] = \hat{\underline{Y}}(r, Y_j)$ for $Y_j \in (\underline{Y}(r), \underline{Y}(2r))$, which equates the default probabilities.

Proposition 9. *Under Appendix assumption A9, and if unofficial penalties are severe enough, the repayment rate is lower for groups with higher covariance of returns.*

Proof: see Appendix A.

As discussed above, default occurs in two types of situations. If both returns are low, i.e. less than $\underline{Y}(r)$ (box A in Fig. 3), borrowers unanimously default. Higher correlation raises the probability of this event since borrower outcomes are relatively similar (both low). Default also occurs when one borrower wants to repay but only for himself, $\underline{Y}(r) \leq Y_j < \underline{Y}(2r)$ say, and the other borrower wants to default despite official and unofficial penalties, $Y_i < \hat{\underline{Y}}(Y_j)$ (boxes AB below the Default Region boundary). This event is arbitrarily rare as unofficial penalties get stronger. Thus, while higher correlation may raise or lower the probability of this event,[17] the effect is arbitrarily small relative to correlation's effect on the prevalence of unanimous default. Graphically, strong unofficial penalties eliminate arbitrarily much of the AB boxes from the Default Region, guaranteeing that the probability mass added or subtracted within box A is the dominant effect of correlation.[18]

1.4 Adverse Selection: Ghatak 1999

Here agents' project types are fixed and they repay whenever possible; their only decisions are whether and with whom to borrow. Due to the same kind of limited liability as in Stiglitz and BBG, borrowing is more attractive to agents with riskier projects. Safe borrowers may thus be excluded from the market. Joint liability, Ghatak shows, can be used to take advantage of information borrowers have about each other's types to draw into the market borrowers who would otherwise be excluded.[19]

Agents weigh the outside, non-borrowing option payoff $\underline{u} > 0$ against that of undertaking their endowed project using capital borrowed in a joint liability group. Agents differ in the riskiness of their endowed projects; there is a density $g(p) > 0$ of borrowers at each project type $p \in [\underline{p}, 1]$. Project type is observable among borrowers but not to the outside lender. As in Stiglitz and BBG, an agent carrying out a project of type p realizes output $Y(p)$ with probability p and zero otherwise. As in Stiglitz, a borrower pays gross interest rate r if he

[17]Note that here borrower outcomes may be relatively similar – for example, Y_i, Y_j near $\underline{Y}(r)$ – or dissimilar – for example, Y_i near zero and Y_j near $\underline{Y}(2r)$.

[18]Even with our correlation parameterization, no simple result is available without assuming unofficial penalties are strong. To see this, imagine unofficial penalties are arbitrarily weak, and official penalties are sufficiently weak that no borrower would ever bail out the other but strong enough to induce individual repayment sometimes ($\underline{Y}(2r) > Y_{max} > \underline{Y}(r)$). In this case, default occurs in every case except when both borrowers are successful, $Y_i, Y_j \geq \underline{Y}(r)$. This non-default outcome involves relatively similar returns (both high); thus higher correlation raises its probability and makes default less likely. (Graphically, this corresponds to $b \geq 1$ in Fig. 3 and weak unofficial penalties; the only area leading to repayment would be a single box in the upper-right corner of (Y_i, Y_j) space.) This result would require joint assumptions on $F(\cdot)$, r, c^o, and c^u.

[19]Joint liability can be used to screen borrowers, as examined in Ghatak (2000); safer borrowers are more willing to accept higher q since their partners are safer. Here we focus on the pooling case of Ghatak (1999), where joint liability improves efficiency by lowering the subsidy to risk-taking. The BAAC seems to be pooling, not screening, since they offer just one standard group contract in terms of interest rates and joint liability stipulations (though q may vary for reasons outside the contract, e.g. landholdings). The BAAC does offer individual contracts also, but they require collateral, so the screening there is best thought of as on collateral.

succeeds and an additional joint liability payment q if he succeeds and his partner fails (loan size is normalized to one). Thus, a borrower of type p who pairs with one of type p' has expected payoff

$$pY(p) - pr - p(1 - p')q. \tag{13}$$

This incorporates risk neutrality but is otherwise identical to Stiglitz (equation 1).

The first decision centers on group formation: who pairs with whom? Ghatak shows that groups form *homogeneously* in risk-type, p. While everyone would prefer a safer partner, safe borrowers prefer them more strongly, since they succeed more often and thus are in the position of being potentially liable for their partner more often. Thus $p' = p$ in payoff 13.

The second decision is whether or not to borrow. In contrast to Stiglitz and BBG, benefits of borrowing, $pY(p)$, are assumed not to vary with project risk:

$$pY(p) = E, \quad \forall p \in [\underline{p}, 1]. \tag{A8}$$

Thus all borrowers have equally worthwhile projects in an expected value sense, but differ only in second-order risk (higher p implies lower risk, e.g. variance). However, costs of borrowing, i.e. expected repayment $pr + p(1 - p)q$, do vary: they are higher for safer borrowers (for $q \leq r$), since payments to the bank are made only upon success. Thus, assuming that not everyone borrows, only borrowers riskier than some cutoff risk-type will borrow, while safer borrowers will take the outside option. This marginal type, $\hat{p}$, solves the following **Selection Equation**:

$$E - \hat{p}r - \hat{p}(1 - \hat{p})q = \underline{u}, \tag{14}$$

which sets the borrowing payoff of the marginal type equal to the outside option. Only agents with $p \in [\underline{p}, \hat{p}]$ borrow. Expected repayment burdens are too high for safer borrowers.

Unlike the others, this model does not produce a probability of repayment p as a function of key variables (r, q, and so on). Rather, it delivers a *range* for the probability of repayment, $[\underline{p}, \hat{p}]$, where $\hat{p}$ is a function of key variables through the Selection Equation. Observing r, q, and so on, our best guess for the repayment rate is then $E(p|p \leq \hat{p}) \equiv \tilde{p}$; $\tilde{p}$ is thus the analog to the p's of the other models. Since $\tilde{p}$ varies positively and monotonically with $\hat{p}$ ($d\tilde{p}/d\hat{p} > 0$), we can focus on $\hat{p}$ rather than $\tilde{p}$.

Thus the Selection Equation is the key to understanding repayment determinants. In general, *any change that makes borrowing more attractive draws in more borrowers; and since a larger borrowing pool is a less risky one (the marginal borrowers are always the safer than the average borrowers), this raises the expected repayment rate.*

1.4.1 Checking q

A higher joint liability payment makes borrowing relatively less attractive. Thus the higher a group's q, the smaller and more risky the pool from which it is drawn.

Proposition 10. *Under assumption A8, the expected group repayment rate is lower for groups with higher q.*

Proof. By total differentiation of the Selection Equation, $\partial\hat{p}/\partial q < 0$ for $q \leq r$. ■

1.4.2 Subtracting screening ability

What happens when homogeneous matching is replaced with random matching? In particular, assume that borrowers do not know each other's types, but only the distribution of borrowing types. Matching is random and each borrower expects to match with a partner of average risk within the borrowing pool. Compared with homogeneous matching, safe borrowers are worse off and risky borrowers better off. Since safe borrowers are the marginal ones, they are driven out of the market and the residual borrowing pool is more risky.

Specifically, the expected repayment rate is $\tilde{p}' \equiv E(p|p \leq \hat{p}')$, where $\hat{p}'$ is the new cutoff risk-type, defined as the value[20] for p satisfying a modified Selection Equation

$$E - \hat{p}'r - \hat{p}'(1 - \tilde{p}')q = \underline{u}. \tag{15}$$

The left-hand side involves the expectation over all potential partners, which is just $\tilde{p}'$ when the marginal type is $\hat{p}'$. For $p < \hat{p}'$ ($p > \hat{p}'$), the payoff $E - pr - p(1 - \tilde{p}')q$ is strictly larger (smaller) than $\underline{u}$. Thus $\hat{p}'$ is the equilibrium cutoff risk-type.

