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The Equity Impacts of Targeted Smallholder Agricultural Credit

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Abstract

We examine the distributive impacts of two alternative approaches to deliver agricultural credit to smallholders: TRAIL (or trader-agent intermediated lending), where local traders recommend village residents for individual liability micro-leans, and GBL (or group-based lending), where households self-select into groups and receive joint liability loans. We use data from a field experiment in eastern India to estimate how the effects of these schemes differ by economic (proxied by landownership) and social (proxied by caste and religion) status of households. Our method accounts for endogenous selection frequencies in each group and the treatment effects on farm income conditional on selection, to estimate the impacts of each scheme on Atkinson-based measures of welfare and inequality. We find that TRAIL loans increased farm incomes for all land groups, but particularly for landless households. As a result, across land groups, the TRAIL scheme generated significantly greater welfare than the GBL scheme, irrespective of inequality aversion. The GBL scheme generated larger effects among the socially disadvantaged minority groups. This suggests that the efficiency and equity implications of the two schemes might be different depending on how we partition households.

Keywords: agricultural finance, agent based lending, group lending, distributive impacts

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1 Introduction

An important question in public economics is how private benefits should be targeted. When governments cannot observe individuals' needs and productivity, how can they ensure that the benefits go to those who will gain from them the most ((Zeckhauser, 1971, Akerlof, 1978, Blackorby and Donaldson, 1988, Besley and Coate, 1992))? This question is particularly relevant in developing countries, where arguably the information constraints are more severe. Even when programs are decentralized and administered by local officials who have better information about individual beneficiaries, there remains the threat that elite groups will capture benefits (see for example Bardhan and Mookherjee, 2005, Galasso and Ravallion, 2005). Is it possible to design programs that can leverage local information to target beneficiaries without succumbing to corruption and elite capture?

This paper examines this question in the context of agricultural credit programs. Policy-makers and practitioners have long grappled with the challenge of delivering credit to poor farmers excluded by formal financial institutions. Many state-sponsored attempts at rural lending have failed because unsecured loans have high default rates. Microcredit has high repayment rates, but the loans are designed to be used in small businesses with high-frequency cash flows; their use in agriculture is limited. A central problem here is that both formal lenders and MFI loan officers do not often know enough about the households in the rural communities that they serve to predict whether their agricultural projects are likely to succeed, and concurrently whether they are likely to repay the loans. However we know that members of the local community observe each others' characteristics and participate in networks that rely on this knowledge.

In this project we examine agent-intermediated lending, a credit delivery approach that attempts to use this information. A local "agent" recommends borrowers for individual liability loans. The agent is an integral part of the community and has extensive experience and knowledge about the creditworthiness of village residents. He receives commissions that depend on the loan repayment by borrowers whom he recommended. It is expected that this would induce him to recommend borrowers who are likely to repay the loans. If borrowers' default risk is negatively correlated with their ability to earn high returns on agricultural projects, then the borrowers whom the agents recommends are likely to be productive farmers. In turn these loans are likely to generate large returns.

In previous work we have argued that the efficiency gains from such a lending scheme are large (Maitra, Mitra, Mookherjee, Motta, and Visaria, 2016). However, what effect would such a scheme have on the aggregate welfare of the population? In particular, what are the equity effects of the agent-intermediated lending model? Might they outweigh the positive efficiency effects? This paper is concerned with these questions.

In Maitra, Mitra, Mookherjee, Motta, and Visaria (2016) (henceforth MV) we discuss one variant of this lending approach called Trader Agent-Intermediated Lending (or TRAIL), where the agent is a local trader who regularly enters into economic transactions with local farmers: as a seller of agricultural inputs, a buyer of agricultural output, or a provider of credit. In a field experiment, the TRAIL scheme was implemented over a three-year period (2010–2013) in 24 randomly selected villages in two districts of West Bengal in India. To prevent a situation where the agent only recommends the most wealthy or powerful households in the village, the scheme stipulates that only the landless and small landowners are eligible to participate. We found that the average recommended household earned 22% more per year if it received a TRAIL loan than otherwise. The annualized rate of return on a TRAIL loan is estimated to be 101%.

We also examine an alternative group-based lending scheme (or GBL) that was implemented in another randomly-selected set of 24 villages. In this scheme, loans were offered to 5-member joint-liability groups that self-formed within each village.[1] Here as well, eligibility was restricted to landless and small landowners. However, any eligible household could participate if they could find a group that would accept them. We find that that GBL loans had a non-significant effect on farm value added for the average recommended household.

In MV we showed that the borrowers whom the agent recommended for the TRAIL loans were on average more productive than the borrowers who self-selected into GBL groups. These differences in selection patterns explained 30-40% of the difference between the average treatment effects of the two schemes. However, this raises the concern that TRAIL might be less equitable than GBL. If the more productive farmers were richer to begin with, then by purposively selecting and then rewarding them, TRAIL could amplify income differences across households. This paper ascertains if this is indeed the case.

To address this question, we examine the distributive impacts of the two schemes. We partition the sample of households along two alternative dimensions of well-being or status: either four economic classes based on landownership (no land, 0–0.5 acres, 0.5–1 acre and 1–1.5 acres), or three social groups based on caste and religion (scheduled castes/scheduled tribes, non-Hindus and general caste Hindus).[2] Both these measures of status are significantly correlated with education, occupation, housing quality, ownership of consumer durables and access to formal financial instruments. Moreover, each measure is pre-determined and unlikely to be affected by the treatments.

[1]The GBL model is similar in some aspects to the joint liability lending model used by microfinance institutions around the world. For evaluations of these programs (see Banerjee, 2013, Augsburg, Haas, Harmgart, and Meghir, 2015, Attanasio, Augsburg, Haas, Fitzsimons, and Harmgart, 2015, Banerjee, Karlan, and Zinman, 2015, Banerjee, Duflo, Glennerster, and Kinnan, 2015, Tarozzi, Desai, and Johnson, 2015, among others).

[2]Scheduled Castes (SCs) and Scheduled Tribes (STs) are official designations given to various groups of historically disadvantaged indigenous people in India. In our sample all Non-Hindus are Muslims.

We use our experimental data to estimate the impacts of the TRAIL and GBL schemes on average farm incomes for each economic or social group separately. Then we use the Atkinson (1970) approach to compute the resulting changes in welfare for the average household, for a wide range of parameters of inequality aversion.

An important contribution of our paper is that it provides a method for estimating distributional impacts of interventions where the selection of beneficiaries is endogenous. Given the nature of the schemes being evaluated, it is not possible to directly estimate the effect that a loan might have had on a randomly selected household. However, we can ask the following question: What effect could a randomly selected household in group g expect if the loan scheme were introduced into its village? The answer depends in turn on the answers to two questions: in a randomly chosen village exposed to any particular scheme, (a) what is the selection frequency for group g, or what fraction of group g households are likely to be recommended by the TRAIL agent, or to self-select into GBL groups; and (b) what is the conditional treatment effect (CTE) of the scheme on group g, or, conditional on selection, by how much does the loan change these households' farm income? The product of the selection frequency and the CTE gives us the *expected treatment effect* (ETE) on farm income for group g. Using an isoelastic welfare function with an elasticity determined by the parameter of inequality aversion, we can then estimate expected welfare impacts on each group g. These can then be aggregated across groups to generate a welfare measure for the village as a whole.

Due to the concavity of the welfare function, groups that start with lower baseline incomes receive a higher welfare weight. An increase in the parameter of inequality aversion (θ) in an iso-elastic welfare function is associated with an increase in the welfare weight of low-income households. We can then compare the aggregate welfare impact of the two schemes for a given value of θ. The welfare comparison may vary with changes in θ, which allows us to examine how the schemes compare on efficiency and equity objectives. A summary measure of inequality can also be computed for any given level of θ, along the lines suggested by Atkinson (1970).

Our main findings can be summarized as follows. First, in the TRAIL scheme, the point estimates of the conditional treatment effects on farm value-added are large and positive for all land classes. The largest proportional expected treatment effects are realized for the landless and for households with intermediate landholding. This results in welfare increases at all values of inequality aversion that we consider. In the GBL scheme, we find positive point estimates for all households that own less than 1 acre of land, whereas the 1–1.5 acre households have a negative point estimate. The positive effects slightly outweigh the negative, and there are equalizing effects on farm income. As a result there are positive effects on welfare at all values of θ, but these are smaller than the corresponding effects under the TRAIL scheme. These differences are statistically significant.

When we conduct the analysis by social group, we find that in the TRAIL scheme, all groups receive increases in income but the proportional effects are largest for the general castes (who also happen to be the richest), followed by the non-Hindus. Thus the scheme increases inequality between social groups. In the GBL scheme, the proportional expected treatment effects are largest for the two disadvantaged groups: SC/STs and non-Hindus. Thus we find a decrease in inequality as well as an increase in the incomes of the more disadvantaged. As a result at high levels of inequality aversion we find that the point estimates of the welfare impacts are larger for the GBL scheme. However the treatment differences in welfare impacts are not statistically significant.

In this way, we examine more than the average treatment effects of the two lending schemes. Whereas there is now a large body of evidence suggesting that group-based lending does not increase average incomes significantly, relatively little attention has been paid to its effect on inequality within the areas where it is offered. In this paper we show that despite small and non-significant average treatment effects, group-based lending schemes may lower inequality.

Our method can also be used to evaluate programs where program officials do not explicitly select beneficiaries, but instead beneficiaries self-select into the program. Many programs require that individuals or household first "apply" to participate, and then select a random subset into the treatment group. Consider for example a job training program where individuals are invited to apply, and then applicants are randomly allocated to either receive the training (i.e. assigned to the treatment group) or not (assigned to the control group). The average treatment effect is estimated as the difference between the outcome of the treated and the non-treated applicants. However, to estimate the welfare impacts of such a program, it is important to account for the application rate. For example, even if the estimated treatment effects of a program are large, if only a small fraction of the eligible population applies, the expected treatment effects and welfare impacts are likely to be small. The reverse is of course also true: small estimated treatment effects could be magnified if application rates are high. Our approach provides a framework for evaluating welfare effects in such situations. We show how the conditional treatment effects (conditional on application, or "selection" in our case) need to be scaled by the selection frequency (or application frequency) in order to estimate the expected treatment effects. These can be used to compute the welfare effect of the program.

While in the literature on cost-benefit analysis of projects it is common to estimate distributive impacts by assuming iso-elastic welfare functions with different parameters of inequality aversion (see for example Newbery and Stern, 1987), the recent development economics literature does not examine welfare effects (barring structural estimation exercises). However the literature in public economics has followed this approach. Hughes (1987) examines the welfare implications of fuel tax reform in Indonesia, Thailand and Tunisia by comparing Atkinson inequality indices. Newbery (1995) examines the distributional implications of trade liberalization and tax reform in Hungary and the UK. He too uses an iso-elastic social welfare function and computes the welfare impacts of price changes using different parameters of inequality aversion. Blundell, Costa-Dias, Meghir, and Shaw (2016) use a similar approach to estimate the welfare implications of tax and benefit reform.

We offer some explanations for the patterns in the conditional treatment effects that underlie our results. We find that across all land classes, TRAIL agents tended to recommend borrowers with whom they interacted frequently either in the economic or social sphere. If in each land class TRAIL agents interacted more with the more able households, then this could explain why in each land class, including the landless, the TRAIL loans increased farm incomes.

