BUSINESS LITERACY AND DEVELOPMENT: EVIDENCE FROM A RANDOMIZED CONTROLLED TRIAL IN RURAL MEXICO*

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Abstract

Women in developing countries often earn income through small enterprises such as making and selling food and craft items or re-selling wholesale goods. Several previous studies have established that women's returns in these enterprises are low, often lower than those of male-run small enterprises in the same area. One possible explanation for this finding is that women have especially deficient basic business skills. Working with an NGO, we devised a randomized controlled trial in which female entrepreneurs were given 48 hours of training, over six weeks, on topics such as measuring costs, setting prices, maximizing profits, marketing, and handling the legal issues that arise in a small business. We find that the entrepreneurs who were randomly assigned to treatment earn higher profits, have larger revenues, and serve a greater number of clients. We also find that they are more likely to use formal accounting techniques and know how profitable they are. Furthermore, these effects do not appear to be transitory, as positive treatment effects persist into the medium term, two and a half years after the training.

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1. Introduction

A persistent puzzle in developing countries is the observation that some female micro-entrepreneurs are not efficiently running their businesses; for example, through the misallocation of capital and labor in the firm (see **?** for a review of the literature). Given the importance of entrepreneurship in the development process, especially amongst women, it is of utmost importance to understand both how business decisions are made and if poor decisions are caused by a lack of financial literacy and managerial knowledge.

In response to this perceived underperformance of poor women entrepreneurs, a considerable number of NGOs around the world provide free or low cost business training. Presumably, this training will enable women to increase profits, through better management of their business. However, there is yet little evidence that this type of intervention (i) is needed and (ii) is effective. Among economists, there is an increasing interest in understanding the links between the variation in firm profits and financial and managerial practices in developing countries (see **?**; **?**; and **?**). On the other hand, more research is required to understand the way poor entrepreneurs make their investment decisions (**?**).

This research question matters because a large proportion of the poor in developing countries is self-employed, often engaged in the sale of goods. In fact, according to the International Development Research Center, women in the informal sector in developing countries are more likely to be self-employed than in wage paying jobs. Furthermore, there is evidence to suggest that enterprises run by women are not able to invest as profitably as those run by men (**?**). Thus, programs targeting human capital deficiencies amongst low-income women entrepreneurs have the potential to be cost-effective methods to promote growth.

However, identifying the causal link between business literacy, managerial skills and profits is a challenging task. Field experiments, in which individuals are randomly assigned to either a treatment or control group, have proved to be one way to overcome this barrier in a wide array of situations (**?**). In this paper we analyze the effects of providing business training to small and micro female entrepreneurs in rural Mexico through a Randomized Controlled Trial. The type of business training provided is rather basic and focuses on the application of the concept discussed in class on the participants' businesses, for example basic accounting exercises applied to actual women's businesses.

There are three distinctive characteristics of our intervention: i. the focus is on the application of

the concepts covered in class; ii. intensive training with a total of 48 hours of classes over 6 weeks; iii. our sample does not receive any other treatment, e.g. not part of lending programs.

The experiment was conducted in the Mexican state of Zacatecas, a poor state with a high number of male migrants. Our working sample includes 17 communities and about 900 entrepreneurs.[1] We completed a pre-intervention (baseline) survey in the summer of 2009. Then the business training classes began in late October 2009 for the eligible participants. The entrepreneurs included in the study are engaged in many different enterprises, such as making and selling food, making craft items, or small re-sale shops. We then re-surveyed the sample in the summer of 2010 and the spring of 2012, this allows us to look at short and medium run outcomes as well as increasing the statistical power of our testing strategy.

Specifically, our research will answer two questions: (i) Why are these micro-entrepreneurs not running their businesses efficiently? and (ii) Is the policy intervention of classroom training an effective and efficient remedy?

We find that the intervention significantly raises profits, revenues (to a smaller extent), and the number of clients served. Importantly the use of formal accounting techniques increases as a result of the intervention. We also find that the effects are present both in the short and the medium-run, i.e. after 7-8 months and about 2.5 years.

Our paper contributes to the growing literature on the effects of business literacy training on firms profitability. For example, **?** in India, **?** and **?** in Perú, **?** in the Dominican Republic, **?** in Tanzania, **?** in Bosnia-Herzegovina, and **?** in Pakistan, and **?** in the United States. There is at the same time a growing literature on the effects of management services in developing countries (**?**; **?**).

The rest of the paper is as follows: in Section **??** we present the content of the business literacy training; Section **??** illustrates the experimental design; Section **??** describes the data; **??** presents the empirical analysis and discusses the causal effects of the intervention; finally, Section **??** concludes.

2. The Business Literacy Training

In 2008, we partnered with the Mexican NGO *CREA* to develop and implement a business literacy training program targeted at small firms headed by female entrepreneurs.[2] The training program

[1] We will discuss the construction of our working sample in more details in Section **??**.

[2] CREA also manages two other programs, one which fosters mutual support groups for entrepreneurs and one which helps small producers make relationships with national or international wholesalers. Importantly, none of our subjects were offered these services during the study period. More information on CREA can be found at `www.crea.org.mx`

consists of two four-hours classroom meetings per week, and runs for six weeks - a total classroom time of 48 hours. This is a relatively long and intensive training, for example many training programs associated with microfinance organizations last 30 minutes, added on to weekly or monthly borrower meetings (see for example, **?**).

Another important difference between the current intervention and most of the existing literature is that, for our sample, business training was the only intervention these women were exposed to during the study period. For example, CREA did not offer microfinance and only 4.5 percent of our sample had received a loan from a microfinance institution or the government in the previous 12 months. While in **?**, **?**, **?**, business training is combined with micro-finance interventions. This is important as a recent paper by **?** finds substantial complementarities between business training and loans availability, making it hard to identify the clean effect of business training.

The program covers six main topics: The first consists of understanding costs (unitary, marginal, fixed, and total) and how they should be measured. The second concerns how to optimally set prices. In this module, emphasis is placed on the concepts of profit maximization and pricing to reflect marginal costs, rather than average or fixed costs. The third reviews basic legal rights and obligations of small business owners. Since the vast majority of participants own informal businesses, this module included a discussion of the costs and benefits of formally registering a business with the government. The fourth covers general business organization and the choice of products to produce or sell. The fifth module covers marketing, including concepts related to knowing and responding to competition. The final section covers discuss how to be an effective salesperson.

Classes were designed to be small and inclusive, with two instructors for an average class size of about 20 women. Instructors are experienced local university professors, graduate students, or undergraduates that are chosen on the basis of their teaching experience. The concepts and teaching style is intentionally simplified so as to be understandable to population at hand, the majority of whom have low levels of formal educational. Furthermore, classes emphasize practical examples and encourage active student participation.

For each of the six modules, students received a 30 page "textbook" which discussed (1) the importance of the concept at hand, (2) the definition of the concept, (3) examples of how to compute or use the concept (e.g., how to do basic business accounting or compute unitary costs), (4) in-class exercises, and (5) exercises for homework. In sum, the general structure of the class was first to introduce

the main concepts, then apply those concepts to simple examples, and finally to apply those main concepts to the participants' businesses through specific homework exercises. Furthermore, teachers were instructed to collect homework and provide feedback. An example of an in-class example and exercise can be seen in Figure **??**. This practical and applied focus of the classes is one of the key elements we wish to study through our intervention.

There is no tuition for attending the classes. In fact, to encourage participation, CREA offers participants several incentives including: a certificate from CREA, the Institute for Women of Zacatecas (a government agency and CREA partner), and the Autonomous University of Zacatecas (the local university) upon successful completion of the program; an in-class raffle for small prizes (such as a CREA hat or stationary supplies) each week conditional on attendance and homework completion; and the promise of acceptance in future CREA courses conditional on regular attendance to the current one.

3. The Experimental Design and Population of Study

Working with CREA, we designed and implemented a two-stage randomized controlled trial designed to uncover the causal effect of the business training classes on participants, as well as potential spill-over effects, or Indirect Treatment Effects (**?**), on non-participants in program villages.

We identified the entrepreneurs to be included in the study through a two-stage procedure, first choosing villages and then conducting a census of women entrepreneurs in those villages. Such a census is desirable for two reasons: first, our results are externally valid for a broad sample of the population, and second because such a census allows us to investigate the within-village general equilibrium effects of the intervention.

Our original sample frame included all villages in the state of Zacatecas that met three criteria: that they (i) had between 100 and 500 women entrepreneurs, as identified by the 2005 Mexican census, (ii) are within a two hour drive from the City of Zacatecas, and (iii) had less than 1500 households (also identified by the 2005 Mexican census).[3] This selection process identified 25 villages, and in practice only excluded the smallest hamlets and the largest three cities in the state. As the state of Zacatecas is a high-altitude, dry, and agricultural region, most villages are geographically isolated, separated by farms and arid land. There is good road access to all included villages, but the inhabi-

[3]The second criterion was necessary to ensure that the CREA instructors who lived in Zacatecas City would be able to reach participating villages.

tants are none-the-less isolated in most of their daily activities - it is therefore unlikely that there are program spillovers across villages.

Within chosen villages, we attempted to identify the universe of women entrepreneurs that produced and/or sold goods as follows: First, we contacted the elected village leader (a mayor-like position) and asked him/her to introduce us to at least three knowledgable women. Second, we asked this group to list all of the women in the village that (i) work for themselves and (ii) sell a good.[4] This process yielded about 50 women entrepreneurs per village, to whom we applied a pre-intervention questionnaire between July and September of 2009.

Pre-randomization into treatment status (but post-baseline survey), the NGO realized they did not have sufficient funds to treat more than seven villages. Furthermore, a projected budget shortfall prevented us from keeping more than ten villages as controls. We therefore dropped a random set of eight villages from our original sample of 25 villages leaving us with a working sample of 17 villages. In order to assign women to treatment, we used information on business activity (including profits and revenues) and demographics from the baseline survey to perform the random assignment at both the village and intra-village levels.[5] Thus, one set of villages serve as a "pure" control group and the set of treatment villages contains both eligible and ineligible women.

In early October, 2009, eligible women were contacted in person by a CREA staff member informing them of their selection into the program; classes began in late October and ran through December 2009. We conducted two post-intervention surveys, the first between July and September 2010 and the second between March and May of 2012. The second follow-up provides us the ability to look into longer run effects of the business training classes as well add power to our statistical analysis. All interviews were conducted by local enumerators with no connection to CREA.

4. Data and Sample

4.1 Data

We collected detailed data on an array of business activities and socio-economic characteristics. Our analysis focuses on self-reported measures of business performance such as profits and revenues

[4] We did not include the services sector as CREA believed the classes, as designed, would be only tangentially beneficial to such entrepreneurs.

[5] Our randomization algorithm involved first choosing a "seed" group of seven villages and then choosing 50 percent of the sample in each treatment village to be offered the program. We repeated this assignment 10,000 times as to minimize the (squared) sum of the distances of predicted profits between treated and control units.

(both daily and weekly), and the number of clients served. Self-reported measures of profits and revenues have been shown in other developing country contexts to be as accurate as using formally computed accounting statistics (**?**). At the same time we also collected data on sales, prices, and unit costs for most products women sold, as well as monthly fixed costs, we can then compute profits, revenues, costs, prices and a measure of mark-up on those specific goods. We also collected data on the sector of business, the number of workers or co-owners involved in the business, the average number of hours worked per week by the owner, and the age of the business.

We assessed women's knowledge of basic math with a simple exercise related to production and sales; see Figure **??**. This question was applied both pre- and post-treatment. We score each of the four sections as either correct or incorrect, summing to create a total score for the exercise. To capture important heterogeneity we also gathered information on age, education, asset ownership (e.g. type of dwellings and number of rooms), risk aversion, reservation wages, credit availability, and the size of business investments.

Importantly, we asked the entrepreneurs how they kept accounts for their business, whether through personal notes or a formal accounting method, or whether they didn't keep any accounts. We then recorded and verified attendance to the classroom training for the participants.

4.2 Sample

Our working sample includes 17 villages - seven treatment and ten pure control - and a total of 875 women: 164 eligibles, 189 controls in treatment villages and 522 in pure control villages.[6] Of the 164 eligible women, 57 (about 35 percent) did not attend any classes despite several in-person invitations (after the initial offer) that were made by both CREA staff and village participants that had already chosen to participate. As such, we will estimate both an Intent to Treat parameter (ITT) and use an instrumental variables estimator to recover the Treatment effect on Treated women (TT), where we focus on the effect on the 65% of eligible women who attended at least one class.

4.3 Summary Statistics and Baseline Balance

Figure **??** shows that the sample (at baseline) has a majority of firms involved in the sale of food, either prepared or ready-to-eat (a total of about 65 percent of the sample). General grocery store owners and other re-sale comprise a little over 25 percent of the sample. While handicrafts and

[6] See Figure **??** for a map of the included villages, and Appendix Figure **??** for a map which also includes those villages excluded after the baseline survey but before the randomization and the intervention.

clothing sum-up to about 10 percent.

Table **??** contains mean baseline characteristics by treatment group, along with p-values from F-tests of their equality. No characteristics are significantly different across groups at the 5 percent level, suggesting that the randomization was successful.

This baseline data paints a sobering picture of the economic lives of these entrepreneurs. Weekly profits average around 400 pesos (approximately $37), with a large variation: the 10th percentile is 25 pesos and the 90th is 1000 pesos.[7] It is interesting to notice how the profits to revenues ratio is about the same order of magnitude as the one found in Sri Lanka by **?**.

Women work for about 40 hours per week on average, but again with large variation. The total value of the capital stock is about $800. Interestingly, the entrepreneurs in our sample seem to have access to credit that would allow them to replace the business capital at a high (albeit common for this type of population) 6 percent monthly interest rate. Businesses are small, on average 1.6 workers including the owner, and about 60 percent of businesses have no workers other than the owner. The average age of a firm is about seven years, again with large variation.

Importantly, the women in our sample know how to make basic calculations, but do not know how to determine profits or how to set their prices. For example, 93 percent of women said that they know how to make simple math calculations (data not shown), however, on average, women answered less than two out of the four questions in the math exercise correctly. Analyzing the questions of the math exercise separately, less than 50 percent could calculate profits correctly and only 18 percent could calculate the optimal price to set (again, data not shown).

As mentioned above, the take-up rate for the business literacy classes is less than full (at 65 percent). We defining a subject as having attended the program if she attended at least one class; however, class attendance was somewhat irregular with about 65 percent of the invited ever attending a class and among those who attended at least one class we have an average of six classes attended out of the 12 offered. Such take-up rates are consistent with similar studies (see for example **?**).

Table **??** contains mean baseline characteristics by attendance status for all women in the treatment group, along with p-values from F-tests of their equality across groups. Despite the fact that no characteristics are significantly different across groups at the five percent level, there are noticeable differences in profits and revenues between those that attended and those that were offered the classes,

[7] The dollar peso exchange rate in 2008-2009 was approximately 13 Mexican pesos to 1 U.S. dollar.

but did not attend; daily and weekly profits and revenues are about 50 percent higher for women who did not attend compared to those who attended. Again such findings are consistent with **?** and **?**. No other significant differences between these groups are observed. In general we notice that attendees are less successful entrepreneurs with respect to non-attendees. In what follows we are most interested in the comparison between eligible and ineligible women, and thus focus on the Intent to Treat parameter while presenting also the Treatment on Treated parameters.[8]

It is here important to discuss the dynamic characteristics of our sample as we surveyed our sample over the period of almost 3 years. Attrition at the time of the first post-intervention survey (summer 2010) was 15 percent. Virtually all of the attrited women either moved out of the village or were not available on the day of the interview; only three subjects refused to participate. Importantly, attrition rates at the first follow-up are indistinguishable across treatment groups (p-value = 0.39), at 13 and 15 percent for the treatment and control respectively. Furthermore, there is no significant observable difference (on average) between attrited women in the treatment and control groups (results available upon request).

A further 9 percent of the baseline sample attrited by the second follow-up (spring 2012), yielding a cumulative 26 percent attrition rate. (The attrition rate is again indistinguishable between treatment and control groups (p-value=0.30).) Importantly, attrited entrepreneurs are observably different from non-attrited ones; specifically, attrited entrepreneurs have significantly fewer clients, have fewer workers, and are more educated (see Table **??**).

Amongst the non-attriters, 21 percent of the sample had stopped running their business by the time of the first follow-up survey, while 50 percent had quit by the second follow-up. This implies that business related measures are missing for these women in the post treatment period. Quit rates are indistinguishable across treatment groups in both the first follow-up (p-value=0.70) as well as at the second follow-up (p-value=0.47).[9] Furthermore, there is no observable difference between quitters in the treatment and control group at either follow-up survey (again, results available upon request). Perhaps not surprisingly, quitters have lower profits and revenues at baseline than non-quitters (although only marginally significant differences, those differences appear economically important). Furthermore, (see Table **??**) quitters have significantly higher education (an extra one-half of a year), are

[8]Interpreting the treatment on the treated effect is as usual quite problematic given the selection into attending the classes.

[9]Quitting one's business can certainly be considered an outcome that could be affected by the intervention; for example, if the training made the entrepreneur realize that her business was indeed operating at a loss.

about three years younger, and are poorer in terms of the one indicator of wealth that we observe (the roof of their house is made out of a temporary material).

Although on average surviving firms are not statistically different in terms of baseline characteristics between treatment and control group. It is quite relevant to notice that the treatment group loses the bottom 2% of firms in the baseline (weekly) profits distribution (see Figure **??**) and the control group (see Figure **??**).

5. Empirical Strategy and Results

The experimental design allows us to undertake simple mean comparisons to isolate the causal impact of being offered the business training classes, that is, Intent to Treat (ITT) parameters. Towards this end, we estimate (among others) a series of difference in differences models, comparing invitees and control women before and after the intervention. The two post-intervention waves allow us to estimate both a model that permits different treatment effects over time and a model which pools both post-intervention waves together, as in:

$$y_{it} = \alpha + \beta T_i + \sum_{t=2}^{3} \delta_t WAVE_t + \sum_{t=2}^{3} \gamma_t (T_i * WAVE_t) + \varepsilon_{it} \tag{1}$$

$$y_{it} = \alpha + \beta T_i + \delta POST_t + \gamma (T_i * POST_t) + \varepsilon_{it} \tag{2}$$

y is the outcome interest, e.g. profits or revenues, T is an indicator for treatment status with $T = 1$ for those women invited to the classroom training and $T = 0$ for those not invited, $WAVE_t$ are indicators for the two post-intervention surveys, $POST$ is an indicator for the post-intervention period, and ε is an error term. The parameters of interest are γ_t and γ which identify the Intent to Treat.

Imperfect compliance amongst women offered treatment implies that women self-selected into actual classroom attendance. In order to investigate the effect of treatment (being offered the class) on the treated (class attendees) (TT), we estimate models where the attendance status (which is presumably endogenous) is instrumented for by the (exogenous) treatment status; needless to say, the randomized offer of classes implies treatment status is a valid and powerful instrument. However as the interpretation of such parameters is not clear cut we will mainly focus on the well defined $ITT's$ parameters.

In both the TT and ITT models, statistical inference is complicated by the small number of clusters (villages), implying that standard methods for computing standard errors will lead us to incorrect standard errors based on asymptotic results. We thus use wild bootstrap (**?**) and randomization inference to construct hypothesis tests of treatment effects (**?**). For the randomization inference we simulate the distribution of the effects by permutation. In practice, given the very large number of total permutations (seven treatment villages out of 17 total villages, and 25 women out of about 50 per treatment village) we implement the randomization inference procedure by simulating 5000 replications for the assignment into treatment and control villages and groups.[10]

Further to that our preferred estimation uses only between village variation, excluding then the control women living in treatment villages, this is because we notice that the indirect treatment effects ($ITE's$) and spill-over effects are economically and, in certain cases, statistically significant (see appendix Tables **??**, **??** and **??**). Also, there are good theoretical reasons why we might want to exclude the control women in treatment villages from the estimation, as in practice these two groups operate in the same market, it would be hard to exclude any substitution or general equilibrium effects in such small markets.

Table **??** reports the main results along with robust, cluster-adjusted standard errors and p-values from the wild bootstrap procedure and the randomization inference exercise. We first examine the effect of the program on daily and weekly profits. Many women do not work the full week or regular hours; as such, they might be better able to remember daily profits rather than compute weekly profits. We consider both daily and weekly profits in our analysis. As we cannot detect any statistical (and economic) difference in treatment effects between the two post intervention waves (see Table **??** we will focus on the results from pooling the two post intervention waves and highlight the differences when arising. Looking at Table **??** on the logarithm of daily profits, the point estimate of the intent to treat effect is about 0.39, which indicates that the solicitation to participate in the business classes has a positive effect on daily profits of about 45 percent. The corresponding treatment on the treated is obviously larger and equal to 0.42, which implies a 54% increase in daily profits. Such effect is quite large but more than comparable to **?**. The results are statistically significant at conventional level also when taking into account the small number of clusters.

If we look at weekly profits the positive ITT effect appears smaller and roughly equal to 34

[10]For example, considering only the village level, there are $\#P = (17 * 16 * ... * 11)/2 \approx 50$ million permutations. Importantly, the results are robust to the number of replications used.

percent with a treatment on the treated effect of 0.34 log points, or 40 percent. We take the evidence as consistent with a positive effect of the classes on profits. We also present results on a standardized measure of profits, revenues, and number of clients, which essentially collapses our main outcomes in one standardized index (as in **?**), i.e. we standardize each of the variables with respect to the baseline control group values (daily and weekly profit, revenues, and number of clients) and take the individual level average of such standardized measures. The rational for doing so is to reduce the number of multiple outcomes tested, which might suffer from well known problems in multiple hypotheses testing (**?**). We find that the ITT is about 0.17 of a standard deviation while the TT is about 0.22.

The results above are confirmed once one takes into account the small number of clusters in the analysis (17 villages) and inference is based on permutation tests (to be completed) or wild bootstrap that are applicable in such instance. In particular we show, in square brackets in Table, that the randomization inference (permutation tests as in **?**) provides support for the claims above as the p-values constructed under exact size testing, which is distribution free, essentially confirm the results above.

It is also important to notice that the estimated effects seem to last in the medium run, as we still detect them about 2.5 years after the intervention.

The estimated effects are robust to various alternative specifications, i.e. not controlling for baseline characteristics as in Table **??** (not surprisingly given the RCT design) or bounding exercise where we confirm the sign of our main estimates.

5.1 Mechanisms

We then try to understand whether such an impact arises from increased revenues, number of clients, or from better accounting practices, costs and pricing behavior as well as changing the goods composition or modifying the business structure and labor supply. In terms of revenues we have positive but insignificant effects on daily revenues, which is somewhat surprising given that we have a positive and (marginally) significant effect on weekly revenues, and again given that we have positive effects on profits both weekly and daily we feel that the results on daily revenues should probably be regarded with caution. In particular, given that we estimate a larger number of clients about 20 and 30 percent as the ITT and TT respectively (the effects appear marginally significant).

Quite interestingly one of the effects of the business classes appear to be that our female en-

trepreneurs report to know their profits. This lines up with the crucial effect of accounting practices as we detect a substantial increase in formal accounting among the treated, an effect of 6 percentage points and a very low base, as only 3 percent of the control used formal accounting at baseline. Our investigation of the mechanisms which leads to the overall positive effect on profits points towards several factors as already mentioned. In particular more formal accounting, is accompanied by lower prices, and costs, as well as more goods being offered and a possible increase in the labor supply see Tables **??**, **??**).

It is also important to note that as in any policy evaluation, the existence of spillover or general equilibrium effects to the control group will bias the parameter estimates. However, given our two-stage randomization procedure we are able to estimate potential spillover to the control women within treatment villages. Those effects are sizeable economically although with large confidence interval (see Tables **??**, **??**, **??**), so that if we were to use those observations we would have biased estimates.

6. Conclusions

The existing evidence on enterprises in developing countries suggests that those firms are often run inefficiently (**?**;**?**) and often lack working capital (**?**; **?**). At the same time it could be that the crucial barrier to growth and profitably arises from the lack of human capital, i.e. basic business literacy. In recent years there has been an increasing interest in such an issue with a series of interventions offering some form of business or financial training and working capital (through micro-finance), see for example **?**, **?**, and **?**.

We contribute to this literature in several ways. First, we provide intensive practical training, the duration of our classes is at the very top end of the interventions provided by other authors. Second, we only provide such a training which is not confounded by the provision of micro-loans. Third, we follow our sample for up to two and a half years after the intervention. Our results indicate that basic training in business practices are capable of producing quite large effects on profits, through a combination of higher revenues, number of clients served a reduction of costs possibly due to better accounting methods.

Figure 1: Geographical distribution of treatment and control villages. Red pins are treatment villages, blue bulbs are control villages.

Figure 2: Example of an in-class example (Panel A) and an in-class exercise (Panel B).

Panel A

Supose that Belen has a store that sells beauty products. She sells makeup, hair products, and products for nails. Below is a list of articles that she sold today:

Belen's Beauty Products			
No.	**Article**	**Unit Price**	**Subtotal**
3	Nail files	$10	$30
1	Anti-dandruf shampoo	$30	$30
2	Eye shadow	$20	$40
		TOTAL	$100

As we can see in this bill of sale, Belen sold 3 nail files for 10 pesos each (3 x $10), generating a revenue of 30 pesos, 1 anti-dandruff shampoo for 30 pesos (1 x $30) gererating a revenue of 30 pesos, and 2 eye shadows for 20 pesos each (2 x $20) generating a revenue of 40 pesos. In total, Belen had revenue of 100 pesos today.

Panel B

Leticia has a business selling pineapple candy that she produces herself along with a small store in which she sells her candies and many other food items, from fruit and vegetables to cookies, flour, soda, etc. Leticia needs you to help her calculate her revenue from September 17th. Below is a list of products that she sold. Please calculate the revenue for each item and then calculate her total revenue.

Lety's Corner Store Sales on September 17th			
No.	**Article**	**Unit Price**	**Subtotal**
20	Pineapple candy	$3.50	
5	Kilos of tomatoes	$6	
10	Kilos of onion	$5	
4	Kilos of orange	$10	
6	Gansitos Marinela ®	$4	
8	Bottles of Coca-Cola ®	$5	
		TOTAL	

Figure 3: The applied math question asked to women in the baseline and follow-up surveys.

Section 10 Exercise

Now we are going to do an exercise, but I want to let you know that the numbers are invented, as is the example. If you have any questions, please ask me.

If they do no answer of don't want to answer, STOP, and leave the other parts blank.

Part 1: Imagine that you produce 5 tablecloths every week and that each tablecloth costs 10 pesos.

Suppose the first week you sell	1 tablecloth
The second week you sell	2 tablecloths
The third week you sell	2 tablecloths
and the fourth week you sell	5 tablecloths

a) How many tablecloths do you have left over at the end of the month? [ ]

b) What is your income for this month? [ ]

Part 2: Each week, you spend 5 pesos for cloth and 5 pesos in salaries in order to make tablecloths. Each month has 4 weeks.

c) How much are your profits at the end of the month? That is, how much money do you earn this month? [ ]

d) If your profits were to be zero for this month, what price should you have set for your tablecloths? [ ]

Figure 4: Sectors of micro-enterprise activity at baseline.