Proposition 11. *Under assumption A8, the expected group repayment rate is higher for groups with the ability to screen.*

Proof. Equation 14, equation 15, and the fact that $\hat{p}' > \tilde{p}'$, respectively, give that

$$E - \hat{p}r - \hat{p}(1 - \hat{p})q = \underline{u} = E - \hat{p}'r - \hat{p}'(1 - \tilde{p}')q < E - \hat{p}'r - \hat{p}'(1 - \hat{p}')q. \tag{16}$$

Since $E - pr - p(1 - p)q$ is decreasing in p, inequality 16 implies that $\hat{p}' < \hat{p}$. ■

1.4.3 Adding loan size

Here we take a simple version of loan size determination: the lender makes loan offers that are random across groups, but equal for both borrowing partners within a group. Borrowers then choose to borrow any amount up to the lender's offer, or take their outside option. Assumptions A6 and A8 give the borrower payoff, under loan size L and homogeneous matching, as

$$EF(L) - prL - p(1 - p)qL. \tag{17}$$

We assume some properties of F in the appendix, including strict concavity and Inada conditions.

The effect of a change in loan size on expected repayment is non-monotonic. First, assume loan sizes are small, such that all borrowers would prefer larger loans. Observing a higher loan size means borrowing is more attractive relative to the outside option. Hence the pool of borrowers from which the group was drawn is larger and safer, and the expected repayment rate is higher. Second, assume loan sizes are large. In this context and under diminishing returns to capital, observing a larger loan implies that (the upper bound on) the cost of capital of the borrower must be lower. This is because the marginal product of a larger loan is smaller, yet still must be above the borrower's cost of capital since the borrower did not revise his loan size downward. Since cost of capital declines with risk in this limited liability setting, the borrower is drawn from a riskier pool and the expected repayment rate is lower.

[20] There may be multiple solutions, in which case the highest value can be chosen, giving the upper bound for $\hat{p}'$. Regarding existence, it is possible to show that if equation 14 has a solution, so does equation 15.

Proposition 12. *Under assumptions A6, A8, and A10 (in Appendix), there exists an $\hat{L}$ such that for $L < \hat{L}$ ($L \geq \hat{L}$), the expected group repayment rate is higher (coarsely lower) for groups with higher L.*

Details and proof are in Appendix A and Ahlin and Townsend (2002). In empirical tests we will allow for a non-monotonic relationship between expected repayment and loan size.

1.4.4 Adding correlation

Here we use the same parametrizations of correlation as in our modification of the Stiglitz model; see earlier section 1.1.3 for details.[21] Given that homogeneous matching still obtains,[22] the Selection Equation becomes

$$E - \hat{p}r - [\hat{p}(1-\hat{p}) - \epsilon(\hat{p},\hat{p})]q = \underline{u}. \tag{18}$$

Proposition 13. *Under assumptions A8 and either A3 or A4, the expected group repayment rate is higher for groups with higher project return correlation (higher ϵ or ρ).*

Higher correlation implies that if a borrower is successful, his partner is more likely to be. Hence, the borrower's chances of having to make the joint liability payment are lower. Higher-correlation groups thus have higher borrowing payoffs, and are drawn from a larger and safer pool.

2 Empirical Results

In this section we discuss our results from data on Thai joint liability borrowing groups and the villages where they are located. We discuss our methodology in section 2.1. Data, sampling, and variables are described in section 2.2, with Appendix B and Table 2 giving greater detail on construction of the variables. In section 2.3 and Table 3, we report the results and discuss how they fit the theoretical predictions. Robustness checks and empirical concerns are discussed in section 2.4.

2.1 Methodology

Our empirical goal given cross sectional data on group repayment R (a binary variable) and characteristics $X = (X_1, ..., X_M)$ is to see how the frequency of repayment R varies across groups with different characteristics X. Estimating the partial derivatives in this way will be the analog to the analytical partial derivatives and comparative statics of Table 1 and section 1.

One of our more interesting if challenging goals is to try to distinguish the models. To clarify, it seems useful to adopt the definitions of the econometric literature: Two models f and h are said to be completely nested if for each parameter θ under model f, for all R and

[21] For technical reasons, we assume that risk-types are bounded away from one, i.e. that the support of $g(p)$ is $[\underline{p}, \overline{p}]$ for some $\overline{p} < 1$.

[22] This is verified in Ahlin and Townsend (2002); under assumption A4, we must restrict ρ to be positive.

X, with repayment $P_f(R|X,\theta)$, we can find in model h a parameter φ with an equivalent repayment: $P_h(R|X,\varphi) = P_f(R|X,\theta)$. That is, the two models could not be distinguished in the data because we could always rationalize the results from one, the relationship among observables (R, X), by a configuration of the other. Two models are partially overlapping if this happens some (but not all) of the time. On the other hand, if the derivative under f were $\partial P_f(R|X,\theta)/\partial X_m > 0$ for all X and θ and $\partial P_h(R|X,\varphi)/\partial X_m < 0$ for all X and φ, then the two models must be completely non-nested because the derivatives have opposite signs over the entire (relevant) range of (R, X). Thus in principle the models can be distinguished by the sign of the derivative in the data, subject to statistical tests. Inspection of Table 1 reveals that the models' predictions about some variables are unanimous; other variables are uniquely featured by just one of the models; and the models give conflicting predictions about a third set of variables. While all predictions will be tested, it is the second and especially the third category of variable that allow for distinguishing the models.

If we were to parameterize the models, for example, specifying θ and φ in the above discussion, then we could proceed by maximum likelihood methods, comparing as in Vuong (1989) across non-nested models by examining (adjusted) likelihood ratios. In that way the sign restrictions inherent to each model would be loaded automatically into the probability and in a sense forced onto the data. But our goal is to be explicit about the consistency or inconsistency of a model with the data by looking more deeply into the determination of the likelihoods, at the signs of the derivatives. Moreover we seek to do this in a relatively non-parametric way, for example specifying that agents are risk averse in Stiglitz without pinning down the exact degree of curvature of the utility function, i.e. the parameter θ.

On the other hand, though it is possible to determine the shape of the entire probability of repayment surface $P(R|X)$ in each of the theories, it is not possible with data, especially with limited sample size, to reliably plot the non-parametric version of the corresponding multi-dimensional histograms. Thus we focus on first derivatives and make some simplifying approximations. We note in particular that the cross partial derivatives $\partial^2 P(R|X)/\partial X_m \partial X_n$ are determined in each of the models, and typically many of these cross partial terms are not zero. But we do not have enough data to estimate these.[23] Indeed it is difficult to estimate the direct partial, $\partial P(R|X)/\partial X_m$ without making some simplifying, approximation assumptions about how the X_n, $n \neq m$, enter.

The picture grows more complicated if agents can select into "models" based on characteristics X and unobservables correlated with error terms influencing repayment rates. In this case, varying a particular X_m would not trace out the function P of *one* model, but segments of the P functions from several models. Most likely, the predominant model in the data would then determine the sign. In theory, however, cases could arise in which the sign reflects not any one model's partial, but the effect of switching between models. One potential way to solve this issue would be to embed selection into the models where it is not already endogenous (i.e. all but Ghatak), and look for identifying restrictions that ensure one model or another is or is not in force. At this point identifying restrictions seem hard to come by.

Our main approach to testing the repayment predictions is the most structural. It involves

[23] Indeed the insertion of interactive effects into the logits described below failed to uncover significant terms and in some cases undercut the significance of coefficients on the variables entered in levels.

making two simplifying assumptions on the models themselves. First we assume that for each model, $P(R^g = 1|X^g)$ can be written as a function $P(\beta' X^g)$, where β is an $Mx1$ vector of parameters and X^g is an $Mx1$ vector containing group g's values for the M covariates, $g = 1, ..., G$. This restricts covariates to enter repayment probabilities as a linear combination while leaving the function P unrestricted. This is the single-index model, studied by Ichimura (1993) among others, and potentially computationally complex to estimate. Our second assumption is that $P = \Lambda$, that is the probability function is logistic. This is the logit model, easily estimated by maximum likelihood, as in equation 19:

$$\prod_{g=1}^{G} P(R^g = 1|X^g)^{R^g}[1 - P(R^g = 1|X^g)]^{1-R^g}. \tag{19}$$

This approach forces all models into the same structure of the function $P(R|X)$, but allows the data to determine the signs of the coefficients.

We also used two bivariate, non-parametric approaches. One simply tested for mean repayment differences across high and low values of each X_m. For robustness, we varied the cutoff value defining "high" and "low" in a systematic way. The second used locally linear non-parametric regressions (see Cleveland 1979 and Fan 1992). These regressions calculated an expected repayment rate at each value X_m^g of the covariate X_m using only the 80% of the sample closest to X_m^g, in a weighted least squares regression with the tri-cube weighting function (see Cleveland 1979). Standard errors were obtained from bootstrap techniques.