When instead households are differentiated on the basis of social group, we obtain somewhat different results. GBL households were likely selected both from the high- and the low-ability households in the GBL villages.[3] Despite this, we see that both non-Hindus and SC/STs earned larger increases in incomes than the most well-off group of general caste Hindus. We present some descriptive evidence suggesting that non-Hindus and SC/STs belonged to more homogenous groups, than general caste Hindus did. This possibly allowed them to share information and extend greater help to each other within the group, which in turn allowed them to increase their incomes by more.

2 The Loan Interventions

Our intervention was conducted in the districts of Hugli and West Medinipur in the state of West Bengal, India. The TRAIL scheme was implemented in 24 randomly selected villages. In another 24 villages, an MFI implemented the GBL scheme.[4] Each sample village was at least 10 kilometres away from all other sample villages, to help minimize the spread of information across TRAIL and GBL villages that could potentially compromise the experiment. This MFI had not previously operated in any of the sample villages. In general MFI penetration was low in these parts of India at the time that our project began in 2010.

Potato is the most important cash crop in this region and our schemes were designed to facilitate potato cultivation. In each scheme, borrowers were offered multiple cycles of loans of 4-month durations at an annual interest rate of 18%. The initial loans were capped at ₹2000, and were disbursed in October-November 2010, to coincide with the potato-planting season.[5] Repayment was due in a single lumpsum after 4 months. Borrowers who repaid the full amount became

[3] In this respect our result differs from the Ghatak (2000) argument that only high-ability (or low-risk) borrowers would participate in GBL schemes. We explain this disparity between our and his results in Section 7.

[4] In yet another 24 villages, an alternative version of the agent intermediated lending scheme (called GRAIL) was implemented, where a member of the village council (*Gram Panchayat*) was appointed as the agent. The GRAIL agent is likely to have been motivated by the political benefits of participating in the scheme. We do not analyze the GRAIL scheme in this paper.

[5] ₹is the currency of India. At the time the loans were disbursed, ₹2000 was equal to approximately US $50.

eligible for a 33 percent larger loan in the subsequent cycle, on the same terms as before. Those who repaid less than 50 percent of the amount due were not allowed to borrow again. Others were eligible to borrow 133 percent of the principal repaid.[6] Both schemes had an in-built index insurance scheme, so that the required repayment would be revised downward if the revenue per acre for potatoes fell 25 percent below a three year average in the village, as assessed through a separate village survey.

2.1 The Trader-Agent-Intermediated Lending (TRAIL) Scheme

In each of the 24 TRAIL villages, the lender consulted with prominent persons in the village to draw up a list of traders and business people who had at least 50 clients in the village, and had been in business in the village for three or more years. One person from the list was randomly chosen and invited to become an agent.[7] The agent was asked to recommend as potential borrowers 30 village residents who owned no more than 1.5 acres of agricultural land.

Loans were offered to 10 households. These households were chosen through a public lottery, where each recommended household had an equal likelihood of being selected. We refer to these as the TRAIL Treatment households. Of the remaining 20 recommended who were not randomly selected for the loans, 10 were randomly drawn into the survey sample; we refer to them as TRAIL Control 1 households. The average conditional treatment effect of the TRAIL scheme can then be estimated as the difference in the farm incomes of TRAIL Treatment and TRAIL Control 1 households.

At the beginning of Cycle 1, the agent was required to put down a deposit of ₹50 per borrower. The deposit was refunded at the end of two years, in proportion to the loan repayment rates of his recommended borrowers. At the end of each loan cycle he received as commission 75% of the interest received on these loans. The agent's contract was terminated at the end of any cycle in which 50% of borrowers whom he had recommended failed to repay. Agents were also promised an expenses-paid holiday at a local sea-side resort if they survived in the program for two years.

Official interactions between loan officers and borrowers were limited to loan disbursement and collections at the beginning and end of each cycle, which occurred at the borrowers' residences. Loan officers were not required to engage in any monitoring or collection effort, and borrowers were not required to report to the loan officers their intended or actual use of the loan.[8]

[6] To facilitate credit access for post-harvest storage, borrowers were allowed to repay the loan in the form of cold storage receipts (or "bonds") instead of cash. In that case the repayment was calculated at the prevailing price of potato bonds.

[7] The experimental protocol stated that if the person approached rejected the offer, the position would be offered to another randomly chosen person from the list. In practice, the first person offered the position accepted it in every village.

[8] In our household surveys we asked respondents to tell us how they used each loan.

2.2 The Group-based Lending (GBL) Scheme

In the GBL villages, the MFI began operations in February-March 2010 by inviting residents who owned no more than 1.5 acres of land to form 5-member groups. They then organized bi-monthly meetings for each group, where each member was expected to deposit ₹50 per month into the group account. Of the groups that survived until October 15, 2010, two were randomly selected into the scheme through a public lottery where each group had an equal likelihood of being selected. The 10 households belonging to these two groups are referred to as GBL Treatment households. Of the remaining groups, two were randomly selected and all their members were drawn into the survey sample; these are called the GBL Control 1 households. The average conditional effect of the GBL scheme is then estimated as the difference in the farm incomes of TRAIL Treatment and TRAIL Control 1 households.

Each group member received a loan of ₹2,000 in Cycle 1, for a total of ₹10,000 for the entire group. Just as in the TRAIL scheme, these loans had four-month durations and were payable in a single lump sum. All group members shared liability for the entire ₹10,000: if less than 50% of the due amount was repaid in any cycle, all members were disqualified from future loans; otherwise the group was eligible to borrow in the next cycle an amount 33% larger than the previous loan. Bi-monthly group meetings continued throughout. At the end of each loan cycle the MFI received as commission 75% of the interest received on these loans.

2.3 Data and Descriptive Statistics

Concurrent with the 8 loan cycles, we conducted eight rounds of surveys with a sample of 50 households in each of the 48 villages. In each village, the sample included the 10 Treatment and 10 Control 1 households as defined above. In addition, of the households that were not recommended (in TRAIL villages) or did not self select into groups (in GBL villages), 30 households were randomly selected into the sample. These are referred to as Control 2 households.

Our household surveys were conducted every four months and collected information about household demographics, landholding and land use, household assets, both consumer durables and productive assets, cultivation and input use, production, sales and storage, labour and non-agricultural incomes, and economic relationships in the village. We supplemented these with administrative loan record data from our partner MFI. There was no attrition: all sample households answered all eight rounds of the survey. In each household, the same individual answered the survey questionnaire in every round.

Table 1 presents descriptive statistics about the characteristics of the sample villages. Panels A–C use data from the Census of India 2011 and Cycle 1 of the household surveys conducted in

2010 in all 48 villages. Since we drew a purposive sample of Treatment, Control 1 and Control 2 households, we do not expect our sample means to be representative of the village populations. To ensure that we estimate representative means, we re-weight the sample to inflate each household in inverse proportion to the probability that they would be selected into the sample. Thus, Treatment and Control 1 households each receive a weight of $\frac{30}{N}$ and Control 2 households receive a weight of $\frac{N-30}{N}$, where N denotes the total number of households in the village that the household belongs to (as reported in the 2011 Census). Thus we can scale up the sample proportions in each land class and social group to arrive at the population proportions. In Panel D, we use data from village surveys conducted in the sample villages in 2007 in 46 of the 48 villages.[9]

Villages had 400 households on average, only 17 percent of which owned more than 1.5 acres of land. Thus 83 percent of the households were eligible to participate in the loan schemes. A little less than a fifth of the households were landless. Although the average TRAIL village had about 40 percent fewer households than the average GBL village in our sample, this difference is not statistically significant.[10] The different land classes appear in the two treatment arms in equal proportions.

General caste Hindus formed about half of the village population. Scheduled castes and scheduled tribes (SC/STs) were a sizeable minority at 33 percent. Comparing across treatment arms, a larger proportion of the households in TRAIL villages were non-Hindu than in the GBL villages, whereas there were slightly greater proportions of SC/STs in GBL villages. However these differences are not statistically significant.

More than three quarters of the villages had primary schools, but only about one quarter had primary health centres. Bank branches existed in only 8 percent of villages. Sixty percent of village households had electric connections. No microfinance institutions had offices in any of the sample villages. About a third had all-weather roads. We reject the null hypothesis that these village-level characteristics can jointly explain assignment to treatment and consequently infer that the villages were balanced in terms of these observables (p-value = 0.76).

In Table 2 we present (re-weighted) mean characteristics of households in the TRAIL and GBL villages. Most characteristics are very similar across the two treatment arms, and the pair-wise differences are statistically non-significant. The exception is that household heads in TRAIL villages were 4 percentage points more likely to report that their primary occupation was cultivation. However, we cannot reject the null hypothesis that on average, households in TRAIL and GBL villages were identical in observable household characteristics (p-value = 0.994).

[9] The village surveys were conducted in 2007 for a different project. We intended to work in exactly the same set of villages in this study, but due to Maoist violence during 2010, we had to replace 2 of the 48 original villages. Therefore we have data on village characteristics only for 46 villages.

[10] When we compare relative welfare impacts of the two schemes, we will also consider a hypothetical alternative where the relative increase in welfare caused by the GBL scheme is 40 percent larger.

Tables 3 and 5 present descriptive statistics for the sub-sample of our sample households that owned no more than 1.5 acres of land. Column 1 of each table provides a picture of the characteristics of representative households (based on the re-weighting procedure). We can see from columns 2–5 in Table 3 that education levels, occupation, landholding and asset ownership all varied substantially across land class. In households that owned more land, heads were more likely to have completed primary school, were more likely to report their main occupation as cultivation and less likely to report it as casual labour.[11] Households with more land were more likely to live in brick and mortar (*pucca*) houses, more likely to have electric connections, and were more likely to have separate kitchens and toilets in their homes. They were also more likely to own electronic appliances, motorized vehicles and telephones, and to have access to formal financial services such as bank savings accounts and insurance policies.

Columns 2–5 of Table 5 make it clear that there is also a systematic ordering in economic status by social group. General caste Hindus were the most well-off, and scheduled castes (SCs) and scheduled tribes (STs) were the most disadvantaged in terms of educational attainment, landholding, asset ownership and financial inclusion.

Consistent with the gradation of households by land category and social group in Tables 3 and 5, in Figure 1 and Figure 2 we see that SC/ST households were much more likely to be landless than any other social group. As we move up the land ownership scale, general castes are better represented. in each land category decreases monotonically and the proportion of general caste households increases monotonically as we move up along the scale of land ownership.

In Tables 4 and 6 we check that the characteristics of households were balanced across treatment arms within each land class and social group. With very few exceptions, the t-tests indicate that differences between the TRAIL and GBL households were small and non-significant. For each group we are unable to reject the null hypothesis that the differences in characteristics are jointly equal to zero.

To the extent that caste and religion categories change very rarely, and land markets are thin, the data above indicate that landholding and social group provide good proxies for the socio-economic status of a household.[12] This motivates our analysis of the distributive impacts of the TRAIL and GBL schemes along land and social (caste and religion) categories.

[11] However it should be noted that there is an active land rental market, so that even landless households do engage in agriculture.

[12] Across the 2400 households in our sample, there were 16 land sales, purchases or transfers over the 3 years of the study. Caste and religion are also difficult to change, at least in the short run.

3 Methodology

Suppose that a village has G groups indexed $g = 1, \ldots, G$. Group g has n_g households indexed $i = 1, \ldots, n_g$. The baseline income of household i in group g is denoted by y_{ig}. Following Atkinson (1970), suppose the welfare of this household can be written as

$$V(y_{ig}) = \begin{cases} \frac{y_{ig}^{1-\theta}}{1-\theta} & \theta > 0;\ \theta \neq 1 \\ \log(y_{ig}) & \theta = 1 \end{cases} \tag{1}$$

Then, the average welfare of the village at baseline is

$$w = \frac{1}{N} \sum_{g=1}^{G} \sum_{i=1}^{n_g} V(y_{ig}) \tag{2}$$

where $N \equiv \sum_g n_g$.