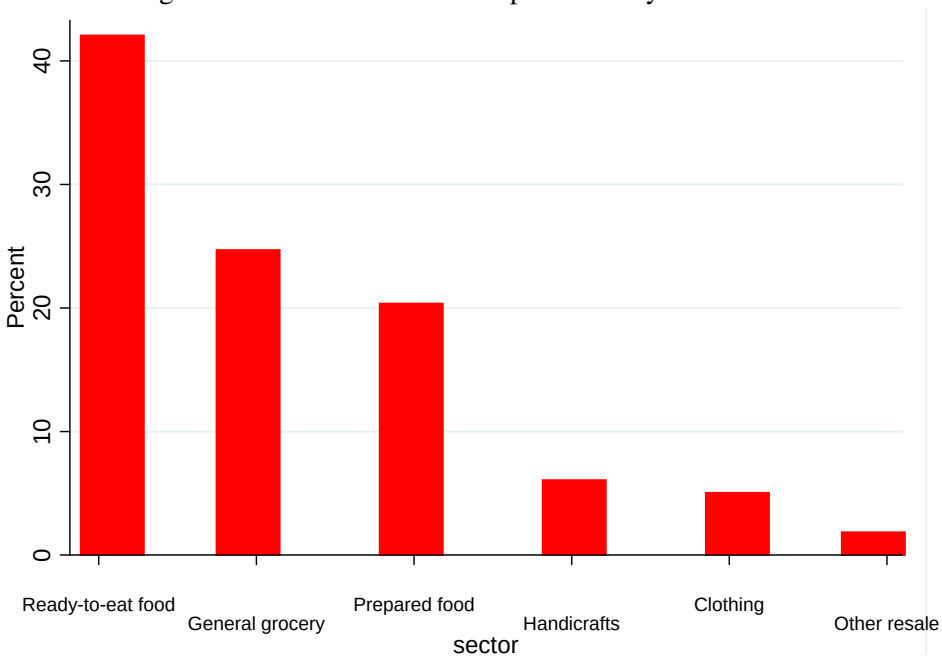

Figure 5: Baseline (Log) Weekly Profits for Whole and Survived Sample (Controls)

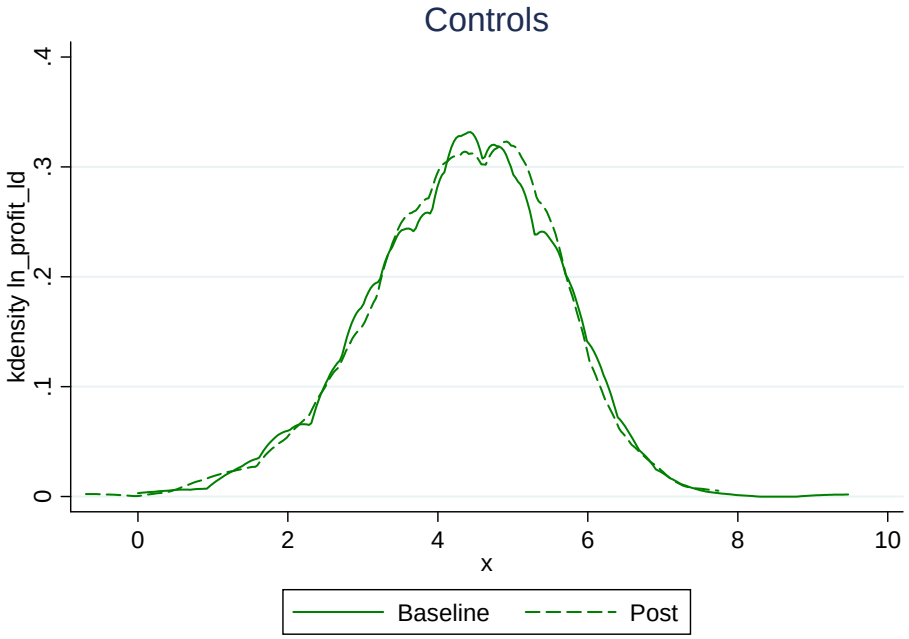

Figure 6: Baseline (Log) Weekly Profits for Whole and Survived Sample (Treated)

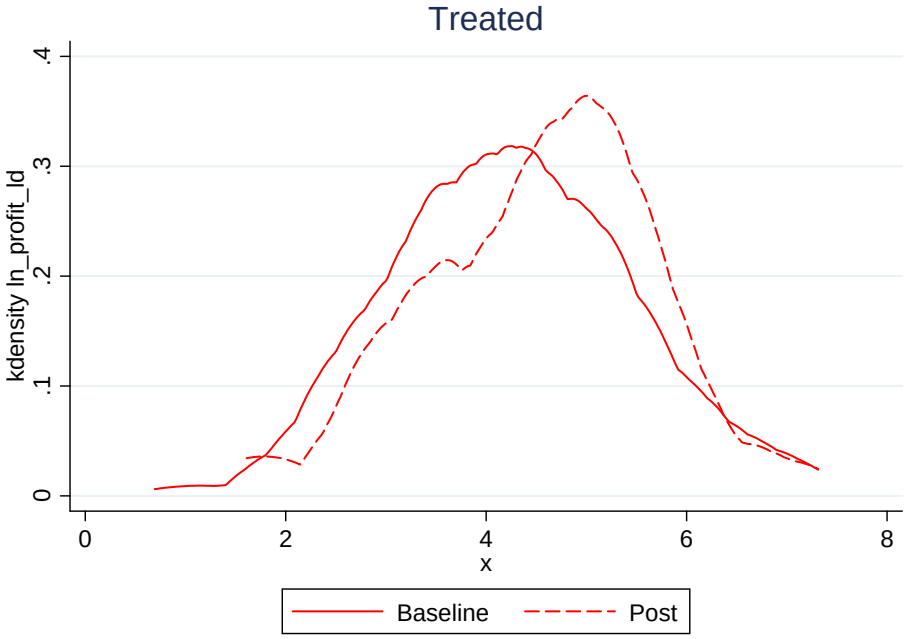

Table 1: Baseline Characteristics, by treatment group.

	Treatment	Control	(1)=(2) p-value	Entire sample 10th percentile	Entire sample 90th percentile	N
	(1)	(2)	(3)	(4)	(5)	(6)
Business Characteristics						
Daily profits	132.24	154.92	0.42	10.00	300.00	760
	(16.06)	(22.61)				
Weekly profits	364.39	400.79	0.36	25.00	1000.00	731
	(26.28)	(33.71)				
Knows daily profits	0.87	0.91	0.48	1.00	1.00	848
	(0.06)	(0.03)				
Knows weekly profits	0.83	0.89	0.34	0.00	1.00	843
	(0.06)	(0.03)				
Daily revenue	456.16	405.96	0.90	1.00	0.00	874
	(55.18)	(35.89)				
Weekly revenue	1,311.55	1,291.49	0.81	0.00	84.00	628
	(110.95)	(95.53)				
Number of daily clients	16.99	17.61	0.22	6.00	240.00	875
	(2.04)	(1.33)				
Total number of workers, including owner	1.58	1.65	0.22	1.00	3.00	865
	(0.05)	(0.04)				
Keeps formal business accounts	0.01	0.04	0.09	0.00	0.00	873
	(0.01)	(0.01)				
Weekly hours worked by the owner	39.43	39.19	0.95	6.00	84.00	866
	(3.19)	(1.65)				
Age of business (months)	81.24	91.47	0.37	4.00	240.00	874
	(10.10)	(7.75)				
Replacement value of business capital	8,062.61	9,238.82	0.30	0.00	12200.00	875
	(1,009.51)	(1,023.20)				
Personal Demographics						
Reservation wage, monthly	2,986.29	2,974.28	0.94	1000.00	5000.00	696
	(92.06)	(140.90)				
Maximum loan available if needed	8,703.94	9,016.38	0.89	500.00	20000.00	689
	(1,079.86)	(1,951.88)				
Monthly interest rate on a potential loan	5.48	6.43	0.17	0.08	10.00	506
	(0.62)	(0.32)				
Score on math exercise (percent correct)	0.39	0.47	0.10	0.00	0.75	864
	(0.04)	(0.03)				
Years of education	5.96	6.07	0.72	2.00	9.00	846
	(0.32)	(0.13)				
Age	46.04	45.67	0.60	28.00	65.00	869
	(0.48)	(0.53)				
Roof is made of temporary material	0.33	0.32	0.92	0.00	1.00	844
	(0.09)	(0.05)				

Notes:

(1) Sample includes all women interviewed in the baseline survey.

(2) Robust (s.e.) clustered at the village level.

(3) All monetary variable are measured in Mexican Pesos (~13 pesos / 1 U.S. dollar).

(4) Reservation wage is the minimum stated monthly wage a women would accept in order to quit her business.

Table 2: Baseline characteristics for treatment group women, by attendance.

	Among those assigned to treatment					
	Attended	Did not attend	(1)=(2) p-value	10th percentile	90th percentile	N
	(1)	(2)	(3)	(4)	(5)	(6)
Business Characteristics						
Daily profits	110.83	177.91	0.34	10.00	300.00	141
	(28.90)	(43.62)				
Weekly profits	286.11	536.22	0.13	25.00	1000.00	131
	(44.80)	(107.25)				
Knows daily profits	0.90	0.81	0.17	1.00	1.00	164
	(0.04)	(0.10)				
Knows weekly profits	0.86	0.79	0.22	0.00	1.00	163
	(0.04)	(0.10)				
Daily revenue	337.85	690.53	0.18	1.00	0.00	164
	(75.24)	(243.80)				
Weekly revenue	1,018.70	1,897.25	0.74	0.00	84.00	130
	(173.77)	(462.05)				
Number of daily clients	16.61	17.73	0.37	6.00	240.00	164
	(1.99)	(3.56)				
Total number of workers, including owner	1.64	1.48	0.37	1.00	3.00	159
	(0.06)	(0.13)				
Keeps formal business accounts	0.01	0.02	0.72	0.00	0.00	164
	(0.01)	(0.02)				
Weekly hours worked by the owner	37.84	42.43	0.36	6.00	84.00	162
	(4.02)	(4.03)				
Age of business (months)	80.18	83.23	0.86	4.00	240.00	164
	(7.92)	(19.53)				
Replacement value of business capital	7,441.43	9,228.68	0.45	0.00	12200.00	164
	(1,310.72)	(1,819.19)				
Personal Demographics						
Reservation wage, monthly	3,064.04	2,808.85	0.50	1000.00	5000.00	128
	(140.02)	(271.85)				
Maximum loan available if needed	8,479.91	9,190.24	0.79	500.00	20000.00	130
	(1,595.83)	(1,792.58)				
Monthly interest rate on a potential loan	5.94	4.38	0.15	0.08	10.00	101
	(0.64)	(1.07)				
Score on math exercise (percent correct)	0.39	0.38	0.79	0.00	0.75	164
	(0.05)	(0.06)				
Years of education	6.07	5.76	0.57	2.00	9.00	161
	(0.41)	(0.44)				
Age	46.98	44.25	0.32	28.00	65.00	163
	(0.91)	(1.80)				
Roof is made of temporary material	0.38	0.22	0.03	0.00	1.00	160
	(0.11)	(0.07)				

Notes:

(1) Sample includes all women interviewed in the baseline survey.

(2) Robust (s.e.) clustered at the village level.

(3) All monetary variable are measured in Mexican Pesos (~13 pesos / 1 U.S. dollar).

(4) Reservation wage is the minimum stated monthly wage a women would accept in order to quit her business.

Table 3: Baseline characteristics for treatment group women, by attrition

	Attrition in 2nd Follow-up					
	Attrited	Present	(1)=(2) p-value	10th percentile	90th percentile	N
	(1)	(2)	(3)	(4)	(5)	(6)
Business Characteristics						
Daily profits	125.38	155.65	0.23	10.00	300.00	760
	(15.47)	(21.78)				
Weekly profits	441.46	384.72	0.40	25.00	1000.00	731
	(66.29)	(28.59)				
Knows daily profits	0.87	0.90	0.32	1.00	1.00	848
	(0.03)	(0.03)				
Knows weekly profits	0.87	0.88	0.70	0.00	1.00	843
	(0.04)	(0.03)				
Daily revenue	359.27	426.92	0.32	1.00	0.00	874
	(29.59)	(35.86)				
Weekly revenue	1,532.55	1,246.13	0.81	0.00	84.00	628
	(265.15)	(71.28)				
Number of daily clients	17.14	17.57	0.04	6.00	240.00	875
	(1.83)	(1.14)				
Total number of workers, including owner	1.52	1.66	0.04	1.00	3.00	865
	(0.07)	(0.03)				
Keeps formal business accounts	0.03	0.03	0.84	0.00	0.00	873
	(0.02)	(0.01)				
Weekly hours worked by the owner	42.57	38.57	0.19	6.00	84.00	866
	(2.84)	(1.57)				
Age of business (months)	86.35	90.20	0.78	4.00	240.00	874
	(11.73)	(7.98)				
Replacement value of business capital	8,072.53	9,209.35	0.55	0.00	12200.00	875
	(1,426.11)	(1,097.91)				
Personal Demographics						
Reservation wage, monthly	3,223.48	2,927.60	0.43	1000.00	5000.00	696
	(324.63)	(132.60)				
Maximum loan available if needed	8,262.71	9,101.00	0.69	500.00	20000.00	689
	(1,035.06)	(1,921.05)				
Monthly interest rate on a potential loan	6.87	6.11	0.21	0.08	10.00	506
	(0.42)	(0.36)				
Score on math exercise (percent correct)	0.44	0.46	0.64	0.00	0.75	864
	(0.04)	(0.03)				
Years of education	6.44	5.97	0.04	2.00	9.00	846
	(0.23)	(0.14)				
Age	45.41	45.81	0.75	28.00	65.00	869
	(1.29)	(0.41)				
Roof is made of temporary material	0.32	0.32	0.92	0.00	1.00	844
	(0.07)	(0.05)				

Notes:

(1) Sample includes all women interviewed in the baseline survey.

(2) Robust (s.e.) clustered at the village level.

(3) All monetary variable are measured in Mexican Pesos (~13 pesos / 1 U.S. dollar).

(4) Reservation wage is the minimum stated monthly wage a women would accept in order to quit her business.

Table 4: Baseline characteristics for women, by quitting status.

	Quit Business in 2nd Follow-up					
	Quit	No Quit	(1)=(2) p-value	10th percentile	90th percentile	N
	(1)	(2)	(3)	(4)	(5)	(6)
Business Characteristics						
Daily profits	125.48	185.82	0.14	10.00	300.00	636
	(12.64)	(39.23)				
Weekly profits	335.44	433.36	0.09	25.00	1000.00	608
	(34.57)	(43.78)				
Knows daily profits	0.91	0.89	0.30	1.00	1.00	705
	(0.03)	(0.03)				
Knows weekly profits	0.88	0.88	0.78	0.00	1.00	699
	(0.03)	(0.04)				
Daily reveune	390.83	462.28	0.07	1.00	0.00	727
	(49.98)	(54.37)				
Weekly revenue	1,073.08	1,418.66	0.94	0.00	84.00	518
	(86.81)	(137.43)				
Number of daily clients	17.64	17.49	0.25	6.00	240.00	728
	(1.64)	(1.40)				
Keeps formal business accounts	1.62	1.71	0.25	1.00	3.00	719
	(0.04)	(0.06)				
Total number of workers, including owner	0.02	0.04	0.27	0.00	0.00	727
	(0.01)	(0.01)				
Weekly hours worked by the owner	37.46	39.65	0.33	6.00	84.00	721
	(2.34)	(1.39)				
Age of business (months)	78.58	101.60	0.04	4.00	240.00	727
	(9.19)	(10.04)				
Replacement value of business capital	8,423.58	9,978.04	0.18	0.00	12200.00	728
	(1,257.23)	(1,220.67)				
Personal Demographics						
Reservation wage, monthly	2,729.23	3,128.03	0.14	1000.00	5000.00	581
	(152.15)	(211.34)				
Maximum loan available if needed	9,615.53	8,566.25	0.78	500.00	20000.00	571
	(3,482.60)	(1,294.74)				
Monthly interest rate on a potential loan	6.12	6.11	0.97	0.08	10.00	422
	(0.49)	(0.40)				
Score on math exercise (percent correct)	0.45	0.46	0.69	0.00	0.75	719
	(0.03)	(0.03)				
Years of education	6.26	5.69	0.02	2.00	9.00	702
	(0.16)	(0.18)				
Age	44.36	47.22	0.00	28.00	65.00	723
	(0.66)	(0.53)				
Roof is made of temporary material	0.40	0.24	0.00	0.00	1.00	701
	(0.06)	(0.04)				

Notes:

(1) Sample includes all women interviewed in the baseline survey.

(2) Robust (s.e.) clustered at the village level.

(3) All monetary variable are measured in Mexican Pesos (~13 pesos / 1 U.S. dollar).

(4) Reservation wage is the minimum stated monthly wage a women would accept in order to quit her business.

Table 5: The Effects of Business Training on Selected Outcomes

	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE
Outcome =	ln(Daily Profits)		ln(Weekly Profits)		ln(Daily revenues)		ln(Weekly revenues)		ln(Daily Clients)		ln(Standardized)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment	-0.075	-0.040	-0.102	-0.145	-0.005	0.018	0.005	0.008	-0.016	-0.009	-0.010	-0.001
	(0.115)	(0.206)	(0.117)	(0.174)	(0.138)	(0.221)	(0.095)	(0.173)	(0.118)	(0.181)	(0.085)	(0.139)
Post	0.057	0.082	0.255	0.288	0.026	0.061	0.062	0.085	-0.062	-0.056	-0.051	-0.027
	(0.075)	(0.071)	(0.092)**	(0.087)***	(0.065)	(0.070)	(0.115)	(0.120)	(0.053)	(0.055)	(0.030)	(0.031)
Treatment*Post	0.390	0.423	0.295	0.337	0.172	0.211	0.304	0.436	0.161	0.193	0.166	0.202
	(0.097)***	(0.143)***	(0.113)**	(0.158)**	(0.127)	(0.180)	(0.127)**	(0.199)**	(0.144)	(0.208)	(0.063)**	(0.091)**
p-values wild boot	(0.001)		(0.019)		(0.195)		(0.029)		(0.279)		(0.019)	
lower bound	0.131	0.118	0.148	0.171	0.089	0.096	0.144	0.172	0.062	0.093	0.091	0.111
Observations	1,411	1,411	1,324	1,324	1,515	1,515	1,469	1,469	1,355	1,355	1,795	1,795

Notes: ***p<0.01, ** p<0.05, * p<0.1. (1) Robust (s.e.) clustered at the village level. P-values of wild bootstrap to account for small number of village clusters (Cameron, Gelbach and Miller, 2008). Lower bounds estimated using a matching procedure described in the text. In all regressions we control for baseline: size, sector, business age, replacement value, lack of business skills, risk aversion, age, education, # of rooms, exercise score, and dummy indicators for missing controls.

Table 6: Possible Mechanisms: Accounting

	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE
Outcome =	1{Account}		ln(Monthly Profits good-by-good)		ln(Monthly Revenues good-by-good)		ln(Mark-up good-by-good)		ln(Mean Prices)		ln(Mean Costs)		ln(# goods)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Treatment	-0.024	-0.034	-0.083	-0.101	-0.066	0.001	-0.047	-0.079	0.045	0.054	0.078	0.088	-0.037	-0.063
	(0.016)	(0.023)	(0.138)	(0.217)	(0.157)	(0.256)	(0.063)	(0.098)	(0.090)	(0.162)	(0.100)	(0.163)	(0.092)	(0.140)
Post	0.014	0.016	-0.119	-0.070	-0.488	-0.440	0.143	0.133	0.076	0.087	0.105	0.097	-0.119	-0.112
	(0.009)	(0.009)*	(0.141)	(0.154)	(0.153)***	(0.167)**	(0.067)**	(0.066)*	(0.045)	(0.044)*	(0.110)	(0.113)	(0.042)**	(0.042)**
Treatment*Post	0.046	0.064	0.373	0.426	0.647	0.867	0.138	0.195	-0.030	-0.045	-0.329	-0.456	0.162	0.224
	(0.022)**	(0.030)**	(0.269)	(0.361)	(0.279)**	(0.392)**	(0.098)	(0.140)	(0.099)	(0.128)	(0.132)**	(0.173)**	(0.076)**	(0.109)*
p-values wild boot	(0.049)		(0.186)		(0.034)		(0.180)		(0.769)		(0.024)		(0.024)	
lower bound	0.049	0.074	0.031	0.047	0.344	0.529	0.112	0.172	-0.155	-0.237	0.109	0.148	0.131	0.187
Observations	1,432	1,432	755	755	958	958	879	879	1,196	1,196	926	926	1,354	1,354

Notes: ***p<0.01, ** p<0.05, * p<0.1. (1) Robust (s.e.) clustered at the village level. P-values of wild bootstrap to account for small number of village clusters (Cameron, Gelbach and Miller, 2008). Lower bounds estimated using a matching procedure described in the text. In all regressions we control for baseline: size, sector, business age, replacement value, lack of business skills, risk aversion, age, education, # of rooms, exercise score, and dummy indicators for missing controls.

Table 7: Possible Mechanisms: Employment

	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE
Outcome =	ln(Size)		ln(Paid Employment)		ln(Co-owners)		ln(Unpaid employment)		ln(Hours per week)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment	-0.018	0.054	-0.008	-0.015	0.013	0.048	-0.023	-0.038	0.185	0.533
	(0.023)	(0.088)	(0.038)	(0.058)	(0.027)	(0.041)	(0.022)	(0.038)	(2.954)	(4.654)
Post	0.025	0.071	0.056	0.045	0.132	0.155	0.196	0.202	-1.070	-1.047
	(0.053)	(0.059)	(0.033)	(0.038)	(0.059)**	(0.068)**	(0.053)***	(0.054)***	(1.828)	(1.894)
Treatment*Post	-0.001	-0.040	0.016	0.034	-0.201	-0.281	0.188	0.255	3.481	4.293
	(0.127)	(0.172)	(0.061)	(0.089)	(0.085)**	(0.118)**	(0.097)*	(0.134)*	(3.663)	(5.446)
p-values wild boot	(0.996)		(0.800)		(0.031)		(0.070)		(0.356)	
lower bound	0.003	-0.045	-0.027	-0.079	-0.075	-0.140	0.223	0.332	-0.347	-0.645
Observations	1,432	1,432	755	755	958	958	879	879	1,068	1,196

Notes: ***p<0.01, ** p<0.05, * p<0.1. (1) Robust (s.e.) clustered at the village level. P-values of wild bootstrap to account for small number of village clusters (Cameron, Gelbach and Miller, 2008). Lower bounds estimated using a matching procedure described in the text. In all regressions we control for baseline: size, sector, business age, replacement value, lack of business skills, risk aversion, age, education, # of rooms, exercise score, and dummy indicators for missing controls.

Table 8: The Indirect Effects of Business Training on Selected Outcomes

	ITE	ITE	ITE	ITE	ITE	ITE
Outcome =	ln(Daily Profits)	ln(Weekly Profits)	ln(Daily revenues)	ln(Weekly revenues)	ln(Daily Clients)	ln(Standardized)
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.121	-0.001	0.034	0.103	-0.014	0.018
	(0.162)	(0.159)	(0.140)	(0.136)	(0.136)	(0.111)
Post	0.054	0.243	0.018	0.052	-0.057	-0.052
	(0.073)	(0.093)**	(0.063)	(0.116)	(0.055)	(0.031)
Treatment*Post	-0.032	-0.006	-0.055	0.027	-0.028	-0.001
	(0.132)	(0.143)	(0.121)	(0.157)	(0.124)	(0.087)
p-values wild boot	(0.810)	(0.966)	(0.657)	(0.867)	(0.825)	(0.995)
Observations	1,175	1,109	1,227	1,218	1,114	1,458

Notes: ***p<0.01, ** p<0.05, * p<0.1. (1) Robust (s.e.) clustered at the village level.

Table 9: Possible Indirect Mechanisms: Accounting

	ITE	ITE	ITE	ITE	ITE	ITE	ITE
Outcome =	1{Account}	ln(Monthly Profits good-by-good)	ln(Monthly Revenues good-by-good)	ln(Mark-up good-by-good)	ln(Mean Prices)	ln(Mean Costs)	ln(# goods)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	-0.013	-0.061	-0.173	0.016	0.012	0.061	-0.016
	(0.018)	(0.149)	(0.150)	(0.077)	(0.148)	(0.123)	(0.090)
Post	0.014	-0.123	-0.487	0.146	0.073	0.089	-0.116
	(0.009)	(0.142)	(0.153)***	(0.068)**	(0.046)	(0.111)	(0.042)**
Treatment*Post	0.057	-0.012	0.403	0.016	0.103	0.154	0.072
	(0.019)***	(0.280)	(0.279)	(0.104)	(0.096)	(0.162)	(0.075)
p-values wild boot	(0.009)	(0.967)	(0.168)	(0.882)	(0.300)	(0.355)	(0.350)
Observations	1,501	793	1,005	930	1,252	977	1,417

Notes: ***p<0.01, ** p<0.05, * p<0.1. (1) Robust (s.e.) clustered at the village level.

Table 10: Possible Indirect Mechanisms: Employment

	ITE	ITE	ITE	ITE	ITE
Outcome =	ln(Size)	ln(Paid Employment)	ln(Co-owners)	ln(Unpaid employment)	ln(Hours per week)
	(1)	(2)	(3)	(4)	(5)
Treatment	0.073	-0.012	0.009	0.048	-4.216
	(0.040)*	(0.043)	(0.039)	(0.030)	(2.293)*
Post	0.025	0.057	0.134	0.196	-1.158
	(0.053)	(0.031)*	(0.060)**	(0.053)***	(1.759)
Treatment*Post	-0.080	0.001	-0.150	0.032	3.560
	(0.072)	(0.069)	(0.073)*	(0.085)	(2.322)
p-values wild boot	(0.280)	(0.992)	(0.055)	(0.709)	(0.145)
Observations	1,469	1,256	1,257	1,260	1,112

Notes: ***p<0.01, ** p<0.05, * p<0.1. (1) Robust (s.e.) clustered at the village level.

Table 11: The Effects of Business Training by Wave (with $X's$)

	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE
Outcome =	ln(Daily Profits)		ln(Weekly Profits)		ln(Daily revenues)		ln(Weekly revenues)		ln(Daily Clients)		Standardized Outcomes		1[Accounting]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Treatment	-0.079	-0.117	-0.128	-0.186	-0.050	-0.074	-0.109	-0.165	-0.072	-0.110	-0.047	-0.072	-0.032*	-0.035
	(0.128)	(0.194)	(0.111)	(0.162)	(0.149)	(0.223)	(0.119)	(0.183)	(0.134)	(0.206)	(0.093)	(0.143)	(0.017)	(0.020)
1{Wave=2}	-0.055	-0.055	0.214**	0.214**	0.038	0.038	0.181**	0.181**	-0.065	-0.065	0.074*	0.074*	0.002	0.001
	(0.072)	(0.072)	(0.094)	(0.094)	(0.068)	(0.068)	(0.083)	(0.083)	(0.080)	(0.080)	(0.036)	(0.036)	(0.013)	(0.011)
1{Wave=3}	0.169*	0.169*	0.394***	0.394***	0.126	0.126	0.244***	0.244***	-0.066	-0.066	0.100*	0.100*	0.083***	0.087***
	(0.089)	(0.089)	(0.082)	(0.082)	(0.082)	(0.082)	(0.078)	(0.078)	(0.074)	(0.074)	(0.052)	(0.052)	(0.019)	(0.019)
Treatment*1{Wave=2}	0.340***	0.462***	0.217	0.304*	0.065	0.096	0.215	0.313	0.251	0.337	0.116	0.165	0.052	0.033
	(0.108)	(0.156)	(0.130)	(0.173)	(0.129)	(0.193)	(0.145)	(0.218)	(0.148)	(0.210)	(0.071)	(0.109)	(0.034)	(0.021)
Treatment*1{Wave=3}	0.279*	0.383*	0.203	0.288	0.191	0.262	0.140	0.206	0.159	0.226	0.130	0.182	0.073	0.059
	(0.152)	(0.210)	(0.157)	(0.220)	(0.171)	(0.245)	(0.177)	(0.244)	(0.208)	(0.294)	(0.106)	(0.150)	(0.066)	(0.083)
Observations	1,407	1,407	1,320	1,320	1,536	1,536	1,471	1,471	1,358	1,358	1,795	1,795	1,844	1,844
Treatment*1{Wave=2}=Treatment*1{Wave=3}	0.752	0.772	0.936	0.946	0.396	0.411	0.763	0.752	0.619	0.635	0.899	0.910	0.790	0.784

Notes: ***p<0.01, ** p<0.05, * p<0.1. (1) Robust (s.e.) clustered at the village level.

Appendix Figure 1: Geographical distribution of treatment villages, control villages, and excluded villages. Red pins are treatment villages, blue bulbs are control villages, and yellow bulbs are excluded villages.

Table 12: The Effects of Business Training (without $X's$)

	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE	ITT	TTE
Outcome =	ln(Daily Profits)		ln(Weekly Profits)		ln(Daily revenues)		ln(Weekly revenues)		ln(Daily Clients)		ln(Standardized)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment	-0.039	-0.058	-0.131	-0.191	-0.034	-0.051	-0.082	-0.123	-0.070	-0.106	-0.034	-0.051
	(0.143)	(0.213)	(0.143)	(0.206)	(0.166)	(0.249)	(0.145)	(0.220)	(0.154)	(0.236)	(0.112)	(0.171)
Post	0.056	0.056	0.294	0.294	0.090	0.090	0.105	0.105	-0.057	-0.057	-0.026	-0.026
	(0.076)	(0.076)	(0.082)***	(0.082)***	(0.074)	(0.074)	(0.119)	(0.119)	(0.073)	(0.073)	(0.033)	(0.033)
Treatment*Post	0.297	0.397	0.219	0.307	0.118	0.169	0.273	0.387	0.172	0.240	0.140	0.195
	(0.104)**	(0.153)**	(0.125)*	(0.176)	(0.131)	(0.194)	(0.144)*	(0.212)*	(0.170)	(0.247)	(0.072)*	(0.112)
p-values wild boot	(0.052)		(0.134)		(0.392)		(0.086)		(0.350)		(0.114)	
lower bound	0.080	0.121	0.115	0.176	0.033	0.050	0.116	0.177	0.069	0.106	0.074	0.114
Observations	1,114	1,114	1,051	1,051	1,164	1,164	1,163	1,163	1,063	1,063	1,389	1,389

Notes: ***p<0.01, ** p<0.05, * p<0.1. (1) Robust (s.e.) clustered at the village level.