The two univariate approaches gave results consistent with the multivariate logits in many cases, but not all. To sort these cases out, our final approach involved the same locally linear regressions, but with linear multivariate controls. That is, we assume a partially linear model – where all regressors but one affect R linearly, and the remaining regressor's effect can take any smooth shape. We estimate this model using Yatchew's (1998) differencing method for estimating and removing the linear regressors' effects, then using the local linear regression to plot the residual relationship. Almost without exception, these tests confirm the results of the multivariate, logit specification. Hence, for brevity we focus almost exclusively on results from the logits in this paper; the one exception will be to examine the effect of loan size in a partially linear model.[24]

2.2 Data

The data used in this paper are from the Townsend Thai data base, in particular from a large cross section of l92 villages, conducted in May l997. The survey covers 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, and within each village fifteen households were

[24]For more results using this and the non-parametric techniques, see Ahlin and Townsend (2002).

administered a Household instrument. There are thus 2875 households in the household data base. We call this instrument the HH survey. Of key importance for the paper here, 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, 62 of which are the only groups in their respective village. We call this instrument the BAAC survey. Each group designates an official leader, and the leader responded to questions on behalf of the group.

The BAAC is a government-operated development bank in Thailand. It was established in l966 and is the primary formal financial institution serving rural households. By its own estimates, it serves 4.88 million farm families, in a country with just over sixty million inhabitants, about eighty percent of which live in rural areas. In the data here, BAAC loans constitute 34.3% of the total number of loans, but we include in this total loans and reciprocal gift giving from friends, relatives, and moneylenders (see Kaboski and Townsend, 1998). Indeed, commercial banks in the sample here have only 3.4% of total loans, and provide loans to only about 6% of the household sample. Occasionally a village will have established a local financial institution, but typically these are small and constitute on average only 12.8% of total loans. Informal loans, though 39.4% of the total, are also small in size.

The BAAC requires some kind of collateral for all loans, but it allows smaller loans to be backed with social collateral in the form of joint liability. Thus loans underwritten by a BAAC group do not in principle require land or other physical collateral, only the promise that individual members be jointly liable. Loans larger than 50,000 baht must be backed by an asset such as land. Any particular loan is classified as a group-guaranteed or individual loan, and the appropriate collateral box checked off on the loan form.

The nature of BAAC lending justifies our decision not to impose a zero-profit constraint in our theoretical work. For one, the BAAC receives a non-trivial government subsidy. Its subsidy dependency index, the amount that would be necessary to raise the average on-lending rate in order to break even, has been estimated at 35% (Townsend and Yaron 2001). Under its charter the BAAC is responsible for the well-being of farmers and those in rural areas, and it carries out that responsibility by charging a lower interest rate to small clients.

Even a subsidized bank may tailor interest rates to borrowers. The BAAC appears to do so only very broadly. There is an exogenous, pre-specified, unified national schedule mapping loan size into interest rates. For example in l997, at the time the data used here were collected, all loans under 60,000 baht carried a 9% interest rate, while loans between 60,000 baht and 1,000,000 baht charged 12.25% interest rates. Thus, except for the highest loan amounts and any exceptions to the policy, we should see virtually no variation. Observed variation may be due in part to measurement error, as respondents do not distinguish clearly between the part of repayment which is principal and the part which is interest. We are thus dealing with a bank that does not attempt to break even by adjusting interest rates based on risk or other group and location specifics.

We turn briefly to descriptions of variables, which are described in greater detail in Appendix B and summarized (including statistically) in Table 2. Our measure of default is a binary dummy from the BAAC survey, which equals zero if the BAAC has ever, in the history of the group, raised the interest rate as a penalty for late payment, and one otherwise. Twenty seven percent of the groups responded affirmatively. This relatively high figure should not be taken as a mark against the BAAC lending program. Annual default rates are much lower, whereas this measures default over the entire history of the group (median group age is ten years). Further, imposing an interest rate penalty is one of the first remedial actions in a dynamic process the BAAC uses with delinquent group-guaranteed borrowers; repayment ultimately may have occurred.[25]

[Table 2 about here]

We include several control variables that are not featured in any of the four models: log-age of group; size of group; a measure of village-wide risk; a measure of village-average household wealth; and two measures of village-wide non-BAAC credit options, measuring village-wide prevalence of commercial bank membership and production credit group (PCG) membership, respectively. The age of group is particularly important to control since our measure of default applies to default at any time during the history of the group. Others of these control variables could fruitfully be added explicitly to the theory, but we do not so here.

Our proxy for the degree of joint liability q is the fraction of the group that is landless. This has validity because, in case of default, the BAAC has the option of taking legal action to seize assets, often land, of a borrower *or* his guarantors. The more borrowers are landless, the more likely guarantors will end up liable. While the BAAC rarely takes legal action, there have been such cases and certainly instances of group members being pressured to repay for a delinquent borrower in their group. All told, the threat seems to carry some credibility.

Of course, if used alone, this variable might capture group wealth more closely than joint liability. However, we control for group average land-holdings, so the partial effect of the landlessness variable is to capture the lopsidedness of group landholdings conditional on the mean. Average group landholdings, along with average education in the group, are included as productivity shifters.

Two BAAC survey dummy variables proxy screening, one reflecting whether group members know the quality of each other's work (a key assumption in the Ghatak model), the other reflecting whether there are households who would like to join but are screened out of a given group. Cost of monitoring is measured by the percent of the group living in the same village and the percent of group members who have a close relative in the group, both from the BAAC survey. However, BBG inextricably ties monitoring to imposing penalties, making the degree of relatedness a mixed signal. It can also be thought of as a measure for cooperation.

Cooperation is further captured by two measures of sharing and cooperation within groups, among related and unrelated group members, respectively. These measures are based on questions about whether there has been sharing of free labor or coordination to procure inputs, for example, within the group in the past six months. We also use a village-wide measure based on a poll of nearby villages in the HH survey that ranks villages based on the amount of cooperation. Finally, we use an index of joint decision-making within the group regarding production.

[25] We are currently trying to get data from the BAAC on other, more severe forms of default.

We proxy covariance by the degree of occupational homogeneity within the group and by a village-level measure that captures the degree of agreement in the village about which year of the past five was worst for income.

Official penalties are proxied by a poll of nearby villages that ranks villages based on availability and quality of institutions. This captures to some degree the legal infrastructure, which is related to the official penalties the BAAC can impose on borrowers. Unofficial penalties are reflected in a village-wide measure reflecting the frequency of village-wide denial of credit to, or loss of reputation of, a borrower who defaults on a loan. This captures very directly a form of unofficial penalties – widespread exclusion from future credit transactions.

Finally, data on groups' loan sizes and interest rates come from the BAAC survey which asks about maximum and minimum loan sizes and interest rates within the group; in each case we take a weighted average of the two. As noted above, however, variation in the interest rate should be rare due to a standardized national policy. We discuss endogeneity issues, which may be particularly acute with r and L, in section 2.4.

2.3 Results

Logit results on all variables simultaneously are listed in Table 3. There are 219 groups included in the regression incorporating both regions; 43 are excluded for missing data. Of these 130 observations are in the northeast region, and 89 in the central region. To focus on the within-village variation, we include a specification with village dummies, of course only for the villages with two groups represented in the data (of which there are 75).

[Table 3 about here]

In analyzing the results, we focus primarily on whole-sample results, since they contain the most data. Of the control variables, the log-age of group exhibits a consistent significantly negative correlation with repayment. This is almost certainly because the dependent variable involves default at any time in the history of the group, which is more likely for older groups. There is some evidence for village income variability predicting lower repayment, and a slight amount for village wealth. Outside credit options, particularly the informal village-based production credit groups, also are associated with lower repayment to the BAAC.

There are three kinds of variables that shed light on the theory derived in this paper (see Table 1). The first type of variable is the focal variable in exactly one of the models. This includes screening in the Ghatak model, cost of monitoring in BBG, and penalties in BC. BC is confirmed along this dimension, with official and unofficial penalties being good predictors of repayment, especially in the northeast sample. We seem to be the first to document the effect of unofficial penalties on repayment; to our knowledge, other research that examined informal sanctions found little effect (Wydick 1999). Our measure for unofficial penalties – the exclusion of a delinquent borrower from future credit in his village – also appears to be unique.