In any given loan scheme r (TRAIL or GBL), a subset of all households is selected to participate according to a non-random procedure. We call the fraction p_g^r of group g households that are selected, the selection frequency. Selected households may have different baseline incomes from those not selected.

In our experiment, a subset of these selected households were randomly chosen to receive the loans through the scheme (these are the Treatment households). Those sample households that were "selected" but not randomly assigned to be Treatment households are called Control 1 households. The conditional treatment effect (CTE) for group g is the difference between the incomes earned by Treatment and Control 1 households belonging to group g.[13] Assuming that all selected households in group g in treatment r have the same baseline income y_g^r, and would experience the same treatment effect $T_g^r y_g^t$, ending up with farm income $y_g^r(1 + T_g^r)$, the change in welfare for a member of group g conditional on being selected can be written as

$$\frac{1}{1-\theta}[(y_g^r + T_g^r y_g^r)^{1-\theta} - (y_g^r)^{1-\theta}] \tag{3}$$

Next, if we assume that there are no spillover effects on non-treated households, the change in average village welfare resulting from treatment r can be written as[14]

[13] In practice, we run a regression of farm incomes on treatment status that also controls for household characteristics and time dummies.

[14] Given an average village size of 400 and the fact that only 10 households in each village were offered the loans, it is unlikely that there were significant spillover effects.

$$\Delta^r w = \begin{cases} \sum_{g=1}^{G} \alpha_g p_g^r [\frac{(y_g^r + T_g^r y_g^r)^{1-\theta} - (y_g^r)^{1-\theta}}{1-\theta}] & \text{for } \theta \neq 1 \\ \sum_{g=1}^{G} \alpha_g p_g^r [\ln(y_g^r + T_g^r y_g^r) - \ln(y_g^r)] & \text{for } \theta = 1 \end{cases} \tag{4}$$

Here α_g denotes the demographic weight of group g, given by the proportion of households in the villages assigned to scheme r that belong to group g. To compute the change in welfare ($\Delta^r w$) we then need to estimate the demographic weights (α_g), the selection frequencies (p_g^r), conditional treatment effects ($T_g^r y_g^r$) and baseline incomes (y_g^r) of Control 1 households for treatment r.

Our welfare function allows us to estimate the change in welfare for different degrees of inequality aversion as given by different values of the parameter θ. For example, when $\theta = 0$, the intervention has the same exact impact on a household's welfare as its impact on its absolute income. When $\theta = 1$, the welfare function is logarithmic, so that the welfare impact of an intervention is the proportional change in the household's income. Thus, for a low income household, the same absolute increase in income is likely to increase welfare by more when $\theta = 1$ than when $\theta = 0$. As θ increases, the welfare function becomes more concave and accordingly low income households will receive higher welfare weights.

Expressions (4) and (**??**) describe the absolute welfare impact of treatment r corresponding to inequality aversion θ. The corresponding proportional welfare impact is given by the ratio of $\frac{\Delta^r w}{w}$. We compute baseline welfare w as function of baseline incomes for Control 2 households as well as for Control 1 households within each group.

We can also compute Atkinson's index of inequality, given by

$$I = 1 - \frac{y_e^r}{\bar{y^r}} \tag{5}$$

where $\bar{y^r} = \sum_{g=1}^{G} \alpha_g \bar{y_g^r}$ denotes mean income. The equally distributed equivalent income y_e^r is defined by the solution to

$$w^r = \frac{\bar{y_e^r}^{1-\theta}}{1-\theta} \tag{6}$$

By computing each measure both for the pre-intervention (baseline) income distribution and the post-intervention (endline) income distribution, we are able to evaluate whether and in what direction the intervention changed inequality. Due to the random assignment of treatment among selected households, the incomes of Control 1 households provide the counterfactual for the incomes of Treatment households.

Therefore, baseline welfare w_B^r is computed using the incomes of Control 1 and Control 2 households as:

$$w_B^r = \frac{1}{1-\theta} \sum_{i=1}^{N_{C1C2}} (y_i^r)^{1-\theta} \tag{7}$$

and the baseline mean income is given by

$$\bar{y_B^r} = \sum_{i=1}^{N_{C1C2}} \bar{y_i^r} \tag{8}$$

where N_{C1C2} is the appropriately weighted measure of Control 1 and Control 2 households in the economy, with weights defined as in page 8, so that they are representative of the population.

The endline welfare (w_E^r) and incomes $\bar{y_E^r}$ are calculated according to the same formulae, except that all Control 1 households are replaced by Treatment households.

4 Distributive Impacts by Land Category

We are interested in the effects of the two schemes on farm incomes at different points of the distribution of households, where households can be classified according to land ownership or social group. We then wish to examine the effects of the schemes on aggregate welfare.

We begin by presenting the empirical results for the distributive impacts, where households are grouped according to their land ownership.

As discussed in Section 3, the welfare effects of the lending schemes depend on multiple components. For each group g in the distribution, we estimate the conditional treatment effects of the loan scheme and then compute an expected treatment effect by multiplying these CTEs with the selection frequency for that group. We then compute a weighted average of these expected treatment effects (ETEs) across groups, where each group is assigned a weight equal to their proportion in the population of households. Below we discuss each of these components, before combining them and computing the welfare effects.

4.1 Population Proportions (α_g)

In Panel A of Table 7, columns 1 and 3 present the population proportions for each land class, taken as a share of the total eligible households, viz. those that owned up to 1.5 acres of land. It is clear that about a fifth of eligible households were landless, 38–40 percent owned 0–0.5 acres, 28–29 percent owned 0.5–1 acres and 10–14 percent owned more than 1 acre.

4.2 Selection Frequencies (p_g)

When a particular lending scheme is introduced into a village, a household can only expect a direct benefit if it is selected to participate.[15] Thus the selection frequency is a key component. In Table 7 we present the estimated selection frequencies for each group g, defined as the fraction of households in the treatment villages in group g, who are selected to participate in the scheme. Here selection should be understood as recommendation by the agent in TRAIL villages, and as self-selection into groups that then survive the 6-month initiation period in GBL villages.

Start by noting that in each TRAIL village, the agent was asked to recommend up to 30 households. Of these 30, our sample consists of up to 20 (10 Treatment households and 10 Control 1 households), or a maximum of 480 selected households. In practice, we have data on 461 selected households.[16] Across the 24 TRAIL villages, there were 6714 households that owned up to 1.5 acres of land. Thus the average eligible household had a 6.9 percent likelihood of being selected into the scheme.

Naturally, this selection frequency could vary by the group g that the household belongs to. Table 7 shows that landless households in TRAIL villages had a slightly lower 5.9 percent chance of being selected. Households in the other land classes were about equally likely at 7.4, 6.8 and 7.0 percent chance of selection. Thus across the land classes there appears to be limited variation in selection frequencies. In particular, there is not much evidence that the scheme was strongly biased against households with lower landholdings.

Selection in GBL villages follows a different pattern. First, there was no restriction on how many groups could form in GBL villages. However our sample is still restricted to 20 selected households per village, or four 5-member groups per village, for a total of 480 households. Instead we have data on 449 households. This is because in 13 out of the 24 GBL villages, fewer than 20 households joined GBL groups. Thus, despite the fact that the population of eligible households in GBL villages was on average larger, households participated in the GBL scheme at a lower rate than in the TRAIL scheme. An average eligible household had a 5.1 percent likelihood of participating in the scheme, compared to 6.9 percent in TRAIL. The selection frequencies vary by land class: landless households had a 7.3 percent chance of participating, but the frequency declined as we examine higher land classes, so that only 3.2 percent of households with 1-1.5 acres participated in the scheme.

Since the GBL scheme involved bi-monthly group meetings and a savings requirement of ₹50 per

[15] Recall that we assume away any spillover or general equilibrium effects on non-participants. Since only 10 households in each village received treatment, these effects are likely to be small.

[16] The number differs from the maximum possible of 480 because in some villages, the TRAIL agent recommended fewer than 30 households, and in some villages, a few of the recommended households were ineligible for the loan because they owned more than 1.5 acres of land.

household per month, we expect that it was more costly for the average household to participate in GBL than in the TRAIL scheme. The fact that poorer land groups participated at higher rates and that the participation rate fell monotonically with landholding suggests that the opportunity cost of time was an important element of this cost.

4.3 Conditional Average Treatment Effects

Before we estimate the CTEs for each land group, we replicate the average treatment effect estimates of the two schemes that we found in MV. The regression is run on the pooled sample of Treatment and Control 1 households in TRAIL and GBL villages, and follows the specification:

$$y_{ivt} = \beta_0 + \beta_1 \text{TRAIL}_v + \beta_2 \text{Treatment}_{iv} + \beta_3 (\text{TRAIL}_v \times \text{Treatment}_{iv}) + \gamma \mathbf{X}_t + \delta \text{Info}_v + \epsilon_{ivt} \quad (9)$$

where y_{ivt} denotes either aggregate farm value-added or its logarithm, for household i, in village v, in year t. The variable TRAIL_v takes the value 1 if the village was randomly assigned to TRAIL treatment and 0 if it was assigned to the GBL treatment. Treatment_{iv} is an indicator variable for Treatment households i in village v, so that the value 0 indicates Control 1 households. The vector $\mathbf{X}_t$ is a set of household covariates in year t, and Info_v is a dummy variable for a price information treatment that was orthogonal to the credit treatment.[17]

Here β_2 and $\beta_2 + \beta_3$ give us the average (conditional) treatment effects for GBL and TRAIL households respectively. All households that were offered the loans in the lottery receive the value 1 for the variable Treatment_{iv} regardless of whether or not they took the loans. Thus these are intent-to-treat estimates.[18]

Our dependent variable is the aggregate farm value-added that household i in village v earned in year t. We see in column 1 of Panel A that the average Treatment household in the TRAIL scheme earned ₹2269 more in farm value-added over the three years of the study than the average Control 1 household in the TRAIL scheme. In the second row, the dependent variable is the logarithm of farm value-added, so that the estimated treatment effects can be interpreted as proportional changes. Thus the absolute effect of ₹2269 translates into a 22% increase in farm value-added over the mean for recommended households. Panel B reports analogous estimates for the GBL loans. The average conditional treatment effect is negative though statistically non-significant ₹251 (or

[17] The price information intervention was undertaken for a separate project aimed at examining the effect of providing information about potato prices to farmers and is similar to the public information treatment described in Mitra, Mookherjee, Torero, and Visaria (2017). Villages were assigned to the information treatment randomly and orthogonally to the credit intervention that is the focus of this paper. The results are unchanged if we do not include this information village dummy in the regression specification.

[18] To the extent that the take-up rate is below 100%, this may understate the true effect of the loans. However in MV when we instrument actual take-up with assignment to treatment we continue to find that the GBL loans had insignificant effects on farm value-added.

–2.6 percent).