Group lending with heterogeneous types[1]

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Abstract

Group lending has been widely adopted in the past thirty years by many microfinance institutions as a means to mitigate information asymmetries when delivering credit to the poor. This paper proposes an empirical method to address the potential omitted variable problem resulting from unobserved group types when modeling the repayment behavior of group members. We estimate the model using a rich dataset from a group lending program in India. The estimation results support our model specification and show the advantages of relying on a type-varying method when analyzing the probability of default of group members.

Key Words: Group lending, heterogeneous types, repayment behavior

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1 Introduction

Since the establishment of Grameen Bank in Bangladesh in the mid-seventies, microfinance has boomed. As of December 2010, 3,652 microfinance institutions reported reaching over 205 million clients worldwide, and every two out of three borrowers were among the poorest when they took their first loan (Maes and Reed 2012). Such expansion can be partly attributed to the widely adopted practice of group lending in microfinance programs. In contrast to individual lending, group lending with joint liability grants a loan to a group of borrowers, and the whole group is liable for the debt of any individual member in the group.[2] This practice allows microfinance programs to rely mainly on information advantages among group members, rather than on financial collateral, to mitigate information asymmetries between lenders and potential borrowers. Given that the poor often lack appropriate financial collateral, group lending programs provide a feasible way of extending credit to poor people who are usually kept out of traditional banking systems.

Despite its rapid growth, there is an ongoing debate on whether group lending programs are sustainable and able to achieve and maintain sound repayment performance while serving poor borrowers, without the support of third parties such as international organizations. Armendariz and Morduch (2005) show, for example, that Grameen Bank has experienced losses close to eighteen percent of their outstanding loans over the period 1985-1996 after properly adjusting for their portfolio size. It is also often argued that the high transaction costs faced by micro finance institutions in identifying and screening their clients, processing applications and collecting repayments keep interest rates high and prevent them from reaching new clients and expanding their operations (Armendariz and Morduch 2004; Shankar 2006; Field and Pande 2008). Understanding the factors affecting repayment performance, which may vary by (unobserved) group types, are thus of great policy relevance. In particular, more accurate risk scoring tools can help to overcome information asymmetries by aiding lending institutions to better classify their potential clients and understand the factors driving their behavior, further promoting the development and sustainability of microcredit markets.

This paper contributes to the ongoing debate and to the literature by more explicitly dealing with the unobserved group heterogeneity. In particular, we make three contributions to the literature. First, the paper develops a basic framework with both peer selection and moral

[2] Joint liability is one of the most common varieties of group loan contracts.

hazard that shows how joint liability can lead to the coexistence of different group types, which implies the necessity to account for these group heterogeneities when modeling repayment behavior in group lending. Second, the paper proposes and applies an empirical model to explicitly deal with the problem of unobserved group heterogeneity. The paper discusses the identification and conducts a test on the specification of the empirical model proposed. Finally, the estimation results of the mixture model are more informative than standard probabilistic models about the potential factors driving repayment behavior, which may differ by group type, and the results are further shown to attain a higher predictive power.

In most group lending programs, individuals voluntarily form a group based on a set of common characteristics, which are generally observed by peers but not by lenders (and econometricians). This peer selection in the group formation process helps to lessen adverse selection as individuals screen each other when forming groups. On this matter, Ghatak (1999, 2000) and van Tassel (1999) show that in a context of individuals with heterogeneous risk types and asymmetric information (where borrowers know each other's type but lenders do not), group lending with joint liability will lead to the formation of relatively homogenous groups of either safe or risky borrowers.[3] The intuition behind is that while a borrower of any type prefers a safe partner because of lower expected joint-liability payments, safe borrowers value safe partners more than risky partners because they repay more often. This positive assortative matching is supported by empirical evidence in Ahlin (2009), who also finds that borrowers will anti-diversify risk within groups in order to lower their chances of facing liability for group members.

However, in a similar manner as self-selection, peer selection creates an omitted variable problem in the empirical literature on repayment behavior (Karlan 2007). The omitted variables may include, for example, the risk type, entrepreneurial spirit, economic opportunities, solidarity, reciprocity and trust among group members, which affect repayment performance and are likely correlated with the indicators generally used to account for group heterogeneity and social ties when modeling repayment behavior. Yet, different from the omitted variable problem due to

[3] In contrast, Armendariz de Aghion and Gollier (2000) suggest that non assortative matching equilibrium can exist in the case where a borrower knows her own type but has no ex-ante information about the other borrowers' types. Guttman (2008) indicate that negative assortative matching is possible if a riskier borrower can provide side-payments to get a safer peer. However, side-payments are usually infeasible when the group is relatively large. And group members often know each other well enough because groups are typically formed by people living in the same geographical area or in contiguous areas. In fact, the information advantage (local information) of group members over lenders is one of the main factors to justify the idea of group lending over individual lending.

self-selection, the omitted variable problem due to peer selection has largely been overlooked in the literature (Hermes and Lensink 2007). Most of the empirical studies that explore determinants of repayment in group lending programs treat the group as a decision maker and employ single-agent choice models to examine how different group characteristics, including proxies for social ties, affect the group repayment performance (e.g., Sharma and Zeller 1997; Zeller 1998; Wydick 1999; Paxton et al. 2000; Hermes et al. 2005; Ahlin and Townsend 2007; Cull et al. 2007).

In addition, groups may also differ in their effort levels and/or effectiveness of peer monitoring and peer pressure among members, which is also unobserved by lenders and have direct implications on the observed repayment performance of group members. Besides mitigating adverse selection through peer screening, group lending helps alleviate moral hazard behavior and enforce repayment because members can more closely monitor each other's use of loans and exert pressure to prevent deliberate default.[4] The success of peer monitoring and peer pressure efforts across groups may be further correlated with peer screening because individuals are more likely to select safe borrowers who are also less costly to monitor and less likely to deliberately default. Overall, group-level unobservables may result from a combination of factors, which include endogenous group formation due to ex-ante peer selection and ex-post peer monitoring and pressure efforts.

We propose and implement an empirical method to address the potential omitted variable problem in group lending resulting from unobserved types. We use a mixture model to explicitly account for unobserved group types when modeling the repayment behavior of group members. In the model, individuals make repayment decisions based on their unobserved group type as well as on observable individual and loan characteristics. Average member characteristics and other group and village characteristics help, in turn, to identify the group types. We further allow the marginal effects in the repayment equation to vary across types. We estimate the model using a rich dataset from a group lending program in Andhra Pradesh in India.[5] While the type-varying groups in the empirical model may be explained by peer selection and variations (if any) in peer efforts and the effectiveness of peer monitoring and enforcement rules, as well as by other

[4] See, e.g., Stiglitz (1990), Varian (1990), Banerjee et al. (1994), Armendariz de Aghion (1999) and Chowdury (2005) for theoretical models showing how group lending with joint liability may help solving moral hazard and monitoring problems.

[5] Group loans account for 93% of the microfinance in India (Shankar 2006).

unobserved factors like social cohesion, disentangling these effects is beyond the scope of the study.[6]

The estimation results support our model specification and show the advantages of relying on this method when analyzing the probability of default of group members. The model clearly distinguishes two group types: a first group type where members are more inclined to fulfill their credit obligations and a second group type where members are more inclined to default. We also provide evidence supporting that the group types are not simply identified by the functional form of the proposed model. We further find important differences in the marginal effects of the different individual and loan characteristics included in the repayment equation, which suggests that the underlying factors driving repayment behavior may differ across group types. In addition, the type-varying model shows a higher predictive performance than standard probabilistic models.

The remainder of the paper is organized as follows. Section 2 further discusses the implications of group lending with joint liability and heterogeneous types using a simple model of adverse selection and moral hazard. Section 3 describes in detail the group lending program considered for the study and the data. Section 4 presents the empirical model used to account for the potential omitted variable problem resulting from unobserved group types when modeling the repayment behavior of group members. Section 5 reports and discusses the estimation results. Section 6 concludes.

2 A simple model of group lending with peer selection and moral hazard

Ghatak (1999, 2000) and van Tassel (1999) develop models that describe how joint liability with heterogeneous types and local information can lead to positive assortative matching through peer selection. We extend Ghatak (1999) base model by taking into account both peer selection and moral hazard. In particular, we allow individuals to differ on their risk type (creditworthiness) and on their level of effort.

Assume borrowers are risk-neutral and endowed with one risky project, which requires one unit of capital. Individuals have no initial wealth and must borrow the required amount of

[6] For a formal evaluation of ex-post peer effects on individual repayment behavior, refer to Karlan (2007) and Li et al. (2012). Karlan (2007) exploits a unique quasi-random group formation process to isolate peer selection and examine the impact of monitoring and enforcement on repayment; Li et al. (2012) estimate a structural model that takes into account interactions across group members and incorporates group-level unobservables as random effects.

capital. Further assume that there are two types of borrowers: risky individuals of type a and safe individuals of type b.[7] The probability of success of borrower i's project (k_i) depends on her inherent probability of success ($p_i > 0$) determined by her risk type and on her effort level ($e_i \geq 0$), where $i = a, b$. In particular, a risky type borrower has a success probability of $k_a = p_a + e_a$ and a safe type has a success rate of $k_b = p_b + e_b$, with $p_a < p_b$ and $0 < k_a, k_b \leq 1$. Without loss of generality, if the project is successful the output takes the value of Y and 0 otherwise.

In the presence of local information, all borrowers know each other's risk type, but the outside lender (bank) does not. Following Ghatak (1999), in the absence of financial collateral the bank requires potential borrowers to form groups of size two where both members are jointly liable for each other. The bank offers to each group the joint liability contract (r, q), where $r > 0$ is the gross interest rate and $q > 0$ is the liability payment. Hence, r is the payment made by the individual who succeeds and q is the additional payment made by the individual when she succeeds and her partner fails. A borrower who fails pays the bank nothing. The expected payoff for type i borrower matched with type j borrower is, then, given by

$$E\pi_{ij} = (p_i + e_i)Y - (p_i + e_i)r - q(p_i + e_i)(1 - p_j - e_j) - 1/2\gamma e_i^2 \qquad (1)$$

where the disutility of the effort is captured by $-1/2\gamma e_i^2$, with parameter $\gamma > 0$.

We assume a non-cooperative game setting where each borrower maximizes her own expected payoff $E\pi_{ij}$ with respect to her effort e_i. We solve the maximization problem in Appendix B. The main results are summarized below:

1. A borrower's optimal effort level (e_{ij}^*, $i = a, b$) is higher if she is a safe type and/or if her partner is a safe type. That is, $e_{bb}^* > e_{ab}^* > e_{ba}^* > e_{aa}^*$.
2. A borrower prefers a safe partner to a risky partner, despite of her own type. That is, $E\pi_{bb}^* > E\pi_{ba}^*$ and $E\pi_{ab}^* > E\pi_{aa}^*$.

[7] In this model, we assume that the type refers to the riskiness of borrowers, but the type could also refer to other factors associated with the creditworthiness of borrowers like their entrepreneurial spirit, reciprocity, solidarity, trust or level of responsibility. In the empirical setup below, the group types may aggregate all these factors.

3. Joint liability with varying risk types and effort levels leads to a single equilibrium of positive assortative matching in group formation. More specifically, $E\pi^*_{bb} - E\pi^*_{ba} > E\pi^*_{ab} - E\pi^*_{aa}$. The net expected loss for a safe borrower of having a risky partner compared to having a safe partner is higher than the next expected gain of a risky borrower of having a safe partner compared to having a risky partner. As noted by Ghatak (1999), this equilibrium condition is similar to the optimal sorting property in Becker (1993), such that borrowers not in the same group should not be able to form a group without making one or both of them worse off.

The second and third results above are consistent with the results from Ghatak (1999). The intuition behind is that while a borrower of any type prefers a safe partner because of lower expected joint-liability payments, safe borrowers value safe partners more than risky borrowers because safe partners repay more often their loans and are more likely to realize the gains of having a safe partner. By allowing the probability of success to also depend on the effort level of borrowers, we additionally find that groups of safe partners will exhibit a higher effort, which translates into further higher repayment probabilities. This result reinforces the notion of a separating equilibrium in that borrowers of the same type will pair together and safe pairs will show an even higher likelihood of repayment than risky pairs.

We also allow for a cooperative game setting where each borrower maximizes the total payoff of her group with respect to her effort. We obtain the same key results of the non-cooperative game: a single equilibrium with positive assortative matching where groups of safe partners exhibit a higher effort than groups of risky partners. The derivation under this alternative setup is detailed in Appendix B.

Thus, a simple framework with peer selection and moral hazard helps to show how joint liability can lead to a separating equilibrium with the coexistence of two opposed groups: a group of safe borrowers with a higher probability of repayment (success) reinforced by higher effort levels, and a group of risky borrowers with a lower probability of repayment and lower efforts. The coexistence of different group types, driven by unobserved factors like risk and effort levels, implies the necessity to account for potential group types when modeling repayment behavior in group lending. Certainly, there are mechanisms other than joint liability through which group lending without financial collateral can lead to higher or lower repayment rates and varying group types; for example, the unobserved informal risk-sharing and social

cohesion among group members.[8] The empirical method proposed below is flexible enough to allow for varying group types driven by a wide set of factors, which are not necessarily observable and may shape the repayment behavior of a group.

3 Data

3.1 Background and Data

The groups under study are located in Andhra Pradesh in India.[9] They are organized following a new self-help groups (SHG) model promoted by the World Bank, which targets poor women in rural areas. The model combines savings generation and micro-lending with social mobilization. In particular, women who generally live in the same village or habitat voluntarily form SHGs with the understanding of a joint liability mechanism. A typical SHG consists of 10-20 members who meet regularly to discuss social issues and activities. During the group meetings each member also deposits a small thrift payment into a joint bank account. Once enough savings have been accumulated, group members can apply for internal loans that draw from the accumulated savings at an interest rate to be determined by the group. After the group establishes a record of internal savings and repayment, it becomes eligible for loans through a commercial bank or program funds. This process of internal savings and repayments helps members to further screen each other as some individuals may leave the group prior to obtaining a formal loan.

The group as a whole, then, borrows from a commercial bank or program funds where all group members are held jointly liable for the debts of each other. The group generally allocates the loan to its members on an equal basis, and the group is not eligible for further loans unless it has made full repayment.[10] The loans may be used for labor activities or consumption smoothing. Groups also have the option of implementing non-lending programs with the support of the program funds such as in-kind credit for subsidized rice, marketing and insurance programs.

In this study, we focus on the first "expired" loan borrowed from commercial banks by each group. An "expired" loan refers to a loan that had passed its due date by the time the survey

[8] For empirical evidence on this matter see Gine and Karlan (2009) and Feigenberg et al. (2011).
[9] Andhra Pradesh is the fourth largest state in India by area and the fifth largest by population.
[10] Naturally, a woman who maintains a good record and ends in a group where not all members fulfill their loan obligations, may join another group in the future.

was conducted. In Andhra Pradesh, commercial banks carry out microfinance activities in non-overlapped territories, so groups located in contiguous villages borrowed from the same bank.

The sample includes 1,110 different group loans which were allocated to a total of 12,833 women. The data are from a SHG survey conducted between August and October 2006 in eight districts in Andhra Pradesh, which were chosen to represent the state's three macro-regions (Rayalaseema, Telangana, and Coastal AP).[11] The SHG survey contains socioeconomic characteristics of group members (households) such as education background, housing condition, land and livestock ownership, occupation, and caste. It also includes group characteristics such as age, meeting frequency of members and programs and services available within the group. More importantly, the survey directly recorded from SHG account books the information on all loans that were taken between June 2003 and June 2006. The information includes the terms of each loan, the members the loan was allocated to, and how much of the loan had been repaid by each member at the time of the survey.[12]

The SHG survey was complemented with a previous village survey that covered all the villages from which the SHGs were sampled. From the village survey, we construct four indicators to account for the economic environment of the sample groups. These indicators include availability of financial institution, public bus, telephone and post office.

Table 1 presents descriptive statistics of our full sample.[13] The top panel (Panel 1) reports member characteristics based on 12,833 observations while the bottom panel (Panel 2) reports group and loan characteristics based on 1,110 observations. Approximately twenty-three percent of the group members are literate and thirty-one percent belong to a scheduled tribe or scheduled caste. Around six percent of the members are disabled or have family members who are disabled. About sixty-five percent of households own some land, and thirty-three percent live in pucca houses, twenty-two percent in kutcha houses, and the other forty-five percent live in semi-pucca houses.[14] Similarly, about sixty-one percent are agricultural laborers who do not own land or

[11] The eight districts are Srikahulam, Adilabad, Anantapur, Kadapa, Warangal, Nalgonda, Nellore, and Visakhapatnam.

[12] The survey instrument included a separate section where the allocation of loans to members (member loans) was recorded. See Li et al. (2012) for further details on how the information on group loans and member loans was matched together.

[13] A detailed description of the variables used in the analysis is provided in Table A.1 in Appendix A.

[14] A pucca house has walls and roofs made of burnt bricks, stones, cement concrete, and timber while a kutcha house uses less sophisticated materials such as hays, bamboos, mud, and grass. A semi-pucca house uses a combination of materials from the other two types.

own such a small amount of land that they have to provide agricultural labor for others, twenty percent are self-employed agricultural workers, and the rest have other occupations (such as those self-employed and employed in non-agricultural sectors and housewives). The table also indicates that eighty percent of the group members in our sample fully repaid their loan by its due date (i.e. not defaulted). Figure A.1 in Appendix A further plots a histogram of the percentage of the loan repaid by each member. It follows that most of the data points are clustered at the endpoints, which supports the discrete treatment of the repayment (default) behavior in the empirical model.

Turning to the group and loan characteristics, the groups range from seven to twenty members and have close to thirteen members on average. The groups are from all of the three macro-regions in the state: about forty-five percent are located in Telangana, twenty-six percent in Rayalaseema, and the remaining twenty-nine percent in Coastal AP. The average group age is six years and roughly in nine of every ten groups the members meet on a regular basis (at least monthly). About twenty-eight percent of the groups have a food credit program (in-kind credit for subsidized rice), fifteen percent have a marketing program, and twenty-five percent have an insurance program. The group loan was allocated on average to twelve members and the average loan size received by a member is 3,338 rupees (about US67 dollars). The annual rate of interest is about 12.8 percent, which is much lower than the prevailing rate of moneylenders in India. The average duration of a loan is roughly one year and the majority of loans (ninety-six percent) required the groups to make repayments at least monthly.

3.2 Preliminary Analysis

A first look at the data is indicative of a separating equilibrium with apparently two group types. Table 2 shows that in more than 9 out of every 10 groups in our sample, either all of the members do not default or all of them default. In particular, in 76% of the groups (848 out of 1,110 groups) all of the group members fully repaid their loans or never defaulted and in another 17% of the groups (188 groups) all of the members defaulted. As discussed earlier, this repayment behavior may result from a combination of elements such as positive assortative matching ("matching likes") in group formation, in a context of joint liability, heterogeneous types and asymmetric information between borrowers and lenders.[15] Recall that under the SHG

[15] See Ahlin (2009) for a formal test on homogenous risk-matching in group lending.

model, groups have an initial period of internal savings and repayment, which also serves as an extended (ex-ante) screening period prior to applying for a commercial loan. This initial period also promotes social interaction among members, which may result in stronger social ties among them (see also Feigenberg et al. 2011). The observed pattern may also reflect variations (if any) in the level of effort and effectiveness of peer monitoring and peer pressure across groups, which may be correlated with peer screening. The theoretical model developed above indicates that groups composed of safe borrowers will also exhibit a higher level of effort than groups composed of risky borrowers. Hence a preliminary look at the data suggests the existence of mainly two group types: a "responsible" group of apparent "low risk" individuals with probably high efforts and/or effective monitoring and enforcement rules and strong social cohesion, and an "irresponsible" group of apparent "high risk" individuals with probably low efforts and/or ineffective monitoring and enforcement rules and lack of social cohesion.[16]

There is also the possibility of external factors, like a negative weather shock, affecting the likelihood of repayment of all members in a group, which generally live close to one another and perform similar labor activities. However, groups where all members defaulted in our sample are not concentrated at a particular location, which reduces the possibility of specific weather shocks or other contextual factors explaining inter-group variation on default behavior. In particular, Figure A.2 shows that villages with a high proportion of groups where all members default are well dispersed across the eight districts of our sample in Andhra Pradesh.[17] In addition, the estimation results presented below indicate that the variables included in the repayment equation (individual and loan characteristics) have a differentiated effect on the likelihood of default by group type, which further supports the existence of type-varying groups.

To further examine the possibility of homogenous sorting among groups, Table A.2 reports the number of groups in which the intra-group variance is less than or equal to the overall variance considering all groups in the same village and mandal for different borrower

[16] The existence of the mixed group (7% of our group sample) suggests that the observed defaults are not necessarily strategic defaults. If some members fail to repay some installments, the other members still have the incentive to repay on time because they do so in hope that the delinquent borrowers will repay their installments on a future date. In addition, individuals that maintain a good repayment record are more likely to join a "better" group in the future (if necessary). Formally addressing the dynamic aspects of installment repayments is beyond the scope of our paper.

[17] For areas with available weather data (rainfall) and vegetation information (Normalized Difference Vegetation Index or NDVI) during the period of analysis, we also did not find any significant correlation between these measures and default behavior.

characteristics.[18] The characteristics include literacy, household characteristics, land ownership, occupation and caste. The results show that individuals with similar observable characteristics appear to group together. On average, in 70-72% of the cases the intra-group variance for a given characteristic is smaller than the intra-village or intra-mandal variance. There is a relatively higher degree of homogeneity among group members in terms of belonging to a scheduled tribe or caste and being self-employed agricultural worker, and a lower level of homogeneity in terms of literacy.

Overall, a preliminary look at the data is indicative of the coexistence of different types of groups in our sample. This suggests the necessity to allow for potential unobserved group types when examining repayment behavior in group lending.

4 Empirical Model

This section develops an empirical model to address the potential omitted variable problem in group lending with unobserved types. We use a mixture model to explicitly account for unobserved group types when evaluating the repayment behavior of individual members. The unobserved types may result from peer selection as well as from variation in the level of effort and effectiveness of peer monitoring and pressure and other unobserved factors like social cohesion. The probability of default is conditional on the unobserved type and depends on observable individual and loan characteristics, while average member characteristics and other group and village characteristics (observed by lenders) may help to identify the group type the individual belongs to.

Let the default behavior of individual *i* in group *j* be given by

$$D_{ij} = 1(\alpha + X_{ij}\beta_1 + C_j\beta_2 + T_j^* + u_{ij} > 0) \qquad (2)$$

where D_{ij} is the observed binary outcome, i.e. D_{ij} equals one if the individual defaults (i.e. does not fully repay her loan) and equals zero otherwise, α is a constant, X_{ij} is a vector of observable individual characteristics, C_j is a vector of loan characteristics, T_j^* is the unobserved

[18] The comparisons exclude all villages (150 out of 457) and mandals (3 out of 97) where there is only one group in the village or mandal. A mandal is the equivalent to a sub-district in India and comprises several villages.

group type which is likely correlated with X_{ij} (and C_j), and u_{ij} is an error term. On the correlation between X_{ij} and T_j^*, we can think, for example, of a proxy for the social ties of an individual, included in X_{ij} and potentially correlated with the social ties of her peers (who generally live in the same neighborhood), which partly describe T_j^*.

If group heterogeneity is solely based on observables, the observed group characteristics (Z_j) like average member characteristics and other group controls, including social ties, would be sufficient to identify the group types, and Z_j could be used as a proxy for T_j^* to estimate equation (2) using a standard probabilistic regression (e.g., Probit, Logit). However, the unobserved group type is more accurately characterized by both observable and unobservable factors such that $T_j^* = Z_j\delta + W_j + \varepsilon_j$, where W_j is unobserved, Z_j and W_j are potentially correlated, and ε_j is an error term. Following the previous example, a proxy for the social ties or connections of a group, included in Z_j, is likely correlated with the unobserved economic opportunities and entrepreneurial spirits of the group members, which are comprised in W_j and further affect repayment.

Hence a standard probabilistic regression of equation (2) with only Z_j in the right-hand side will result in an omitted variable bias as W_j will be embedded in the error term. Another option is to incorporate the unobserved group component or type as fixed effects in a conditional logit model. Yet, a fixed-effects logistic regression mainly exploits within-group variation and will drop all groups without intra-group differences in default behavior (i.e. more than 90 percent of our sample). Further, the observed factors affecting repayment performance may vary by group type.

To address this potential omitted variable problem we propose an alternative model, where group heterogeneity can be captured by allowing groups to be one of two types with a specific probability. In particular, we assume that T_j^* can take two possible values, T_j^H if the group is "responsible" and T_j^L if the group is "irresponsible". In broader terms, we can think of the first group as a group mainly composed by "safe" borrowers with effective monitoring and enforcement efforts and high reciprocity and solidarity among members, and of the second group

as a group of "risky" borrowers with less effective monitoring and enforcement efforts and low reciprocity and solidarity among members. We could easily relax this assumption to allow for a wider set of types (based on different combination of factors) but our data seems to support a two-type model. In particular, we also estimated a three-type model but the two-type model provides a better fit based on the Schwarz Bayesian Information Criterion (SBIC).[19]

Then, the repayment behavior of individual *i* in group *j* is given by

$$D_{ij} = \begin{cases} 1(\alpha_H + X_{ij}\beta_{1,H} + C_j\beta_{2,H} + u_{ij,H} > 0) & \text{if } T_j^* = T_j^H \\ 1(\alpha_L + X_{ij}\beta_{1,L} + C_j\beta_{2,L} + u_{ij,L} > 0) & \text{if } T_j^* = T_j^L \end{cases} . \tag{3}$$

In this specification, the effect of T_j^* is absorbed by the constant terms α_H and α_L, and $Cov(X_{ij}, u_{ij}) = 0$. We further allow for varying coefficients across group type, which permits to capture varying effects of different factors on repayment behavior by type.[20]

The probability of being in type-*H* group ($T_j^* = T_j^H$) can be further modeled as

$$\Pr(T_j^* = T_j^H) = \Pr(\overline{X}_j\delta_1 + G_j\delta_2 + v_j > 0) \tag{4}$$

where $\overline{X}_j$ is a vector of average characteristics of group members, G_j is a vector of group and village controls (G_j), and v_j is an error term.[21] Hence while the individual characteristics of each group member (X_{ij}) help us to approximate their default probability, the average characteristics of all group members ($\overline{X}_j$) can help us to identify their group type. The member characteristics considered for the analysis include literacy, land ownership, housing condition, occupation and caste.[22] Thus, while belonging to a certain caste, for example, may directly affect

[19]The SBIC of the two-type model is 0.838 versus 0.849 of the three-type model. Further, the predicted probability of being in the potential third type group is close to zero.

[20] This flexibility is similar to Gan and Hernandez (2013) who allow for varying coefficients across potential collusive and non-collusive regimes when modeling the pricing and occupancy rate behavior of hotels under a switching regression framework.

[21] The underlying assumption is that the probability of being a certain group type varies with some observable characteristics; in this case with $\overline{X}_j$ and G_j.

[22] This type of personal information is also generally disclosed during credit application processes.

the likelihood of repayment, the percentage of members belonging to a similar caste (included in $\overline{X}_j$) can serve as a proxy for social ties within the group, which will also have an indirect effect in the probability of default.[23] We also account for loan characteristics (C_j) in the repayment equation (e.g., loan amount, interest rate, length, repayment frequency) and we use other group and village controls (G_j) to help us identify the group type (e.g., age, number of members, location, access to programs and services).

Note that since T_j^* is likely determined by both observable ($\overline{X}_j, G_j$) and unobservable (W_j) characteristics, the parameters in equation (4) may not be consistently estimated. However, the fact that we do not observe W_j does not result in inconsistent estimates of the parameters in the repayment equation (3); we only require some but not full information about T_j^* to identify the parameters in the repayment equation. Intuitively, the identification is similar to that underlying a two-stage least squares (2SLS) procedure, where the consistency of the 2SLS estimations does not require the consistency of the first-stage regression. Mahajan (2006) refers to ($\overline{X}_j, G_j$) as instrumental-like variables (ILV). Henry et al. (2010) study the identification of this type of model. They conclude that the current model is fully identifiable if ($\overline{X}_j, G_j$) are conditionally independent of the errors in equation (3). Gan et al. (2011) also provide a discussion on the identification condition.

Formally, the key identifying assumption in the proposed model is that conditional on the group type, both observable and unobservable factors that characterize T_j^* are not related to the probability of defaulting. That is,

$$\Pr(D_{ij} = 1 \mid T_j^* = T_j^H, \overline{X}_j, G_j, W_j) = \Pr(D_{ij} = 1 \mid T_j^* = T_j^H) . \qquad (5)$$

[23] Particularly, we generate a variable of percentage members belonging to the leading caste (defined as the caste with the largest number of members in the group) to capture social ties. Unfortunately we do not have more detailed information, like number of relatives, to more accurately control for social ties within the group.

Consequently, any association between $\overline{X}_j$, G_j and W_j and the probability of defaulting is solely driven by the association between these former variables and the probability of being of a certain group type.