Some evidence in favor of BBG is present with percent of group living in village positively predicting repayment in one specification.[26] The percent of members with a relative in the

[26]Hermes et al. (2005) find evidence that stronger monitoring by the group leader, but not by group members, mitigates moral hazard.

group is negatively associated with repayment in one specification. This contradicts the cost of monitoring prediction of the BBG model. However, that model equates monitoring with the ability to impose penalties; it may be that imposing penalties is harder among relatives.

The evidence for Ghatak is not strong along this dimension of our data, if anything slightly negative (though outside conventional significance levels). However, we do not place significant weight on this result since our proxies are dummy variables, one with very little variation (KNOW_TYPE), and may not fully capture the phenomenon of screening.

A second kind of comparison involves variables about which the models disagree – L, q, covariance, and cooperation – and leads to the possibility of rejecting one model in favor of another. The evidence on q and L favors Ghatak, especially in the central region, at the expense of Stiglitz and BBG. Joint liability q, as proxied by the landless fraction of the group, robustly predicts lower repayment. (Note that this result holds controlling for group average land.) This is consistent with the Stiglitz story of higher q raising the repayment burden and encouraging gambling and with the Ghatak story of higher q driving out marginal, safer borrowers. It may seem an interesting result, perhaps paradoxical, result given the popularity of these types of contract. But recall, the main idea of the authors' models is that increasing q allows a decrease in r, while here we (and the BAAC) hold r fixed and vary q.

The results on L are not overwhelming, and should be downplayed due to potential endogeneity. However, they best fit the Ghatak model's non-monotonic prediction, that larger loans draw in marginal, safer borrowers when loans are small but signal riskier borrowers with lower expected repayment costs when loans are large. Nonparametric estimates of the relationship, where the other covariates are controlled for linearly, as discussed above and in Appendix C, are presented in Fig. 4. Especially in the central region the inverted-U is pronounced in the function estimates. The results are not conclusive, though, due to lack of data at high loan sizes. However, the upward-sloping segment of the relationship is well-supported, and this portion of the curve is enough to favor the Ghatak model.

[Fig. 4 about here]

The evidence on covariability is weak but favors Stiglitz and Ghatak at the expense of BC. The direct measure of village covariance of output is a significant predictor of good repayment, in the whole-sample logits at least. This result is consistent with the Stiglitz story that higher covariation of income can differentially increase safe project payoffs and the Ghatak story of higher covariation drawing in marginal, safer borrowers. It is at odds with BC under certain assumptions as well as the empirical literature, which assumes high correlation should lead to lower repayment.

Finally, the evidence on cooperation is rich but seems to turn in favor of BBG and BC at the expense of Stiglitz, pointing toward a negative relationship between cooperation and repayment rates (though not necessarily borrower welfare). Most prominently, the degree of relatedness and the amount of sharing among non-relatives in the group show up as significant negative predictors of repayment. The village cooperation poll also registers as negative in the northeast region. These results are consistent with the BBG and BC stories that groups behaving cooperatively may choose not to repay rather than pressure each other more than is optimal. A minor exception is sharing among group relatives, but this coefficient turns negative (but insignificant) if the two sharing indices are combined or sharing among group non-relatives is excluded.[27]

A potential exception to this conclusion arises in the index for the number of production decisions made cooperatively, which is a positive predictor of repayment in several specifications. However, JOINT_DECISIONS may not measure cooperation in the sense of being able costlessly to *enforce* agreements, but rather may reflect a transfer of knowledge and expertise.[28] A second possibility is that the ability to cooperate in project choice is different from the ability to cooperate in punishment behavior. Since the Stiglitz model focuses on cooperation in project choice, and predicts a positive effect, while (our extensions of) BBG and BC focus on cooperation in punishment behavior, and predict a negative effect, this would be an interesting reconciliation of the results.[29]

The negative association between cooperation and repayment seems to conflict with conventional wisdom and with empirical results of Karlan (this issue).[30] Karlan explores a group lending program in which groups are formed randomly by the lender, so all social ties must be exogenous; he finds some measures of social ties positively predict repayment. One key difference between our results seems to be the *range* of social ties that we observe. In a program of random group formation, the range of social ties in the realized groups is likely to be low – certainly not comparable to our case where the mean group has nearly sixty percent relatives. Thus, one might view Karlan's results as indicating positive effects of social ties in a neighborhood of zero, while ours indicate negative effects as social ties vary across more substantial levels. While the theory in this paper does not point to such a reconciliation, future work potentially could.

The third kind of variable elicits unanimous predictions from multiple models. This includes r and productivity. In both cases there is some evidence to support the model's unanimous predictions. The negative results on r are at best suggestive, due to a combination of little variation and potential endogeneity. The positive and significant result on education is to our knowledge new; the measure of human capital used in previous studies was literacy, and the coefficient was not significantly different from zero (see Zeller 1998).

In summary, the unanimous predictions of the models receive some support; the unique predictions are not strongly upheld with the exception of BC's focus on unofficial penalties; and the conflicting predictions go both for and against almost every model, depending on the prediction, with only the Ghatak model not being contradicted.

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[27] Thus the positive result on sharing among group relatives is only due to controlling for sharing among group non-relatives. This suggests that sharing per se within the group is bad for repayment; but holding fixed sharing among non-relatives, sharing among relatives is good for repayment. Explaining this result seems to require a theory more precise than a casual invoking of "social capital".

[28] Under this interpretation, JOINT_DECISIONS could fit under the heading of borrower productivity, and a positive sign would thus match our other results and all the models' predictions. Varian (1990) examines incentives for the transfer of human capital between jointly liable borrowers.

[29] One fact that supports both interpretations is that the correlation of JOINT_DECISIONS with each of the other measures of cooperation is statistically insignificant. Thus it appears to be measuring a different type of cooperation or a different phenomenon entirely.

[30] Cassar et al. (this issue) also find positive effects of social ties – measured by group homogeneity and survey measures of trust between group members – on repayment, in experimental games performed in South Africa and Armenia.

Pooling all the evidence by region, it can be said that BC is upheld in the northeast region, in particular its focus on unofficial penalties, and not contradicted in any. In the central region, however, Ghatak does well in matching the results on q and L. It is quite possible, and not surprising, that different mechanisms are at work in the different regions, with joint liability potentially solving more of a selection problem in the central region and an enforcement problem in the northeast.

What is it about the regions that leads to different results? Two dimensions along which the regions differ significantly are wealth (the northeast being poorer) and financial access (the northeast having less access). This is seen in our data in significant regional differences in VILLAGE_WEALTH and BANK_MEMBERSHIP. Accordingly, we stratify by these two variables, running the same logits on the respective above-median and below-median samples. Though the overlap in both cases is quite high, it is the low-financial-access sample that parallels very closely the northeast region results on unofficial penalties while the low-wealth sample turns up insignificant results for unofficial penalties. The results are suggestive that the lack of basic infrastructure (physical and legal) for a formal financial system in the northeast, not the lack of wealth, makes informal penalties an effective substitute method for guaranteeing loans.

2.4 Robustness Checks and Empirical Concerns

How representative are our data? The BAAC is not a universal bank. BAAC clients are more educated and wealthier than the typical rural household for example, particularly so for those taking out individual loans. However, this paper does not seek to explain among all rural households of the sample who borrows. Rather, this paper follows the models in taking as given the selection of some of the rural population into BAAC groups and then focusing on the potential inner workings of those groups themselves. The major exception is our examination of Ghatak's adverse selection model, with its implication that group members are more risky than those who take the outside option (for which we find evidence, see Ahlin and Townsend, forthcoming).

We also note that the data here do not capture groups that have gone out of existence, perhaps because of a pattern of default. This may lead to bias in estimated coefficient magnitudes; however, our focus is on the sign not the magnitude. Further, this seems to be a relatively unsubstantial tail of the data. Using a survey of village heads from the same villages, we find that there are 469 BAAC groups reported in 192 villages, and 6 BAAC groups reported to have once existed but since disbanded. That is, only 1.3 groups have disappeared for every 100 active groups. Of these, some doubtless disbanded for non-default reasons. The turnover is slightly higher, but still not alarming, at the individual level: in the household survey, for every 100 households reporting to be members of a BAAC group there are 4.1 households reporting that they were, but are no longer, members of a BAAC group. Our data thus appear to be broadly representative.

