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REDUCING VULNERABILITY THROUGH MICROFINANCE: EVIDENCE FROM INDIAN SELF
HELP GROUP PROGRAM

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Reducing Vulnerability through Microfinance: Evidence from Indian Self Help Group Program

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Abstract

We investigate if participation in Indian Self Help Group microfinance program (SHG) results in reducing vulnerability. Vulnerability estimates are constructed using cross-sectional SHG rural household survey data, collected in 2003. The potential selection bias is eliminated by propensity score matching to estimate the average treatment on treated effect using nearest neighbour matching and local linear regression algorithm. We find that despite a disproportionately high percentage of poor in the SHG members, vulnerability is not significantly different between the SHG and non-SHG members. This result is found to be robust using sensitivity analysis and Rosenbaum bounds method.

JEL Classifications: D14, G21, I32.

Keywords: Microfinance, Vulnerability, Poverty, Self Help Groups.

1. Introduction

An extensive literature has verified the positive impact of microfinance in alleviating poverty (Morduch, 1999; Amin et al., 1999; Puhazhendi and Badatya, 2002; De Aghion and Morduch, 2006). A few studies have however challenged this view expounding that the results are more mixed (Morduch, 1999; de Aghion and Morduch, 2006; Karlan, 2007).¹ Exploring beyond poverty this paper investigates if microfinance reduces household vulnerability. In other words, do microfinance programs reduce the household exposure to future shocks and improve their ability to cope with them? Answering this question is crucial since the goal of poverty alleviation is not just about improving economic welfare via increased incomes and consumption. It is also about devising means for preventing households from falling into poverty. Enabling them to meet household survival needs including food security, make productive investments and not liquidate their limited resources in times of income or expenditure shocks.

Several studies have expressed concerns regarding the adequacy of standard poverty measures alone in understanding vulnerability.² Static poverty measures are helpful in assessing the current poverty status of households but tend to ignore poverty dynamics over time. Thus even though average household incomes do not fall into poverty levels, their degree of vulnerability or the risk of being poor in the future, can still remain high. The cumulative impact of microfinance programs on the household's wellbeing may therefore not be captured by standard poverty measures alone.

Our objective in this paper is two-fold. One, to estimate two important dimensions of household well-being namely: poverty and vulnerability using our household survey data. Second, to empirically investigate whether microfinance programs like Self Help Group bank linkage program (SHG) lead to a reduction in vulnerability. Vulnerability in our study is defined as a forward-looking, ex-ante measure of the household's to cope with future shocks

¹ The differences in the empirical findings spring from varying measures of poverty, different country contexts and types of microfinance organizations being analyzed, use of different theoretical models, survey designs and econometric techniques, and/or different time periods covered by the studies.

² See Glewwe and Hall, 1998; Calvo and Dercon, 2005; Carter and Ikegami, 2007; Ligon and Schechter, 2002; Dercon and Krishnan, 2000; Dercon, 2005.

and proneness to food insecurity that can undermine the household's survival and the development of its members' capabilities.

A limited literature on impact of microfinance on vulnerability provides evidence that microfinance strengthens crisis coping mechanisms, helps diversify income-earning sources, and enables asset creation. In fact, a few studies suggest that it has a more significant impact in reducing vulnerability than income-poverty (Hashemi et al., 1996; Morduch, 1999).

The empirical analysis is based on data collected by one of the authors on the Indian SHG program, in 2003. We first estimate vulnerability following Chauduri, Jalan and Suryahadi (2002) whose methodology allows for the estimation of household vulnerability using cross-sectional data. We correct for the SHG participation bias using propensity score matching to obtain the average treatment on treated effect (impact) on vulnerability. Finally we test the sensitivity of the results to unobservables. Our results show that even though SHG member households have a higher proportion of poor than the non SHG member households (control group), SHG members are not more vulnerable as compared to them. These results are found to be robust using the sensitivity analysis and Rosenbaum bounds method.