The unconditional probability of default can, in turn, be written as

$$\begin{aligned}\Pr(D_{ij}=1) &= \Pr(D_{ij}=1, T_j^* = T_j^H) + \Pr(D_{ij}=1, T_j^* = T_j^L) \\ &= \Pr(D_{ij}=1 \mid T_j^* = T_j^H)\Pr(T_j^* = T_j^H) + \Pr(D_{ij}=1 \mid T_j^* = T_j^L)\Pr(T_j^* = T_j^L).\end{aligned} \tag{6a}$$

Similarly,

$$\Pr(D_{ij}=0) = \Pr(D_{ij}=0 \mid T_j^* = T_j^H)\Pr(T_j^* = T_j^H) + \Pr(D_{ij}=0 \mid T_j^* = T_j^L)\Pr(T_j^* = T_j^L). \tag{6b}$$

If we further assume that the error terms in equations (3) and (4) have a $F(\cdot)$ and $J(\cdot)$ cumulative distribution function (cdf), respectively, the log likelihood for individual *i* in group *j* is given by

$$\begin{aligned}\ln l_{ij} = {} & D_{ij}\ln[F(\alpha_H + X_{ij}\beta_{1,H} + C_j\beta_{2,H})J(\overline{X}_j\delta_1 + G_j\delta_2) \\ & + F(\alpha_L + X_{ij}\beta_{1,L} + C_j\beta_{2,L})(1 - J(\overline{X}_j\delta_1 + G_j\delta_2))] \\ & + (1 - D_{ij})\ln[1 - F(\alpha_H + X_{ij}\beta_{1,H} + C_j\beta_{2,H})J(\overline{X}_j\delta_1 + G_j\delta_2) \\ & - F(\alpha_L + X_{ij}\beta_{1,L} + C_j\beta_{2,L})(1 - J(\overline{X}_j\delta_1 + G_j\delta_2))].\end{aligned} \tag{7}$$

We approximate $F(\cdot)$ and $J(\cdot)$ with a logistic cdf.[24]

5 Results

We now turn to our estimation results. For comparison purposes, we first report the results using a standard probabilistic regression model, which does not account for unobserved types when modeling the likelihood of default. Table A.3 presents the parameter estimates (and standard

[24] We also estimated the model using a normal cdf and obtained qualitative similar results.

errors) of a Probit model using three alternative specifications.[25] The first model only accounts for member and loan characteristics. Although most of the coefficients of the member characteristics generally have the expected signs, in the sense that the variables associated with a low (high) economic status are positively (negatively) correlated with the probability of default, they are generally not statistically significant at conventional levels. We only observe a positive and significant correlation between the probability of default and belonging to a scheduled caste. The loan characteristics, in turn, show a higher correlation with repayment behavior. A larger loan amount, higher interest rate, longer duration and lower repayment frequency are all associated with a higher probability of default.

The second model adds average (leave-me-out) member characteristics and other group and village controls, which are intended to account for contextual factors that could also affect an individual's repayment decision. While the positive correlation between the probability of default and belonging to a scheduled caste disappears, a higher proportion of members of a scheduled caste in the group is associated with a lower repayment probability; the other member characteristics (and the corresponding group averages) remain not significant. The effects of most of the loan characteristics also remain intact. Several of the other group and village controls exhibit an important association with the probability of default. In particular, having a marketing and insurance program in the group, frequent meetings between group members, and the existence of a financial institution in the village, are all positively correlated with the probability of repayment. In contrast, members of groups with a food program, which is distinctive of poorer groups, show a higher probability of default. Finally, in smaller groups (less than thirteen members), an additional member in the group decreases the individual probability of default probably due to stronger peer monitoring and pressure effects while in larger groups (thirteen members or more) occurs the contrary as coordination, monitoring and enforcement efforts are probably more difficult to become effective in considerably large groups.

While in the first and second model we account for the potential correlation in the repayment decision among group members by clustering the error term by group, in the third model we explicitly control for the potential within-group correlation by estimating a Probit model with random effects. The inclusion of the random group term in the estimated regression

[25] We use a Probit model because it provides a better fit and performance than a Logit and a linear probability model. Details are available upon request.

although improves the model fit (the within-group correlation is also highly significant), it does not improve the model performance discussed below. Most of the effects of the explanatory variables also remain similar.[26]

As noted above, however, all these models do not account for the unobserved group-type component, embedded in the error term of the repayment equation and potentially correlated with some of the explanatory variables. Table 3 shows the estimation results of the alternative mixture model proposed, which explicitly accounts for unobserved group types when modeling the default behavior of group members. The model allows for two group types (type *H* and type *L*) and the repayment decision is conditional on the unobserved type, where the marginal effects of the member and loan characteristics may vary by type. The average member characteristics and other group and village controls, in turn, help to identify the group type.

Several important patterns emerge from the table. First, the conditional probability of default is considerably different between the two group types, as reported at the bottom of the table. More specifically, the estimated probability of default conditional on being in a group of type-*H* individuals is 9.5 percent versus 62.8 percent in a group of type-*L* individuals. Hence the model clearly distinguishes two group types: one type (type *H*) likely composed of "responsible" individuals with probably high levels of effort and/or effective monitoring and enforcement rules who are more likely to repay their loans, and a second type (type *L*) composed of "irresponsible" individuals with probably low levels of effort and/or less effective monitoring and enforcement rules who are less likely to repay their loans. Similarly, the average probability of being a type-*H* group is roughly 80 percent in our sample and, interestingly, groups where all members pay back their loan exhibit a higher probability of being a type-*H* group than other groups.[27] In particular, in groups where none of the members defaulted the likelihood of being a type-*H* group is 82.9 percent versus 76.4 percent in groups where some members defaulted and 66.9 percent in groups where all members defaulted. These results further support the identification of seeming "responsible" and "irresponsible" groups by our model.

An analysis of the factors used to describe the probability of being in a type-*H* group also indicates that "responsible" groups are more likely characterized, for example, by women who

[26] In this third model, individuals in groups with a higher proportion of disabled members in the household are also expected to fully repay their loans and group age is positively correlated with the probability of default (up to groups of eleven years old).

[27] Recall that in our raw data we observe full repayment by all members in 76% of the groups and in another 17% of the groups all members default.

are literate, own some portion of land, live in semi-pucca houses, are related to agricultural activities and belong to a scheduled tribe but not necessarily to a leading caste. Similarly, "responsible" groups are more likely to hold frequent meetings between its members, have a marketing and insurance program but not a food credit program for its members, and have access to additional services in the village such as a financial institution and telephone. Microfinance institutions should probably look for these characteristics when trying to identify potential "responsible" groups and/or areas where to operate or expand. Holding frequent meetings appear to be particularly important, as we further detail below. This is in line with other studies that suggest that, besides facilitating peer monitoring and enforcement, frequent group meetings may directly increase social contact and reduce lending risks (Gine and Karlan 2009; Feigenberg et al. 2011).[28] The existence of other programs in the group (like marketing and insurance programs), could also stimulate social cooperation and strengthen social ties, in addition to providing additional services to members, thereby increasing the risk-sharing among members.[29]

Figure A.3 provides additional support to the correct identification of "responsible" and "irresponsible" groups by our model, based on the observed behavior patterns in the data. For example, the probability of being a type-*H* ("responsible") group is positively correlated with the proportion of literate women in the group; a closer look at the data shows that effectively among groups with more than half of the women in the group literate, there is a higher proportion of groups with no members defaulting (82 percent) and a lower proportion of groups with all members defaulting (13 percent), as compared to groups with less than half of the women literate (76 and 17 percent). The differences are more pronounced when comparing the distribution of intra-group default behavior between groups with high and low frequency meetings. Among groups that at least hold monthly meetings, which is also distinctive of type-*H* groups, the proportions of groups with no members defaulting and all members defaulting are 80 and 14 percent; among groups that hold less than monthly meetings, the corresponding proportions are 48 and 41 percent. Similar patterns are observed when comparing groups with and without marketing programs and a financial institution in the village, which are also correlated with the likelihood of being a type-*H* group in the model. These findings suggest that several of the

[28] Gine and Karlan (2009) find that groups with stronger social networks are less likely to experience default problems after removing joint liability. Feigenberg et al. (2011) show that repeated interactions can facilitate cooperation by allowing individuals to sustain reciprocal economic ties.

[29] Fearon et al. (2009) and Feigenberg et al. (2011) also show, in different settings, the importance of community development programs to encourage social cohesion.

factors included in the type-probability equation indeed help to identify potential group types and, in particular, that the types in the model are not purely identified by functional form.

Another important pattern that emerges from Table 3 is the difference in direction, magnitude and statistical significance of several of the parameter estimates in the default equation between the two group types. This suggests that the factors driving individual repayment behavior may vary by type. Table 4 shows the conditional marginal effects for the different individual and loan characteristics included in the repayment equation after accounting for group type.[30] We do not observe major changes in the probability of default among type-*H* group members after a change in most of the individual covariates; being a self-employed agricultural worker and living in pucca houses decrease the probability of default by roughly three and one percentage point, while owning some portion of land increases the likelihood of defaulting by less than one percent. Among type-*L* group members, in contrast, being a self-employed agricultural worker increases the probability of default by 14 percentage points; being an agricultural laborer also substantially increases the likelihood of defaulting by 29 percentage points, as well as belonging to a scheduled caste (31 percentage points). Owning some portion of land or living in either pucca or kacha houses (relative to semi-pucca houses), in turn, decrease the probability of default by 8-16 percentage points.

Regarding the loan covariates, monthly (or higher) repayment frequencies and an additional member receiving a loan decrease, for example, the likelihood of defaulting by three and 0.2 percentage points among type-*H* group members; among type-*L* group members, the corresponding decrease is of 26 and five percentage points. An increase in the loan amount, interest rate and loan duration also results in a much higher increase in the probability of default among type-*L* group members than among type-*H* group members.

These varying effects by type can help lenders to better assess their clients and understand the factors driving their behavior. Owning some portion of land, housing conditions, labor activities and belonging to a scheduled tribe seem to matter among type-*L* groups, in contrast to type-*H* groups where the effects (if any) are much more limited. The loan characteristics are also more relevant for type-*L* groups than for type-*H* groups. These differences further have important policy implications and can help lending institutions to reduce

[30] The normal-based confidence intervals reported for the estimated marginal effects are based on 200 bootstrap replications and are biased-corrected. Although not reported, the bootstrap means are very similar to the estimated marginal effects, which support the bootstrap procedure implemented.

their transaction costs. Field and Pande (2008), for example, point out the important tradeoff between imposing higher repayment frequencies (a standard practice among microfinance institutions to encourage fiscal discipline and reduce default risk) and the substantial increase in transaction costs of installment collection. The authors find that switching to lower frequency repayment schedules could allow lenders to significantly reduce their transaction costs with virtually no increase in client default, particularly among first-time borrowers. Our results suggest that the fiscal discipline imposed by frequent repayment is critical among groups suspected (or with a higher probability) of being type-*L* groups, but not on type-*H* groups where less costly repayment schedules could be implemented; the cost savings are likely higher than the (marginal) increase in the default rate in this type of groups. Encouraging longer term investments through higher loan terms also seems more reasonable among type-*H* groups, which could improve the borrowers' repayment capacity in the long run (in a similar way as a more flexible repayment schedule).

The parameter estimates in the two-type model are also different from those obtained under a standard probabilistic regression, which does not allow for unobserved consumer types. To better appreciate these differences, Table 5 reports the unconditional marginal effects on the probability of default for all the variables included in the regression analysis for the Probit and two-type model specifications.[31] In the full two-type model (last column), the average member characteristics and other group and village characteristics affect the likelihood of defaulting through the probability of being in a type-*H* group or "responsible" group. A direct comparison between the full Probit model and the two-type model reveal that the two models produce different marginal effects.[32] For example, being an agricultural laborer or belonging to a scheduled caste increases the overall probability of default by roughly four percentage points in the two-type model (all else equal), while in the Probit model the change in the probability is not significant; a similar pattern is observed for the condition of living in pucca houses or being self-employed agricultural workers, which decrease the overall probability of default by three and one percentage points in the type-varying model and are not significant in the Probit model. Similarly, monthly (or higher) repayment frequencies will decrease the likelihood of defaulting

[31] The marginal effects of the Probit model with random effects, excluded from the table, are qualitatively similar (although smaller) to those of the full Probit model. For comparison purposes, the confidence intervals of the marginal effects for all models were derived using 200 bootstrap replications.

[32] Note that the marginal effects decrease as we move across the two Probit-model specifications, for the variables they can be compared.

by six percentage points in the two-type model and by seven percentage points in the Probit model, while an additional year in the length of the loan will increase the likelihood of defaulting by four percentage points in the first model and by more than eight percentage points in the second model. Interestingly, an additional member in a group seems to increase the probability of default in the type-varying model while in the Probit model is the converse, at least in smaller groups; it seems that the stronger peer monitoring and pressure effects do not necessarily outweigh the higher coordination costs of having additional members in the group.

From the two models, however, it is also clear the importance of frequent meetings among group members, for individuals to not fall behind in their loan repayments (probably resulting in better peer monitoring and pressure and/or higher social interactions). In particular, in groups where members meet at least on a monthly basis, the individual probability of default is 30 percentage points lower in the Probit model and 45 percentage points lower in the type-varying model than in groups where members meet less frequently. Both models also suggest the importance of promoting marketing and insurance programs among group members, which are negatively correlated with defaulting, and the inverse for subsidized food credit programs, which are also distinctive of poorer groups. The existence of a financial institution and a telephone in the village is also highly correlated with a positive repayment behavior under the two models.

Overall, the results indicate the importance of having a flexible, type-consistent model, which allows for varying effects by type and provides better insight about the possible factors affecting the members' repayment behavior. The proposed model can also help lenders to better identify and screen their potential clients, as we further discuss below.

5.1 Model Identification

Next, we further evaluate the identification of our empirical model. As noted above, a formal implication of the type-varying model is that we require some but not full information about the factors describing group heterogeneity (T_j^*) to identify the parameters in the main repayment equation.[33] Our model setup allows for both the presence of observable ($\overline{X}_j, G_j$) and unobservable (W_j) characteristics. Hence, even a subset of the observed factors used to identify

[33] See also Gan et al. (2011) for further details.

the group types may produce consistent estimates of the parameters in the main repayment equation.

Tables A.4 through A.6 report the estimation results of the two-type model when excluding different subsets of the variables used to identify the type-*H* group. In particular, we separately exclude the average member characteristics, group size and age, group programs, if group has frequent meetings, group location, and village characteristics. We observe that the coefficients of both the individual and loan characteristics, included in the repayment equation, are generally not much sensitive to the inclusion or exclusion of different variables in the group-type equation. In our full sample estimations in Table 3, for example, the coefficients for self-employed agricultural worker is -0.593 (0.184) among type-*H* groups and 1.173 (0.266) among type-*L* groups, while the coefficients for interest rate is 0.083 (0.013) among type-*H* groups and 0.277 (0.034) among type-*L* groups. When excluding different subsets of variables in the group-type equation, the corresponding coefficients fluctuate between -0.521 (0.113) – -0.644 (0.074), 0.979 (0.317) – 1.451 (0.331), 0.082 (0.013) – 0.094 (0.011), and 0.234 (0.040) – 0.284 (0.039). The Hausman tests reported in Table A.7 further indicate that in most cases there are not systematic differences between the coefficients in the repayment equation of the baseline model and the corresponding coefficients in these alternative specifications, at least at a 5 percent level of significance. This exercise provides additional support for the robustness of the mixture model proposed.

5.2 Predictive Performance

We now analyze whether allowing for different group types yields better out-of-sample predictions for the probability of default. We want to examine if the proposed type-varying model has a higher predictive power than standard probabilistic methods, which can further help to reduce information asymmetries in micro lending and aid lenders to correctly identify and select their current and future clients (groups). To conduct the performance assessment, we follow a standard cross-validation procedure and randomly partition our dataset into a design sample for model estimation (60% of the observations) and a test sample for further analysis (40% of the observations). The partition is conducted at the group level and both samples maintain the population proportions of default and non-default actions.

Table 6 provides performance indicators for the different models estimated.[34] The indicators include the average predicted default probability, the mean square predicted error and several performance indicators based on converting the estimated default probabilities to a binary regime prediction using the standard 0.5 rule (i.e. if the estimated default probability is greater or equal to 0.5 the individual is predicted to default, while if the estimated probability is less than 0.5 the individual is predicted to not default). For the two-type model, the performance assessment is based on two alternative calculations of the probability of default. Generally speaking, a lender could evaluate granting a loan based on the estimated unconditional probability of default or based on the conditional probability of default, depending on the likelihood of being in a group of a certain type. Hence different mixtures for estimating the probability of default could be used.

The two approaches considered are:

(1) A "naïve" type-consistent approach that only uses the unconditional probability of default such that,

$$\begin{aligned}\Pr(D_{ij}=1) &= F(\alpha_H + X_{ij}\beta_{1,H} + C_j\beta_{2,H})J(\overline{X}_j\delta_1 + G_j\delta_2) \\ &\quad + F(\alpha_L + X_{ij}\beta_{1,L} + C_j\beta_{2,L})(1 - J(\overline{X}_j\delta_1 + G_j\delta_2)).\end{aligned}$$

(2) A "conservative" type-consistent approach which takes into account the likelihood of being in a type-*H* group. In particular,

$$\Pr(D_{ij}=1) = \begin{cases} F(\alpha_H + X_{ij}\beta_{1,H} + C_j\beta_{2,H}) & \text{if } \hat{\Pr}(T_j^* = T_j^H) \text{ in upper quintile} \\ F(\alpha_H + X_{ij}\beta_{1,H} + C_j\beta_{2,H})J(\overline{X}_j\delta_1 + G_j\delta_2) & \\ + F(\alpha_L + X_{ij}\beta_{1,L} + C_j\beta_{2,L})(1 - J(\overline{X}_j\delta_1 + G_j\delta_2)) & \text{if } \hat{\Pr}(T_j^* = T_j^H) \text{ in 2nd - 4th quintile} \\ F(\alpha_L + X_{ij}\beta_{1,L} + C_j\beta_{2,L}) & \text{if } \hat{\Pr}(T_j^* = T_j^H) \text{ in lower quintile} \end{cases}$$

[34] The results are based on 200 repeated 60-40% partitions. The results are also not sensitive to alternative data partitions (70-30% and 50-50%).

where $\hat{\Pr}(T_j^* = T_J^H)$ is the estimated probability of being in a type-*H* group.[35]

As shown in the table, the "naive" approach produces a mean default probability (19.9%) closer to the observed sample mean of 21% than the full Probit model (18.6%) and the "conservative" approach (23.7%). The "naïve" and "conservative" approach also report a lower mean squared prediction error than the Probit model (0.145 and 0.156 versus 0.159). The two type-consistent approaches also show a higher overall predictive performance based on McFadden et al. (1977) standard measure.[36] In particular, the "naïve" approach has a predictive performance of 76.4% and the "conservative" approach has a predictive performance of 76% versus 74.7% of the Probit model. The poorer performance of the Probit model is largely explained by its lower correct default classification rate (i.e. identification of "bad" borrowers): 17.2% versus 21.9% of the "naïve" approach and 31.3% of the "conservative" approach. Regarding the correct non-default classification rate (i.e. identification of "good" borrowers), the Probit model performs better than the "conservative" approach, but poorer than the "naïve" approach.

An alternative way to evaluate the out-of-sample performance consists in examining the number of "good" clients the model rates as "bad" (Type I error) and the number of "bad" clients the model rates as "good" (Type II error) for varying cutoff values of the probability of default. In Table 6, we used the standard 0.5 rule for the performance assessment. Figures 1 and 2 compare the percentage of "good" borrowers rejected and the percentage of "bad" borrowers accepted across the Probit, "naïve" and "conservative" type-consistent approaches for different cutoff values. In the case of Type I errors, the "naive" approach and the Probit model outperform the "conservative" approach for most of the cutoff values. More specifically, for cutoff values above 0.1 the lending institution will do better in identifying "good" clients by relying on the "naïve" approach or Probit model. In the case of Type II errors, however, both the "naïve" and "conservative" approach outperform the Probit model for basically the entire range of cutoff values, and for values above 0.3 the "conservative" approach has a considerably higher (and

[35] This approach is in line with Gan and Mosquera (2008) who examine unobserved consumer types in the Ecuadorian credit card market.

[36] McFadden et al. (1977) overall performance measure is equal to $p_{11} + p_{22} - p_{12}^2 - p_{21}^2$, where p_{ij} is the *ij*th entry (expressed as a fraction of the sum of all entries) in the 2x2 confusion matrix of actual versus predicted (0,1) outcomes using the 0.5 rule.

increasing) performance than the "naïve" approach. For sufficiently lenient acceptance rules (cutoff values above 0.5), the differences in the percentage of "bad" accepted between the "conservative" approach and the other models are in the order of 10-23 percentage points.

Hence, we generally attain a higher predictive power when allowing for unobserved group types when modeling the probability of default of group members, as compared to a standard probabilistic regression model. If the lending institution is more interested in minimizing the number of "bad" clients (classified as "good" by the model), the lender should probably follow a "conservative" approach, while if the lender is more interested in identifying "good" clients (classified as "bad" by the model) it should follow a "naïve" approach; the Probit model will also perform well for the latter. Yet, for more lenient acceptance rules using a "naïve" approach or Probit model will also result in a much higher acceptance rate of "bad" clients relative to the "conservative" approach. For example, for a cutoff value of 0.4 the "naïve" approach outperforms the "conservative" approach by three percentage points in terms of the rejection rate of "good" clients, while the "conservative" approach outperforms the "naïve" approach by a similar degree in terms of the acceptance rate of "bad" clients; but for a cutoff value of 0.6, the "naïve" approach outperforms the "conservative" approach by four percentage points when identifying "good" clients, while the "conservative" approach outperforms the "naïve" approach by fourteen percentage points when identifying "bad" clients.

6 Concluding Remarks

This paper proposes an empirical model to address the potential omitted variable problem resulting from group lending with unobserved types. We use a mixture model to explicitly account for group types when modeling the repayment behavior of group members. In the model, individuals make repayment decisions based on their unobserved group type as well as on observable individual and loan characteristics. Average member characteristics and other group and village characteristics help, in turn, to identify the group types. We also allow the marginal effects in the repayment equation to vary across types.

The estimation results support our model specification and show the advantages of relying on a type-consistent method when examining the probability of default of group members. First, the model clearly distinguishes two group types: an apparent "responsible" group with a low probability of default among group members and another "irresponsible" group

with a high probability of default. Second, we find important differences in the marginal effects of the different individual and loan characteristics included in the repayment equation across group types. Third, the type-varying model shows a higher predictive performance than standard probabilistic models. From a policy perspective, our model helps to better understand the underlying factors driving repayment behavior, which appear to differ across groups. These differences can aid lenders when designing loan contracts for different "types" of clients. Similarly, the model can help to attenuate information asymmetries in micro lending by aiding lenders to correctly classify their potential clients. A more accurate risk scoring tool is essential to reduce the high transaction costs faced by micro finance institutions. It can also prevent including potential "bad" borrowers and excluding "good" borrowers from sensitive microcredit markets in developing regions.

Finally, it is worth noting that the analysis has focused on a two-type model given the nature of our data. The apparent two types may result from a combination of factors, including peer selection, peer monitoring and pressure and other unobserved factors like social cohesion, but disentangling these effects is beyond the scope of the study. Certainly, there can be a wider set of types in other contexts, and the proposed method can be easily adapted to allow for additional types. Considerably increasing the number of types, however, may require imposing restrictions on the value of the coefficients in the repayment equation (for example, not necessarily allowing for different marginal effects across all types) in order to avoid a highly parameterized model, which could be difficult to estimate in practice. Our analysis also follows a discrete treatment of the repayment decision given the observed behavior of most of the borrowers in the sample (either full repayment or no payment). Yet, the model can be adapted to examine instead the percentage of loan repaid by members. Future research should further attempt to incorporate dynamic aspects in the repayment decision of members under a type-varying setting.

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Table 1
Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Panel 1: Individual characteristics (12,883 observations)				
If defaulted	0.20	0.40	0.00	1.00
If literate	0.23	0.42	0.00	1.00
If disabled member in household	0.06	0.24	0.00	1.00
If owns land	0.65	0.48	0.00	1.00
If lives in pucca house	0.33	0.47	0.00	1.00
If lives in kacha house	0.22	0.42	0.00	1.00
If self-employed agricultural worker	0.20	0.40	0.00	1.00
If agricultural laborer	0.61	0.49	0.00	1.00
If belongs to scheduled tribe/caste	0.31	0.46	0.00	1.00
If belongs to leading caste	0.92	0.27	0.00	1.00
Panel 2: Group and loan characteristics (1,110 groups)				
Average member characteristics				
% literate	0.22	0.21	0.00	0.94
% disabled member in household	0.05	0.10	0.00	0.94
% own land	0.59	0.31	0.00	0.95
% live in pucca house	0.32	0.31	0.00	0.95
% live in kacha house	0.21	0.26	0.00	0.95
% self-employed agricultural worker	0.18	0.30	0.00	0.95
% agricultural laborer	0.56	0.36	0.00	0.95
% belong to scheduled tribe/caste	0.31	0.43	0.00	1.00
% belong to leading caste	0.91	0.14	0.36	1.00
Other group and village characteristics				
Age of group (years)	6.44	2.49	1.00	25.00
If group has food credit program	0.28	0.45	0.00	1.00
If group has marketing program	0.15	0.35	0.00	1.00
If group has insurance program	0.25	0.43	0.00	1.00
If group meets at least monthly	0.89	0.31	0.00	1.00
If located in Telangana	0.45	0.50	0.00	1.00
If located in Rayalaseema	0.26	0.44	0.00	1.00
If located in Coastal AP	0.29	0.45	0.00	1.00
Number of group members	12.52	2.37	7.00	20.00
If financial institution in village	0.34	0.47	0.00	1.00
If public bus in village	0.66	0.48	0.00	1.00
If telephone in village	0.75	0.43	0.00	1.00
If post office in village	0.63	0.48	0.00	1.00
Loan characteristics				
Amount of loan (rupees)	3,338	2,685	400	25,000
Number of members with loan	11.61	3.24	2.00	20.00
Annual interest rate (%)	12.83	3.10	6.00	25.00
Length of loan (years)	1.11	0.46	0.17	5.00
If repayment at least monthly	0.96	0.19	0.00	1.00
If loan due in 2004	0.11	0.31	0.00	1.00
If loan due in 2005	0.49	0.50	0.00	1.00
If loan due in 2006	0.40	0.49	0.00	1.00

Table 2
Intra-group default behavior

Default behavior	Groups	
	#	%
If none of the members defaulted	848	76.4
If all of the members defaulted	188	16.9
If some of the members defaulted	74	6.7
Total	1,110	100.0

Table 3
Probability of default, Two-type model

Variable	Type *H*		Type *L*	
	Coeff.	Std. Error	Coeff.	Std. Error
	Dependent variable: If default			
Constant	-3.399	0.629	7.775	28.740
If literate	0.160	0.105	0.540	0.206
If disabled member in household	0.258	0.163	-0.263	0.383
If owns land	0.180	0.119	-0.556	0.181
If lives in pucca house	-0.198	0.122	-0.997	0.186
If lives in kacha house	0.022	0.124	-0.844	0.209
If self-employed agricultural worker	-0.593	0.184	1.173	0.266
If agricultural laborer	0.120	0.140	1.748	0.155
If belongs to scheduled tribe/caste	0.082	0.110	2.736	0.279
If belongs to leading caste	-0.092	0.163	0.260	0.383
Amount of loan (1,000 rupees)	0.068	0.016	0.462	0.049
Number of members with loan	-0.062	0.090	-0.338	0.151
Number of members with loan squared	0.001	0.004	0.003	0.007
Annual interest rate (%)	0.083	0.013	0.277	0.034
Length of loan (years)	0.508	0.081	0.963	0.193
If repayment at least monthly	-0.497	0.244	-10.989	30.416
If loan due in 2005	-1.267	0.435	-0.128	0.287
If loan due in 2006	1.052	0.189	1.229	0.286
Probability of type-*H* Group				
Constant	-2.901	2.501		
% literate	1.921	0.409		
% disabled member in household	1.630	0.777		
% own land	0.707	0.212		
% live in pucca house	-1.124	0.276		
% live in kacha house	-1.052	0.228		
% self-employed agricultural worker	0.697	0.323		
% agricultural laborer	1.902	0.318		
% belong to scheduled tribe/caste	0.623	0.167		
% belong to leading caste	-1.020	0.496		
Age of group (years)	0.025	0.066		
Age of group squared	-0.004	0.004		
If group has food credit program	-0.951	0.115		
If group has marketing program	1.688	0.277		
If group has insurance program	0.443	0.139		
If group meets at least monthly	3.105	0.223		
If located in Telangana	2.320	0.255		
If located in Rayalaseema	0.652	0.211		

(Cont.)