Another potential problem with the data is that our repayment proxy reflects the entire history of the group, while our covariates are for the most part contemporaneous measures. We thus implicitly assume that the covariates are stable over time. This is certainly true of some (e.g. education) and may be less true of others (e.g. sharing). However, if the covariates are not stable, our sense is that the most probable bias in estimates would be due to independent measurement error and thus uniformly toward zero. We discuss cases in which default itself may plausibly cause changes in covariates below. At any rate, the ideal case would involve both dynamic models and dynamic data.

For robustness, we experiment with several different controls and specifications. We use the coefficient of variation of village wealth, both in addition to and as a substitute for village wealth. Entered together, they are both insignificant. By itself village wealth inequality shows the same behavior as village wealth – negative and (marginally) significant in the fixed-effect specification only. We also add a regional dummy to the logit regressions and find it insignificant in the baseline but significant in the fixed-effect specification, predicting lower repayment in the northeast. It does not change other results appreciably.

One might be concerned that using several proxies for a given factor, such as both landholdings and education for productivity, may confound the result for any given proxy. Accordingly, we run the baseline logit specification using one proxy at a time for each factor, rather than all simultaneously, and find no appreciable difference in results. Relatedly, each model, as studied here, makes predictions over a different set of variables. It might then be preferable to use model-specific sets of variables in the regressions rather than the same set for all models. However, to say whether one variable does or does not fit into a given model is somewhat arbitrary. In this paper we choose to carry out some extensions based on simplicity of assumptions needed, but more could be done if one is willing to make stronger assumptions. For example, L and q are not inherently absent from the BC model, they are just not introduced here. Thus defining the appropriate set of variables for a model is not straightforward. That said, we do run the logits using for each model only the variables with predictions marked in Table 1. The results are not appreciably different.

It is also a departure from the theory to enter the variables additively. The models make predictions about the own- and cross-partials of the repayment rate. We therefore add in various interactive terms suggested by the theories. However, the insertion of these interactive effects failed to uncover significant terms and in some cases undercut the significance of coefficients on the variables entered in levels. We attribute this to lack of data. Further, the logit model already builds in non-zero cross-partials even when terms are entered additively.

Though we have not established causality beyond doubt, we view most of the evidence as strongly suggestive of causal relationships between key variables and repayment. There are exceptions. In principle, group-level variables may themselves be functions of repayment history, or may be correlated with unobserved determinants of repayment (due to a group selection or other effect). This appears somewhat likely for interest rate r (to the extent it deviates from the national schedule) and loan size L, though not as likely as if the BAAC were satisfying a zero-profit constraint. Loan size in particular varies for a number of reasons including borrower seniority, borrower's estimated revenue, government targeting of specific regions, but also perhaps based on assessment of the client's reliability in repayment. Accordingly, though some exogenous variation seems to exist, we are cautious about inferring a direction of causation. We also note that the results on other variables are robust to a more cautious approach that excludes r and L from the logits.

Other group-level variables are plausibly exogenous to repayment history and do not appear correlated with unobserved repayment determinants. Average landholdings in the group and our proxy for q, the landless fraction of the group, are likely stable with respect to repayment history given the rarity of full default and consequent seizure of land by the

BAAC (which of course does not imply the threat is non-credible). Education levels are in general predetermined with respect to repayment history. Other characteristics of group members such as relatedness, location, and occupation are relatively fixed over time. One might worry that groups re-sort after a default experience to change the composition of these characteristics, perhaps expelling non-relatives or borrowers from other villages. But the relatively low turnover of borrowers cited previously makes this less of a concern.

It is also possible that the sharing variables may respond to group repayment history. If sharing decreases after repayment problems, this would push toward a positive correlation between repayment and sharing; we see the opposite. On the other hand, intra-group transfers may be higher after default within the group, if one member is repaying another. However, the sharing question is worded so as to imply sharing per se rather than activities with an explicit quid pro quo. More importantly, groups were asked whether one or more members have ever repaid for another in the history of the group. About ten percent responded affirmatively. Excluding these groups from the logits still turned up a negative and significant coefficient on sharing among group non-relatives; this suggests that the negative correlation between repayment and sharing is not being driven by those groups that have experienced internal bailouts. Indeed, the correlation between sharing within the group and past internal bailouts is not significantly different from zero. A related concern is that the result is due to sharing being correlated with some unobserved determinant of repayment, income risk for example. While this cannot be completely ruled out, we note that risk is controlled for at the village level by VILLAGE_RISK and at the group level by OCCUPATIONAL_HOMOGENEITY and (in the unreported robustness check) by existence of an intra-group bailout.

Village-level variables are unlikely to be functions of the group's repayment history, since a group makes up only a fraction of the village population. They may, however, be correlated with other unobserved village-level characteristics that are the actual determinants of repayment. For example, the negative results on outside lenders might be questioned if the prevalence of PCGs indicated the presence of a village attribute that caused it to be shunned by institutional lenders. In this case, it would not be outside lenders per se, but the negative village attribute leading to low repayment. However, this does not appear to be the case, as there is a positive, not negative, correlation between village borrowing from the BAAC and PCG prevalence. We calculate a correlation coefficient not statistically different from zero – 0.072 – between percentage of villagers' loans that come from the BAAC with percentage of villagers who are PCG members. One might think the BAAC and PCGs are both partly driven by social missions that lead them to difficult areas. But, the correlation between PCG prevalence and commercial bank prevalence is also not statistically different from zero – 0.031 – suggesting that PCGs do not tend to exist primarily in regions of commercial institutional abandonment.

One might also wonder if an unobserved village attribute is driving the result on unofficial penalties. In particular, our measure may be correlated with the number of different lenders in the village, since it may be harder to coordinate a shutdown of lending against a delinquent borrower if there are more lenders. We construct a measure of the number of lenders in a village, using data on outstanding loans and their sources from the household survey. We use both the absolute number of lenders represented in this village sample of loans, and the number of lenders normalized by the number of loans in the village sample. Entering either into the baseline regression does not change the sign and significance of the coefficient on unofficial penalties.

Our measure of covariability of returns, the coincidence across villagers of bad years within the past five, might be correlated with a village having experienced a negative aggregate shock. For example, even if all villages have the same covariability of returns, those which happened to have a large negative shock recently would register both low repayment and high covariability. This negative relationship between covariability and repayment would be non-causal. However, this would predict a negative relationship between repayment and covariability, while the data show a positive one. Further, the mean and standard deviation of this variable indicates that aggregate shocks were not common (see Table 2), at least not in the five years prior to data collection in early 1997.

Group education levels may also reflect a non-education related village-level phenomenon correlated with well-functioning schools. This does not appear to be the case; the result on group education levels continues to hold even when we include the village-average education level in the logits.

Our interpretation of landlessness as reflecting joint liability, rather than wealth, may be questioned. We do note that the specifications all control for average landholdings in the group, so the partial effect of landlessness should capture the lopsidedness of the distribution conditional on the amount of land. If wealth mattered per se, and linearly (relative to the index), then average landholdings should show up as a positive predictor of repayment. It does not, in the baseline specifications and in specifications that are identical to them but exclude the landlessness variable. Even if wealth mattered positively and non-linearly, it seems highly likely that average landholdings would show up as a positive predictor of repayment; it does not. One might hypothesize a non-monotonic relationship between wealth and repayment, where default is worst at either wealth extreme. If this were true, however, one would expect a negative relationship between average landholdings and repayment, controlling for landlessness. This is not what we find; see Table 3. Further evidence is provided in the village-wealth variable, which is an insignificant, and if anything slightly negative, predictor of repayment. So, while we cannot completely rule out the interpretation of landlessness as capturing a wealth effect, we find it unlikely.

Overall, then, all results except on r and L seem plausibly to suggest causal relationships.

3 Conclusion

We have compiled and helped construct a theoretical framework through which to view repayment data of joint liability borrowing groups and to test between theories regarding them. We accept for now that the current models have their limitations or shortcomings. For example, the models are static and involve borrowing groups of fixed size (two). Our goal here instead is to evaluate these current, widely-used theories by a confrontation with the data. Hopefully the insights provided can be used in future research, including the construction of revised models.

Using this framework and rich data from Thailand on group characteristics and the villages where they are located, four models were compared. We find that the Besley and Coate model of social sanctions that prevent strategic default performs remarkably well, especially in the low-infrastructure northeast region. The Ghatak model of peer screening by risk type to overcome adverse selection is supported in the central region, closer to Bangkok.

The strongest facts that future modeling should take into account include the negative relationship of the repayment rate with the rate of joint liability (ceteris paribus); its positive relationship with the strength of local sanctions; its potentially positive relationship with correlated returns; and its sometimes negative relationship with more benign social ties such as relatedness and sharing.