The paper is organized as follows. Section 2 discusses the notions of vulnerability and the conceptual framework used in the estimation of vulnerability. Section 3 explores the role of microfinance SHGs in reducing poverty and vulnerability. Section 4 provides an overview of the sample data used in our analysis. Section 5 discusses the propensity score matching (PSM) method used to remove the participation bias and the methodology for estimating vulnerability. It then provides the poverty and vulnerability estimates for SHG and non-SHG members. Sensitivity analysis and Rosenbaum bounds method is used to test the robustness of the propensity score matching estimates in section 6. Concluding remarks are presented in the final section.

2. Understanding Vulnerability

It should be noted that vulnerability, as a notional concept, has been viewed differently by researchers, thus leading to varied definitions and measures. Some see vulnerability as an aspect, which can cause poverty or hinder people from escaping out of poverty (Prowse, 2003: 9). Others such as Calvo (2008) treat vulnerability as a dimension of poverty itself and

give it a multi dimensional meaning by defining ‘vulnerability’ as a threat of suffering any form of poverty in the future.³ In Calvo and Dercon’s (2005) model, vulnerability is seen as a combination of poverty (failure to reach a minimum outcome) and risk (dispersion over states of the world) that translates into a threat of being poor in the next period. This notion of vulnerability builds upon the probability of outcomes failing to reach the minimal standard as well as on the uncertainty about how far below that threshold the outcome may turn out to be. The latter point relates to uncertainty as a source of distress so that uncertainty impinges directly on well-being. On the other hand, Ligon and Schechter (2003) takes a utilitarian approach in defining vulnerability, arguing that it depends not only on the mean of household consumption but also on variation in consumption in the context of a risky environment. The risk faced by the household is decomposed into aggregate and idiosyncratic risk.

Chauduri, Jalan and Suryahadi (2002) in their study of Indonesian household vulnerability to poverty, define vulnerability within the framework of poverty eradication as the ex-ante risk that a household will, if currently non-poor, fall below the poverty line, or if currently poor, will remain in poverty. (p. 4). Others have taken a different perspective of vulnerability whereby poverty is viewed as one element, which may contribute to an enhanced vulnerability (Cardona, 2004). Some have taken the view that poor people are generally more vulnerable, regardless of the hazard, although there is by no means a mandatory interconnection (Cannon et al., 2003; Feldbrügge and von Braun, 2002).

A growing number of empirical studies have proposed varied measures of vulnerability as well (Zimmerman and Carter, 2003; Calvo and Dercon, 2005; Glewwe and Hall, 1999; Ligon and Schechter, 2003; Carter and Barrett, 2006; Morduch, 2005). Vulnerability assessments have to be, by definition, explicitly forward-looking; it is an ex-ante measure of a household’s well-being, whereas poverty is an ex-post measure of a household’s well-being (or lack thereof). The observed consumption expenditures at a point in time is the result of a dynamic process that is occurring over time. Some estimates of vulnerability therefore make use of household panel data, where available, to analyze the extent of consumption fluctuations over time as households experience income fluctuations (Morduch, 2005; Kamanou and Morduch, 2005). Other studies examine the impact of various forms of shocks on households’

³ This concept is based on the notion that “future is uncertain, and the possibility of failing to reach some standard of minimal achievement in any well-being dimension is at least a disturbing background noise for some, and an ever-present, oppressing source of stress and dismay for many others” (Calvo, 2008: 1011).

consumption (Ligon and Schechter, 2003; Carter et al., 2007), or other aspects of household well-being, for instance, health (Dercon and Hoddinott, 2005). While there are efforts to address these data issues through the collection of household panel data and of information about households' shocks, for the most part, empirical analyses of vulnerability remain severely constrained by the paucity of panel data in many developing countries and by limited information on the idiosyncratic and covariate shocks experienced by households (Günther and Harttgen, 2009:1222-23).