Variable	Type *H*		Type *L*	
	Coeff.	Std. Error	Coeff.	Std. Error
	Dependent variable: If default			
Number of group members	0.132	0.360		
Number of group members squared	-0.014	0.014		
If financial institution in village	0.979	0.139		
If public bus in village	0.139	0.117		
If telephone in village	1.076	0.168		
If post office in village	-0.684	0.130		
Predicted probability of being Type-*H* group				
Average				79.8%
Group, no members defaulting				82.9%
Groups, all members defaulting				66.9%
Groups, some members defaulting				76.4%
Predicted individual default probability				
Average				19.6%
Conditional on being in Type-*H* group				9.5%
Conditional on being in Type-*L* group				62.8%
# observations				12,883
Log-likelihood				-5,111.6

Table 4
Conditional marginal effects (percentage points)

Variable	Type *H*			Type *L*		
	Mg. Effect	[95% Conf. Interv.]		Mg. Effect	[95% Conf. Interv.]	
Individual characteristics						
If literate	0.84	-0.14	1.81	7.33	2.39	11.57
If disabled member in household	1.44	-0.54	3.53	-4.21	-24.12	11.92
If owns land	0.89	0.23	1.69	-7.87	-13.13	-2.19
If lives in pucca house	-0.97	-1.91	-0.06	-16.44	-21.08	-9.58
If lives in kacha house	0.11	-0.78	1.19	-14.47	-21.46	-8.02
If self-employed agricultural worker	-2.57	-3.91	-1.19	13.95	7.65	18.10
If agricultural laborer	0.60	-0.72	1.82	29.16	19.65	36.86
If belongs to scheduled tribe/caste	0.42	-0.18	1.14	31.20	24.78	36.05
If belongs to leading caste	-0.48	-2.48	1.18	4.15	-8.23	14.55
Loan characteristics						
One thousand rupees increase in loan	0.36	0.22	0.50	5.92	4.08	6.88
One more member with loan	-0.23	-0.32	-0.13	-4.77	-7.24	-1.04
One-percent increase interest rate	0.44	0.32	0.52	3.77	2.39	4.68
One more year in length of loan	3.23	2.27	3.95	10.39	6.79	12.36
If repayment at least monthly	-3.08	-5.08	-1.11	-26.28	-35.23	-13.69
If loan due in 2005	-6.60	-8.33	-4.97	-1.91	-6.85	4.88
If loan due in 2006	6.03	4.10	7.43	17.05	12.08	20.68

Note: The marginal effects are calculated at the means of the covariates. For continuous variables, the corresponding change is indicated in the table. For discrete variables, the change is from 0 to 1. The confidence intervals reported are normal-based and biased-corrected using 200 bootstrap replications.

Table 5
Unconditional marginal effects (percentage points)

Variable	Probit model			Full Probit model			Two-type model		
	Mg. Effect	[95% Conf. Interv.]		Mg. Effect	[95% Conf. Interv.]		Mg. Effect	[95% Conf. Interv.]	
Individual characteristics									
If literate	-0.81	-2.01	0.51	-0.18	-1.84	1.58	1.56	0.54	2.50
If disabled member in household	-1.62	-4.01	0.72	-0.04	-3.15	3.21	0.82	-1.45	2.76
If owns land	-0.84	-1.71	0.27	0.18	-1.37	2.18	-0.08	-0.80	0.76
If lives in pucca house	-0.37	-1.48	0.64	-0.73	-2.86	1.22	-2.68	-3.67	-1.50
If lives in kacha house	2.82	1.43	4.26	-0.11	-2.30	2.19	-1.50	-2.74	-0.20
If self-employed agricultural worker	-0.37	-2.09	1.02	0.04	-3.25	2.76	-0.74	-2.13	0.51
If agricultural laborer	0.76	-0.67	2.02	0.59	-2.12	3.16	3.76	2.30	5.03
If belongs to scheduled tribe/caste	6.10	5.40	6.83	-1.98	-5.35	1.17	3.83	2.38	5.33
If belongs to leading caste	3.12	1.06	4.76	-0.23	-3.37	2.05	0.03	-1.94	1.51
Loan characteristics									
One thousand rupees increase in loan	1.60	1.46	1.76	1.45	1.30	1.63	0.97	0.77	1.11
One more member with loan	0.01	-0.14	0.16	0.15	-0.06	0.34	-0.74	-0.95	-0.37
One-percent increase interest rate	1.19	1.13	1.26	1.37	1.30	1.45	0.81	0.65	0.89
One more year in length of loan	7.90	7.47	8.26	8.31	7.90	8.69	4.02	3.21	4.48
If repayment at least monthly	-14.03	-15.83	-12.55	-6.78	-8.28	-5.51	-5.65	-7.60	-3.39
If loan due in 2005	-6.01	-6.59	-5.36	-5.84	-6.44	-5.14	-6.08	-7.17	-4.85
If loan due in 2006	9.52	8.90	10.18	10.64	9.97	11.35	7.25	5.55	8.39
Average member characteristics									
10-% increase literate				0.00	-0.21	0.21	-1.34	-1.66	-1.04
10-% increase disabled member				-0.94	-1.35	-0.56	-1.15	-1.64	-0.56
10-% increase own land				-0.51	-0.74	-0.33	-0.52	-0.80	-0.28
10-% increase pucca house				-0.12	-0.33	0.12	0.88	0.60	1.13
10-% increase kacha house				0.45	0.20	0.68	0.82	0.46	1.25
10-% increase self-employed ag. worker				0.12	-0.19	0.48	-0.51	-0.92	-0.05
10-% increase agricultural laborer				0.18	-0.11	0.47	-1.33	-1.64	-1.01
10-% increase scheduled tribe/caste				0.75	0.42	1.11	-0.46	-0.72	-0.28
10-% increase leading caste				0.49	0.24	0.85	0.80	0.29	1.53
Other group and village characteristics									
One more year of age of group				1.19	1.03	1.36	0.06	-0.21	0.37
If group has food credit program				8.08	7.67	8.57	8.46	4.94	13.33
If group has marketing program				-6.12	-6.49	-5.76	-8.36	-9.43	-7.51
If group has insurance program				-5.29	-5.75	-4.88	-3.07	-4.50	-2.20
If group meets at least monthly				-30.11	-30.88	-29.49	-44.59	-47.40	-42.51
If located in Telangana				-9.58	-10.03	-9.13	-18.01	-22.78	-13.68
If located in Rayalaseema				-2.79	-3.32	-2.28	-4.27	-5.33	-3.02
One more member in group				-1.41	-1.63	-1.15	1.27	0.60	1.73
If financial institution in village				-6.01	-6.39	-5.65	-6.59	-8.22	-5.45
If public bus in village				1.19	0.83	1.59	-1.06	-1.72	-0.12
If telephone in village				-3.43	-3.83	-3.01	-9.96	-11.56	-8.18
If post office in village				0.97	0.66	1.34	4.85	3.89	6.31

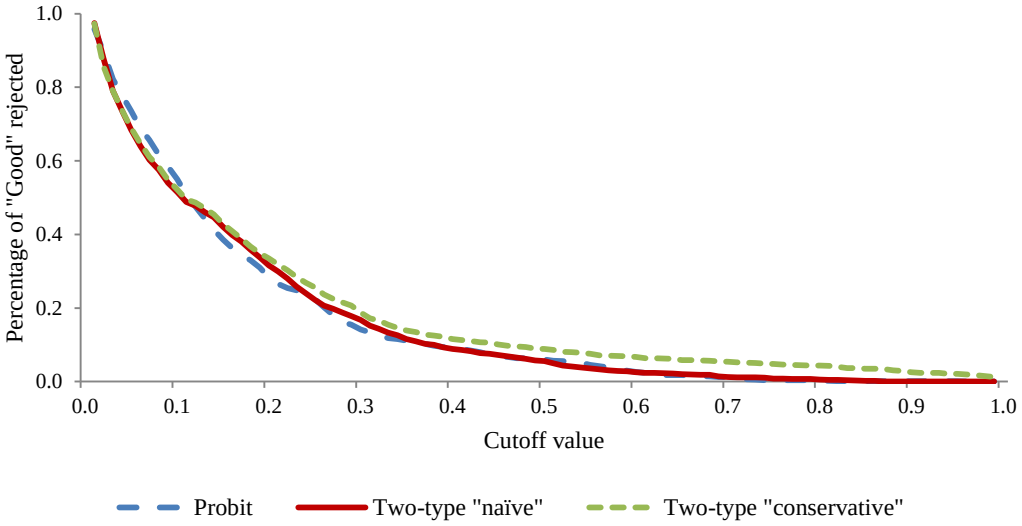
Note: The marginal effects are calculated at the means of the covariates. For continuous variables, the corresponding change is indicated in the table. For discrete variables, the change is from 0 to 1. The confidence intervals reported are normal-based and bias-corrected using 200 bootstrap replications.

Table 6
Predictive performance of alternative models

Indicator	Probit model	Full Probit model	Two-type "naïve"	Two-type "conservative"
	Out-of-sample performance (5,068 obs.)			
Average predicted default probability (observed=0.210)	0.185	0.186	0.199	0.237
Mean Square Predicted Error	0.160	0.159	0.145	0.156
Predictive performance	73.7%	74.7%	76.4%	76.0%
Correct default/non-default classification	77.9%	77.9%	79.2%	78.6%
Correct default classification (sensitivity), 1,062 defaults	2.2%	17.2%	21.9%	31.3%
Correct non-default classification (specificity), 4,006 non-defaults	98.0%	94.0%	94.4%	91.2%

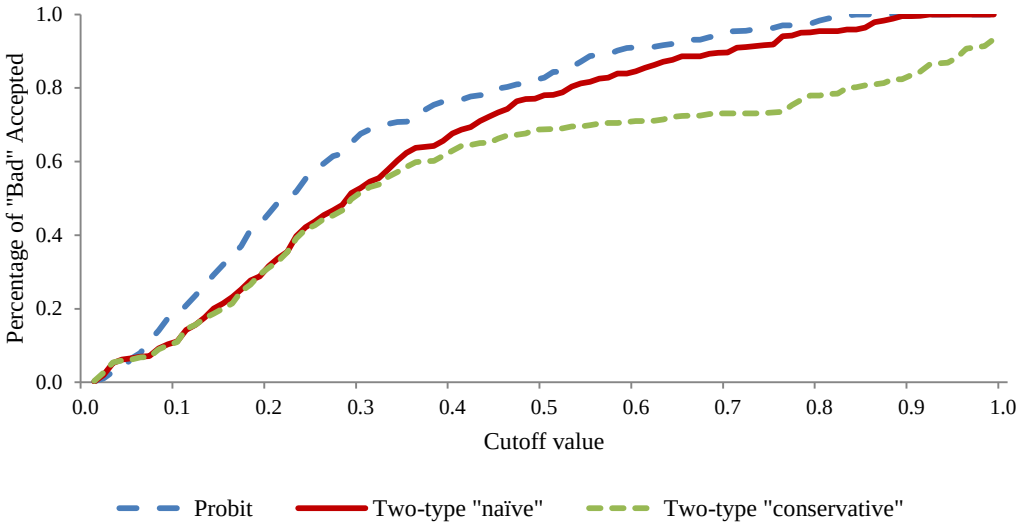
Note: The "naïve" approach is based on the unconditional probability of default of each individual. The "conservative" approach uses the probability of default based on the probability of individual of being in a particular group type. The performance and classification rates are based on converting the estimated default probabilities to a binary regime prediction using the standard 0.5 rule. The predictive performance measure is based on McFadden, Puig, & Kirschner (1977); the measure is equal to $p_{11} + p_{22} - p_{12}^2 - p_{21}^2$ where p_{ij} is the *ij*th entry in the standard 2x2 confusion matrix of actual versus predicted (0,1) outcomes in which the entries are expressed as a fraction of the sum of all entries. Sensitivity accounts for the percentage of cases in which individuals defaulting are also predicted to default, while specificity measures the percentage of cases in which individuals not defaulting are also predicted to not default. The results are based on 200 repeated 60-40% data partitions (averages reported).

Figure 1
Comparison of Type I errors



Note: The “naïve” approach is based on the unconditional probability of default of each individual. The “conservative” approach uses the probability of default based on the probability of individual of being in a particular group type. The results are based on 200 repeated 60-40% data partitions (averages reported).

Figure 2
Comparison of Type II errors



Note: The “naïve” approach is based on the unconditional probability of default of each individual. The “conservative” approach uses the probability of default based on the probability of individual of being in a particular group type. The results are based on 200 repeated 60-40% data partitions (averages reported).

Appendix A

Table A.1
Data description

Variable	Description
Default	If member failed to fully repay loan
Literate	If member can read and write
Disabled	If any household member has a disability
Own land	If member owns any land
Pucca house	If member lives in a house made of stone, bricks, concrete or timber
Kacha house	If member lives in a house made of hay, grass, mud or bamboo
Self-employed	If member is self-employed agricultural worker
Agricultural laborer	If member provides agricultural labor for someone else
Scheduled tribe/caste	If member belongs to a scheduled tribe or caste
Leading caste	If member belongs to a leading caste
Age of group	Group age in years
Food credit program	If group members receive a food credit program
Marketing program	If group members are provided with a marketing program
Insurance program	If group members are provided with an insurance program
Group meets at least monthly	If group members meet at least on a monthly basis
Located in Telangana	If the group is located in Telangana
Located in Rayalaseema	If the group is located in Rayalaseema
Located in Coastal AP	If the group is located in Coastal Andhra Pradesh
Number of group members	Number of members in the group
Financial institution in village	If there is a financial institution in the village
Public bus in village	If public bus service is available in the village
Telephone in village	If telephone service is available in the village
Post office in village	If there is a post office in the village
Amount of loan	Amount of loan borrowed by member in rupees
Number of members with loan	Number of members in the group who borrowed loan
Annual interest rate	Annual interest rate of the loan
Length of loan	Length of the loan in years
Monthly repayment frequency	If repayment frequency of the loan at least monthly
Loan due in 2004	If loan is due in 2004
Loan due in 2005	If loan is due in 2005
Loan due in 2006	If loan is due in 2006

Table A.2
Sorting based on observables

If intra-group variance is less than or equal to intra-village or intra-mandal variance by member characteristic				
	Intra-village		Intra-mandal	
	# groups	% total groups	# groups	% total groups
If literate	538	56.0	646	58.4
If disabled member in household	636	66.3	727	65.7
If owns land	606	63.1	755	68.2
If lives in pucca house	591	61.6	746	67.4
If lives in kacha house	627	65.3	768	69.4
If self-employed agricultural worker	761	79.3	866	78.2
If agricultural laborer	703	73.2	863	78.0
If belongs to scheduled tribe/caste	863	89.9	1018	92.0
If belongs to leading caste	680	70.8	763	68.9
Average	667	69.5	795	71.8

Note: The intra-village comparisons exclude 150 villages where there is only one group in the village, while the intra-mandal comparisons exclude 3 mandals.

Table A.3
Probability of default, One-type model

Variable	Probit model		Probit model full		Random-effects Probit model	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
	Dependent variable: If default					
Constant	-1.827	0.562	0.502	1.370	0.646	2.121
If literate	-0.032	0.055	-0.007	0.020	0.039	0.118
If disabled member in household	-0.065	0.080	-0.002	0.032	-0.030	0.194
If owns land	-0.033	0.071	0.008	0.026	0.010	0.139
If lives in pucca house	-0.015	0.082	-0.031	0.037	-0.189	0.149
If lives in kacha house	0.107	0.086	-0.005	0.047	0.056	0.152
If self-employed agricultural worker	-0.014	0.119	0.002	0.077	0.212	0.221
If agricultural laborer	0.030	0.089	0.025	0.056	0.247	0.173
If belongs to scheduled tribe/caste	0.229	0.094	-0.085	0.113	0.300	0.298
If belongs to leading caste	0.128	0.081	-0.009	0.036	0.288	0.204
Amount of loan (1,000 rupees)	0.061	0.016	0.059	0.018	0.071	0.021
Number of members with loan	0.009	0.072	0.065	0.095	0.126	0.195
Number of members with loan squared	0.000	0.003	-0.003	0.005	-0.003	0.010
Annual interest rate (%)	0.046	0.014	0.056	0.015	0.182	0.024
Length of loan (years)	0.274	0.108	0.304	0.113	0.867	0.168
If repayment at least monthly	-0.460	0.249	-0.256	0.269	-0.463	0.423
If loan due in 2005	-0.235	0.156	-0.247	0.163	-0.803	0.286
If loan due in 2006	0.359	0.158	0.430	0.170	1.138	0.275
% literate			0.000	0.237	-0.034	0.448
% disabled member in household			-0.405	0.426	-1.730	0.987
% own land			-0.220	0.178	-0.467	0.325
% live in pucca house			-0.051	0.190	0.050	0.353
% live in kacha house			0.189	0.216	0.584	0.380
% self-employed agricultural worker			0.050	0.259	-0.143	0.471
% agricultural laborer			0.074	0.188	-0.310	0.337
% belong to scheduled tribe/caste			0.310	0.160	0.337	0.356
% belong to leading caste			0.206	0.334	0.338	0.583
Age of group (years)			0.076	0.074	0.299	0.109
Age of group squared			-0.003	0.004	-0.012	0.006
If group has food credit program			0.319	0.108	0.910	0.172
If group has marketing program			-0.288	0.144	-0.775	0.236
If group has insurance program			-0.238	0.118	-0.513	0.193
If group meets at least monthly			-0.952	0.144	-2.935	0.203
If located in Telangana			-0.409	0.141	-1.140	0.227
If located in Rayalaseema			-0.122	0.154	-0.490	0.247

(Cont.)

Variable	Probit model		Probit model full		Random-effects Probit model	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
	Dependent variable: If default					
Number of group members			-0.346	0.204	-0.933	0.331
Number of group members squared			0.013	0.008	0.033	0.013
If financial institution in village			-0.266	0.116	-0.765	0.189
If public bus in village			0.051	0.103	0.152	0.166
If telephone in village			-0.140	0.119	-0.250	0.186
If post office in village			0.041	0.109	0.147	0.171
$\ln(\sigma^2 u)$					2.836	0.103
Rho					0.945	0.005
Predicted default probability		19.5%		19.5%		7.6%
# observations		12,883		12,883		12,883
Log likelihood		-5776.26		-5237.50		-1121.56

Note: The standard errors reported in the Probit model are robust, clustered by group. The $\ln(\sigma^2 u)$ term in the random-effects model represents the group-level variance component and Rho captures the proportion of the total variance contributed by the group-level variance component.

Table A.4
Two-type model exclusion tests: average member characteristics and group size and age

Variable	Excluding member characteristics				Excluding group size and age			
	Type *H*		Type *L*		Type *H*		Type *L*	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
	Dependent variable: If default				Dependent variable: If default			
Constant	-3.477	0.216	7.782	21.388	-3.492	0.339	7.570	29.829
If literate	-0.020	0.107	0.176	0.212	0.158	0.097	0.602	0.244
If disabled member in household	0.161	0.173	-0.563	0.334	0.253	0.155	-0.454	0.365
If owns land	-0.015	0.025	-0.787	0.235	0.073	0.058	-0.581	0.153
If lives in pucca house	-0.069	0.076	-0.713	0.212	-0.054	0.015	-1.092	0.180
If lives in kacha house	0.205	0.117	-0.542	0.207	0.102	0.116	-0.908	0.203
If self-employed agricultural worker	-0.592	0.164	1.451	0.331	-0.644	0.074	1.302	0.316
If agricultural laborer	-0.150	0.119	1.383	0.222	0.061	0.107	1.807	0.155
If belongs to scheduled tribe/caste	-0.060	0.103	2.454	0.196	-0.047	0.035	2.825	0.637
If belongs to leading caste	0.103	0.149	0.145	0.313	-0.132	0.125	0.231	0.433
Amount of loan (1,000 rupees)	0.101	0.018	0.564	0.091	0.090	0.016	0.463	0.050
Number of members with loan	-0.045	0.105	-0.344	0.125	-0.031	0.050	-0.318	0.242
Number of members with loan squared	0.001	0.005	0.004	0.004	0.001	0.002	0.003	0.010
Annual interest rate (%)	0.085	0.012	0.261	0.047	0.082	0.013	0.284	0.039
Length of loan (years)	0.585	0.086	1.012	0.351	0.555	0.020	0.825	0.358
If repayment at least monthly	-0.444	0.241	-10.982	21.541	-0.567	0.225	-11.081	31.719
If loan due in 2005	-1.269	0.546	-0.117	0.084	-1.351	0.409	-0.066	0.044
If loan due in 2006	0.730	0.160	1.607	0.346	0.894	0.157	1.233	0.289
Probability of type-*H* Group								
Constant	-2.777	5.297			-3.006	0.402		
% literate					2.055	0.530		
% disabled member in household					1.699	0.117		
% own land					0.469	0.230		
% live in pucca house					-1.005	0.136		
% live in kacha house					-0.992	0.215		
% self-employed agricultural worker					0.518	0.063		
% agricultural laborer					1.748	0.350		
% belong to scheduled tribe/caste					0.473	0.170		
% belong to leading caste					-1.149	0.509		
Age of group (years)	-0.036	0.064						
Age of group squared	0.000	0.003						
If group has food credit program	-0.814	0.129			-1.011	0.109		
If group has marketing program	1.397	0.218			1.567	0.306		
If group has insurance program	0.526	0.122			0.300	0.125		
If group meets at least monthly	3.036	0.303			2.963	0.262		
If located in Telangana	2.341	0.306			2.060	0.093		
If located in Rayalaseema	0.809	0.420			0.912	0.025		

(*Cont.*)

Variable	Excluding member characteristics				Excluding group size and age			
	Type *H*		Type *L*		Type *H*		Type *L*	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
	Dependent variable: If default				Dependent variable: If default			
Number of group members	0.156	0.747						
Number of group members squared	-0.010	0.029						
If financial institution in village	0.961	0.054			0.870	0.119		
If public bus in village	0.166	0.078			0.138	0.057		
If telephone in village	0.829	0.107			1.135	0.074		
If post office in village	-0.571	0.115			-0.535	0.104		
# observations				12,883				12,883
Log-likelihood				-5173.4				-5153.9

Table A.5
Two-type model exclusion tests: group programs and frequency of meetings

Variable	Excluding group programs				Excluding group meetings			
	Type *H*		Type *L*		Type *H*		Type *L*	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
	Dependent variable: If default				Dependent variable: If default			
Constant	-3.355	0.557	7.795	21.128	-3.461	0.635	7.572	35.427
If literate	0.095	0.106	0.426	0.200	0.081	0.113	0.429	0.218
If disabled member in household	0.254	0.161	-0.113	0.377	0.228	0.173	-0.167	0.444
If owns land	0.161	0.096	-0.278	0.125	0.100	0.111	-0.406	0.194
If lives in pucca house	-0.211	0.114	-0.992	0.203	-0.109	0.139	-1.043	0.204
If lives in kacha house	-0.130	0.127	-0.588	0.186	0.087	0.131	-0.948	0.219
If self-employed agricultural worker	-0.621	0.184	1.214	0.270	-0.638	0.204	1.103	0.285
If agricultural laborer	0.087	0.143	1.574	0.218	0.081	0.141	1.729	0.215
If belongs to scheduled tribe/caste	0.082	0.103	2.683	0.254	0.071	0.117	2.895	0.297
If belongs to leading caste	-0.086	0.154	0.149	0.412	-0.052	0.149	0.272	0.445
Amount of loan (1,000 rupees)	0.062	0.017	0.470	0.056	0.076	0.018	0.430	0.058
Number of members with loan	-0.050	0.069	-0.350	0.195	-0.067	0.077	-0.356	0.267
Number of members with loan squared	0.001	0.003	0.002	0.006	0.004	0.003	0.005	0.011
Annual interest rate (%)	0.087	0.012	0.270	0.038	0.083	0.013	0.283	0.040
Length of loan (years)	0.472	0.079	0.987	0.148	0.472	0.082	0.826	0.208
If repayment at least monthly	-0.548	0.237	-11.009	20.329	-0.681	0.222	-11.231	37.088
If loan due in 2005	-1.059	0.109	-0.070	0.204	-1.145	0.092	-0.207	0.243
If loan due in 2006	0.998	0.188	1.405	0.241	0.887	0.154	1.153	0.293
Probability of type-*H* Group								
Constant	-3.065	2.244			-2.674	0.881		
% literate	1.624	0.263			2.228	0.425		
% disabled member in household	1.353	0.584			1.881	0.637		
% own land	0.777	0.194			0.456	0.243		
% live in pucca house	-1.047	0.193			-0.971	0.229		
% live in kacha house	-0.907	0.223			-0.849	0.233		
% self-employed agricultural worker	1.018	0.258			0.448	0.324		
% agricultural laborer	1.585	0.245			2.053	0.241		
% belong to scheduled tribe/caste	0.707	0.167			0.634	0.172		
% belong to leading caste	-1.236	0.440			-0.885	0.516		
Age of group (years)	0.051	0.058			0.038	0.073		
Age of group squared	-0.004	0.003			-0.005	0.004		
If group has food credit program					-0.890	0.130		
If group has marketing program					1.441	0.185		
If group has insurance program					0.588	0.135		
If group meets at least monthly	2.972	0.117						
If located in Telangana	2.301	0.135			2.146	0.117		
If located in Rayalaseema	0.865	0.095			0.975	0.154		

(*Cont.*)

Variable	Excluding group programs				Excluding group meetings			
	Type *H*		Type *L*		Type *H*		Type *L*	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
	Dependent variable: If default				Dependent variable: If default			
Number of group members	0.148	0.312			0.080	0.144		
Number of group members squared	-0.014	0.013			-0.001	0.006		
If financial institution in village	0.769	0.135			1.237	0.129		
If public bus in village	0.209	0.108			0.358	0.123		
If telephone in village	1.163	0.099			1.322	0.162		
If post office in village	-0.627	0.075			-0.569	0.157		
# observations				12,883				12,883
Log-likelihood				-5223.0				-5418.5

Table A.6
Two-type model exclusion tests: group location and village characteristics

Variable	Excluding group location				Excluding village characteristics			
	Type *H*		Type *L*		Type *H*		Type *L*	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
	Dependent variable: If default				Dependent variable: If default			
Constant	-3.536	0.745	7.808	30.180	-3.423	0.537	7.796	49.901
If literate	0.153	0.094	0.679	0.226	0.212	0.102	0.344	0.233
If disabled member in household	0.177	0.125	-0.411	0.445	0.235	0.159	-0.409	0.409
If owns land	0.059	0.075	-0.738	0.098	0.180	0.094	-0.514	0.216
If lives in pucca house	-0.020	0.078	-0.814	0.370	-0.040	0.102	-0.921	0.193
If lives in kacha house	0.201	0.063	-0.875	0.220	0.070	0.117	-0.651	0.223
If self-employed agricultural worker	-0.521	0.113	1.319	0.312	-0.554	0.181	0.979	0.317
If agricultural laborer	-0.037	0.114	1.912	0.423	0.167	0.128	1.611	0.292
If belongs to scheduled tribe/caste	0.002	0.148	2.519	0.889	-0.047	0.103	2.825	0.473
If belongs to leading caste	-0.116	0.131	0.338	0.451	-0.044	0.156	0.246	0.441
Amount of loan (1,000 rupees)	0.104	0.025	0.519	0.199	0.056	0.016	0.512	0.048
Number of members with loan	-0.013	0.265	-0.328	0.587	-0.060	0.080	-0.336	0.164
Number of members with loan squared	0.000	0.013	0.007	0.019	0.001	0.004	0.002	0.006
Annual interest rate (%)	0.094	0.011	0.234	0.040	0.082	0.013	0.265	0.038
Length of loan (years)	0.583	0.053	0.596	0.300	0.611	0.096	0.881	0.277
If repayment at least monthly	-0.548	0.222	-10.967	33.708	-0.533	0.263	-10.956	50.313
If loan due in 2005	-1.237	0.234	-0.102	0.240	-0.992	0.170	-0.221	0.241
If loan due in 2006	0.811	0.140	0.998	0.514	0.910	0.180	1.141	0.288
Probability of type-*H* Group								
Constant	-2.742	9.305			-2.637	0.603		
% literate	1.759	0.206			2.138	0.370		
% disabled member in household	1.858	0.352			1.843	0.577		
% own land	0.881	0.210			0.479	0.243		
% live in pucca house	-1.300	0.580			-0.820	0.241		
% live in kacha house	-1.322	0.215			-0.992	0.230		
% self-employed agricultural worker	0.857	0.095			0.424	0.308		
% agricultural laborer	1.722	0.435			1.925	0.233		
% belong to scheduled tribe/caste	0.618	0.508			0.327	0.159		
% belong to leading caste	-0.957	0.174			-0.869	0.475		
Age of group (years)	0.033	0.097			0.022	0.068		
Age of group squared	-0.006	0.006			-0.003	0.004		
If group has food credit program	-1.205	0.066			-0.934	0.124		
If group has marketing program	1.813	0.108			1.622	0.187		
If group has insurance program	0.132	0.064			0.687	0.160		
If group meets at least monthly	2.822	0.449			3.220	0.154		
If located in Telangana					1.994	0.180		
If located in Rayalaseema					0.826	0.079		

(*Cont.*)

Variable	Excluding group location				Excluding village variables			
	Type *H*		Type *L*		Type *H*		Type *L*	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
	Dependent variable: If default				Dependent variable: If default			
Number of group members	0.090	1.566			0.153	0.166		
Number of group members squared	-0.003	0.067			-0.014	0.007		
If financial institution in village	0.711	0.131						
If public bus in village	0.421	0.258						
If telephone in village	1.207	0.057						
If post office in village	-0.411	0.118						
# observations				12,883				12,883
Log-likelihood				-5236.6				-5191.6

Table A.7
Hausman tests: Baseline model versus alternative specifications

Variables excluded	H_0: Difference in coefficients of repayment equation between baseline model and alternative specifications not systematic
Average member characteristics	16.610
	(0.165)
Group size and age	31.648
	(0.084)
Group programs	12.402
	(0.574)
Frequency of group meetings	32.087
	(0.076)
Group location	11.307
	(0.662)
Village characteristics	45.828
	(0.000)

Note: Hausman Chi-squared statistics reported and *p*-values in parenthesis.