This is one of the most striking aspects of the results for policy implications:[31] strong social ties – measured by sharing among non-relatives, cooperation, and clustering of relatives, and village-run savings and loan institutions (PCG's) – having seemingly *adverse* effects on repayment performance. This result has not been seen in the previous empirical literature, nor focused on in the theoretical models, though Ghatak and Guinnane (1999) provide an insightful discussion using historical and contemporary examples. On the contrary, social ties are typically seen as positive for group lending.

This idea must be qualified. Social structures that enable penalties can be helpful for repayment, while those which discourage them can lower repayment. However, a higher repayment rate is not always synonymous with higher welfare. It may merely reflect the use of cheap penalties to enforce repayment when it is not (ex ante) Pareto optimal for the group. Thus joint liability lending may flourish most in areas where social penalties are especially severe, even more severe than the borrowers themselves would prefer.[32]

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[31] For more discussion of policy implications of this and related work, see Ahlin (2005).

[32] See Rahman's (1999) study of Grameen borrowers. Of course, if they still borrow, they are probably better off doing so than not.

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A Proofs

Proof of Proposition 5. The minimum penalty needed to enforce a project choice p is

$$c(p, r, L) = F(L)[E(\underline{p}) - E(p)] + rL(p - \underline{p}), \tag{20}$$

exactly analogous to equation 5. The new Monitoring Equation is

$$q = M'[c(p, r, L)]c_p(p, r, L)/L. \tag{21}$$

Totally differentiating with respect to p and L gives that

$$\frac{\partial p}{\partial L} = -\frac{M''(c)c_p c_L + M'(c)[c_{pL} - c_p/L]}{M''(c)c_p^2 + M'(c)c_{pp}}. \tag{22}$$

The denominator can be shown strictly positive using assumption A7, equation 20, and the fact that M is increasing and convex.

Turning to the second term in the numerator of $\partial p/\partial L$, equation 20 gives that

$$c_{pL} - c_p/L = E'(p)[F(L)/L - F'(L)].$$

The concavity of F ensures that $F'(L) \leq F(L)/L$. Using this along with the fact that M is increasing and assumption A7 gives that this second term is positive.

Turning to the first term, M is convex by assumption and c_p is positive by assumption A7. One can show that c_L is zero at $p = \underline{p}$ and is elsewhere positive because it is increasing in p:

$$c_{pL} = r - F'(L)E'(p) > r - rLF'(L)/F(L) = \frac{rL}{F(L)}[F(L)/L - F'(L)] \geq 0. \tag{23}$$

The strict inequality uses assumption A7 directly, and the weak inequality comes from the concavity of F. Thus the first term of the numerator is positive. ■

Supplement to and Proof of Proposition 9. Let f be the density function associated with F, with $[0,1]$ its support. Under zero correlation, the joint density is $f(Y_i)f(Y_j)$. Let $\phi(Y_i, Y_j)$ be a generalized joint density:

$$\phi(Y_i, Y_j) = f(Y_i)f(Y_j) + \kappa\,\gamma(Y_i, Y_j). \tag{24}$$

Essentially, $\kappa\gamma(Y_i, Y_j)$ is the added (or subtracted) density, relative to the zero-correlation case, at a point (Y_i, Y_j). This parametrization is without loss of generality and allows choice in the structure $(\gamma(Y_i, Y_j))$ and amount (κ) of the added or subtracted density. It does not guarantee that the marginal densities are preserved; necessary and sufficient for this is that $\gamma(Y_i, Y_j)$ integrate to zero over Y_i and Y_j, separately. To guarantee this, we parametrize further:

$$\gamma(Y_i, Y_j) = g(Y_i, Y_j) - \int_0^1 g(Y_i, Y_j)dY_i - \int_0^1 g(Y_i, Y_j)dY_j + \int_0^1 \int_0^1 g(Y_i, Y_j)dY_i dY_j. \tag{25}$$

This parametrization is without loss of generality in the sense that it does not rule out any $\gamma(Y_i, Y_j)$ that preserves the marginal densities.[33] Its usefulness is in allowing us to choose any integrable function $g(Y_i, Y_j)$ without worrying about preserving the marginal densities; by construction, the above transformation of $g(Y_i, Y_j)$, i.e. $\gamma(Y_i, Y_j)$, will preserve them.

We parametrize $g(Y_i, Y_j)$, aiming for generality while imposing symmetry on the correlation. Let $\{\alpha_1, \alpha_2, ..., \alpha_N\}$, $\{\beta_1, \beta_2, ..., \beta_N\}$, and Q be strictly positive numbers; we assume

$$g(Y_i, Y_j) = Q - \sum_{k=1}^{N} \beta_k |Y_i - Y_j|^{\alpha_k}. \tag{A9}$$

This formulation adds mass Q everywhere on the unit square, but also subtracts mass according to an arbitrary, monotonic, polynomial function of the distance between returns. The more disparate the output realizations, the more mass is subtracted. Assumption A9 encompasses simple examples like absolute difference $Q - |Y_i - Y_j|$ and squared difference $Q - (Y_i - Y_j)^2$. Intuitively, assumption A9 should lead to positive correlation, and it does.[34] Combining it with equations 24 and 25 and carrying out some detailed integration gives

$$Cov(Y_i, Y_j) = \kappa \sum_{k=1}^{N} \frac{\alpha_k \beta_k}{2(\alpha_k + 1)(\alpha_k + 2)(\alpha_k + 4)}. \tag{26}$$

This is strictly positive and linear in κ. Thus κ parametrizes the intensity of covariance.

[33] To see this, let $\gamma(Y_i, Y_j)$ be any function that preserves the marginal densities. Then $g(Y_i, Y_j)$ can just be set equal to $\gamma(Y_i, Y_j)$, and the integrals in equation 25 are all zero.

[34] Note that though $g(Y_i, Y_j)$ requires only the distance $|Y_i - Y_j|$, the corresponding $\gamma(Y_i, Y_j)$ requires the individual values Y_i and Y_j. This is because adding mass proportional only to the distance $|Y_i - Y_j|$ would alter the marginal densities. To see this, one can compare the vertical slices of the unit square when $Y_i = 0$ and $Y_i = 1/2$, respectively. The distance $|Y_i - Y_j|$ on the former slice varies from zero to one, and on the latter slice from zero to one half. Clearly, if the mass added strictly increases with distance $|Y_i - Y_j|$, it cannot sum to zero over both of these slices. Thus $g(Y_i, Y_j)$ is transformed via equation 25 to add more weight than the distance term alone would imply, near the boundaries of the square.

We turn now to the proof. Let $a \equiv \underline{Y}(r)$ and $b \equiv \underline{Y}(2r)$. Modifying equation 10 to incorporate the generalized joint density function $\phi(Y_i, Y_j; \kappa)$ gives

$$p(\kappa) = 1 - \int_0^a \int_0^a \phi(Y_i, Y_j; \kappa) dY_i dY_j - 2 \int_a^b \int_0^{\hat{\underline{Y}}(Y_i)} \phi(Y_i, Y_j; \kappa) dY_j dY_i. \tag{27}$$

From equation 24, we get that $d\phi/d\kappa = \gamma(Y_i, Y_j)$. Using this in equation 27 gives

$$\partial p/\partial\kappa = -\left[\int_0^a \int_0^a \gamma(Y_i, Y_j) dY_i dY_j + 2 \int_a^b \int_0^{\hat{\underline{Y}}(Y_i)} \gamma(Y_i, Y_j) dY_j dY_i\right]. \tag{28}$$

This equation merely says that the effect of higher correlation on p is inversely related to the amount of mass that the introduced correlation adds to the Default Region.