Chauduri et al. (2002) and Günther and Harttgen (2009) propose a method for estimating vulnerability that can be applied to cross-sectional household surveys such as the 2003 Indian SHG household sample survey, thus avoiding the data problems mentioned above. A discussion of this vulnerability estimation method is presented in section 4.

3. Microfinance Self-help Groups and Household Vulnerability

It is now widely acknowledged that a major aspect of rural people's lives involve developing mechanisms to mitigate risks and to minimize the effects of shocks. There are threats of loss of non-farm income as well as fluctuations and decline in farm earnings. Yield risks are especially significant when agricultural price and other supports are inadequate or non-existent. In addition, there are unexpected shocks due to illness, death, and chronic health conditions of household members that affect well-being and can undermine the household's ability to meet its future consumption needs, especially when they have stringent liquidity constraints and are compelled to use their resources in order to cope with these economic stresses.

A few studies have explored the effect of microfinance in terms of reducing vulnerability and provide evidence in support of this hypothesis. For instance, studies on Bangladeshi microfinance institutions conclude that microfinance access has led to consumption smoothing or a reduction in the variance in consumption by member households across time periods (Khandker, 1998; Morduch, 1999). Puhazhendi and Badatya (2002) SHG study finds that microfinance provides loans for both production and consumption purposes, thereby allowing consumption smoothing and enabling households to mitigate the effects of negative shocks.

We argue in Bali Swain and Floro (2007) that SHG participation helps the member households in the face of liquidity constraints and multitude of risks, thereby reducing their vulnerability. For instance, members of SHG may share each other's risk through institutionalized arrangements, by loans to those members who face liquidity constraints in meeting investment needs or in meeting unexpected consumption expense. The SHG (production and consumption) loan can assist households in increasing their productivity and earnings and in coping with the contingencies of life. The training of members provided by the SHG program can enhance their entrepreneurship skills as well as their ability to perceive and process new information, evaluate and adjust to changes, thus increasing both their productivity and self-confidence (Bali Swain and Wallentin, 2009; Bali Swain and Varghese, 2009).

In addition to the effects of loan provision and training, SHGs can promote or strengthen social networks that provide mutual support by facilitating the pooling of savings, regular meetings, etc that help empower their members, especially women. This *non-pecuniary effect* of SHGs can reduce the vulnerability of the members and by association, that of their households in ways that may not be adequately captured by change in household earnings alone.

The likely impact of SHG on vulnerability, therefore, goes beyond provisioning of loans to meet the liquidity constraints faced by the household. SHGs provide other non-financial services such as training and the use of group meetings to discuss communal issues that can affect the households' ability to manage risks and to deal with shocks. Hence, SHGs are likely to reduce the vulnerability of their members' household through the *income effect* (that increases future consumption levels) but also through *their non-pecuniary effect* (that are not captured by changes in incomes alone) (Bali Swain and Floro, 2007).

SHGs are however likely to be ineffective in the face of 'covariate' shocks, including flooding, declining crop prices or lack of demand for their produce (Zimmerman and Carter, 2003; Morduch, 2004; Dercon, 2005).⁴ While the protection afforded by SHG in dealing with aggregate shocks may be weak or partial, SHG groups can be of help in cases when a

⁴ Rural livelihoods in developing countries like India often exhibit high correlations between risks faced by households in the same village or area. Hence, when farm prices decline, or there is a drought or flood in the area, all households are adversely affected simultaneously. Idiosyncratic shocks are, by definition, uncorrelated across households in a given community and therefore can be mutually insured within communities.

household faces an idiosyncratic shock. Hence, the vulnerability effect of SHGs is likely to be concentrated on the ability of households to deal with the latter.

4. Data and Methodology

4.1 Data Description

The NABARD SHG-bank linkage program is one of the largest and fastest-growing microfinance programs in the developing world. Self-help groups typically include ten to twenty (primarily female) members in the village. In the initial months, the group members save and lend amongst themselves and thus build group discipline. Once the group demonstrates stability and financial discipline for six months, it receives loans of up to four times the amount it has saved. The bank then disburses the loan and the group decides how to manage the loan. As savings increase through the group's life, the group accesses a larger amount of loans.