Figure A.1
Histogram of percentage of loan repaid by member

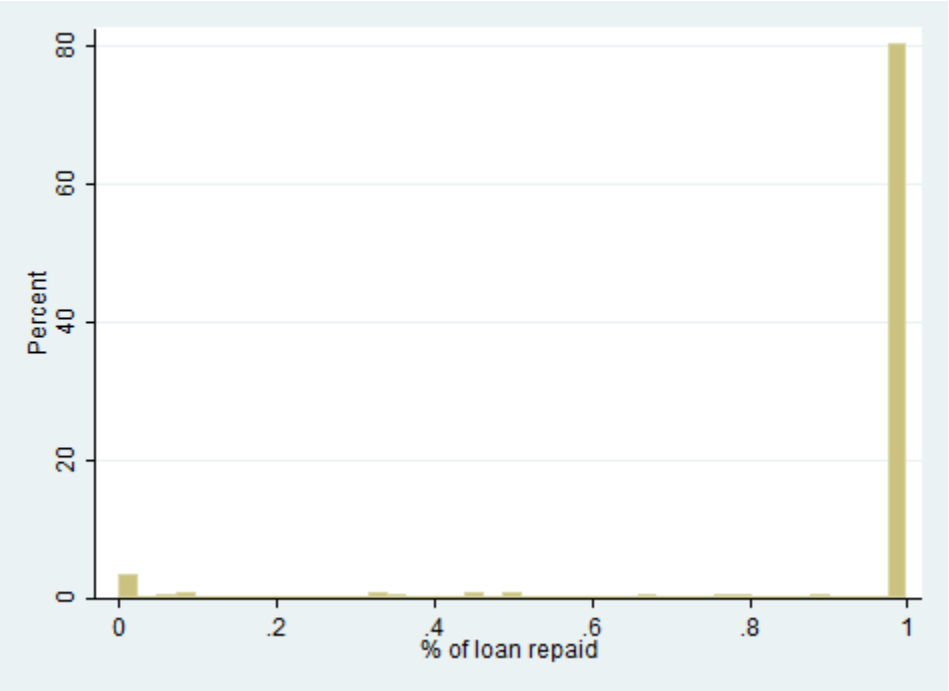
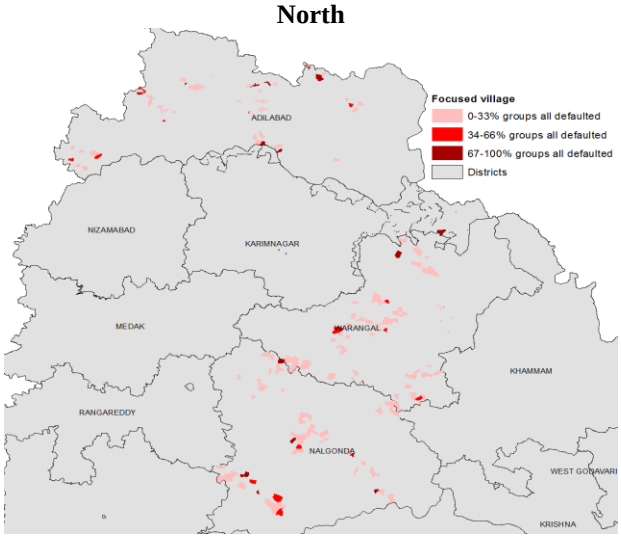
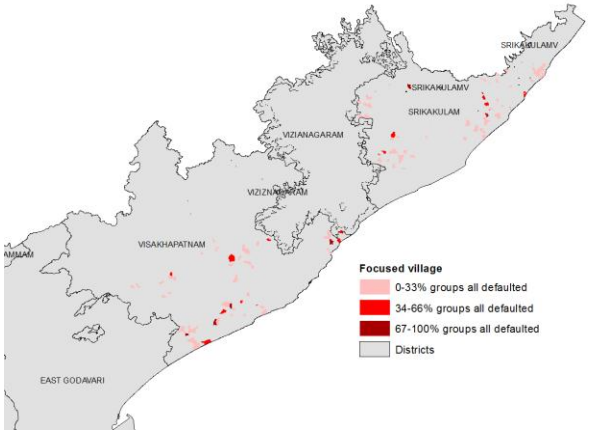


Figure A.2
Location of villages in Andhra Pradesh and group default behavior

North



North East



South

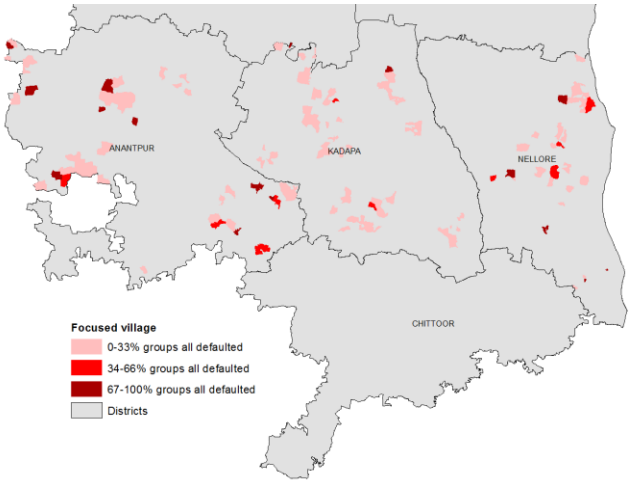
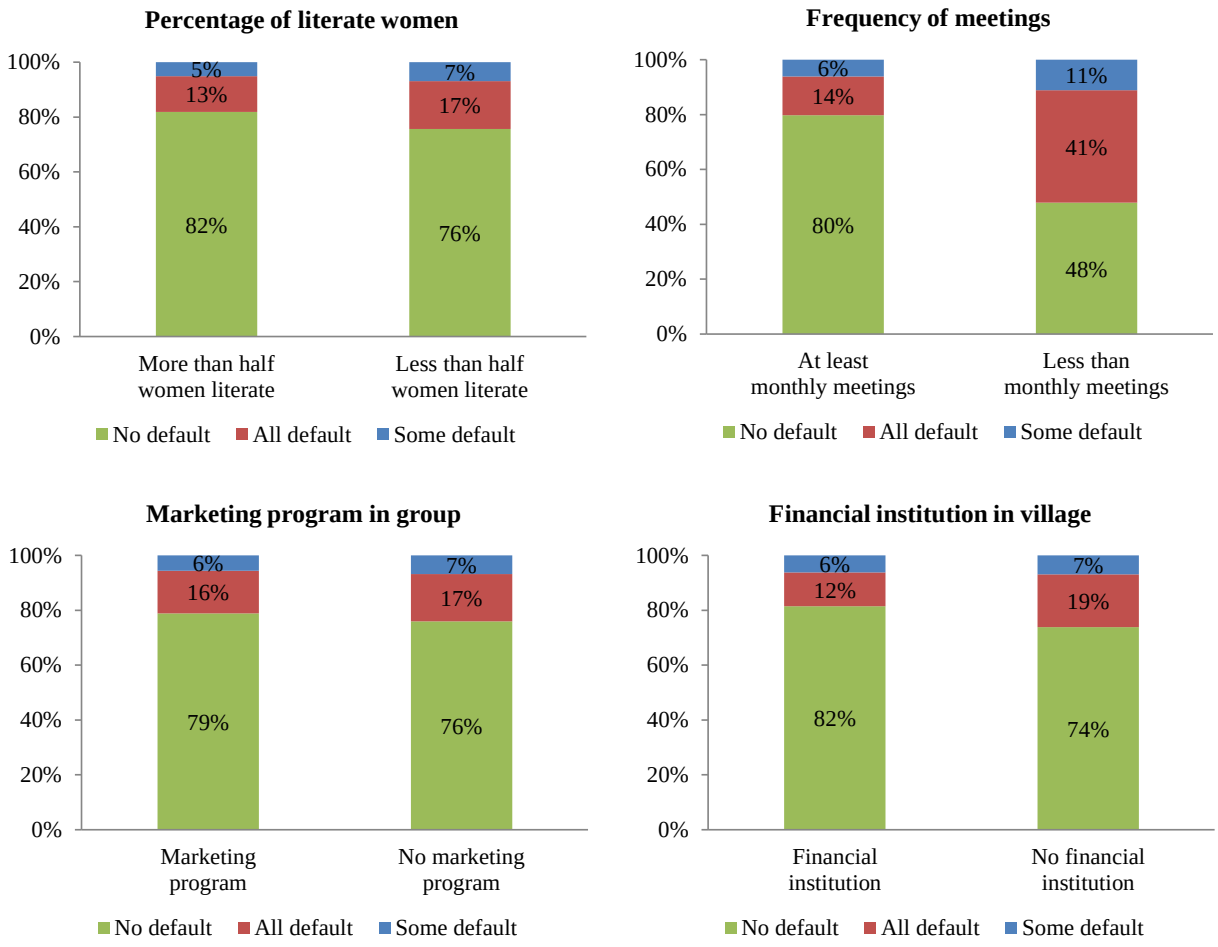


Figure A.3
Distribution of intra-group default behavior by different group characteristics



Appendix B: Solution to model with peer selection and moral hazard

In this appendix, we solve the model with peer selection and moral hazard outlined in Section 2. The model is an extension of Ghatak (1999) basic model, where we allow borrowers to vary on their risk type and effort level. The model setup is presented in Section 2. We also assume that $Y > r + q$, i.e. a successful borrower can make a profit even when her partner loses. This assumption is innocuous because if it does not hold, a borrower with a failed project may have a higher payoff than one with a successful project, which is an unreasonable scenario. We consider both a non-cooperative game scenario where each borrower maximizes her own payoff and a cooperative game scenario where matched borrowers maximize the total payoff of their group.

In the non-cooperative game setting, the maximization problems of the matched borrowers are given by

$$\max_{e_i} E\pi_{ij} = (p_i + e_i)Y - (p_i + e_i)r - q(p_i + e_i)(1 - p_j - e_j) - 1/2\gamma e_i^2$$

$$\max_{e_j} E\pi_{ji} = (p_j + e_j)Y - (p_j + e_j)r - q(p_j + e_j)(1 - p_i - e_i) - 1/2\gamma e_j^2$$

$$s.t.\ \ e_i \geq 0, \quad e_j \geq 0 .$$

The first order conditions (FOCs) are:

$$\partial E\pi_{ij} / \partial e_i = Y - r - q(1 - p_j - e_j) - \gamma e_i \leq 0$$

$$\partial E\pi_{ji} / \partial e_j = Y - r - q(1 - p_i - e_i) - \gamma e_j \leq 0$$

$$e_i \geq 0$$

$$e_j \geq 0$$

$$e_i[Y - r - q(1 - p_j - e_j) - \gamma e_i] = 0$$

$$e_j[Y - r - q(1 - p_i - e_i) - \gamma e_j] = 0 .$$

Solving the FOCs, we have

$$e_{ij}^* = 0, \text{ if } \gamma \leq q$$

$$e_{ij}^{*} = \frac{(\gamma + q)(Y - r) - q[q(1 - p_i) + \gamma(1 - p_j)]}{\gamma^2 - q^2} \text{ if } \gamma > q.$$

We change the subindex of effort from i to ij because the optimal effort of borrower i depends not only on her own type but also on the type of her partner. To eliminate the corner solution under which the second order condition (SOC) is violated, we assume $\gamma > q$. Hereafter we only consider the interior solution. We note that the SOC of the internal solution is satisfied and we have

$$e_{bb}^{*} > e_{ab}^{*} > e_{ba}^{*} > e_{aa}^{*}.$$

The above result suggests that a borrower's optimal effort level is higher if she is a safe type and/or if her partner is a safe type.

Substituting e_{ij}^{*} into $E\pi_{ij}$ and denoting *M*, *A* and *B* as

$$M = Y - r - q,$$

$$A = e_{bb}^{*} - e_{ba}^{*} = e_{ab}^{*} - e_{aa}^{*} = \frac{\gamma q(p_b - p_a)}{\gamma^2 - q^2},$$

$$B = e_{ba}^{*} - e_{aa}^{*} = e_{bb}^{*} - e_{ab}^{*} = \frac{q^2(p_b - p_a)}{\gamma^2 - q^2},$$

we obtain

$$\begin{aligned} E\pi_{bb}^{*} - E\pi_{ba}^{*} &= AM + qp_b(p_b - p_a) + qp_b B + q(e_{bb}p_b - e_{ba}p_a + e_{bb}^2 - e_{ba}e_{ab}) - 0.5\gamma A(e_{bb} + e_{ba}) \\ &> AM + qp_b(p_b - p_a) + qp_b B + qe_{bb}(p_b - p_a) - (\gamma - q)Ae_{bb} \\ &= AM + qp_b(p_b - p_a) + qp_b B + q^2(p_b - p_a)e_{bb}/(\gamma + q) > 0, \end{aligned}$$

and

$$
\begin{aligned}
E\pi^*_{ab} - E\pi^*_{aa} &= AM + qp_a(p_b - p_a) + qp_aB + q(e_{ab}p_b - e_{aa}p_a - e^2_{aa} + e_{ba}e_{ab}) - 0.5\gamma A(e_{ab} + e_{aa}) \\
&> AM + qp_a(p_b - p_a) + qp_aB + qe_{ab}(p_b - p_a) - (\gamma A - qB)e_{ab} \\
&= AM + qp_b(p_b - p_a) + qp_bB > 0.
\end{aligned}
$$

The above results suggest that a borrower prefers a safer partner despite of her own type.

We then examine if positive assortative matching is the only equilibrium. Following Ghatak (2009, such equilibrium must satisfy the optimal sorting property (Becker, 1993). That is, the net expected loss for a safe borrower of having a risky borrower is higher than the net expected gain for a risky borrower of having a safe partner. Therefore, a risky borrower does not have sufficient incentives to pay enough money to a safe borrower to match with her. We find

$$
\begin{aligned}
(E\pi^*_{bb} - E\pi^*_{ba}) - (E\pi^*_{ab} - E\pi^*_{aa}) &= q(p_b - p_a)^2 + 2q(p_b - p_a)B - \gamma AB + q(e^2_{bb} + e^2_{aa} - 2e_{ba}e_{ab}) \\
&= q\gamma^4(p_b - p_a)^2/(\gamma^2 - q^2)^2 > 0.
\end{aligned}
$$

Consistent with Proposition 1 in Ghatak (1999), this result suggests positive assortative matching is the only equilibrium.

Next, we keep the same model setup but assume a cooperative game setting where matched borrowers maximize their joint payoff given by

$$
\begin{aligned}
\max_{e_i, e_j}(E\pi_{ij} + E\pi_{ji} &= (p_i + e_i)Y - (p_i + e_i)r - q(p_i + e_i)(1 - p_j - e_j) - 1/2\gamma e_i^2 \\
&\quad + (p_j + e_j)Y - (p_j + e_j)r - q(p_j + e_j)(1 - p_i - e_i) - 1/2\gamma e_j^2
\end{aligned}
$$

$$s.t.\ \ e_i \geq 0, \quad e_j \geq 0.$$

The FOCs are:

$$\partial E\pi_{ij}/\partial e_i = Y - r - q + 2q(p_j + e_j) - \gamma e_i \leq 0$$

$$\partial E\pi_{ji}/\partial e_j = Y - r - q + 2q(p_i + e_i) - \gamma e_j \leq 0$$

$$e_i \geq 0$$

$$e_j \geq 0$$

$$e_i[Y - r - q + 2q(p_j + e_j) - \gamma e_i] = 0$$

$$e_j[Y - r - q + 2q(p_i + e_i) - \gamma e_j] = 0 .$$

Solving the FOCs, we have

$$e_{ij}^* = 0 \text{ if } \gamma \le 2q$$

$$e_{ij}^* = \frac{(\gamma + 2q)(Y - r - q) + 2q[2qp_i + \gamma p_j)]}{\gamma^2 - 4q^2} \text{ if } \gamma > 2q .$$

We impose the assumption $\gamma > 2q$ to eliminate the corner solution. For the interior solution, the SOC is satisfied. Similar to the non-cooperative game, we obtain

$$e_{bb}^* > e_{ab}^* > e_{ba}^* > e_{aa}^* .$$

We next prove that a group with two safe borrowers has a higher joint payoff than a group with one safe borrower and one risky borrower. Plugging e_{ij}^* into $E\pi_{ij}$, we have

$$E\pi_{bb}^* - E\pi_{ba}^* = A'M + qp_b(p_b - p_a) + qp_b B' + q(e_{bb}p_b - e_{ba}p_a) + q(e_{bb}^2 - e_{ba}e_{ab}) - 0.5\gamma(e_{bb}^2 - e_{ba}^2),$$

$$E\pi_{bb}^* - E\pi_{ab}^* = B'M + (p_b - p_a)M + qp_b(p_b - p_a) + q(2p_b e_{bb} - p_a e_{ba} - p_a e_{ab}) + q(e_{bb}^2 - e_{ba}e_{ab}) - 0.5\gamma(e_{bb}^2 - e_{ab}^2),$$

where $A' = e_{bb}^* - e_{ba}^* = e_{ab}^* - e_{aa}^* = \dfrac{2\gamma q(p_b - p_a)}{\gamma^2 - 4q^2}$, $B' = e_{ba}^* - e_{aa}^* = e_{bb}^* - e_{ab}^* = \dfrac{4q^2(p_b - p_a)}{\gamma^2 - 4q^2}$. We note

$$\begin{aligned}
& q(e_{bb}^2 - e_{ba}e_{ab}) - 0.5\gamma(e_{bb}^2 - e_{ba}^2) + q(e_{bb}^2 - e_{ba}e_{ab}) - 0.5\gamma(e_{bb}^2 - e_{ab}^2) \\
&> 2q(e_{bb}^2 - e_{ba}^2 - e_{ab}^2) - \gamma e_{bb}^2 + 0.5\gamma(e_{ab}^2 + e_{ba}^2) \\
&= -0.5(\gamma - 2q)A(e_{bb} + e_{ba}) - 0.5(\gamma - 2q)B(e_{bb} + e_{ab}) \\
&> -(\gamma - 2q)(A + B)e_{bb} = -(A + B)M - 2qp_b(A + B).
\end{aligned}$$

Then,

$$
\begin{aligned}
& 2E\pi_{bb}^{*} - (E\pi_{ab}^{*} + E\pi_{ba}^{*}) \\
& > (A+B)M + 2qp_b(p_b - p_a) + (p_b - p_a)M + qp_bB + q(e_{bb}p_b - e_{ba}p_a) + \\
& \quad + q(2p_be_{bb} - p_ae_{ba} - p_ae_{ab}) - (A+B)M - 2qp_b(A+B) \\
& = 2qp_b(p_b - p_a) + (p_b - p_a)M + q(e_{bb}p_b - e_{ba}p_a) + q(2p_be_{bb} - p_ae_{ba} - p_ae_{ab}) - 2qp_bA - qp_bB \\
& > 2qp_b(p_b - p_a) + (p_b - p_a)M + qp_bA + qp_bA + qp_bB - 2qp_bA - qp_bB \\
& = 2qp_b(p_b - p_a) + (p_b - p_a)M > 0
\end{aligned}
$$

Therefore, a safe borrower will prefer a safe to a risky borrower.

We finally examine if positive assortive matching is the only equilibrium, which is implied by

$$2E\pi_{bb} + 2E\pi_{aa} - 2(E\pi_{ba} + E\pi_{ab}) > 0 .$$

We have

$$
\begin{aligned}
E\pi_{bb} + E\pi_{aa} - (E\pi_{ba} + E\pi_{ab}) &= (E\pi_{bb}^{*} - E\pi_{ba}^{*}) - (E\pi_{ab}^{*} - E\pi_{aa}^{*}) \\
&= q(p_b - p_a)^2 + 2q(p_b - p_a)B' - \gamma A'B' + q(e_{bb}^2 + e_{aa}^2 - 2e_{ba}e_{ab}) \\
&= q(p_b - p_a)^2 + B'[2q(p_b - p_a) - \gamma A'] + \frac{4q^5(\gamma^2 + 4q^2)(p_b - p_a)^2}{(\gamma^2 - 4q^2)^2} \\
&= q(p_b - p_a)^2 - \frac{32q^5(p_b - p_a)^2}{(\gamma^2 - 4q^2)^2} + \frac{4q^5(\gamma^2 + 4q^2)(p_b - p_a)^2}{(\gamma^2 - 4q^2)^2} \\
&= q(p_b - p_a)^2\left[1 + \frac{-32q^4 + (\gamma^2 + 4q^2)4q^2}{(\gamma^2 - 4q^2)^2}\right] \\
&= q\gamma^2(p_b - p_a)^2/(\gamma^2 - 4q^2) > 0
\end{aligned}
$$

This result indicates that the model also leads to positive assortative matching in the cooperative game setting.

Women Empowerment, Gender Bias and *Susu* Collection in Ghana*

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I analyze women's empowerment and gender-bias in formal-informal financial markets, focusing on *susu* collection in Ghana. If susu creditors and clients share the same gender, homophily may facilitate a relatively better understanding of clients' circumstances, and improve economic outcomes. On the other hand, cross-gender discrimination may adversely affect the efficiency of merged formal and informal financial arrangements. The study uses a social network framework based on undirected flows of funds (savings and credit). Using quasi-random variation in matching collectors with clients, I show that female collectors do not replicate the gender-bias historically attributed to their male counterparts. Yet the network analysis shows that female clients are less likely to contribute savings to collectors of the same gender, while male collectors show a higher propensity to save with a female collector. Social distance (educational attainment) and contributing savings on different schedules help explain the results.

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1 Introduction

> Reading the scribbled words, my heart jerked as if hit by a lightning bolt. The note showed my salary, listed next to the three male managers' salaries: I was earning $44,724 while the highest-paid man earned $59,028 and the other two followed close behind, earning $58,464 and $58,226. Maybe I was seeing things. Maybe this note was a serious mistake or a bad joke, though I knew in my gut it wasn't.
>
> –Lilly Ledbetter, quoted in *Why I fight for equal pay for women* (Ledbetter and Isom, 2012).

What are the mechanisms and consequences of gender-discrimination? Theoretical and empirical studies of gender-based prejudice as a social norm tend to be based on an agent (the recipient of discrimination) subject to the biases of a principal (the discriminator). The assumption is that an agent is embedded in a "one-sided" setting of bias. This focus is often appropriate because of our research and policy interest in the causal agents of bias and discrimination. However, women who encounter bias in different walks of life are not necessarily passive in the face of bias from males (or other females). Expected female discrimination (the anticipation of gender-bias against women) may lead to economic behavior that is reactional. For example, women work more than men do for equal compensation in formal work—perhaps when the incidence of gender bias would not surprise them. Therefore, there are reasons to believe that bias occurs in "two-sided" (or in network terminology, *undirected*) environments in formalized markets (such as the one in represented in the above quote).

However, understanding the mechanisms and consequences of gender-bias in the *informal* economic sector is arguably even more important. Gender bias in this area has implications for the women who dominate economic activity in developing countries. Although understudied, informal finance is an important avenue for discussing gender dynamics (e.g. Ardener and Burman, 1995). For example, gender-bias persists in traditional and informal economic institutions with significant impacts on female-headed businesses (see for e.g., Field, Jayachandran and Pande (2010) for a study of the Hindu

caste system's gender-biased economic constraints in India). However, institutional change may have implications on gender-bias as a norm, both within a gender, and across genders. No study, to my knowledge, empirically distinguishes between cross-gender discrimination and same-gender matching within such settings (for e.g. Eeckout and Munshi (2010) provide a discussion on group-based (and therefore gender-neutral) matching in Indian informal institutions).

Yet, there is an important distinction between cross-gender bias (e.g. males discriminating against females), and same-gender matching (*homophily* by gender (meaning people gravitating towards or being matched with others of the same gender). The difference is that since homophily restricts to a specific gender, this concept of matched agents implies a weak notion of gender-bias (relative to discriminating against some of the opposite gender). The sole empirical focus on matching by gender has been on unilateral or directed gender-bias from principals to agents in microfinance (Beck, Behr and Madestam 2011). Yet, undirected networks[1]are significant in models of two-sided networks and their best-response processes (e.g. Golub and Jackson 2009). To my knowledge, no study has applied this theory to the phenomenon of merged formal and informal institutions. On the other hand, such financial arrangements have exploded in popularity in much of Africa since the 1990s (e.g. Steel, Aryeetey, Nissanke and Hettige, 1997).

The paper focuses on gender dynamics and institutional change in the Ghanaian susu financial system. I ask two related questions: (i) is there gender bias or discrimination in *susu* credit outcomes? (ii) Does the gender of the susu collector create or mitigate biases in credit provision? I study a program that uses male and female savings deposit collectors (called susu collectors in Ghana) to merge formal and informal financial institutions. Since susu collection has historically been a male-dominated phenomenon (Aryeetey 1994), a new initiative for hiring female susu collectors makes

[1]I only study networks at the simplest level in this paper, between two agents, or "nodes" that are joined by links. A network (or graph) is "undirected" if all links are bilateral, so that there is no order to the direction of a (unilateral) relationship between nodes.

this comparison of bias and own-gender-preferences possible.

If gender-bias is a function of *both* cross-gender bias and being matched with other agents of the same gender, then each *individual* perspective is by definition, limited. However, both perspectives can be reconciled if we consider that gender-bias is an out of equilibrium belief (or an outcome that is not tied down by the definition of Bayesian Nash equilibrium according to Cho and Kreps (1987). When no agent should conform to a norm, a Nash equilibrium allows that anything could be inferred about a person who does not conform. Although I do not explicitly model gender-bias in the present paper, signaling (Spence 1973, 1974) provides a useful mechanism to explain observed gender-bias when rooted in same-gender matching based on social networks. This approach is particularly useful because there are prima facie reasons why gender-bias as well as reactions to such discrimination within networks are potentially important for our understanding of reverse gender-bias, or policy initiatives supporting female empowerment.

I use a signaling model reflecting that gender-bias represents an out of equilibrium belief as well as a matching framework to connect gender bias with gender-matched networks in the empirics. In the results, I therefore find evidence of both cross-gender bias (against women) and homophily in gender-based matching of women and credit, although women provide less savings to collectors of the same gender. These results are in broad agreement with the signaling model showing that clients of the gender opposite to their collector may contribute more savings to signal their creditworthiness.

Comparative information on male and female agents interacting with male and female clients are relatively rare when the context represents the merging of formal and informal financial institutions. Although data on informal finance is hard to access (almost by definition), there are reasons why discrimination in informal systems may exceed formal institutions, such as amorphous legal boundaries. On the other hand, it is not obvious that gender-bias in the informal should disappear on contact with the

formal sector (since gender discrimination is nearly universal). Although I cannot answer this question directly, a gender-based study on the Ghanaian *susu* collection can help further the discussion on gender and institutional adaptation in informal financial systems. The phenomenon of merging formal and informal finance within the susu institution has occurred in a milieu of significant institutional change.

Since *susu* involves both savings and credit, I can also test whether gender-bias is reciprocated, using the signaling model mentioned above. Own-preferences have been investigated in phenomena such as law enforcement (Donohue and Levitt 2001, Welch, Combs and Gruhl 1988) as well as credit markets in the United States (e.g. Munnell, Tootell, Browne and McEneaney 1996, Berkovec, Canner, Gabriel and Hannan 1998; Ross and Yinger 2002), but gender remains understudied in two-sided financial markets. To my knowledge, this is the first study to consider own-gender preferences as a possibly reciprocated phenomenon.

The data I collected in 2010 include detailed information on economic networks linking 15 susu collectors to 384 clients in the Central Region of Ghana. The information represents the flow of funds in both directions (between susu collectors and a sample of their clients) in undirected networks of nodes. Clients contribute business savings to susu collectors. Susu collectors provide clients perceived to be creditworthy with loans. Yet, susu collection has traditionally been a male-dominated affair, with the vast majority of collectors being male. Although clients are mainly female in the Ghanaian informal financial sector, they are not necessarily privileged since they tend to receive less credit (Ekumah and Essel (2001)). The availability of records in the data on within-gender and cross-gender susu matched networks is unique. The data on savings mobilization is matched with clients'corresponding credit outcomes.