4.4 Conditional Treatment Effects on Farm Value-added, by Group

The conditional treatment effects on farm value-added for each land group g are estimated by running a regression according to the following specification:

$$y_{igvt} = \sum_{g=1}^{G} \xi_g(Z_{igv}) + \sum_{g=1}^{G} \zeta_g(Z_{igv} \times \text{TRAIL}_v) + \sum_{g=1}^{G} \lambda_g(Z_{igv} \times \text{Treatment}_{igv}) + \sum_{g=1}^{G} \eta_g(Z_{igv} \times \text{TRAIL}_v \times \text{Treatment}_{igv}) + \gamma \mathbf{Y}_t + \delta \text{Info}_v + \epsilon_{igvt} \quad (10)$$

where Z_{igv} is an indicator for whether household i in village v belongs to land group g. The sample is restricted to Treatment and Control 1 households in the TRAIL and GBL villages. The CTE for land group g is as follows:

λ_g: GBL Treatment effect on household in group g.
$\lambda_g + \eta_g$: TRAIL Treatment effect on household in group g.

The results are presented in columns 2–5 of Table 8. Again, in each panel, the first row presents the effects on farm value-added (measured in ₹). Starting with Panel A, we see that the conditional treatment effects of TRAIL loans vary substantially by land category. Although not statistically significant, the point estimate in column 2 suggests that landless households that were selected to receive TRAIL loans earned ₹541.96 more than landless households who were not selected. Households with more land had substantially larger conditional treatment effects, although they are not always statistically significant. The point estimates are ₹1524 for households with 0–0.5 acres, ₹5126 for those with 0.5–1 acres, and ₹4622 for households with 1–1.5 acres.

However, these absolute changes in incomes could create very different proportional changes, depending on the income levels that these households started from. The last row in Panel A clearly shows that households with greater landholding had higher farm value-added at baseline: there is a strong monotonic increasing pattern in the mean farm value-added for Control 1 households as we move to higher land classes. In particular, Control 1 landless households earned only ₹805 in farm value-added, so that the increase of ₹542 represents a 67 percent increase. In contrast, the ₹1524 CTE for 0–0.5 acre households represents a 21 percent increase. The averate household in the intermediate land class of 0.5–1 acres achieved the only statistically significant increase, of 34 percent. In the highest land class (1–1.5 acres) income increased by 19 percent, although the point estimate is not statistically significant.

The corresponding estimates for the GBL scheme are presented in Panel B. The absolute effect for landless households is estimated at ₹559, although not statistically significant. It is remarkable that the point estimates for all other land classes are smaller than this, and in fact the point estimate for the highest land class is imprecisely estimated at negative ₹6847. Since the baseline farm value-added also increases monotonically with landholding in GBL villages, it is no surprise therefore that landless households achieved the largest proportion increase in farm value-added of 40 percent. For households with 0-0.5 acres and 0.5-1 acres, the point estimate is smaller than 1 percent, and for the 1-1.5 acres households it is negative 26 percent.

We remark on a few observations. First, in both schemes, the landless benefitted disproportionately more than the landed. However, in the TRAIL scheme, the benefits decreased gradually as landholding increased, and in fact, the only statistically significant increase is for households with intermediate landholdings. In contrast, in the GBL scheme the benefits are large only for the landless, and then are either negligible or negative for households that owned land. Thus there is little evidence to suggest that either scheme created relatively larger benefits for wealthier households than for the poor.

Second, when we compare the baseline farm value-added of selected households in each land class, we again find no support for the concern that TRAIL agents disproportionately recommended households that were better-off than households that self-selected in the GBL scheme. Selected landless households in the TRAIL villages earned a baseline farm value-added of only ₹805, whereas selected landless households in GBL villages earned about two-and-a-half times as much, ₹2037. Thus even among the landless, the TRAIL scheme appears to targeted poorer households. In contrast, even though there was no explicit gatekeeper preventing particular landless households from participating, it appears that households that earned very low incomes were either unable to or unwilling to form groups.[19]

This difference in baseline incomes also helps to understand why a ₹542 increase in farm value-added translates into a 67 percent increase for landless households in the TRAIL scheme, while a similar ₹559 increase translates into a smaller 40 percent increase in the GBL scheme. This differential drives our subsequent result that the TRAIL scheme generates larger increases in welfare than the GBL scheme, even at high values of inequality aversion.

[19]The literature on group-based microcredit has noted that it does not appear to serve the poorest of the poor (see Morduch, 1999, Navajas, Schreiner, Meyer, Gonzalez-vega, and Rodriguez-meza, 2000, Amin, Rai, and Topa, 2003). This could be for a variety of reasons: if these households have high relative opportunity costs of time they may be unable to participate in time-intensive group meetings; if they have low and/or irregular disposable incomes they may be unable to make regular savings deposits; or their low/irregular incomes may prevent other households from forming groups with them.

4.5 Expected Treatment Effects

The product of a scheme's conditional treatment effect on group g and its selection frequency for group g tells us its expected treatment effect (ETE) on households of group g. As we see in Panel A of Table 8, a randomly selected landless household could expect to earn ₹32 (or 4 percent) more per year if the TRAIL scheme were introduced in its village. The expected treatment effects for more landed households are lower: 1.5 percent, 2.3 percent and 1.3 percent.

Given our discussion above, it is unsurprising that in GBL villages, the expected treatment effects are substantially larger for the landless than for the other land groups. Comparing across schemes, again, we see that landless households could expect a 40 percent larger treatment effect in TRAIL villages than in GBL villages. Similarly, in other land groups as well, the TRAIL scheme outperformed the GBL scheme.

4.6 Impacts on Aggregate Welfare

The impacts on aggregate welfare can now be estimated by implementing equation (4). Table 9 presents the results for welfare functions with six different values of the inequality aversion parameter θ, equal to 0, 1, 2, 3, 4, and 5. We start with the case where $\theta = 0$. Clearly in this case, the change in welfare $\Delta^r w$ is identical to the weighted average of the expected treatment effects.

In Panel A we examine the welfare effects of the TRAIL scheme. Row 1 indicates that the average household with less than 1.5 acres of land in a TRAIL village could expect an increase of ₹182 in its farm income. Given the mean baseline farm income of ₹6396, this translates into a 2.8 percent increase in farm income.[20] A similar calculation in Panel B for the GBL scheme indicates that the average eligible household in a GBL village could expect its farm income to decline by 0.28 percent.

Thus the point estimates indicate that the TRAIL scheme increased aggregate welfare, while the GBL scheme decreased it. To assess if this difference in welfare impacts is statistically significant, we conduct a Mann-Whitney rank sum test on 2000 bootstrap estimates of the welfare effects.[21] The results of these rank sum tests are presented in Panel C. They indicate that the TRAIL

[20] The baseline income for TRAIL (GBL) is the population-weighted average of the farm incomes of Control 1 and Control 2 households in all TRAIL (GBL) villages.

[21] Bootstrap samples were drawn using a stratified (by treatment arm) clustered (by village) random procedure, to ensure that each sample contained all original sample households from an equal number of randomly drawn TRAIL and GBL villages. In each bootstrap sample we estimate the selection frequency for each group g, and multiply this with the estimates of the conditional treatment effects to arrive at the expected treatment effects, which are then used to compute the relative change in welfare in line with equation (4). We then use Hall's percentile method to compute the 90% confidence interval around the estimate of the relative change in welfare from our original sample.

scheme unambiguously increased welfare by more than GBL scheme did.

When $\theta = 1$ the welfare change is the weighted average of the expected proportional treatment effects. As θ rises to 2 and above the impacts on poorer households are weighted increasingly more in the welfare calculation. Recall that the GBL scheme had negative point estimates for expected treatment effects only for the highest land class (those with 1–1.5 acres of land), but all other land classes registered an increase in income. Therefore it is not surprising that when the incomes of poorer households receive more weight, the GBL scheme also increases aggregate welfare, as evidenced by the positive point estimates in the first row of Panel B, from columns 2 through 6. However we see through that the increase in welfare due to the GBL scheme was smaller than that caused by the TRAIL program. Using the Mann-Whitney test we reject, for all values of θ, the null hypothesis that the GBL scheme produced a larger or equal increase in welfare than the TRAIL scheme.

In Panel B of Table 9, we also present the "adjusted" relative changes in welfare for the GBL scheme. The adjustment corrects for the fact that the total population across the GBL villages is 39.7% higher than the total population across the TRAIL villages. Given the restriction on the size of the loan scheme, this could have led to smaller selection frequencies in the GBL scheme on average. Although, as we saw in Table 2 the difference in population across the two treatment arms was not significant, we nevertheless check whether the welfare comparison is robust to this adjustment. We adjust the selection frequency in each group g by 1.397 and then re-estimate the relative change in welfare. As can be seen, this increases the size of the relative change in welfare. However it does not reverse the welfare comparison of the two schemes (see Panel C).

5 Distributive Impacts by Social Group

Religion and caste are important indicators of socio-economic status in the Indian context. To the extent that correlations between landholding and social group are imperfect, we might obtain different results depending on which classification is used to partition households. Therefore, in this section we examine the distributive impacts when we partition households into three categories based on social groups: scheduled caste/scheduled tribe, non-Hindu and general caste Hindus. The estimating equation is again given by equation (10), with g here representing the social groups.

5.1 Population Proportions (α_g)

In Panel B of Table 7, columns 1 and 3 present the population proportions for each social group, taken as a share of the total eligible households. More than half the households in TRAIL villages belonged to the general caste Hindu group. SC/STs were 30 percent of households and thus the largest minority. Non-Hindus (who were all Muslim in our data) formed 18 percent. The proportions were roughly similar in GBL villages: 58 percent were general caste Hindus, 29 percent were SC/STs and 13 percent were non-Hindu. These population proportions will be used to aggregate the welfare effects across social groups.

5.2 Selection Frequencies (p_g)

Once again, the likelihood that households belonging to particular segments of the distribution are selected into (or self-select into) the scheme helps to determine how the treatment effects are distributed across segments. In Panel B of Table 7 columns 2 and 4 present the estimated selection frequencies for each social group g.

In TRAIL villages, SC/ST households have the highest likelihood of being recommended: 7.3 percent of SC/ST households with up to 1.5 acres of land were recommended by the TRAIL agent. However selection frequencies are only slightly lower for the other groups (6.5 percent for non-Hindus and 6.7 percent for general caste Hindus), so that there is not much variation across groups.

In GBL villages also SC/STs had the highest likelihood of selection: 7.3 percent of SC/ST households joined GBL groups that survived the 6-month initiation period. Only 5 percent of non-Hindus did, and an even lower 4 percent of general caste Hindus did. This pattern reflects the pattern we had seen in the analysis with land partitioning: households with higher status appear to have been less willing to participate in the GBL scheme, which may be due to their higher opportunity cost of time.

5.3 Conditional Treatment Effects on Farm Value-added

Once again, we follow equation (10) to estimate the conditional treatment effects of the loan schemes for the three social groups. In the top two rows of Panel A in Table 10 we see that the point estimate for SC/STs is ₹698 (or 12 percent, although it is statistically non-significant). The point estimate for non-Hindus is nearly 3 times as large at ₹2053 (22 percent) although it is also non-significant. The largest conditional treatment effect is estimated at ₹3264 (or 24 percent) for general caste Hindus, statistically significant at the 1 percent level. Thus the largest treatment effects are realized by the general caste Hindus.

The last row of Panel A shows the mean farm value-added of Control 1 households in each group. It is clear from this that SC/STs had the lowest baseline farm incomes, whereas general caste Hindus earned 2.4 times at ₹13360. Thus when we partition households by social group, we see that the most well-off households received the largest increases in income, both in absolute and in proportional terms.