We first show that the first double integral in equation 28 (corresponding to the probability mass added to box A in Fig. 3) is strictly positive. Integration using equation 25 and assumption A9 gives

$$\int_0^a \int_0^a \gamma(Y_i, Y_j) dY_i dY_j = 2a(1-a) \sum_{k=1}^{N} \beta_k \frac{[1 - a^{\alpha_k+1} - (1-a)^{\alpha_k+1}]}{(\alpha_k+1)(\alpha_k+2)} \equiv \mathcal{A}.$$

$\mathcal{A}$ is strictly positive, since $\alpha_k, \beta_k > 0$, $a \in (0,1)$, and $[1 - a^{\alpha_k+1} - (1-a)^{\alpha_k+1}]$ is strictly positive for $\alpha_k > 0$ and $a \in (0,1)$.[35]

We next sketch an argument for why the second double integral in equation 28 is close enough to zero as unofficial penalties get sufficiently severe; for details see Ahlin and Townsend (2002). First, note that the subtracted mass $\gamma(Y_i, Y_j)$ is continuous and so has a maximum and minimum value on $[0,1]^2$. Second, note that $\hat{\underline{Y}}(Y)$ can be arbitrarily close to zero over arbitrarily much of the (a, b) interval. In other words, severe enough unofficial penalties remove an arbitrarily large fraction of the AB boxes from the default region. Combining these, even if the maximum or minimum mass is added or subtracted everywhere in the AB boxes, the total amount *within the Default Region* is arbitrarily small as unofficial penalties get more severe. Thus the second integral can be pinned sufficiently near zero to guarantee the two integrals add to a positive number, which implies $\partial p/\partial\kappa$ is negative. ■

Supplement to and Proof of Proposition 12. We make the following assumptions on F:

$$F(0) = 0, F'(L) > 0, F''(L) < 0, \lim_{L\to 0^+} F'(L) = \infty, \lim_{L\to\infty} F'(L) = 0, \lim_{L\to\infty} F(L) - LF'(L) = \infty. \tag{A10}$$

The last part of this assumption is the only non-standard one and requires that $F(L)$ is unbounded and sufficiently concave asymptotically.[36] All parts are satisfied by $F(L) = L^\alpha$.

[35]Considering $[1 - a^{\alpha_k+1} - (1-a)^{\alpha_k+1}]$, note that it equals zero at $\alpha_k = 0$ and is continuous and strictly increasing in α_k when $a \in (0,1)$.

[36]If $F(L)$ is unbounded, then sufficient for this condition to hold is that the elasticity of the slope $F'(L)$ with respect to L is bounded away from zero as $L \to \infty$. The reasoning is as follows. If $F(L)$ is unbounded and $F(L) - LF'(L)$ is not, it must be that $\lim_{L\to\infty} F(L)/[LF'(L)] = 1$. Using L'Hopital's rule shows that this is equivalent to $\lim_{L\to\infty} LF''(L)/F'(L) = 0$.

Observing an agent borrowing L establishes two facts. First, it must be that the borrowing payoff 17 is greater than the outside option $\underline{u}$. Defining $Z(p) \equiv pr + p(1-p)q$ as the (expected) unit borrowing cost of a type-p agent, this condition is equivalent to

$$Z(p) \leq [EF(L) - \underline{u}]/L. \tag{29}$$

Since $Z(p)$ is increasing in p, this implies that $p \in [\underline{p}, \hat{p}(L)]$, where $\hat{p}(L)$ solves relation 29 at equality. One can also show that the right-hand side of inequality 29 first increases, then decreases in L, implying that $\hat{p}(L)$ does the same; see Fig. 5.

[Fig. 5 about here]

Second, since the borrower can always accept less than the lender's offer,[37] the borrower's payoff cannot be decreasing in loan size. Otherwise, the borrower could have refused some of the loan and increased his payoff. Applying this to payoff 17 gives, after rearranging,

$$Z(p) \leq EF'(L). \tag{30}$$

This guarantees that $p \in [\underline{p}, \check{p}(L)]$, where $\check{p}(L)$ solves relation 30 at equality. The larger L, the tighter the bound of inequality 30, and hence the lower $\check{p}(L)$; see Fig. 5. Larger loans signal a lower (expected) cost of capital, which is true of more risky groups.

Thus, observing L tells us that $p \in [\underline{p}, \min\{\hat{p}(L), \check{p}(L)\}]$. Manipulating inequalities 29 and 30 shows that $\hat{p}(L) < \check{p}(L)$ iff

$$\Gamma(L) \equiv F(L) - LF'(L) < \underline{u}/E. \tag{31}$$

Due to strict concavity, $\Gamma'(L) > 0$, so $\Gamma(L)$ can be inverted. Also due to concavity, $\lim_{L\to 0^+} \Gamma(L) = 0$;[38] and due to the last part of assumption A10, $\Gamma(L)$ is unbounded. Thus there exists an $\hat{L} \equiv \Gamma^{-1}(\underline{u}/E)$, such that $\hat{p} < \check{p}$ ($\hat{p} \geq \check{p}$) when $L < \hat{L}$ ($L \geq \hat{L}$).

Assume first that $L < \hat{L}$. The expected repayment rate is $E[p|p \leq \hat{p}(L)]$. Total differentiation of a modified Selection Equation (relation 29 at equality) gives that $\partial\hat{p}/\partial L = [EF'(L) - Z(\hat{p})]/Z'(\hat{p})$. Ths is strictly positive since in this range of L, $\hat{p} < \check{p}$ so $Z(\hat{p}) < Z(\check{p}) = EF'(L)$.

Assume next that $L \geq \hat{L}$. The group type is in $[\underline{p}, \check{p}(L)]$, but the expected repayment rate is not simply $E[p|p \leq \check{p}(L)]$, where the expectation is with respect to density $g(p)$. The reason is that there is a mass point at type $\check{p}(L)$ corresponding to all groups of type $\check{p}(L)$ who were offered more than L but only accepted L, their optimal amount.[39] We will show that the expected repayment rate is in fact a convex combination of $\check{p}(L)$ and $E[p|p \leq \check{p}(L)]$. Both of these terms are strictly declining in L due to strict concavity of $F(L)$; and both drop (simultaneously) to $\underline{p}$ for L high enough, due to Inada conditions on $F(L)$. However, the convex combination may be non-monotonic if the weights shift sufficiently, as pictured

[37] In keeping with our past treatment of the lender, we assume it does not use the counteroffer to infer the borrower's risk-type and adjust contract terms toward some zero-profit condition.

[38] Note that $0 < LF'(L) < F(L)$ when $L > 0$, due to concavity, and $F(L)$ approaches zero.

[39] The mass point is only at $\check{p}(L)$, since any borrower that accepts less than offered ends up with his optimal loan size; and by definition, L is optimal for type $\check{p}(L)$. When $\hat{p}(L) < \check{p}(L)$, the mass point does not arise because no one has their optimal loan size.

in Fig. 5. The expected repayment rate is thus coarsely decreasing, in the sense that it is bounded between two strictly decreasing functions that approach $\underline{p}$.

It remains to show that the expected repayment rate is a convex combination of $\check{p}(L)$ and $E[p|p \leq \check{p}(L)]$. Let $h(L), H(L)$ be the density and distribution functions of lender loan offers. When $L < \hat{L}$, there are two categories of borrowers with loan size L. The first includes all agents with types $p \leq \check{p}$ who received a loan offer of *exactly* L, of mass $G(\check{p})h(L)$. These agents accepted the loan offer without modification because L is less than their desired amount. The second includes all agents of type $p = \check{p}$ who received a loan offer greater than L but accepted only L since it is optimal for them, of mass $g(\check{p})[1 - H(L)]$.

The probability of observing loan size L is then:

$$P(L) = G(\check{p})h(L) + g(\check{p})[1 - H(L)]. \tag{32}$$

This gives rise to a distribution of types conditional on L, call it $P(p|L)$, modified to include a probability mass at $p = \check{p}$. Specifically, using Bayes rule, $P(p|L)$ is zero if $p > \check{p}$; $g(\check{p})[1 - H(L)]/P(L)$ if $p = \check{p}$; and $g(p)h(L)/P(L)$ if $p < \check{p}$. $E(p|L)$ is the integral $\int_{\underline{p}}^{1} pP(p|L)dp$, where the integration treats $\check{p}$ as a mass point. Carrying out this integration gives the expected group repayment rate as a convex combination of $\check{p}$ and $E(p|p \leq \check{p})$, where the expectation is with respect to density $g(p)$:

$$E(p|L) = \check{p}\frac{g(\check{p})[1 - H(L)]}{G(\check{p})h(L) + g(\check{p})[1 - H(L)]} + E(p|p \leq \check{p})\frac{G(\check{p})h(L)}{G(\check{p})h(L) + g(\check{p})[1 - H(L)]}. \tag{33}$$

■

B Variable Descriptions

LN(GROUP_AGE) is the log-age of the group. If we think of default as having some probability p of occurring each year, then clearly groups with a longer history are more likely to have run into problems. But the effect would be non-linear in age.[40] Results under inclusion of terms for age and age squared, rather than log of age, are similar and not reported here.