Initiated in 1996, the SHG program faced slow progress up to 1999. Since then, it has grown to finance 687,000 SHGs in 2006-07 alone compared to 198,000 SHGs in 2001-02. The cumulative number of SHGs has grown to roughly three million by March 2007 reaching out to more than forty million families. According to NABARD (2006), about 44,000 branches of 547 banks and 4,896 NGOs participate in the SHG bank linkage program.

The data used for the empirical analysis in this paper was collected by one of the authors and forms part of a larger study that investigates the SHG-bank linkage program.⁵ The household sample survey was conducted in 2003 in two representative districts for each of the following five states in India: Orissa, Andhra Pradesh, Tamil Nadu, Uttar Pradesh, and Maharashtra.⁶ Within the states, the study avoided districts with over and under exposure of SHGs. The following sampling strategy was used for the household survey. First, SHG member-

⁵ The process involved discussion with statisticians, economists and practitioners at the stage of sampling design, preparing pre-coded questionnaires, translation and pilot testing with at least 20 households in each of the 5 states (100 households in total). The questionnaires were then revised, reprinted and the data collected by local surveyors that were trained and supervised by the supervisors. The standard checks were applied both on the field and during the data punching process.

⁶ These districts (in parentheses) are Orissa (Koraput and Rayagada), Andhra Pradesh (Medak and Rangareddy), Tamil Nadu (Dharmapuri and Villupuram), Uttar Pradesh (Allahabad and Rae Bareli), and Maharashtra (Gadchiroli and Chandrapur).

households were randomly chosen in each district. Then, members of the control group were chosen to reflect a comparable socio-economic group as the SHG respondents. These were selected from villages that were similar to the SHG villages in terms of the level of economic development, socio-cultural factors and infra-structural facilities, but did not have a SHG program (Bali Swain, 2003). NABARD's choice to expand the SHG program occurs at the district level without any specific policy to target certain villages (Bali Swain and Varghese, 2009). Thus, we choose to sample at the district level, which is the basic administrative unit within a state. After refining the data further and dropping the missing value we are left with a sample of 840 households.

Table 1 compares the characteristics of the SHG members and those that did not participate in the SHG program. On average, the food consumption per capita per month⁷ for the SHG member households is much higher than the non SHG members. In general, SHG members are younger, have higher level of education, have slightly higher dependency ratio and have less non-land wealth. On average their landholdings are greater than those of non-SHG respondents however there is great variability in the overall land quality. SHG households live in villages that are closer to market, bus-stop and primary health care centre but further away from banks, compared to non-SHG households. Using a subjective variable based on the survey response as to whether or not their household experienced severe shortage of food and/or cash in the past three years, a greater proportion (39%) of the SHG households have experienced economic difficulties, compared to non-SHG households (27%). The t-test results confirm a significant difference between the SHG members and non-members in terms of size of landholdings (as of 2000) and their access to market infrastructures and services. These results imply a significant self-selection among the SHG members and non-members.

<Table 1 about here>

4.2 Propensity Score Estimation

In assessing program impact, we need to eliminate the potential selection bias that could arise. The decision to participate in SHGs depends on the same attributes that determine the

⁷ The food consumption of the household is calculated as the sum of the expenditure on staple grains; fruits and vegetables; meat/chicken/ fish and dairy products.

vulnerability of the household. Self-selection bias arises from the potentially unobservable traits of the SHG members. For instance, higher entrepreneurship, ability to recognize opportunity, and other critical aspects make the households more likely to participate in the SHG program. However, the same characteristics would also affect their vulnerability. A number of studies on microfinance have addressed the problem of selection, reverse causality and other biases using different approaches (see Bali Swain and Varghese, 2009).