The results are considerably different when we consider the results for the GBL scheme, presented in Panel B. The treatment effects for SC/STs are about ₹828 (or 18 percent), although not statistically significant. General caste Hindus have a negative point estimate (representing an 11 percent decline in farm income), although this is imprecisely estimated as well. The only group with statistically significant and positive conditional treatment effects is the non-Hindus, whose farm incomes increased by ₹2010, or a substantial 34 percent.

The bottom row of the panel also shows that there is a hierarchy in baseline farm incomes that matches social status. Thus non-Hindus had considerably lower baseline farm incomes than the general caste Hindus, although marginally higher than SC/STs. Thus the results indicate that the GBL scheme increased the incomes of the relatively worse-off households, and if anything, decreased the incomes of the most well-off social groups.

5.4 Expected Treatment Effects

The expected treatment effects in the fourth row of Panel A and Panel B are the products of the conditional treatment effects and the selection frequencies. In the TRAIL scheme, given that the selection frequencies are similar across social groups, it is no surprise that the expected treatment effects in Panel A follow the same pattern as the conditional treatment effects, with the largest effects realized for the most well-off general caste Hindus and the smallest effects for the most underprivileged SC/STs. In Panel B as well, we see that the expected treatment effects are largest for non-Hindus, followed closely by SC/STs. The estimates are naturally negative for the general caste Hindus, although the large baseline incomes of this group imply that their incomes fall by a small percentage.

5.5 Impacts on Aggregate Welfare

Finally, in Table 11 we follow equation (4) and aggregate these expected treatment effects to arrive at welfare effects. Once again, with $\theta = 0$ we are looking at a population-weighted average of the expected treatment effects on farm income for the three social groups. Column 1 in Panel

A indicates that the TRAIL scheme would increase farm income by ₹153 for the average eligible household in a TRAIL village. This would be a 2.4 percent increase over the mean baseline income. In contrast, column 1 in Panel B indicates that the GBL scheme would *decrease* farm income by ₹6 for the average eligible household in a GBL village, which would be a 0.9 percent decrease from mean baseline income. Column 1 in Panel C shows that this difference between the welfare effects of the two schemes is statistically significant: the Mann-Whitney test allows us to reject with near-certainty the null hypothesis that the GBL scheme caused a larger increase in welfare.

From columns 2 through 6 we repeat this exercise, but for increasing values of inequality aversion, which put increasingly larger weight on the welfare of poorer households. Parallel to our analysis in Table 9, we add a large constant to the farm value-added figures to avoid dropping households with negative farm incomes, and we multiply the resulting farm value-added numbers by a positive constant so that the welfare estimates are large enough for the software to operate them. Therefore it is best to only compare welfare effects across the two schemes but not across values of θ.

Recall that we found above that the TRAIL scheme benefited the relatively better-off general caste Hindu households by more than it benefited the SC/ST and non-Hindu households. In contrast the GBL scheme, although it had no significant effects on farm income on average, benefited the non-Hindu and SC/ST households by more. At higher values of θ, it should therefore come as no surprise that the relative increases in welfare are larger in the GBL scheme than in the TRAIL scheme. However, perhaps because the mean effect of the GBL scheme is small and non-significant, the p-values of the Mann-Whitney rank sum tests are always too large to allow us to state with any confidence that the GBL scheme had a larger positive effect on welfare.

6 Effects on Total Inequality

The conditional and expected treatment effects are estimated as a common effect for an entire group g. Thus any inferences we make about the effects of the scheme on inequality are only for between-group inequality. However, aggregate welfare is a function of average income and *total* inequality, which incorporates both between- and within-group inequality. In Table 12 we follow equation (5) and compute measures of total inequality in our sample villages, for the baseline (using the farm incomes of Control 2 and Control 1 households) and for the endline (using farm incomes of Control 2 and Treatment households). This allows us to examine the effect of the scheme on inequality. It is clear from the table that the TRAIL scheme decreased inequality at low values of θ, but increased it at high values of θ. In contrast, the GBL scheme decreased inequality, measured at all values of θ.

Therefore if we only consider inequality, GBL dominates TRAIL. However since we are interested in welfare, TRAIL dominated GBL because of its efficiency advantages. The decrease in inequality in the GBL scheme is not accompanied by an increase in average incomes. In contrast, even though the TRAIL scheme increases inequality somewhat, this negative effect on inequality is dominated by the increase in income.

7 Mechanisms

What drives our empirical results? We start by noting that the TRAIL scheme is no less inclusive than the GBL scheme. It is true that in the TRAIL scheme, only a single agent recommended borrowers, whereas in the GBL scheme, any eligible borrower could form a group. However, in practice, the barriers to entering the GBL scheme may be higher. Despite having a larger population of eligible households, slightly fewer households in GBL villages participated in the loan scheme than in the TRAIL villages. In particular, the GBL scheme appears to have kept out the poorest landless households. Selected landless households in the TRAIL scheme were poorer at baseline than selected landless households in the GBL scheme. This fact matches well the empirical finding in the literature that group-based microcredit does not cater to the poorest of the poor (see Morduch, 1999, Navajas, Schreiner, Meyer, Gonzalez-vega, and Rodriguez-meza, 2000, Amin, Rai, and Topa, 2003). Perhaps the very poor are unable to find groups that will accept them as members. Alternatively, they may be unable to self-organize or to meet the savings requirement necessary to become eligible to borrow.

In contrast, the TRAIL agents do not appear to have avoided poor borrowers. This may be because the agent relied on social or economic networks to identify borrowers whom he recommended, and he was likely to have interacted with (and therefore possibly observed the "ability" of, or had the power to monitor or assist) households across a range of economic and social strata, including the poorest stratum. In Table 13 we see that across land classes, the TRAIL agent was more likely to recommend productive households that he had prior interactions with – either in the economic sphere through having sold or lent to them or employed them, or in the social sphere because they belonged to the same social group as him. Compared to a representative sample of landless households, those that he recommended were more likely to have worked for him (particularly in his field).[22] Among the intermediate land classes, those that he recommended were more likely to have bought or borrowed from him, and among the more landed households, those whom he recommended were more likely to be members of his own religious or caste group. Our results suggest the agent selected them because he knew they were productive. This could explain why even the relatively poorer landless households earned absolute treatment effects in the TRAIL

[22]The representative sample consists of a subset of households in this sample who were included in a stratified random sample of those villages drawn in 2007.

scheme that were comparable to those earned by the better-off landless households in the GBL scheme.[23]

In GBL, the realized benefits appear to be larger for groups with greater social homogeneity and mutual assistance. Table 14 shows that non-Hindu and SC/ST borrowers in the GBL scheme were in groups with other households that were more similar to them. Eighty percent of them said they had joined the group at the invitation of other members, rather than because they had been encouraged to join the group by MFI officers. In contrast, only 61 percent of general caste GBL borrowers gave this answer, and 56 percent of SC/ST GBL borrowers did. Non-Hindu borrowers were also more likely to say that they had received or given assistance from/to other members of their group. Although these groups were relatively diverse in terms of occupation, non-Hindu groups were more likely to be homogeneous (as measured by the proportion of group members who belonged to the same social category and the Herfindahl index of concentration). However, economic inequality (measured by land, education or occupation) was less well correlated with group success. Clearly general castes were in the most diverse groups: only 17 percent of the group members belonged to the same sub-caste as the average general caste Hindu GBL borrower.[24] Hence these results suggest that social capital matters for the success of GBL loans. Since non-Hindus and SC/ST groups which were more homogenous and exhibited greater mutual assistance were also poorer than the general caste Hindus, GBL tended to reduce inequality when households are distinguished by social group.

8 Conclusion

In this paper, using data from a field experiment conducted in India, we examine the equity implications of two alternative approaches to deliver agricultural credit to smallholders. In TRAIL local traders recommended households for individual liability micro-loans. In GBL households self-selected into groups to receive joint liability loans. We estimate how the distributive impacts of these schemes differ by households' economic and social status. Our method accounts for endogenous selection frequencies in each group and the treatment effects on farm income conditional on selection, to estimate the impacts of each scheme on Atkinson-based measures of welfare and inequality. We find that TRAIL loans increased farm incomes for all land groups, but partic-

[23] We show in MV that the GBL scheme creates incentives for both the able and less able households to form groups. Therefore it is less likely that households positively select into participation. Thus in this framework there is no clear prediction in terms of the nature of assortative matching. However, in groups where members were positively assortatively matched on project risk, each borrower would face lower joint liability tax, which would generate greater incentives to succeed.

[24] To compute the estimates for the proportion of group members in same social group, and the Herfindahl index, we use the surname of each general caste Hindu GBL borrower to identify the borrower's position in the social hierarchy of general castes. We classify the sub-castes into three strata: high caste, middle caste and low caste. For a group consisting of any general caste Hindu we then compute the proportion of group members who belong to the same stratum.

ularly for landless households. As a result, across land groups, the TRAIL scheme generated significantly greater welfare than the GBL scheme, irrespective of inequality aversion. The GBL scheme generated larger effects among the socially disadvantaged minority groups. Our results therefore suggest that that that the efficiency and equity implications of the two schemes might be different depending on how we partition households.

In summary, the evidence does not support the view that TRAIL worsened the income distribution and generated negative welfare effects. There are high-ability borrowers among landless households, and that TRAIL agents were able to identify them. Once these households were selected and provided with loans with appropriate incentives to succeed, they were able to achieve large increases in income. In comparison with GBL, TRAIL selected landless households that were poorer, and yet were able to earn similar increases in income. Thus if we focus on landless households alone, TRAIL generated more benign distributive impacts than GBL did. Therefore, when households are distinguished on the basis of land class, TRAIL had superior welfare impacts, regardless of the degree of inequality aversion.

On the other had, we find that even joint liability loans increase borrower incomes for borrowers from disadvantaged social groups. Although it is difficult to pin-point why or how this effect comes about, we note that SC/ST and non-Hindu borrowers belonged to more homogenous groups and reported assisting each other more. When they consider traditional joint liability loans with the usual high-frequency repayment schedules, Banerjee, Duflo, Glennerster, and Kinnan (2015) find that only borrowers at the top end of the income distribution see positive effects. Our result differs from theirs, although the two studies are not directly comparable because of differences in loan duration and repayment schedules.

Nevertheless, this result casts doubt on the idea that joint liabiilty loans generate no income benefits, but that they only enable poor households to withstand shocks. At least on the social dimension, it appears that the disadvantaged can increase their incomes with the help of joint liability microcredit designed to facilitate agricultural investments. Thus there appears to be some evidence for a trade-off between efficiency and equity, at least on the social dimension. To address equity goals, it might be advisable to offer both individual and joint liability programs at the same time.

However before any further policy implications can be drawn, further experimentation with TRAIL and GBL is needed. We do not yet know much about how well these results generalize to other contexts, how the programs would fare if the number of borrowers per village were scaled up, and the trade-offs between commissions to TRAIL agents and financial sustainability. Future work will address these issues.