Individuals who associate with others based on gender may associate more with sub-groups within a particular gender-based network. I therefore compare *homophily by gender* with *homophily by both gender and educational attainment*. There are sim-

ilarly positive credit impacts of female collectors (with male and female clients) when the analysis is limited to collectors and clients who are relatively educated. On the other hand, the gender-bias of male collectors' credit outcomes (against female clients) disappears when education levels exceed the mean. This implies that factors that correlate with homophily (e.g. status or class) are potentially important for policy. Overall economic outcomes may positively impact gender bias, although this is an empirical question.

An interesting starting point may be to consider gender-based homophily within the context of economic effort within the sample. I therefore investigate the impact of homophily by both gender and economic effort. For female clients, there are positive and significant credit impacts of having a male collector when the female client saves on a schedule representing the highest degree of economic effort. The general bias against women in the main results is mitigated for females who signal creditworthiness to a relatively high degree. This result implies that economic effort has consequences for gender-bias against women. The paper proceeds as follows. Section 6.2 summarizes relevant literature. Section 6.3 provides some background to the susu institution and the importance of gender. Section 6.4 explains the frameworks. Section 4 gives the empirical methodology, while Section 6.5 present the main results. Section 6.6 concludes with policy implications.

2 Literature

Several empirical findings support political and economic cases for women empowerment (see World Bank (2001), (2012)) for comprehensive summaries). For example, researchers have argued that using quotas to empower women economically, politically or socially may make institutions and public policy more inclusive (see, e.g. Chattopadhyay and Duflo (2003)) Economic, political and social institutions that have never had

female leadership may require first-hand experience on female ability to update current social and cultural biases against women (note Beaman, Chattopadhyay, Duflo, Pande and Topalova (2008, 2009)).

Noticeably, a significant proportion of female empowerment at the micro-level (especially in the developing world) have occurred independently of quotas: the phenomenon of increasing female economic representation is mainly a corollary of general economic development (World Bank 2001). Notwithstanding this point, the complications of experiencing unequal gender access to markets may actually blunt the gender-parity in observed outcomes attributable to women empowerment. For related reasons, cash loans to female entrepreneurs did not yield significantly better economic outcomes in the Philippines (Karlan and Zinman (2011)), Sri Lanka (De Mel, McKenzie and Woodruff (2009)) or Ghana (Fafchamps, McKenzie, Quinn and Woodruff (2011)).

As noted earlier, Beck, Behr and Madestam (2011) study the impact of microfinance officers' genders on credit outcomes finding males to be discriminatory relative to female officers. Although the study is a natural experiment that considers the incidence of gender discrimination to be randomized, qualitative gender studies literatures in sociology have shown that gender-bias is a function of prior social and demographic characteristics (e.g. Desai 1994, Correll 2004).

Systems of inheritance are also important for gender-related outcomes. Another important related work is Gneezy, Leonard and List (2009) which compares matrilineal and patrilineal societies in terms of gender-based selection into competitive environments. Their main result is that significantly more females choose more competitive environments in strictly matrilineal societies while males favor patrilineal societies.

The above result also has implications for self-selection into gender arrangements. Yet it is not clear how the merging of formal and informal financial arrangements functions in gender-biased environments. In the next section, I discuss the matrilineal Ghanaian Central Region and formal-informal financial markets, focusing on the *susu* institution.

3 Matrilineality, Gender and Entrepreneurship in Central Ghana

As discussed in paper 2, the vast majority of the Central Region's inhabitants inherits kinship identities matrilineally. In such cultural institutions, kin membership is traced such that children belong to their mother's kinship instead of their father's. This cultural phenomenon has influenced several social norms, including employment. Although matrilineal kinship may yield positive implications on female ownership of property (Bortei-Doku Aryeetey 2000), women have often had less collateral and hence financial access. At the same time, Ghanaian women occupy a key position in the production of agricultural and other goods and services mainly for the Ghanaian informal market. In the next sub-section, I discuss the recent phenomenon of female empowerment in Ghanaian financial markets.

3.1 *Susu* Collection, Rural Banks and the Political Economy of Women's Enfranchisement in Central Ghana

I briefly review the discussion on rural and community banks and their relationship with informal financial arrangements in Central Ghana, the third smallest region in the erstwhile Gold Coast. State-motivated rural and community banks are the main providers of formal finance, modeled on rural bank institutions in the Philippines in the 1960s. Such institutions must be majority-owned by the hosting community, and have significantly lower minimum capital requirements than commercial entities that favor the urban elite. The share of supervision costs incurred to the Bank of Ghana by rural banks is disproportionately high relative to commercial banks, and government officials hope that positive externalities from expanding formal rural finance to the productive poor, including women entrepreneurs will justify these costs in the future (see Nair and Fissha 2010).

Due to inadequate access to capital and other factors, a significant proportion of women and men in Ghana mobilize savings through an institution known as *susu* collection (Aryeetey 1994). Deposit collectors mobilize funds for clients on a daily basis, to be returned at the end of the month (sans a commission equal to a day's contribution). *Susu* collection is primarily a savings institution with very scarce and low credit provision. Rural banks, including the collaborative institution for this study, Kakum Rural Bank (established in February 1980) typically rely on employed *susu* collectors to mobilize funds on their behalf, although they have recently transitioned to training and using internal *susu* collector staff over time. Advantages bank *susu* collectors have over their independent counterparts are their ability to provide bank loans, and the absence of commissions. Credit is available to entrepreneurs after mobilizing savings for at least 3 months.

Although clientele skews female, *susu* collection has traditionally and historically been male-dominated. After the boom in informal finance in 1990s, severe gender-bias in credit distribution in the Ghanaian Central Region by the early 2000s. Using male *susu* deposit collectors to reverse credit discrimination against women entrepreneurs have proved difficult in a number of initiatives (Essel 1996, Ekumah and Essel 2001).

During interviews in the region, a cross-section of *susu* entrepreneurs and rural bank officers noted that reasons for the near-nonexistent female participation in past *susu* collection may have been the personal security hazards of mobilizing large sums of money on one's person, and skewed educational outcomes (against females), which have significantly improved as a function of policy and economic development (Sackey (2005)). Currently, the Region hosts a disproportionate number of the best secondary schools in Ghana, ranking third in pass-rates of Mathematics and English in the national Senior Secondary School examination and overall access to educational institutions (see Overseas Development Institute 2009 for a discussion on education policy reform). Kakum rural bank has provided school scholarships for girl students in the

Central Region since the early 1990s. However, table 6.1A shows that female *susu* collectors are in their early 30s on average in the data, and therefore a significant proportion may not have benefitted from such direct educational support. Nevertheless, such initiatives have helped the organization retain some legitimacy in the area as community-oriented institution with an social responsibility for education.

In meetings with local shareholders as well as current and potential entrepreneurial clients, bank hiring officials have decided against using quotas for hiring women *susu* collectors. This decision was taken partly to engage the trust of local entrepreneurs in the competency of female collectors to identify creditworthy clients. The rural bank still emphasizes gender in their vacancy announcements (in radio announcements for example), given the current status of women collectors as underrepresented and the overarching history of low female representation in *susu* collection. During the interview time of the study (in August 2010), the author had access to 10 male and 5 female *susu* collectors.

If *susu* collectors and clients share the same gender, a relatively better understanding of clients' circumstances may improve economic outcomes. On the other, same-gender biases may adversely affect the efficiency of the *susu* institution. I now present a theoretical discussion to isolate the gender-bias impacts of *susu* collection on savings and credit outcomes, given the current context of both male and female collectors. I also discuss the matched networks generated by female collectors having clients of the same and opposite genders, as well as their impacts.

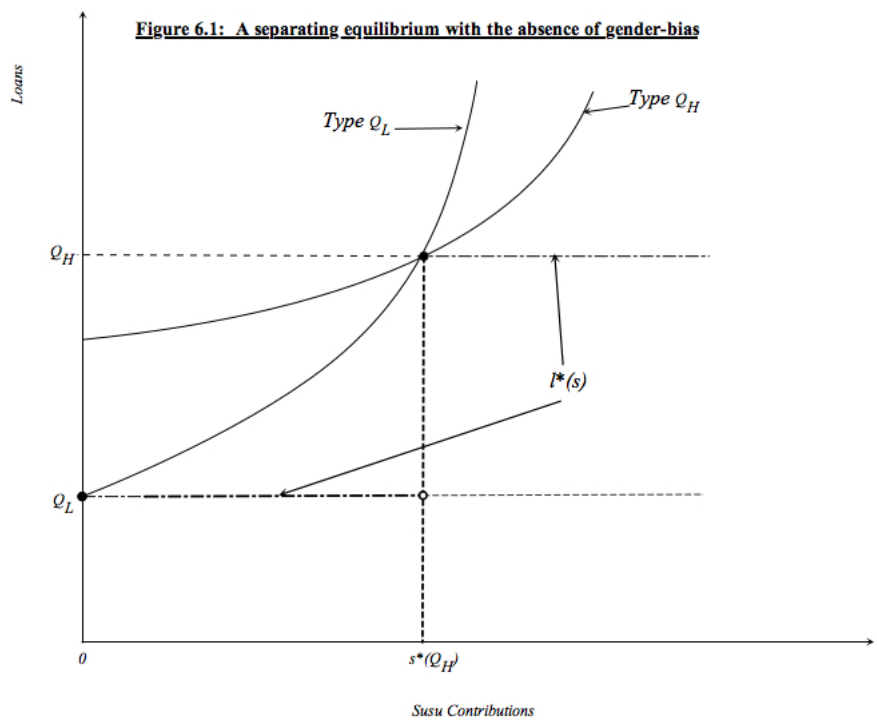
4 Theoretical Models

In this section, I model interactions between susu collectors and clients within two complementary and related frameworks made possible by the data. I first consider cross-gender bias, using discrimination against female clients by male collectors to illustrate. The use of a separating equilibrium draws on work elsewhere in the dissertation (papers 3 and 5), but applied to gender bias. This approach is important because

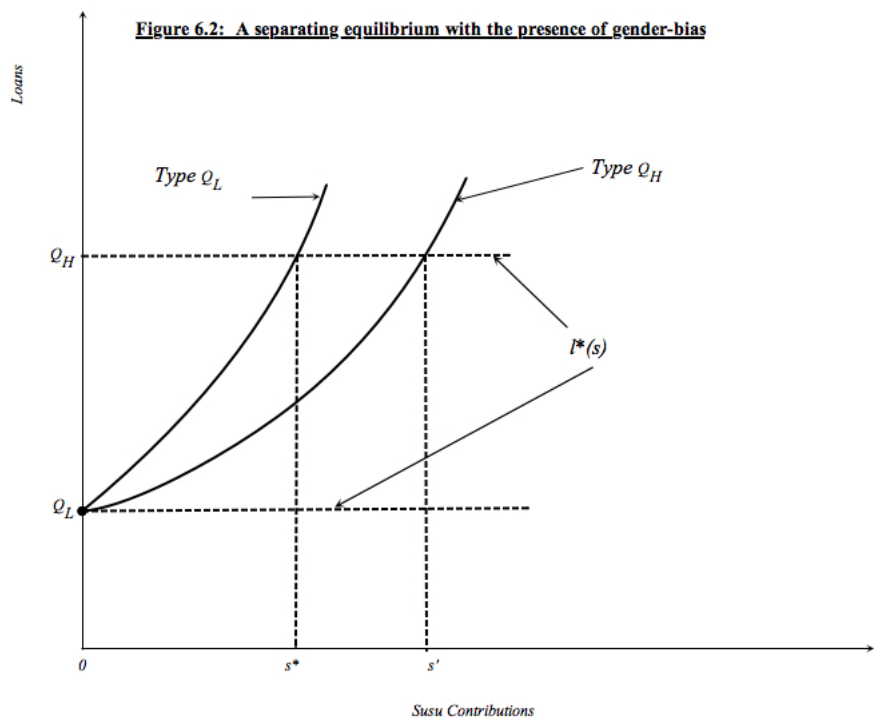
it allows a discussion on possible reactions to gender-bias. I complement this with a discussion on same-gender bias, or bias from homophily: matches of clients and collectors based on gender.

4.1 Signaling and Cross-Gender Bias in *Susu* Savings Mobilization and Credit Provision

To motivate signaling and cross-gender bias, I present a slight adaptation of Opoku-Agyemang and Foltz (2012), which shows how savings contributions may signal creditworthiness in a Spencian form. The argument is summarized as follows: savings contributions may signal creditworthiness to *susu* collectors, who respond by providing credit. If I assume no gender bias in economic outcomes (i.e. males and females are treated alike), then there exists a separating equilibrium as shown in Figure 6.1. In the diagram, the variable Q represents creditworthiness, where $\lambda =$Prob $(Q = Q_H) \in (0,1)$. An individual is either creditworthy Q_H or not creditworthy Q_L. Without gender-bias, the perceived creditworthiness (of male and female clients) should be *equivalent* to a *susu* collector irrespective of client gender. Both female and male individuals who are creditworthy contribute an amount of savings $s^*(Q_H)$, and receive loan amount Q_H. Individuals who are not creditworthy do not make any savings, and receive Q_L. The discussion relies on perfect Bayesian equilibria, and the belief function for the *susu* collector $\nu(s) \in [0,1]$ is derived using Bayes' Rule to respond to creditworthiness based on savings contributions (see Opoku-Agyemang and Foltz (2012) for details). We now discuss the case where gender-bias does exist in the next sub-section.



In this sub-section, I modify the model to reflect the possible role of gender-bias. I present a similar signaling model to explain gender-bias in the interactions between *susu* clients and their collectors. The discussion is in the vein of above discussion where the variable Q represents creditworthiness, where $\lambda =$Prob $(Q = Q_H) \in (0,1)$. An individual is either creditworthy Q_H or not creditworthy Q_L. The main addition to the model is gender: $G = \{F, M\}$, where $F =$female and $M =$male. The theoretical discussion is based on figure 6.2 below:



Using figure 6.2, I focus on the gender-biased economic interactions between *susu* collectors and *susu* clients. As in the case of figure 6.1, Individuals who are not creditworthy save an amount of zero, and receive a credit amount Q_L. In the mould of the previous model, the loan amount of $Q_L$is provided to clients because she is not creditworthy. Following the discussion of Figure 6.1, creditworthy individuals contribute savings $s^*$and receive credit Q_H.

Let the *susu* collector be male, and the *susu* client be female. The belief function of the collector reflects a gender-bias against female clients. In the presence of gender-bias (against women), women who are creditworthy contribute relatively more savings for the same credit amount as (men who are creditworthy). Since this assertion reflects an out of equilibrium belief, I do not prove the statement, but explain it from the above figure (6.2). An absence of gender-bias against women would imply that both female and male clients receive Q_H. However, male collectors are assumed to be biased against

female clients. For this reason, female clients have to contribute $s' > s^*$to receive Q_H. On the other hand, male clients only contribute $s^* < s^*$to receive the same Q_H. Both female and male clients who are not creditworthy receive Q_L. A similar explanation holds if female collectors are biased against male clients.

4.2 Gender Matching and *Susu* Savings Mobilization and Credit Provision

The previous section discussed *cross-gender bias*: susu collectors may be biased against clients of the different gender. Clients may react to bias by saving more than they would have to if gender-bias was absent. At the same time, bias may occur as a matching problem: susu clients may contribute more savings to collectors of the same gender. Similarly, collectors may provide more credit to clients on the same gender. To complement the previous discussion on cross-gender bias, I provide a discussion on bias by gender match in this section.

Gender-based matches of collector-clients create *susu* networks that are potentially important. On the one hand, matching collectors and clients of the same gender may facilitate the susu savings and credit processes. On the other, savings and credit outcomes may be biased toward agents of the same gender, adversely affecting the operation of the susu structure over time. I provide a brief motivation of matched client-collector networks based on a slight variation of Abrevaya and Hamermesh (2011) to focus on gender-based matches of clients and collectors[2]. This provides a same-gender discussion to complement the cross-gender discussion of the previous section.

I provide some illustrations to explain bias by gender match. If female *susu* clients are relatively more generous in contributing savings (than male clients) when matched

[2] The derivation is in the Appendix.

with female *susu* collectors, then I assume female clients to be *positively biased by gender-match*. On the other hand, if female clients are relatively less generous than males when matched with female susu collectors, they are *negatively biased by gender-match.* Similarly, If male *susu* collectors are relatively more generous than males when matched with female clients, the bias by gender-match will be positive. If female collectors are relatively less generous than males when matched with female *susu* clients, the gender-match effect will be negative. Similar explanation holds for male collectors and clients.

4.2.1 Hypotheses

Combining both sections on signaling and gender matching, I now present the following hypotheses. Hypotheses 1 and 2 derive from the signaling model of bias, while hypotheses 3 and 4 follow from the discussion on gender-matched networks.

HYPOTHESIS 1: *Male clients provide less susu savings contributions than female clients.*

If $s^*\left(Q^M\right)$ =the savings of male clients, and $s^*\left(Q^F\right)$ =the savings contributions of female clients, then $s^*\left(Q^M\right) < s^*\left(Q^F\right)$.

HYPOTHESIS 2: *Male clients receive more credit than female clients.*

If $l^*\left(Q^M\right)$ =the credit outcomes of male clients, and $l^*\left(Q^F\right)$ =the credit outcomes of female clients, then $l^*\left(Q^M\right) > l^*\left(Q^F\right)$.

HYPOTHESIS 3: *Clients in gender-matched networks provide more susu savings contributions than clients not matched by gender.*

If $s^*\left(Q^{match}\right)$ =the savings of gender-matched clients, and $s^*\left(Q^{unmatched}\right)$ =the savings contributions of clients not matched by gender,

then $s^*\left(Q^{match}\right) \leq s^*\left(Q^{unmatched}\right)$.

HYPOTHESIS 4: *Clients in gender-matched networks receive more credit than*

clients not matched by gender.

If $l^*\left(Q^{match}\right)$ =the credit outcomes of gender-matched clients, and $l^*\left(Q^{unmatched}\right)$ =the credit outcomes of clients not matched by gender,

then $l^*\left(Q^{match}\right) \geq l^*\left(Q^{unmatched}\right)$.

5 Empirical Tests: Female *Susu* Collectors and Gender-Matched networks

Testing the model's predictions requires identifying variation in both savings mobilization and credit attributable solely to the genders of *susu* clients and collectors. The empirical implementation will focus on individual gender impacts of *susu* collectors and clients, as well as the collective gender impacts of *susu* collector-*susu* client networks as noted in the previous section. The average gender impacts of a *susu* collector on savings contributions and credit outcomes of clients of both genders would be different from the average gender impacts of a *susu* collector when linked exclusively with clients of the same gender.

Since the employment initiative was aimed at enfranchising women as susu collectors, I first focus on female collectors, before isolating gender-bias as well as (collector-client) gender-match impacts. Tables 6.1A, and 6.1B show summary statistics. Female collectors are only 24% of the surveyed *susu* collectors, while male counterparts are in the majority (76%). On the other hand, female and male clients are about 60% and 40% of the client sample (respectively). I introduce the empirics in the next sub-section.

Tables

TABLE 6.1A—SUMMARY STATISTICS FOR MALE AND FEMALE SUSU COLLECTORS' CLIENTS[1]

Variables	Male *Susu* Collector	Female *Susu* Collector	t-statistic
Age (in years)	33.36	32.39	0.97
	(9.67)	(7.50)	
Female	0.53	0.70	-0.17***
	(0.50)	(0.46)	
Secondary school	0.16	0.28	-0.12
	(0.37)	(0.45)	
Married	0.57	0.41	0.15
	(0.50)	(0.50)	
Monthly Income	278.02	76.45	201.58***
	(596.59)	(268.77)	

Notes: [1]Sample size = 384. The male collectors in the sample are responsible for 290 clients while the female collectors are responsible for 94 clients. T-statistics shown are the tests of the difference in means for respective client characteristics between male and female collectors. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 6.1A—SUMMARY STATISTICS FOR MALE AND FEMALE SUSU COLLECTORS' CLIENTS (CONTINUED)[1]

Outcome Variables	Male *Susu* Collector	Female *Susu* Collector
Savings Contributions	9.08 (30.96)	7.84 (20.39)
Credit	513.63 (421.66)	1161.00 (548.05)

Notes: [1]Sample size = 384. The male collectors in the sample are responsible for 290 clients while the female collectors are responsible for 94 clients.

TABLE 6.1B—SUMMARY STATISTICS FOR MALE AND FEMALE SUSU COLLECTORS' CLIENTS[2]

Variable Means and St. Dev.	Male *Susu* Client	Female *Susu* Client	t-statistic
	(1)	(2)	(3) = (1) - (2)
Age (in years)	30.10	35.40	-5.29***
	(8.00)	(8.96)	
Secondary school	0.21	0.17	0.04
	(0.41)	(0.38)	
Married	0.44	0.59	-0.15***
	(0.50)	(0.49)	
Monthly Income	256.30	207.87	48.44
	(533.21)	(548.61)	

Notes: [2]Sample size = 384. The male clients are 165 while the female clients are 219. Standard deviations are in parentheses. T-statistics shown are the tests of the difference in means for respective client characteristics between male and female clients. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 6.1B—SUMMARY STATISTICS FOR MALE AND FEMALE SUSU COLLECTORS' CLIENTS[2] (CONTINUED)

Variable Means and St. Dev.	Male *Susu* Client	Female *Susu* Client
	(1)	(2)
Savings Contributions	12.91 (35.49)	5.90 (22.73)
Credit	665.68 (464.28)	508.22 (548.05)

Notes: [2]Sample size = 384. The male clients are 165 while the female clients are 219. Standard deviations are in parentheses.

5.1 Specifications

In this sub-section, I estimate the following equation for savings mobilization and credit as a function of the gender of the *susu* collector and other social and economic factors.

Preliminary Estimates

To test whether the gender of a client's *susu* collector influences the client's savings mobilization and credit outcomes, we run the following OLS regression:

$$y_i = \alpha + \beta f_i + X_i^{'}\pi + \varepsilon_i$$

where y_i is the economic outcomes (savings contributed or credit received) by client i with *susu* collector s; f is a dummy variable if the client i has his or her *susu* collector being female; $X_i^{'}$ is a vector of the following pre-treatment client i controls: age, gender, married (=1), some secondary schooling, and monthly income. Table 6.2A presents the OLS estimates. Column 1 shows the associations of independent variables with savings contributions while Column 2 shows effects on credit outcomes. While having a female *susu* collector does not show a significant impact on savings mobilization, *susu* collection by gender has a large and significant credit effect. The client controls of gender and income significantly affect savings contributions, while being married has a negative impact on receiving credit. Given our discussion on gender bias and the possibility of discrimination in savings and credit outcomes, self-selection may be important into two ways. First, clients may self-select into a savings arrangement with a collector based on the collector's gender. Secondly, clients may self-select into gender-matched networks based on pre-treatment characteristics. The estimation strategy that follows relies on the above observation that gender impacts may depend on a set of

pre-treatment characteristics.

TABLE 6.2A—OLS BASELINE ESTIMATES: SAVINGS AND CREDIT EFFECTS OF FEMALE SUSU COLLECTORS

Dependent Var.	Savings Contributions (1)	Credit (2)
Female *susu* collector	1.96 (3.73)	556.98*** (150.44)
Age	0.74 (0.53)	4.53 (6.26)
Female client	-12.29** (6.24)	7.65 (105.07)
Married	-0.62 (3.06)	-205.25** (102.54)
Secondary School	10.68 (6.72)	157.73 (176.38)
Monthly Income	0.01** (0.003)	0.07 (0.07)
N	281	137

Notes: Columns 1-2 report OLS coefficients with robust standard errors. *** denotes significance at the 1 percent level; ** refers to significance at the 5 percent level;* implies significance at the 10 percent level.

5.2 Empirical Strategy: Propensity Score Matching

The design of this project allows identification of gender effects in the presence of difficulties first presented by Rosenbaum and Rubin (1983). Direct comparisons between treated and non-treated groups may be misrepresentative when the units exposed to the treatment differ systematically from the units unexposed to treatment. The authors show that if groups of subjects have similar propensity scores, they can be expected to have similar values of background data in the aggregate. Propensity scores can summarize all background information, effectively predict the probability that *susu* clients receive a treatment (instead of a control)– providing unbiased effects of the treatment, or Average Treatment Effects.

Let the differences between treated and non-treated agents be encompassed by observables X, following the literature. A comparison group is accumulated from non-treated groups. The distribution of observables for the comparison group is as similar as possible to that of the treated group. The conditional probability of receiving treatment is estimated using a logit as a function of relevant socioeconomic factors. We use one-to-one matching with replacement and kernel matching using a normal density function[3].

I first use NEAREST NEIGHBOR MATCHING (OR ONE-TO-ONE MATCHING WITH REPLACEMENT) to estimate our Average Treatment Effects based on propensity score matching algorithms. This technique matches treated individuals with comparison individuals based on the similarity of their propensity score. Mapping with replacement means that the matches are usually of a higher quality since an untreated individual can be used more than once in creating a match. Results are based on limiting analyses to the area of common support in each case. Excellent summaries of the advantages of

[3]See Caliendo and Kopeinig (2008) for a general review, and refer to Dehejia and Wahba (2002) for further discussions on one-to-one matching. Other propensity score methods such as subclassification tend to provide similar results to kernel matching (Zhao 2004). Mahalanobis-metric matching are expected to yield similar matching results to my one-to-one approach (Michalopoulos, Bloom and Hill 2004) and are therefore not used in the paper.

one-to-one matching with replacement (relative to without replacement) are provided by Caliendo and Kopening (2008) although the differences may not be very significant overall (Zhao 2004).

I also use KERNEL MATCHING (WITH A NORMAL DENSITY FUNCTION) to estimate Average Treatment Effects of gender and gender-bias. This methodology yields a comparison group by calculating weighted averages of almost all individuals in the control group. Kernel matching estimates derive from a weighted regression of the counterfactual outcome on an intercept with weights given by the kernel weights (Smith and Todd 2005). I use weights from a normal kernel, and derive our matches from a logit regression used to balance the subgroups. An advantage of kernel matching is a lower variance since relatively more data is used in the estimation process. A demerit is the possibility of adverse matches, although this is reduced substantially by imposing the common support, as motivated by the literature[4].

6 Results

The savings and credit Average Treatment Effects are presented in table 6.2B: having a female collector does not have significant savings impacts, but shows strong positive credit impacts. Both one-to-one and kernel matching estimates show that female collectors have positive significant effects on credit outcomes. The positive credit impacts are independent of any significant gender bias in savings impacts. That is, the positive credit effects do not follow from significant savings impacts. It is worth noting that in the results of table 6.2B, the clients involved are not disaggregated by gender. In the next sub-section, I investigate whether client-collector matches (or networks disaggregated by client gender) yield significant economic outcomes relative to unmatched

[4]Note Heckman Ichimura and Todd ((1997), (1998)).

clients.

TABLE 6.2B—ONE-TO-ONE AND KERNEL PROPENSITY SCORE MATCHING: SAVINGS AND CREDIT EFFECTS OF FEMALE SUSU COLLECTORS

Outcome Var.	Savings Contributions (1)	Credit (2)
Treatment: Female collector (One-to-one matching with replacement)	0.29 (2.88)	434.81** (190.03)
Treatment: Female collector (Kernel matching with Normal Density Function)	1.07 (3.42)	631.56*** (132.34)
N	363	194

Notes: Cells represent Average Treatment Effects of having a female susu collector. Results show one-to-one matching with replacement and kernel matching with a normal density function. In both cases, the comparison group is yielded from customers that have a male susu collector. *** denotes significance at the 1 percent level; ** refers to significance at the 5 percent level;* implies significance at the 10 percent level.

6.1 *Susu* Collector-*Susu* Client Gender Networks

The presence of gender-based networks may have implications for the mechanisms of *susu* savings mobilization and credit provision. Gender-bias in the undirected diffusion of funds may be important to economic interactions. Funds transmitted across nodes may or not be reciproal as a result of gender considerations. To explore the relevance of gender bias, we partition our analysis of clients of female *susu* collectors by gender. I provide some descriptive statistics to show the extent to which gender-matched networks are comparable.

Table 6.3A shows summary statistics of male and female clients. The first two columns show male and female clients of female *susu* collectors respectively. The female and male clients are comparable in terms of the variables education, marital status and income. Clients (by gender) are less comparable in terms of age. I show summary statistics for the *susu* networks' outcome variables in table 6.3B. Interestingly, male clients contribute more to female collectors than male ones on average, while female collectors contribute more to male collectors than female ones. On the other hand, female collectors give slightly more credit to female clients relative to male clients. Similarly, male collectors give relatively more credit to clients of their own gender.