To correct for selection bias created by program selection, we use the propensity score matching (PSM) method, which has received substantial attention in recent literature.⁸ This econometric technique allows us to identify the program impact when a random experiment is not implemented, as long as there is counterfactual or control group. In contrast to other regression methods, the PSM does not depend on linearity and has a weaker assumption on the error term. Matching relies on the assumption of conditional independence of potential outcomes and treatment given observables, that is, the selection into the treatment should be driven by factors that can be observed or Conditional Independence Assumption.

We first examine the feasibility of using propensity score matching for our data set. In order to reduce the bias using this method, we checked the data collection method to ensure that the three conditions outlined in Heckman *et al.* (1997) are met. First, the survey questionnaire is the same for participants and non-participants so that the outcome measures are measured in the same way for both. Second, both groups come from the same local markets. Third, a rich set of observables for both outcome and participation variables are available for the performance of the PSM method.

As with any impact evaluation, the main problem with identifying SHG impact is that the outcome indicator for SHG member households with and without program is not observed because by definition, all the participants are SHG members in period 1. Since we only have information on the households once they participate in the program, there is need to identify a control group that allows us to infer what would have happened with the SHG participant household if NABARD program would not have been in place. The PSM uses the “Propensity Score” or the conditional probability of participation to identify a counterfactual group of non participants, given conditional independence.

⁸ We would like to thank the referee of this paper for giving us this very helpful suggestion.

The probability ($P(X)$) of being selected is first determined by a logit equation and then this probability (the propensity score) is used to match the households. Y_1 is the outcome indicator for the SHG program participants ($T=1$), and Y_0 is the outcome indicator for the SHG members ($T=0$), then equation (1) denotes the mean impact:

$$\Delta = E[Y_1 | T = 1, P(X)] - E[Y_0 | T = 0, P(X)] \quad (1)$$

where the propensity score matching estimator is the mean difference in the outcomes over common support, weighted by the propensity score distribution of participants.

The literature proposes several propensity score matching methods to identify a comparison group.⁹ Since the probability of two households being exactly matched is close to zero, distance measures are used to match households. Following Smith and Todd (2005), we first choose the neighbor to neighbor (NN) algorithm (with one person matching). This algorithm is the most straightforward and matches partners according to their propensity score. We further estimate the local linear regression (LLR) method (for bandwidths 1)¹⁰. The LLR method uses the weighted average of nearly all individuals in the control group to construct the counterfactual outcome. Bootstrapped standard errors for the LLR procedures are used (see Abadie and Imbens, 2007; Heckman et al., 1997).

4.3 Estimating Poverty and Vulnerability

We examine the poverty profile of the households, using standard measures of poverty such as the headcount ratio, poverty gap ratio and the squared poverty gap or Foster-Greer-Thorbecke (FGT). The head count ratio measures the proportion of population under the poverty line. The poverty gap ratio measures the depth of poverty and is the total amount that is needed to raise the poor from their present incomes to the poverty line as a proportion of the poverty line and averaged over the total population. The squared poverty gap or FGT

⁹ See Townsend, 1995; Dercon, 2005; Zimmerman and Carter, 2003; and Morduch, 2004.

¹⁰ Bandwidths are smoothing parameters, which control the degree of smoothing for fitting the local linear regression.

index takes inequality among the poor into account and means that the larger gaps count for more than the smaller gaps, and hence it captures the severity of poverty. This index is helpful in examining how the impact on poverty of an economic shock, for example, can differ greatly, depending on the level and distribution of resources among those who are poor.

The poverty line used in our study is based on the official (consumption-based poverty) line for India, which assumes the minimum subsistence requirement of 2400 calories per capita per day for rural areas.¹¹ The official poverty line estimate is derived from the household consumer expenditure data collected by National Sample Survey Organisation (NSSO) of the Ministry of Statistics and Programme Implementation, every fifth year. Since the poverty line estimate is drawn from the 61st round of the NSS which covers period July 2004 to June 2005¹², we adjust the official poverty line using the 2003 Consumer Price Index for agricultural workers in rural areas to correspond with the survey period. Hence our estimated 2003 poverty line is Rs 356.3 per capita per month.