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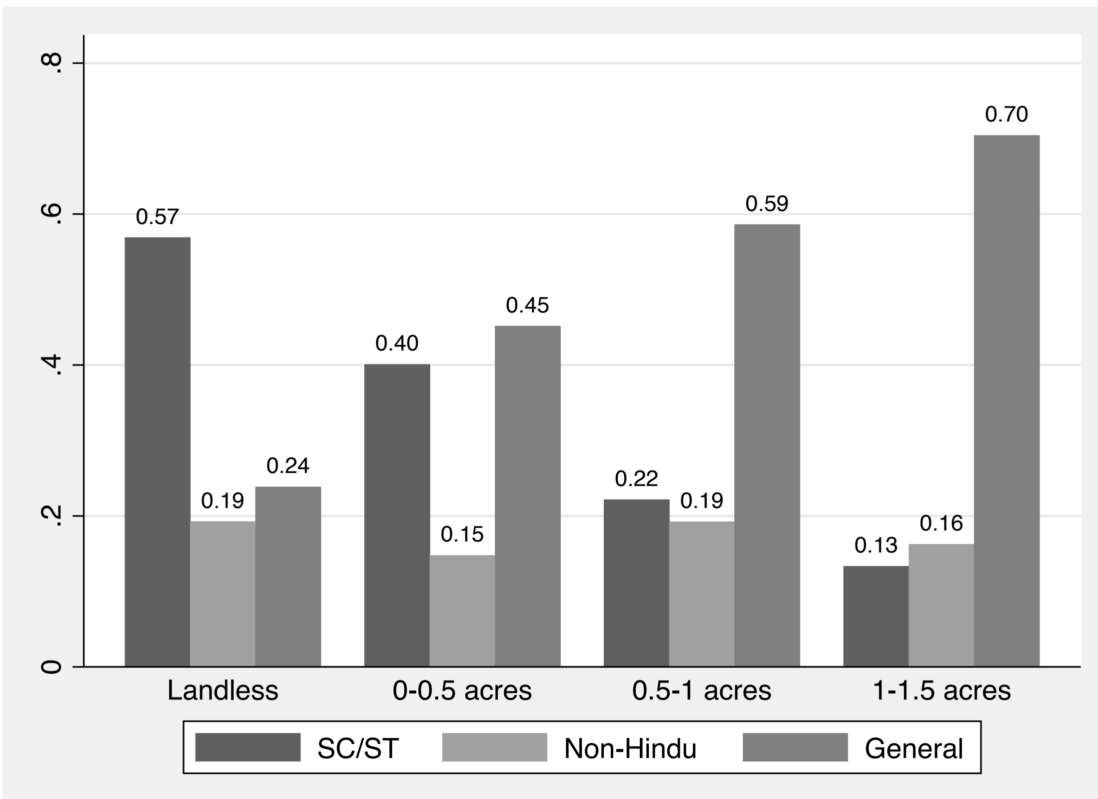
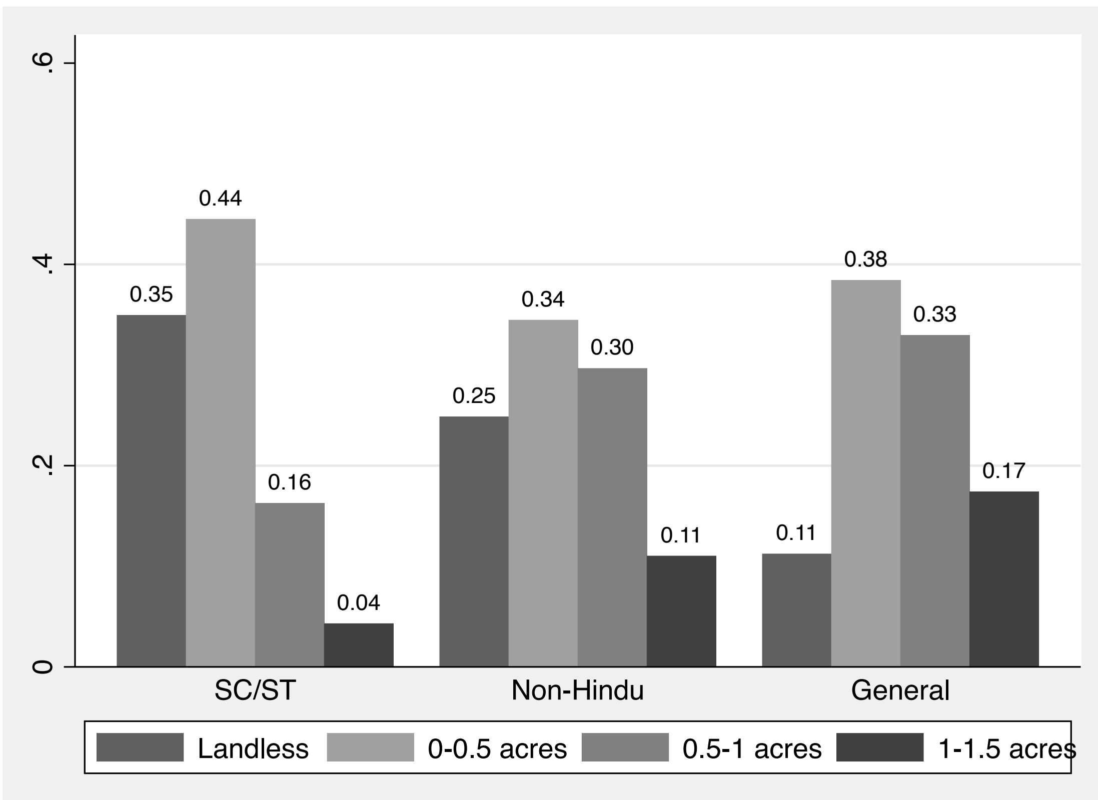
Figure 1: Proportion of each land category, by social group



Note: Sample includes all sample households in TRAIL and GBL villages.

Figure 2: Proportion of each social group, by land category



Note: Sample includes all sample households in TRAIL and GBL villages.

Table 1: Balance of Village Characteristics, TRAIL v. GBL Villages

	TRAIL (1)	**GBL** (2)	**Difference** (3)
Panel A: Village Size			
Number of households	327.63	457.58	-129.96
	(52.28)	(88.35)	(102.66)
Panel B: Distribution by Land Group			
Proportion landless	0.18	0.17	0.02
	(0.03)	(0.02)	(0.03)
Proportion 0-0.5 acres	0.32	0.34	-0.02
	(0.03)	(0.03)	(0.04)
Proportion 0.5-1 acre	0.23	0.22	0.01
	(0.02)	(0.02)	(0.03)
Proportion 1-1.5 acres	0.10	0.11	-0.01
	(0.01)	(0.01)	(0.02)
Proportion $>$ 1.5 acres	0.17	0.17	-0.00
	(0.02	(0.02)	(0.03)
Panel C: Distribution by Social Group			
Proportion SC/ST	0.31	0.33	-0.02
	(0.04)	(0.06)	(0.08)
Proportion Non-Hindu	0.21	0.16	0.05
	(0.06)	(0.06)	(0.09)
Proportion General caste Hindu	0.48	0.53	-0.05
	(0.06)	(0.07)	(0.09)
Panel D: Village Characteristics			
Percent households electrified	0.603	0.591	0.011
	(0.06)	(0.05)	(0.08)
Has primary school	0.773	0.792	-0.02
	(0.09)	(0.08)	(0.12)
Has primary health centre	0.273	0.208	0.064
	(0.10)	(0.08)	(0.13)
Has bank branch	0.00	0.17	-0.17
	(0.00)	(0.08)	(0.08)
Has MFI	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Has *pucca* road	0.273	0.417	-0.144
	(0.10)	(0.10)	(0.14)
F-statistic for test of joint significance		0.66	
p-value		0.76	

Notes:
In Panels A–C, we use data from the Census of India 2011 and Cycle 1 of the household surveys conducted in 2010 in all 48 villages. We use census data on the total number of households in each village to scale up the sample proportions in each land class and social group to estimate the proportions in the entire village. In Panel D, we use data from village surveys conducted in the sample villages in 2007 in 46 of the 48 villages. Treatment and Control 1 households are weighted by the probability that they occur in the sample, which is $\frac{30}{N}$; Control 2 households are weighted by $\frac{N-30}{N}$. Standard errors are in parentheses. $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$

Table 2: Balance of Household Characteristics, TRAIL v. GBL Villages

	TRAIL (1)	GBL (2)	Difference (3)
Head's education: primary and more	0.444	0.429	0.015
	(0.015)	(0.015)	(0.022)
Head's occupation: cultivation	0.454	0.414	0.041*
	(0.016)	(0.015)	(0.022)
Head's occupation: labour	0.357	0.366	-0.010
	(0.015)	(0.015)	(0.021)
Area of house and homestead (acres)	0.053	0.053	0.000
	(0.001)	(0.002)	(0.002)
Separate toilet in house	0.568	0.536	0.032
	(0.015)	(0.016)	(0.022)
Landholding (acres)	0.459	0.433	0.025
	(0.013)	(0.013)	(0.018)
Owns motorised vehicle	0.118	0.110	0.008
	(0.010)	(0.010)	(0.014)
Has savings bank account	0.453	0.428	0.025
	(0.016)	(0.015)	(0.022)
F-statistic for test of joint significance			0.17
p-value			0.994

Notes: Data are taken from cycle 1 of the household surveys. The sample consists of Treatment, Control 1 and Control 2 households in the 48 villages where the TRAIL and GBL loan schemes were implemented. Treatment and Control 1 households are weighted by the probability that they occur in the sample, which is $\frac{30}{N}$; Control 2 households are weighted by $\frac{N-30}{N}$. Standard errors are in parentheses. The statistical significance of differences in column 3 is computed using a two-sided t-test. Significance: $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$.

Table 3: Descriptive Characteristics of Sample Households, by Land Category

	Average (1)	**Landless** (2)	**0–0.5 acres** (3)	**0.5–1.0 acres** (4)	**1.0–1.5 acres** (5)
Age of head (years)	48.82	45.63	48.46	50.49	51.65
	(0.281)	(0.603)	(0.436)	(0.526)	(0.849)
Head's education: primary school or more	0.420	0.211	0.366	0.552	0.654
	(0.011)	(0.019)	(0.017)	(0.021)	(0.031)
Head's primary occupation: cultivation	0.438	0.057	0.374	0.692	0.726
	(0.011)	(0.011)	(0.017)	(0.020)	(0.029)
Head's primary occupation: casual labor	0.332	0.673	0.409	0.091	0.043
	(0.010)	(0.022)	(0.017)	(0.012)	(0.013)
Landholding (Acres)	0.464	0.000	0.261	0.755	1.237
	(0.009)	(0.000)	(0.005)	(0.006)	(0.009)
Area of house and homestead (acres)	0.053	0.037	0.047	0.064	0.075
	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)
Pucca house	0.273	0.171	0.259	0.324	0.377
	(0.010)	(0.018)	(0.015)	(0.020)	(0.031)
Electrified house	0.750	0.634	0.733	0.824	0.838
	(0.010)	(0.023)	(0.015)	(0.016)	(0.024)
Separate kitchen in house	0.527	0.373	0.503	0.622	0.657
	(0.011)	(0.023)	(0.017)	(0.021)	(0.031)
Separate toilet in house	0.558	0.398	0.527	0.650	0.720
	(0.011)	(0.023)	(0.017)	(0.020)	(0.029)
Owns radio/TV/VCR/DVD	0.452	0.325	0.398	0.543	0.636
	(0.011)	(0.022)	(0.017)	(0.021)	(0.031)
Owns motorized vehicle	0.127	0.068	0.073	0.181	0.272
	(0.007)	(0.012)	(0.009)	(0.016)	(0.029)
Owns phone (mobile or landline)	0.591	0.420	0.536	0.712	0.781
	(0.011)	(0.023)	(0.017)	(0.019)	(0.027)
Has savings bank account	0.446	0.250	0.414	0.542	0.667
	(0.011)	(0.020)	(0.017)	(0.021)	(0.030)
Has insurance policy	0.286	0.139	0.247	0.375	0.461
	(0.010)	(0.016)	(0.015)	(0.021)	(0.032)