VILLAGE_RISK is a village-wide measure of risk, taken from the household survey. Households are asked how much they will earn if next year is a good year (Hi), how much if bad (Lo), and how much they expect to earn (Ex). We assume a distribution of income over two of these mass points, Hi and Lo, as do the models. The coefficient of variation is then equal to

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

This quantity is calculated for each villager in the HH survey, and the village average is used. Thus it is a measure of average riskiness of occupation in a given village.

VILLAGE_WEALTH measures average household wealth in the village. Villagers were asked detailed questions about assets of all types – ponds, livestock, appliances, and so on

[40]Specifically, if $P(T)$ is the probability of not having defaulted in T years given an annual probability of not defaulting of p, then $P(T) = p^T$. Further, $P'(T) = \ln(p)p^T < 0$ and $P''(T) = [\ln(p)]^2 p^T > 0$. Thus the function is decreasing at a decreasing rate (in absolute value), as is the (negative) natural log.

– as well as liabilities. Date of purchase was used to estimate current value after depreciation. These different types of wealth were aggregated for each villager, then averaged across villagers. The unit of measure is one hundred thousand 1997 Thai baht.

GROUP_SIZE is the number of members in the group. Groups in our data range in size from five to thirty seven, with eleven being the median. However, each model we consider fixes group size at two. Thus we enter group size as a control variable and leave the introduction of group size into the theory as future work.

BANK_MEMBERSHIP and PCG_MEMBERSHIP are measures of outside borrowing opportunities taken from the HH survey. They give the percent of households surveyed in the group's village who are members of a commercial bank or production credit group (PCG), respectively. PCGs are village-run organizations that collect regular savings deposits from members and offer loans after a member has met some threshold requirement involving length of membership, amount deposited, or both. Often the maximum available loans from these institutions are small, possibly one fifth the size of BAAC loans, and the interest rates are similar or slightly higher (see Kaboski and Townsend, 1998). There do exist PCGs large enough to offer loans as large as BAAC loans. Occasionally joint liability is used with these loans. Commercial banks are conventional lenders, requiring collateral.

The degree of joint liability q is proxied by a variable constructed from the BAAC survey, the percent of the group that owns no land. If all group members own land, it is less likely that a guarantor will in the end have to pay rather than the borrower himself. Conversely, if some members of the group are landless, a guarantor will more often have to repay if a landless borrower defaults.

Covariance is proxied by two measures. COVARIABILITY is a village-level measure taken from the HH survey. Villagers were asked which of the previous five years were the best and worst for income, respectively. Our variable is constructed as the probability that two randomly selected respondents from the same village reported the same year as worst. If N_v is the number of villagers in village v and s_{vy} is the share of villagers in village v who named year y as the worst, this probability is equal to[41]

$$\frac{(\sum_{y=1}^{5} s_{vy}^2) - 1/N_v}{1 - 1/N_v}.$$

HOMOGENEOUS_OCCUPATIONS is taken from the BAAC survey and equals the probability two randomly chosen group members have the same occupation. It is calculated similarly to COVARIABILITY.

Cooperation is measured by four variables. SHARING_RELATIVES, SHARING_NON-RELATIVES are indices from the BAAC survey. They equal the number of positive responses to five out of six yes/no sharing questions: whether sharing of rice, helping with money, helping with free labor, coordinating to transport crops, coordinating to purchase inputs, and coordinating to sell crops has occurred in the past year. We exclude the sharing of rice, since this may reflect the predominance of rice farming. The same set of questions was asked twice, regarding relatives and non-relatives, respectively, within the

[41] This is recognizable as the fractionalization measure, except that here respondents are sampled without replacement. If respondents were sampled with replacement, the measure would be simply $\sum_{y=1}^{5} s_{vy}^2$. Results would not be affected.

group. These lead to SHARING_RELATIVES and SHARING_NON-RELATIVES, respectively. BEST_COOPERATION comes from a poll of villagers in the HH survey. Each is asked which village in his tambon (subcounty) enjoys the best cooperation among villagers. The percentage of villagers in the HH survey naming the village in which a group is resident is the measure we use. Finally, JOINT_DECISIONS counts the number of the following three decisions on which some or all group members, as opposed to the individual farmer, have the final say: which crops to grow, pesticide and fertilizer usage, and production techniques.

Cost of monitoring is measured in two ways, from the BAAC survey. IN_VILLAGE gives the percent of the group living in the same village. RELATEDNESS gives the percent of group members who have a close relative in the group.

Official and unofficial penalties are proxied by two village-level variables from the HH survey. BEST_INSTITUTIONS is a poll similar to BEST_COOPERATION, where the respondent is asked to name the best village in his tambon in terms of availability and quality of institutions. This measure captures to some degree the legal infrastructure, which is related to the official penalties the BAAC can impose on borrowers. SANCTIONS comes from the HH survey and is constructed from a question asking villagers what the penalties for default on their current loans are. We use the percent of loans in the village that have penalties extending beyond the direct participants in the loan agreement. Specifically, we count loans for which the borrower reports that under default, he cannot borrow again from this lender *and other* lenders, or that reputation in the village is damaged.

Screening is proxied by two dummy variables from the BAAC survey. KNOW_TYPE equals one if the group leader answered that members know the quality of each other's work. SCREEN equals one if the group leader answered that there are borrowers who would like to join their group but cannot.

Productivity shifters include AVERAGE_LAND, the average amount of land per group member, measured in rai,[42] and AVERAGE_EDUCATION, average educational attainment in the group. The raw data for education are not years of schooling, but a classification into one of four categories: no schooling; some schooling, but below P4; P4; and higher than P4 schooling. The majority of borrowers have P4 schooling, the minimum level required by the Thai government. Our measure uses the following average: 1*(Pct of group with some schooling, but below P4) + 3*(Pct of group with P4 schooling) + 5*(Pct of group with higher than P4 schooling). The empirical results are robust to various choices of weights.

Data on groups' interest rates r and loan sizes L come from a BAAC survey question asking about the highest and lowest loan size and interest rate experienced by any member of the group over the past year. We take these high (hi) and low (lo) figures and use a weighted average $(lo + 0.1 * hi)/1.1$. The high end is only slightly weighted since the upper tail is often quite long and unrepresentative of the group as whole.

[42] One rai is approximately equal to 0.4 acres.

C Partially Linear Model Estimation

We assume a partially linear model: the repayment rate R is some smooth function of loan size L added to a linear function of the remaining variables, X_{-L}:

$$R = \beta'_{-L} X_{-L} + k(L) + \epsilon,$$

where β_{-L} is a vector of $(M-1)$ coefficients and k is a continuous function. The coefficients β_{-L} are estimated by ordering the observations according to L, differencing across nearby observations (we use optimal fifth-order differencing, described in Yatchew 1998), and regressing (the differenced) X_{-L} on (the differenced) R. This produces an estimate $\hat{\beta}_{-L}$.

Next we run a non-parametric, locally linear regression similar to Lowess (see for example Cleveland 1979 and Fan 1992) where the dependent variable is the residual $R - \hat{\beta}'_{-L} X_{-L}$ (and thus not restricted to equal 0 or 1) and the independent variable is L. For each unique value of L, we calculate a fitted value of the residual from a weighted least squares regression on a "nearby" subset of the total sample. Thus the choices are weights for the regression and a bandwidth which determines the subsample. For each unique value l, say, of L, the bandwidth $h(l)$ is set to ensure inclusion of the 80% of the data whose values l^g are closest to l.[43] The weighting function is the tri-cube weighting function:

$$w_g = (1 - (\frac{|l - l^g|}{1.0001\ h(l)})^3)^3.$$

This function places more weight on observations located more closely to l. Standard errors at 90% confidence are calculated using the bootstrap method. That is, recreating 1000 samples from the original sample by sampling with replacement, and repeating the entire procedure, for each value l the confidence interval is the 51st and 950th smallest fitted value from these samples. Since our main concern is with the shape (slope) of the functions, we normalize the residuals in each estimate to have mean zero.[44]

[43] If there are clusters of observations at the boundary of the bandwidth with the same value for the independent variable, all are included. Thus potentially more than 80% of the sample is used.

[44] Note that the Yatchew procedure identifies the function $k(L)$ up to a constant. De-meaning the residuals is then essentially a normalization of each bootstrapped estimate with respect to the constants. Without this normalization, bootstrap error bands can get large merely because the constants are varying.