TABLE 6.3A—SUMMARY STATISTICS OF *SUSU* COLLECTOR-*SUSU* CLIENT GENDER-MATCHED NETWORKS

Variables (Means and St. Dev.)	Female collectors and male clients **(1)**	Female collectors and female clients **(2)**	t-statistic (2) - (1) **(3)**	Male collectors and female clients **(4)**	Male collectors and male clients[1] **(5)**	t-statistic (4) - (5) **(6)**
Age (in years)	29.79 (4.79)	33.50 (8.17)	3.71** [1.66]	36.22 (9.19)	30.17 (8.52)	-6.05*** [1.04]
Secondary School	0.36 (0.49)	0.24 (0.43)	-0.11 [0.10]	0.14 (0.35)	0.18 (0.39)	0.45 [0.43]
Married	0.39 (0.50)	0.42 (0.50)	0.31 [0.11]	0.67 (0.47)	0.46 (0.50)	-0.21 [0.06]
Monthly Income	72.50 (100.10)	78.12 (314.92)	5.62 [60.94]	263.83 (615.46)	293.87 (576.62)	30.03 [70.27]
N (in each gender network)	28	66	94	153	137	290

Notes: Variable means, standard deviations (in parentheses), standard errors in brackets. *** denotes significance at the 1 percent level; ** refers to significance at the 5 percent level;* implies significance at the 10 percent level.

TABLE 6.3B—SUMMARY STATISTICS OF OUTCOME VARIABLES FOR SUSU COLLECTOR-SUSU CLIENT GENDER NETWORKS

Outcomes Variables (Mean and St.Dev)	Female collectors and male clients	Female collector and female clients	Male collectors and male clients	Male collectors and male clients
Savings contributions	23.51 (34.45)	2.54 (7.51)	7.28 (26.47)	11.18 (35.48)
Credit	1125.41 (533.56)	1250 (625.30)	461.38 (436.86)	577.27 (395.85)
N (in each gender network)	28	66	153	137

Notes: Table 6.3B presents outcome variable means with standard deviations (in parentheses).

In table 6.4, I show OLS estimates of gender-based *susu* networks. From column 1, female clients contribute significantly less savings to collectors of the same gender. However, although female clients contribute more to male collectors, the effect is not statistically significant. Similarly, the savings effect of having a male collector is not significant for female collectors although it is negative. Assignment into a network is not random, since the association of monthly income (on savings contributions) is positive. From the second column, female collectors with female clients have large and significant positive credit impacts. Similarly, female collectors with male clients have significant (but slightly lower) credit impacts.

TABLE 6.4—OLS ESTIMATES OF GENDER NETWORKS: SAVINGS AND CREDIT OUTCOMES

Collector-Client Networks	Savings (1)	Credit (2)
Female collector-Female clients	-9.44**	663.59**
	(4.18)	(298.29)
Female collector-Male clients	12.51	513.90***
	(7.71)	(161.58)
Male collector-Female clients	-6.52	-65.92
	(5.26)	(77.54)
Client Characteristics		
Age	-6.52	0.53
	(5.27)	(4.35)
Married	-0.74	-161.52**
	(2.16)	(79.47)
Secondary School	9.43	207.17
	(5.30)	(153.59)
Monthly Income	0.01**	0.11**
	(0.003)	(0.04)
N	363	194

Notes: Robust standard errors are in parentheses. *** denotes significance at the 1 percent level; ** refers to significance at the 5 percent level;* implies significance at the 10 percent level.

As per the discussion (in the previous section), the non-random assignment motivates our use of one-to-one nearest neighbor matching in table 6.5. The female collector-male client networks show positive and significant impacts on savings contributions: male clients contribute more to female collectors. On the other hand, the male collector-male client effects on savings contributions are not significant. None of the other matches show significant impacts. The female collector-male client networks show significant positive effects on credit, in a positive relationship with the previous savings association. Although female clients did not give significantly less savings to their male collectors, I find that male collectors granted significantly less credit to them. On the other hand, male collectors did not give significantly more credit to male clients.

TABLE 6.5: GENDER MATCHED NETWORKS' IMPACTS ON SAVINGS AND CREDIT:

(ONE-TO-ONE MATCHING WITH REPLACEMENT)

	Outcome Variable Savings Contributions One-to-One Matching (1)	Outcome Variable Credit Provision One-to-One Matching (2)
Treatment Variables: *Collector-Client Matched Networks*		
Treatment: Female collector-Female client	-6.38 (4.20)	366.67 (399.51)
Treatment: Female collector-male client	16.48** (7.85)	524.07** (244.20)
Treatment: Male collector-Female client	-8.87 (8.85)	-358.03** (161.92)
Treatment: Male collector-male client	4.27 (3.85)	-93.51 (125.46)
N	363	363

Notes: Cells represent Average Treatment Effects of a susu collector-client networks by gender. Results show one-to-one matching with replacement and kernel matching with a normal density function. *** denotes significance at the 1 percent level; ** refers to significance at the 5 percent level;* implies significance at the 10 percent level.

The kernel matched results are similar and stronger in some instances (shown in table 6.6). The female collector-male client networks show significant positive effects on credit, following positive savings impacts as in the previous discussion. The female collectors provide significantly more credit to clients of the same gender, although they receive less savings from them. Again, male collectors give significantly less credit to female clients, although female clients do not significantly lower their savings contributions to male collectors. Male collector-male client networks do not have a significant credit (or savings) impact. I now discuss the results at length.

TABLE 6.6—GENDER MATCHED NETWORKS' IMPACTS ON SAVINGS AND CREDIT:

(KERNEL MATCHING WITH NORMAL DENSITY FUNCTION)

	Outcome Variable Savings Contributions Kernel Matching (1)	Outcome Variable Credit Kernel Matching (2)
Treatment Variables: *Collector-Client Matched Networks*		
Treatment: Female collector-Female client	-6.06** (2.46)	694.71*** (257.51)
Treatment: Female collector-male client	16.76** (7.68)	486.78*** (148.23)
Treatment: Male collector-Female client	-5.26 (3.38)	-344.27*** (95.68)
Treatment: Male collector-male client	4.11 (3.68)	-76.94 (90.86)
N	194	194

Notes: Cells represent Average Treatment Effects of a susu collector-client networks by gender. Results show one-to-one matching with replacement and kernel matching with a normal density function. *** denotes significance at the 1 percent level; ** refers to significance at the 5 percent level;* implies significance at the 10 percent level.

Discussion of Main Results

I find that male clients are significantly more likely to contribute savings to a female collector. On the other hand, female clients contribute significantly less savings to female collectors although they share the same gender. The credit results show that female collectors give more credit to clients of the same gender (inspite of the clients contributing less savings.) Female collectors give more credit to male clients, while male collectors give less credit to female clients. Therefore, male collectors show gender-bias against female clients while female collectors do not show gender-bias against male clients.However, this evidence may only be suggestive since we consider homophily in *susu* networks under the single dimension of gender. Considering subsets of gender-based networks where homophily is observed in a different dimension could affect savings mobilization and credit outcomes. We provide a discussion in the next section.

6.2 Alternative Explanations: Education and Effort in Gender-Bias, *Susu* Savings and Credit Provision

Within the gender-based economic networks discussed above, other distinguishing features may increase or decrease gender bias. In this section, I discuss different scenarios that may differently influence the propensity of gender bias to another in savings and credit. I focus on two explanations: the possibility that female collectors and clients may have similar levels of education, which may in turn have implications for savings and credit outcomes by gender. Secondly, I focus on the effort inherent in providing savings by gender, which may have implications for gender-bias in savings mobilization and credit provision.

First of all, related network models with microfoundations that involve homophily

(the tendency of individuals to associate disproportionately with others with similar traits–such as gender in our case)–also predict that homophily may delay convergence toward consensus as agents average their observations of their neighbors to develop beliefs (e.g. Golub and Jackson 2012). However, these models do not account for whether the incidence of homophily in a different dimension has positive or negative implications on already observed homophilous groups. The bias (male collectors discriminating against female clients) may be reinforced by newer homophily related to educational attainment, or alternatively, lessened by it. For instance, it may be that gender-bias occurs in gender-matched groups, but not in gender-matched groups that have higher education attainment in the sample. We test this in the next section.

6.3 Survey Evidence and Mechanisms of Education and Economic Effort

6.3.1 Education and Gender Bias

The presence of gender-bias in formal-informal financial markets is perhaps surprising since the Central Region of Ghana hosts a disproportionate presence of educational institutions, although there still exist significant education constraints. In the data, *susu* clients and clients have attained some level of Junior Secondary schooling and Senior Secondary schooling (or post-primary education) on average. This suggests that relatively educated female collectors and their gendered-client networks with relatively similar levels of educational attainment may affect gender-biases in outcomes. To explore the relevance of education considerations, I first focus on female *susu* collectors whose education levels exceed the mean. Another sub-analysis restricts the discussion to female and male *susu* collectors, partitioning their clients by gender, (as done in the previous section) before further partitioning by educational attainment above the mean.

In table 6.7, I use one-to-one matching (with replacement) and kernel matching (with a normal density function) to isolate the impact of having a female *susu* collector whose educational attainment exceeds the mean on savings and credit outcomes. Column 1 shows the impacts of highly educated female *susu* collectors on savings outcomes, while Column 2 shows the effects of educated female collectors on credit outcomes. The savings outcomes are similar to female collectors in general (with no significant impact). On the other hand, the credit results are positive and statistically significant, with larger co-efficients (or higher economic significance).

TABLE 6.7—THE IMPACT OF HIGHLY EDUCATED FEMALE SUSU COLLECTORS ON SAVINGS AND CREDIT OUTCOMES

Outcome Var.	Savings Contributions (1)	Credit (2)
Treatment: Female collectors with education above the mean (One-to-one matching with replacement)	2.55 (3.12)	527.95** (220.57)
Treatment: Female collectors with education above the mean (Kernel matching with Normal Density Function)	1.27 (3.50)	450.95*** (155.18)
N	363	194

Notes: Cells represent Average Treatment Effects of female susu collectors whose education levels exceed the mean. Results show one-to-one matching with replacement and kernel matching with a normal density function. *** denotes significance at the 1 percent level; ** refers to significance at the 5 percent level;* implies significance at the 10 percent level.

We next show *susu* gender networks' (which have educational outcomes above the mean levels) average treatment effects on savings mobilization and credit outcomes in table 6.8. Similar to the previous results, I find that female clients contribute less savings to collectors of the same gender while collectors provide more credit. On the other hand, male clients that have a female collector contribute *more* savings receive more credit. Male clients contribute more savings to female collectors, but receive less credit, although the credit responses are not statistically significant. The economic interactions between male collector-male client networks are never significant.

TABLE 6.8—THE IMPACT OF EDUCATED GENDER-MATCHED NETWORKS ON SAVINGS AND CREDIT:

(ONE-TO-ONE AND KERNEL MATCHING)

Collector-Client Networks	Outcome: Savings (One-to-One Matching) (1)	Outcome: Savings (Kernel Matching) (2)	Outcome: Credit (One-to-One Matching) (3)	Outcome: Credit (Kernel Matching) (4)
Female collector-Female clients (educated above the mean)	-21.49*** (6.83)	-14.18*** (4.64)	675.00** (330.09)	576.41* (314.56)
Female collector-Male clients (educated above the mean)	24.07** (161.58)	24.57** (9.71)	15.41 (282.41)	460.75*** (166.52)
Male collector-Female clients (educated above the mean)	10.10 (10.62)	10.26 (10.39)	-35.06 (147.15)	-14.66 (101.68)
Male collector-male clients (educated above the mean)	-4.09 (2.88)	-3.70 (4.24)	-142.28 (155.12)	-173.48 (120.28)
N	193	193	123	123

Notes: Cells represent Average Treatment Effects of susu collector-client networks whose education levels exceed the mean. Results show one-to-one matching with replacement and kernel matching with a normal density function. *** denotes significance at the 1 percent level; ** refers to significance at the 5 percent level;* implies significance at the 10 percent level.

Gender-focused savings mobilization and credit provision with educational biases may not reflect the actual effort people take in mobilizing savings. In the final section, we provide some evidence on how different savings schedules affect savings mobilization and credit outcomes, conditional on the collector and network gender factors discussed so far. If effort is important, it may weaken or strengthen the observed bias caused by gender.

6.3.2 Economic Effort and Gender Bias

In the survey, the *susu* clients also have different savings schedules that they self-select into, that influence the frequency of meeting their *susu* collector. Each schedule represents a different degree of financial effort exerted by a *susu* client. *Susu* clients may agree to contribute savings on a daily, twice-weekly, weekly, fortnightly, or monthly basis. In the survey data these schedules represent 26%, 24%, 28%, 17% and 0.04% respectively. Companion pieces to this paper showed that the daily schedule required the most effort and commitment, yielding the most savings, and earned the most credit relative to other more relaxed savings schedules. To explore the relevance of economic effort, I perform another sub-analysis, focusing on female *susu* collectors and networks under different savings schedules. The fortnightly and monthly schedules are dropped from the analysis in the section for less representation across gender-based *susu* networks. For similar reasons, we limit our discussion to OLS estimates. Given gender-bias, clients may receive more credit from collectors of the opposite gender when the degree of financial effort is relatively high.

In table 6.9, I study the impact of having a female *susu* collector under different savings timetables. Columns 1 and 2 show the impacts of varying degrees of economic efforts of using female *susu* collectors on savings outcomes. Columns 3 and 4 shows the effects of different female collector savings schedules on credit outcomes. The

savings outcomes are positive when the savings schedule is two days every week. On the other hand, the savings results become negative when the savings schedule is relaxed into a weekly schedule. Neither savings nor credit outcomes are significant for the daily schedule. The credit outcomes are very significantly positive for clients with a female collector that save two days every week. For clients with a female collector, saving every week had a negative and significant impact on credit outcomes.

TABLE 6.9—OLS FEMALE COLLECTOR IMPACTS ON SAVINGS AND CREDIT (BY SAVINGS SCHEDULES)

Collector Gender	Savings Contributions		Credit	
	(1)	(2)	(3)	(4)
Female collector × Daily schedule	11.57 (8.61)		407.57 (305.86)	
Female collector ×Two days per week schedule	21.86** (9.49)		1138.64*** (263.50)	
Female collector × Weekly schedule		-15.05** (7.16)		-883.07*** (230.92)
Female collector	Yes	Yes	Yes	Yes
Savings schedules dummies?	Yes	Yes	Yes	Yes
Including all other client variables?	Yes	Yes	Yes	Yes
N	281	281	137	137

Notes: Robust standard errors are in parentheses. Savings schedules (daily, twice per week, weekly) refer to the frequency of arranged meetings with a susu collector to contribute savings or receive credit after 3 months. *** denotes significance at the 1 percent level; ** refers to significance at the 5 percent level;* implies significance at the 10 percent level.

We next show *susu* gender networks' schedule effects on savings mobilization and credit outcomes. We first focus on female collector-female client networks in table 6.10. Within gender-based *susu* networks, I find that female clients do not contribute significantly more savings to collectors of the same gender (on a twice-weekly basis), but contribute less on a weekly basis. Female *susu* collectors provide more credit to female clients who save on a twice-weekly basis. On the other hand, female collectors provide less credit to clients who save on a weekly basis.

TABLE 6.10—FEMALE COLLECTOR-FEMALE CLIENT MATCH NETWORK IMPACTS ON SAVINGS AND CREDIT (BY SAVINGS SCHEDULES)

Collector-Client Networks	Savings Contributions	Credit
	(1)	(2)
Female collector-Female client × Daily schedule	-8.91 (9.61)	506.78 (437.81)
Female collector-Female client ×Two days per week schedule	7.88 (12.44)	726.57** (310.83)
Female collector-Female client ×Weekly schedule	-13.70* (7.88)	-707.91*** (267.08)
Female collector	Yes	Yes
Savings schedules dummies?	Yes	Yes
Including all other client variables?	Yes	Yes
N	281	137

Notes: Robust standard errors are in parentheses. Savings schedules (daily, twice per week, weekly) refer to the frequency of arranged meetings with a susu collector to contribute savings or receive credit after 3 months. *** denotes significance at the 1 percent level; ** refers to significance at the 5 percent level;* implies significance at the 10 percent level.

Table 6.11 shows no significant impacts of savings schedules (with cross-gender networks) on savings mobilization, although female collectors lend less to male clients who save on a daily basis. On the other hand, table 6.12 shows a slightly significant impact on female credit from male collectors only when female clients provide savings on a daily schedule. Finally, table 6.13 does not show any significant gender-bias between male collectors and clients irrespective of the schedule.

Of course, gender-based savings mobilization and credit outcomes, even when disaggregated by savings schedlues may not reflect gender-based repayments of loans once credit is received. However, given the strength of the results, the evidence that savings schedules are important lends credence to the view that gender-bias is subject to within-network homophily. In addition, the findings that gender-bias savings and credit may or may not obey a signaling model is consistent with our earlier network-based results. They suggest that gender-bias may both exist independently in savings mobilization and credit outcomes, or may be reciprocated by agents in allocating credit outcomes.

TABLE 6.11—OLS FEMALE COLLECTOR-MALE CLIENT MATCH

NETWORK IMPACTS ON SAVINGS AND CREDIT

(BY SAVINGS SCHEDULES)

Collector-Client Networks	Savings Contributions	Credit
	(1)	(2)
Female collector-male client × Daily schedule	10.39 (10.46)	-632.85* (365.11)
Female collector-male client × Two days per week schedule	17.56 (11.94)	198.16 (365.25)
Female collector-male client × Weekly schedule	-0.29 (6.44)	
Female collector	Yes	Yes
Savings schedules dummies?	Yes	Yes
Including all other client variables?	Yes	Yes
N	281	137

Notes: Robust standard errors are in parentheses. Savings schedules (daily, twice per week, weekly) refer to the frequency of arranged meetings with a susu collector to contribute savings or receive credit after 3 months. *** denotes significance at the 1 percent level; ** refers to significance at the 5 percent level;* implies significance at the 10 percent level.

TABLE 6.12—OLS MALE COLLECTOR-FEMALE CLIENT MATCH NETWORK IMPACTS ON SAVINGS AND CREDIT (BY SAVINGS SCHEDULES)

Collector-Client Networks	Savings Contributions	Credit
	(1)	(2)
Male collector-female client × Daily schedule	8.50 (7.77)	430.19* (226.14)
Male collector-female client × Two days per week schedule	-5.36 (5.97)	-137.58 (179.31)
Male collector-female client × Weekly schedule	0.25 (7.52)	210.41 (186.34)
Male collector	Yes	Yes
Savings schedules dummies?	Yes	Yes
Including all other client variables?	Yes	Yes
N	363	194

Notes: Robust standard errors are in parentheses. Savings schedules (daily, twice per week, weekly) refer to the frequency of arranged meetings with a susu collector to contribute savings or receive credit after 3 months. *** denotes significance at the 1 percent level; ** refers to significance at the 5 percent level;* implies significance at the 10 percent level.

TABLE 6.13—OLS MALE COLLECTOR-MALE CLIENT MATCH
NETWORK IMPACTS ON SAVINGS AND CREDIT
(BY SAVINGS SCHEDULES)

Collector-Client Networks	Savings Contributions	Credit
	(1)	(2)
Male collector-male client × Daily schedule	-7.65 (6.82)	-196.52 (235.31)
Male collector-male client × Two days per week schedule	3.80 (6.12)	-87.28 (177.22)
Male collector-male client × Weekly schedule	13.40 (11.56)	-90.27 (194.03)
Male collector	Yes	Yes
Savings schedules dummies?	Yes	Yes
Including all other client variables?	Yes	Yes
N	363	194

Notes: Robust standard errors are in parentheses. Savings schedules (daily, twice per week, weekly) refer to the frequency of arranged meetings with a *susu* collector to contribute savings or receive credit after 3 months. *** denotes significance at the 1 percent level; ** refers to significance at the 5 percent level;* implies significance at the 10 percent level.

6.4 Discussion of Education and Economic Effort Results

I find that male collectors discriminate against female clients and show evidence of homophily (people being inclined to associate with others who are similar to them) by gender. Yet, homophily does not explain all of the results, since male clients contribute more savings to female collectors. There are also postive credit impacts of female collectors (with male and female clients) when the analysis is limited to collectors and clients whose education levels exceed the mean. The gender-bias of male collectors' credit outcomes (against female clients) disappears when education levels exceed the mean. This implies that factors that correlate with homophily (e.g. status or class) are relevant in the incidence of gender-bias. In line with the signaling model, female clients contribute more to male clients when education levels exceed the mean.

For female clients, there are positive and significant credit impacts of having a male collector when the female client saves on a daily schedule. The daily schedule represents the highest level of internal commitment (see paper 4), and economic effort (see paper 5). Although there is gender-bias against female clients in the general results, the bias is mitigated for females who signal creditworthiness to a relatively high degree. Female collectors give female clients relative more credit conditional on female clients being relatively creditworthy. Female clients on the weekly schedule have a negative credit impact while female clients on a twice-weekly schedule have a positive credit impact. This result implies that economic effort has consequences for gender-bias against women.

7 Conclusion and Policy Implications

The literature on gender in politics and economics tends to focus on agents at the mercy of a principal, although agents may react to perceived gender-bias in economic

decision-making. In practical terms gender-bias is often two-sided, although studies that analyze this are rare. I analyze the gender-biased significance of female empowerment on economic outcomes in Ghana, focusing on formal-informal *susu* deposit collection. The theoretical analyses isolates gender bias in credit and savings outcomes as functions of gender-bias across genders and homophily (same-gender matching in networks). The analyses brings together elements from micro theory, political economy and social network analyses. The data show that female collectors generally do not reciprocate the cross-gender biases attributed to male collectors. Female clients generally save more with male clients, a finding that agrees with a model of signaling gender-bias. If female clients anticipate gender bias in the credit decisions of their male collectors, they save more (than a male client would) for equal credit amounts. On the other hand, gender-bias can be analyzed in a two-sided situation where credit outcomes correlate with savings contributions.

Educational attainment and economic effort (savings schedules) are important for interpreting how rigid gender-bias is in the study. For relatively educated collectors and clients, there results are similar, but the gender-bias of male collectors' credit outcomes (against female clients) disappears when education levels exceed the mean. This implies that other social factors that correlate with homophily (such as social status) may be relevant in the incidence of gender-bias. Further study should study such cases. The impact of economic effort on gender-bias in credit outcomes imply that gender-bias may be lessened. Female collectors only gave more credit to female clients who were on savings schedules reflecting relatively high economic effort (relative to other women on more relaxed schedules). On the other hand, the male collectors have positive credit impacts on female clients when the latter are on savings schedules that reflect high economic effort. For the above reasons, signaling by effort may mitigate gender-bias.

Although informal finance has mainly been biased against women, the issue has persisted in spite of merging formal and informal institutions. The female *susu* collec-

tors were hired in a competition-based system instead of a quota-based intervention. Such broad-based approaches to female empowerment may be important in similar contexts where the efficiency of empowered women is linked to their legitimacy in certain positions. Other microcredit institutions may benefit from having more female officers in credit roles, given possible homophily effects. Although education initiatives for susu collectors may be helpful, self-selection into matched groups is another area that requires attention. Economic effort is very important in lessening outcomes associated with gender-bias. Other avenues that improve information asymmetries between collectors and clients can be researched and implemented as policy.

Appendix

This Appendix contains supplementary information for the paper. The contents are as follows:

A.1: A model on the Average Treatment Effects of Gender-Matching. The explanation is a two-sided discussion of the Abrevaya and Hamermesh (2011) model.

A: Same-Gender Matched Networks

Model

In this section, I model interactions between *susu* collectors and clients within gender-based matched networks. Gender bias arises because clients may contribute more savings to collectors of the same gender–who may respond by providing more credit to clients of the same sex. The model will draw from Abrevaya and Hamermesh's recent

work on gender-based favoritism (2012). However, it deviates from that work by focusing on undirected (i.e. reciprocated) gender-bias. This approach is made feasible by using a basic social network-based framework (e.g. Jackson 2008, Golub and Jackson 2012). I use the model to develop testable implications of gender bias on savings mobilization and credit provision.

Set-up

Let a *susu* collector and her clients represent nodes, $N = \{1, \ldots, n\}$, of a susu network. This susu system is represented by its weighted matrix, which is a symmetric $n \times n$ matrix $\mathbf{S}$ with entries $\{0, 1\}$. We allow $S_{ij} = S_{ji} = 1$, since our discussion is primarily on undirected economic networks as noted earlier.

Every client is linked to a single collector. We let relationships (between a *susu* collector node and a *susu* client node) flow in both directions, so that *susu* clients contribute funds (called savings) to collectors, who respond with funds (called credit). We let $d_i(S) = \sum_j^n S_{ij}$ represent the number of links of node i, so that average degree is denoted $d(\mathbf{S})$**.** As a result, the total number of links in the network is $\mathrm{D}(\mathbf{S}) = \sum_j d_i(\mathbf{S})$**.**

We focus on gender as a distinguishing feature or "type" that influences the propensity of a node to connect to another. As such, the network is partitioned into $2 = N_f \subset N$, where N_f refers to female gender nodes. We focus mainly on two generic nodes by gender: female *susu* clients who contribute savings and female *susu* collectors who provide credit[5].

Gender may be important to *both* the savings contribution and credit allocation events, in two ways. First, gender may be *independently* important to savings mobilization and credit outcomes. Alternatively, gender may be influential to both occurrances jointly. We first discuss the case where the impact of gender on savings and credit are

[5]Note that since the present analyses is identical for male collectors, I omit it in this section.

independently important before dicussing the scenario where gender effects are jointly important.

Matched Gender Network Impacts on Savings and Credit Outcomes

In this section, I develop a model of gender-biased microeconomic outcomes, based on Abrevaya and Hamermesh, henceforth AH (2012), but generalized to a dual-market scenario. This adaptation of the AH (2012) model allows insight into the independent impacts of collectors' and clients' genders on savings mobilization and credit outcomes. Given our two-sided emphasis, we only slightly adjust the model in the second part of this section to introduce the credit impacts of gender, embedding our discussion in the basic network framework introduced earlier. We assume for simplicity that the utility of clients depend entirely on credit while the utility of collectors depend on savings.

Matched Gender Impacts on Savings Mobilization

Susu saving clients are represented by C_i (for $i = 1...I$) while *Susu* (deposit) Collectors are notationally D_j(where $j = 1...J$). Gender is represented by $f(C_i)$and $f(D_j)$ for clients and collectors respectively (= 1 for females.)

The hypothesized impacts of gender on savings and credit outcomes are simplified and presented below. We begin with the gender impact on savings. The utility of collector D_j when matched with customer C_i is:

$$U(C_i, D_j) = \mu_i + \psi_j + \alpha f(C_i) + \beta f(D_j) + \lambda f(C_i) f(D_j) + \varepsilon_{ij}. \tag{1}$$

We consider μ_i to be an idiosyncratic value of the savings contribution, while ψ_j

is the deposit collector's valuation of that amount. The effect ε_{ij} refers to an unobservable. We say that the collector is satisfied with the savings contribution amount if $U(C_i, D_j)$is greater than zero. This event occurs when the probability of the Right-Hand Side of (1) is greater than zero.

Since μ_i and ψ_j are assumed to be random, a composite error term can be constructed from (1) whereby $E_{ij} = \mu_i + \psi_j + \varepsilon_{ij}$. Let the cumulative distribution function of $-E_{ij}$be $G(.)$. This allows the isolation of a crude average treatment effect of gender simplified below.

AVERAGE TREATMENT EFFECT OF GENDER MATCHED NETWORKS ON SAVINGS

- The effect of female deposit collector on male client saving: $G(\alpha) - G(0)$
- The effect of female deposit collector on female client saving: $G(\alpha + \beta + \lambda) - G(\beta)$
- Then, the treatment (difference-in-difference) effect is:

  $[G(\alpha + \beta + \lambda) - G(\beta)]$-$[G(\alpha) - G(0)]$.

If female *susu* clients are relatively more generous than males when matched with female susu collectors, then this impact is greater than zero. If female clients are relatively less generous than males when matched with female *susu* collectors, this effect will be negative.

Matched Gender Impacts on Credit Outcomes

We now consider the effect of gender effect on credit. We assume that the prior

gender influence in the savings event does not influence the present event. The utility of client C_i when matched with collector D_j is:

$$U(D_j, C_i) = \upsilon_j + \nu_i + \gamma f(D_j) + \delta f(C_i) + \tau f(D_j) f(C_i) + \varepsilon_{ji}. \tag{2}$$

Consistent with our recent discussion we construct a compositve error term so that $e_{ji} = \upsilon_j + \nu_i + \varepsilon_{ji}$and let the cumulative distribution function of $-e_{ji}$be H.

AVERAGE TREATMENT EFFECT OF GENDER MATCHED NETWORKS ON SAVINGS

- The effect of female client on male collector credit: $H(\gamma) - H(0)$
- The effect of female client on female collector credit: $H(\gamma + \delta + \tau) - H(\delta)$
- The corresponding average treatment effect is:

$$[H(\gamma + \delta + t\tau) - H(\delta)] - [H(\gamma) - H(0)]$$

If female *susu* collectors are relatively more generous than males when matched with female clients, this impact will be positive. If female collectors are relatively less generous than males when matched with female *susu* clients, this effect will be negative.