Notes: Data are taken from cycle 1 of the household surveys. The sample consists of Treatment, Control 1 and Control 2 households in the 48 villages where the TRAIL and GBL loan schemes were implemented. Treatment and Control 1 households are weighted by the probability that they occur in the sample, which is $\frac{30}{N}$; Control 2 households are weighted by $\frac{N-30}{N}$. Standard errors are in parentheses. $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$

Table 4: Balance of Household Characteristics by Land Category, TRAIL v. GBL Villages

	Landless			0–0.5 acres			0.5–1.0 acres			1.0–1.5 acres		
	TRAIL	**GBL**	**Difference**	**TRAIL**	**GBL**	**Difference**	**TRAIL**	**GBL**	**Difference**	**TRAIL**	**GBL**	**Difference**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Head's education: primary and more	0.255	0.282	-0.028	0.377	0.362	0.015	0.584	0.565	0.019	0.678	0.656	0.022
	(0.030)	(0.029)	(0.042)	(0.024)	(0.024)	(0.034)	(0.029)	(0.031)	(0.042)	(0.043)	(0.043)	(0.061)
Head's occupation: cultivation	0.079	0.062	0.016	0.389	0.348	0.041	0.699	0.0696	0.003	0.771	0.73	0.042
	(0.018)	(0.016)	(0.012)	(0.024)	(0.023)	(0.034)	(0.027)	(0.029)	(0.034)	(0.039)	(0.040)	(0.056)
Head's occupation: labour	0.708	0.668	0.04	0.443	0.447	-0.004	0.098	0.104	-0.006	0.042	0.057	-0.015
	(0.031)	(0.030)	(0.043)	(0.025)	(0.024)	(0.035)	(0.018)	(0.019)	(0.026)	(0.012)	(0.021)	(0.028)
Area of house and homestead (acres)	0.038	0.037	0.001	0.051	0.045	0.006**	0.060	0.069	-0.008	0.073	0.081	-0.009
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.005)	(0.005)	(0.006)	(0.007)	(0.009)
Separate toilet in house	0.449	0.357	0.092	0.554	0.502	0.051	0.643	0.653	-0.009	0.650	0.754	-0.105*
	(0.034)	(0.031)	(0.046)	(0.025)	(0.025)	(0.035)	(0.028)	(0.030)	(0.041)	(0.044)	(0.039)	(0.059)
Owns motorised vehicle	0.06	0.054	0.006	0.078	0.07	0.008	0.175	0.146	0.029	0.229	0.279	-0.05
	(0.016)	(0.015)	(0.022)	(0.013)	(0.013)	(0.018)	(0.022)	(0.022)	(0.032)	(0.039)	(0.041)	(0.056)
Has savings bank account	0.25	0.253	-0.003	0.411	0.383	0.028	0.566	0.562	0.005	0.695	0.639	0.056
	(0.030)	(0.028)	(0.041)	(0.024)	(0.024)	(0.034)	(0.029)	(0.031)	(0.043)	(0.043)	(0.044)	(0.061)
F-statistic for test of joint significance		0.30			0.97			0.81			1.35	
p-value		0.951			0.462			0.583			0.247	

Notes: Data are taken from cycle 1 of the household surveys. The sample consists of Treatment, Control 1 and Control 2 households in the 48 villages where the TRAIL and GBL loan schemes were implemented. Treatment and Control 1 households are weighted by the probability that they occur in the sample, which is $\frac{30}{N}$; Control 2 households are weighted by $\frac{N-30}{N}$. Standard errors are in parentheses. The statistical significance of differences presented in columns 3, 6, 9 and 12 are computed using a two-sided t-test. Significance: $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$.

Table 5: Descriptive Characteristics of Sample Households, by Social Group

	Total (1)	**SC/ST** (2)	**Non-Hindu** (3)	**General** (4)
Age of head (years)	48.829	47.144	47.121	50.794
	(0.281)	(0.467)	(0.697)	(0.397)
Head's education: primary school or more	0.420	0.222	0.317	0.614
	(0.011)	(0.015)	(0.025)	(0.016)
Head's primary occupation: cultivation	0.439	0.284	0.432	0.560
	(0.011)	(0.017)	(0.026)	(0.016)
Head?s primary occupation: casual labor	0.331	0.562	0.276	0.176
	(0.010)	(0.018)	(0.024)	(0.012)
Landholding (acres)	0.465	0.293	0.482	0.590
	(0.009)	(0.013)	(0.022)	(0.014)
Area of house and homestead (acres)	0.053	0.047	0.061	0.055
	(0.001)	(0.001)	(0.003)	(0.002)
Pucca house	0.273	0.112	0.329	0.376
	(0.010)	(0.012)	(0.025)	(0.016)
Electrified house	0.750	0.604	0.792	0.846
	(0.010)	(0.018)	(0.022)	(0.012)
Separate kitchen in house	0.527	0.368	0.536	0.646
	(0.011)	(0.018)	(0.027)	(0.015)
Separate toilet in house	0.558	0.321	0.612	0.719
	(0.011)	(0.017)	(0.026)	(0.014)
Own a radio/ TV/ VCR/ DVD	0.453	0.318	0.387	0.583
	(0.011)	(0.017)	(0.026)	(0.016)
Owns motorized vehicle	0.126	0.030	0.155	0.189
	(0.007)	(0.006)	(0.019)	(0.013)
Owns phone (mobile or landline)	0.590	0.413	0.691	0.687
	(0.011)	(0.018)	(0.025)	(0.015)
Has savings bank account	0.446	0.284	0.408	0.586
	(0.011)	(0.017)	(0.026)	(0.016)
Has insurance policy	0.287	0.161	0.237	0.403
	(0.010)	(0.013)	(0.023)	(0.016)

Notes: Data are taken from cycle 1 of the household surveys. The sample consists of Treatment, Control 1 and Control 2 households in the 48 villages where the TRAIL and GBL loan schemes were implemented. Treatment and Control 1 households are weighted by the probability that they occur in the sample, which is $\frac{30}{N}$; Control 2 households are weighted by $\frac{N-30}{N}$. Standard errors are in parentheses. $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$

Table 6: Balance of Household Characteristics by Social Group, TRAIL v. GBL Villages

	SC/ST			Non-Hindu			General		
	TRAIL (1)	**GBL** (2)	**Difference** (3)	**TRAIL** (4)	**GBL** (5)	**Difference** (6)	**TRAIL** (7)	**GBL** (8)	**Difference** (9)
Head's education: primary and more	0.243	0.249	-0.005	0.287	0.395	-0.108	0.648	0.59	0.058
	(0.023)	(0.022)	(0.032)	(0.032)	(0.040)	(0.050)	(0.022)	(0.022)	(0.031)
Head's occupation: cultivation	0.267	0.274	-0.007	0.436	0.388	0.047	0.593	0.538	0.055
	(0.024)	(0.022)	(0.033)	(0.035)	(0.040)	(0.053)	(0.022)	(0.023)	(0.032)
Head's occupation: labour	0.598	0.590	0.009	0.327	0.303	0.024	0.200	0.201	0.000
	(0.027)	(0.025)	(0.036)	(0.033)	(0.037)	(0.050)	(0.02)	(0.02)	(0.026)
Area of house and homestead (acres)	0.048	0.048	0.000	0.058	0.065	-0.007	0.055	0.054	0.001
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.006)	(0.002)	(0.003)	(0.003)
Separate toilet in house	0.374	0.281	0.092***	0.554	0.697	-0.143	0.709	0.697	0.012
	(0.026)	(0.022)	(0.034)	(0.035)	(0.037)	(0.052)	(0.021)	(0.021)	(0.029)
Landholding (acres)	0.290	0.263	0.027	0.431	0.476	-0.045	0.587	0.562	0.026
	(0.018)	(0.017)	(0.025)	(0.029)	(0.033)	(0.044)	(0.019)	(0.019)	(0.027)
Owns motorised vehicle	0.026	0.009	-0.008	0.153	0.105	0.048	0.168	0.174	-0.006
	(0.035)	(0.009)	(0.013)	(0.025)	(0.024)	(0.036)	(0.017)	(0.017)	(0.024)
Has savings bank account	0.270	0.270	-0.001	0.411	0.401	0.010	0.597	0.567	0.030
	(0.024)	(0.022)	(0.033)	(0.035)	(0.040)	(0.052)	(0.022)	(0.023)	(0.032)
F-statistic for test of joint significance		0.99			1.33			0.47	
p-value		0.455			0.274			0.869	

Notes: Data are taken from cycle 1 of the household surveys. The sample consists of Treatment, Control 1 and Control 2 households in the 48 villages where the TRAIL and GBL loan schemes were implemented. Treatment and Control 1 households are weighted by the probability that they occur in the sample, which is $\frac{30}{N}$; Control 2 households are weighted by $\frac{N-30}{N}$. Standard errors are in parentheses. The statistical significance of differences presented in columns 3, 6, 9 and 12 are computed using a two-sided t-test. Significance: $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$.

Table 7: Population Proportions and Selection Frequencies, by Land Category and Social Group

	TRAIL		GBL	
	Population proportion (α) (1)	**Selection frequency** (p) (2)	**Population proportion** (α) (3)	**Selection frequency** (p) (4)
	Panel A: Land Categories			
Landless	0.226	0.059	0.198	0.073
0–0.5 acres	0.392	0.074	0.377	0.054
0.5–1.0 acres	0.279	0.068	0.285	0.040
1.0–1.5 acres	0.103	0.070	0.140	0.032
	Panel B: Social Groups			
SC/ST	0.303	0.073	0.290	0.073
Non-Hindu	0.177	0.065	0.127	0.050
General	0.520	0.067	0.583	0.040

Notes: The population of households in TRAIL (GBL) villages is defined as the total number of households in all 24 TRAIL (GBL) villages that owned no more than 1.5 acres of land. In columns (1) and (3) we report the proportion of this population that belongs to each land category (in Panel A) and to each social group (in Panel B). In columns (2) and (4) we report the fraction of the households in each land category (in Panel A) or social group (in Panel B) that were selected into the scheme, through recommendation by the agent in the TRAIL villages, and through self-selection into groups in the GBL villages.

Table 8: Conditional and Expected Treatment Effects on Farm Value-added, by Land Category

	Average (1)	**Landless** (2)	**0–0.5 acres** (3)	**0.5–1.0 acres** (4)	**1.0–1.5 acres** (5)
			Panel A: TRAIL		
Conditional treatment effects on:					
Farm value-added	2268.98***	541.96	1524.02	5126.07***	4621.85
	(611.51)	(643.30)	(930.12)	(1590.83)	(4217.93)
Log(Farm value-added)	0.221***	0.671	0.208	0.338***	0.187
	(0.059)	(0.793)	(0.124)	(0.105)	(0.173)
Selection frequency	0.069	0.059	0.074	0.068	0.070
Expected treatment effects on:					
Farm value-added	156.56	31.98	112.78	348.57	323.53
Log(Farm value-added)	0.015	0.040	0.015	0.023	0.013
Mean farm value added, Control 1 households	10142.06	804.64	7381.46	15143.26	23975.78
			Panel B: GBL		
Conditional treatment effects on:					
Farm value-added	-251.22	559.47	72.02	86.95	-6847.16
	(1100.34)	(823.79)	(1118.62)	(2910.12)	(5511.61)
Log(Farm value-added)	-0.026	0.397	0.008	0.009	-0.260
	(0.115)	(0.516)	(0.156)	(0.198)	(0.210)
Selection frequency	0.051	0.073	0.054	0.040	0.032
Expected treatment effects on:					
Farm value-added	-12.81	40.84	3.89	3.48	-219.11
Log(Farm value-added)	-0.001	0.029	0.000	0.000	-0.008
Mean farm value added, Control 1 households	9387.58	2037.06	7073.69	14595.95	26169.03

Notes: Estimates of conditional treatment effects in columns 1 and 2–5 are derived from specifications presented in equations (9) and (10) respectively. Standard errors in parentheses are clustered at the village level. Significance: $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$.

Table 9: Changes in Welfare, Partitioning by Land

	$\theta = 0$ (1)	$\theta = 1$ (2)	$\theta = 2$ (3)	$\theta = 3$ (4)	$\theta = 4$ (5)	$\theta = 5$ (6)
Panel A: TRAIL						
Change in Mean Welfare	181.76	0.019	77.46	6759.88	6.76E+06	6.98E+05
Mean Baseline Welfare	6396.3	9.21	6.60	0.33	0.22	1.61E-05
Relative Change in Mean Welfare × 100	2.84	0.208	1173.56	2.07E+06	3.13E+09	4.34E+12
Panel B: GBL						
Change in Mean Welfare	-20.55	0.002	14.98	669.81	2.95E+05	1.30E+04
Mean Baseline Welfare	7228.7	9.54	6.83	0.34	0.22	1.66E-05
Relative Change in Welfare × 100	-0.284	0.025	219.20	1.98E+05	1.32E+08	7.84E+10
Adjusted Relative Change in Welfare × 100	-0.397	0.035	306.15	2.76E+05	1.84E+08	1.10E+11
Panel C: Larger relative improvement in welfare in						
Without Adjustment	TRAIL	TRAIL	TRAIL	TRAIL	TRAIL	TRAIL
	0.000	0.000	0.000	0.000	0.000	0.000
With Adjustment	TRAIL	TRAIL	TRAIL	TRAIL	TRAIL	TRAIL
	0.000	0.000	0.000	0.000	0.000	0.000

Notes:
For the calculations in columns (2)–(6), we manipulate farm value-added in two ways. First, we add a large constant (c) to the farm value-added numbers so that welfare can be computed even for households whose true farm value-added is negative. Second, to ensure that that the welfare estimates are large enough for the software to operate them, we multiply this value-added-plus with a second positive constant (k). The constant k takes different values at different θ levels, so that welfare estimates are not comparable across columns, but are comparable across the two scheme within a value of θ. For values of θ 2 and above, welfare is estimated as a negative number. Therefore in columns (2)–(6), we multiply the mean baseline welfare by -1 and present positive estimates. In Panel B, adjusted relative changes in welfare are computed by scaling up the sampling frequencies in the GBL scheme by 1.397, which is the ratio by which the total population in GBL villages in our sample exceeds the total population in TRAIL villages. Comparisons of relative improvement in welfare in Panel C are based on Mann-Whitney rank sum tests performed on 2000 bootstrap estimates of the relative change in welfare. p-values indicate the probability that the GBL scheme caused a larger relative change in welfare than the TRAIL scheme did.

Table 10: Distributive Impacts on Farm Value-added, by Social Group

	Average (1)	**SC/ST** (2)	**Non-Hindu** (3)	**General** (4)
		Panel A: TRAIL		
Conditional treatment effects on:				
Farm value-added	2268.98***	698.08	2053.42	3263.69***
	(611.51)	(895.23)	(1486.77)	(1051.14)
Log(Farm value-added)	0.221***	0.121	0.220	0.242***
	(0.059)	(0.156)	(0.161)	(0.078)
Selection frequency	0.069	0.073	0.066	0.067
Expected treatment effects on:				
Farm value-added	156.56	50.96	135.53	218.67
Log(Farm value-added)	0.015	0.009	0.015	0.016
Mean farm value added, Control 1 households	10142.06	5653.03	9177.41	13360.29
		Panel B: GBL		
Conditional treatment effects on:				
Farm value-added	-251.22	828.28	2010.42***	-1557.82
	(1100.34)	(962.21)	(557.95)	(2015.27)
Log(Farm value-added)	-0.026	0.178	0.340***	-0.110
	(0.115)	(0.207)	(0.097)	(0.144)
Selection frequency	0.051	0.073	0.050	0.040
Expected treatment effects on:				
Farm value-added	-12.81	60.46	100.52	-62.31
Log(Farm value-added)	-0.001	0.013	0.017	-0.004
Mean farm value added, Control 1 households	9387.58	4603.34	5680.77	13833.25

Notes: Estimates of conditional treatment effects in columns 1 and 2–5 are derived from specifications presented in equations (9) and (10) respectively. Standard errors in parentheses are clustered at the village level. Significance: $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$.

Table 11: Changes in Welfare, Partitioning by Social Group

	$\theta = 0$ (1)	$\theta = 1$ (2)	$\theta = 2$ (3)	$\theta = 3$ (4)	$\theta = 4$ (5)	$\theta = 5$ (6)
Panel A: TRAIL						
Change in Mean Welfare	153.35	0.013	11.75	129.53	16680.43	240.8
Mean Baseline Welfare	6396	9.21	6.60	0.33	0.22	1.60E-05
Relative Change in Welfare $\times$ 100	2.40	0.136	178.00	39610.4	7.72E+06	1.50E+09
Panel B: GBL						
Change in Mean Welfare	-6.34	0.003	7.77	168.60	33865.32	666.61
Mean Baseline Welfare	7228.7	9.54	6.83	0.34	0.22	1.66E-05
Relative Change in Welfare $\times$ 100	-0.122	0.027	113.66	49840.82	1.52E+07	4.02E+09
Adjusted Relative Change in Welfare $\times$ 100	-0.001	0.038	158.74	69611.08	2.12E+07	5.61E+09
Panel C: Larger relative improvement in welfare in						
Without Adjustment	TRAIL	TRAIL	TRAIL	GBL	GBL	GBL
	0.000	0.000	0.120	0.733	0.962	0.994
With Adjustment	TRAIL	TRAIL	GBL	GBL	GBL	GBL
	0.000	0.002	0.386	0.929	0.996	1.000

Notes:
For the calculations in columns (2)–(6), we manipulate farm value-added in two ways. First, we add a large constant (c) to the farm value-added numbers so that welfare can be computed even for households whose true farm value-added is negative. Second, to ensure that that the welfare estimates are large enough for the software to operate them, we multiply this value-added-plus with a second positive constant (k). The constant k takes different values at different θ levels, so that welfare estimates are not comparable across columns, but are comparable across the two scheme within a value of θ. For values of θ 2 and above, welfare is estimated as a negative number. Therefore in columns (2)–(6), we multiply the mean baseline welfare by -1 and present positive estimates. In Panel B, adjusted relative changes in welfare are computed by scaling up the sampling frequencies in the GBL scheme by 1.397, which is the ratio by which the total population in GBL villages in our sample exceeds the total population in TRAIL villages. Comparisons of relative improvement in welfare in Panel C are based on Mann-Whitney rank sum tests performed on 2000 bootstrap estimates of the relative change in welfare. p-values indicate the probability that the GBL scheme caused a larger relative change in welfare than the TRAIL scheme did.

Table 12: Changes in Inequality

	$\theta = 1$ (1)	$\theta = 2$ (2)	$\theta = 3$ (3)	$\theta = 4$ (4)	$\theta = 5$ (5)
		Panel A: TRAIL			
Baseline	0.3249	0.7236	0.8632	0.9051	0.9234
Endline	0.3205	0.7217	0.8630	0.9053	0.9237
Effect on inequality	$\downarrow$	$\downarrow$	$\downarrow$	$\uparrow$	$\uparrow$
		Panel B: GBL			
Baseline	0.3662	0.8139	0.9247	0.9517	0.9625
Endline	0.3594	0.7947	0.9123	0.9431	0.9561
Effect on inequality	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$

Notes:
Atkinson inequality indices are computed as $1 - \frac{y_e}{\bar{y}}$, where y_e is the equally distributed equivalent income that would generate the same average welfare as the actual income distribution does.

Table 13: Selection Patterns of Borrowers in TRAIL Scheme

	Control 1 households (1)	**Representative sample** (2)	**Difference** (3)
	Panel A: Bought from agent		
Landless	0.233	0.280	-0.047
	(0.079)	(0.092)	(0.120)
0–0.5 acres	0.523	0.333	0.190***
	(0.048)	(0.040)	(0.062)
0.5–1 acres	0.339	0.365	-0.026
	(0.062)	(0.047)	(0.078)
1–1.5 acres	0.318	0.488	-0.170
	(0.102)	(0.079)	(0.131)
	Panel B: Borrowed from agent		
Landless	0.067	0.167	-0.100
	(0.046)	(0.078)	(0.087)
0–0.5 acres	0.349	0.107	0.241***
	(0.046)	(0.026)	(0.050)
0.5–1 acres	0.233	0.173	0.060
	(0.055)	(0.037)	(0.064)
1–1.5 acres	0.227	0.220	0.008
	(0.091)	(0.066)	(0.112)
	Panel C: Worked for agent		
Landless	0.167	0.000	0.167**
	(0.069)	(0.000)	(0.078)
0–0.5 acres	0.182	0.083	0.098**
	(0.037)	(0.023)	(0.042)
0.5–1 acres	0.133	0.086	0.048
	(0.044)	(0.027)	(0.049)
1–1.5 acres	0.000	0.098	-0.098
	(0.000)	(0.047)	(0.064)
	Panel D: Same social group as agent		
Landless	0.353	0.222	0.131
	(0.083)	(0.082)	(0.118)
0–0.5 acres	0.504	0.543	-0.039
	(0.047)	(0.041)	(0.062)
0.5–1 acres	0.672	0.517	0.155**
	(0.059)	(0.047)	(0.077)
1–1.5 acres	0.913	0.689	0.224**
	(0.060)	(0.070)	(0.107)

Notes:
Data are self-reported by households in Cycle 1 of the household surveys. Means and standard errors are reported for Control 1 households in the TRAIL scheme and for households in the representative sample, which is the subset of households in the sample that were included in a stratified random sample of these villages drawn in 2007. $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$

Table 14: Characteristics of GBL Groups (Treatment and Control 1)

	Total (1)	**SC/ST** (2)	**Non-Hindu** (3)	**General** (4)
Invited by group members	0.583	0.536	0.800	0.558
	(0.032)	(0.048)	(0.069)	(0.051)
Encouraged by officials to join group	0.417	0.464	0.200	0.442
	(0.032)	(0.048)	(0.069)	(0.051)
Received assistance from others in the group (Cycle 1)	0.248	0.239	0.361	0.216
	(0.028)	(0.040)	(0.081)	(0.042)
Provided assistance to others in the group (Cycle 1)	0.124	0.080	0.171	0.158
	(0.021)	(0.026)	(0.065)	(0.038)
Proportion members with same occupation	0.624	0.616	0.598	0.642
	(0.015)	(0.022)	(0.036)	(0.023)
Proportion members with same education level	0.530	0.520	0.594	0.516
	(0.012)	(0.019)	(0.034)	(0.018)
Proportion members in same social group	0.522	0.732	0.887	0.192
	(0.027)	(0.038)	(0.044)	(0.033)
Herfindahl Index by social group	0.762	0.873	0.940	0.593
	(0.014)	(0.019)	(0.024)	(0.019)
Coefficient of variation of landholding	0.999	1.217	0.975	0.805
	(0.035)	(0.060)	(0.075)	(0.044)

Notes:
Means and standard errors are reported for sample households that had formed GBL groups in the GBL villages.