Next, we estimate the household's vulnerability i using the Chauduri, Jayan and Suryahadi (2002) approach that allows the estimation of expected consumption and its variance with cross-section data.¹³ This is based on the notion of vulnerability as the probability of being poor and implies accounting for the expected (mean) consumption, as well as the volatility (variance) of its future consumption stream. The stochastic process generating the consumption of the household is dependent on the household characteristics and the error term (with mean zero) captures the idiosyncratic shocks to consumption that are identically

¹¹ The Task Force on the 'Projections of Minimum Needs and Effective Consumption Demands' (1979) defines the poverty line (BPL) as the cost of an all India average consumption basket which meets the calorie norm of 2400 calories per capita per day for rural areas and 2100 for the urban areas. These calorie norms are expressed in monetary terms as Rs. 49.09 and Rs. 56.64 per capita per month for rural and urban areas respectively at 1973-74 prices. Based on the recommendations of a study group on 'The Concept and Estimation of Poverty Line', the private consumption deflators from national accounts statistics was selected to update the poverty lines in 1977-78, 1983 and 1987-88. Subsequently, the expert group under the Chairmanship of late Prof. D.T. Lakdawala recommended the use of consumer price index for agricultural labour to update the rural poverty line and a simple average of weighted commodity indices of the consumer price index for industrial workers and for urban non-manual employees to update the urban poverty line. But the Planning Commission accepted only the CPI for industrial workers to estimate and update the urban poverty line (Economic Survey of Delhi, 2001-2002)

¹² See Poverty Estimates for 2004-05, Government of India, Press Information Bureau, March 2007.

¹³ It is assumed that community level characteristics (and community level covariate shocks) are not as important or household level characteristics (and idiosyncratic shocks). Community characteristics and covariant shocks may also households' consumption indirectly through the returns to household-specific characteristics (Günther and Harttgren, 2009).

and independently distributed over time for each household. Hence, any unobservable sources of persistent or serially correlated shocks or unobserved household specific effects over time on household consumption are ruled out. It also assumes economic stability thus ruling out the possibility of aggregate shocks. Thus, in Chauduri et al. (2002) method, the future consumption shocks are assumed to be idiosyncratic in nature. This does not mean however, that they are identically distributed across households. Furthermore, we assume that the variance of the idiosyncratic factors (shocks) depend upon observable household characteristics.

Following Chauduri et al (2002) approach, we assume that the vulnerability level of a household h at time t , is defined as the probability that the household finds itself consumption poor in period $t + 1$. The household's consumption level depends on several factors such as wealth, current income, expectation of future income (i.e. lifetime prospects), the uncertainty it faces regarding its future income and its ability to smooth consumption in the face of various income shocks. Each of these, in turn, depend on a number of household characteristics, both observed and unobserved, and the socio-economic environment in which the household is situated and the shocks that contribute to differential welfare outcomes for households that are otherwise observationally equivalent. Hence, the household's vulnerability level in terms of its future food consumption can be expressed as a reduced form for consumption determined by a set of variables X_{ht} .

This can be expressed as:

$$\ln c_{ht} = \beta_0 + X_{ht} \beta_1 + \mu_{ht} \quad (2)$$

where $\ln c_{ht}$ represents log of consumption per capita on adult equivalence scale, X_{ht} represents selected household and community level characteristics, and μ_{ht} represent the unexplained part of household consumption. Since the impact of shocks on household consumption is correlated with the observed characteristics, the variance of the unexplained part of consumption μ_{ht} can be expressed as:

$$\sigma_h^2 = \Phi_0 + \Phi_1 X_{ht} + \omega_{ht} \quad (3)$$

which implies that the variance of the error term is not equal across households and depends upon on X_{ht} . The latter include the educational attainment of the respondent, household composition, number of workers in the household, and household wealth. We also take into account the environment characteristics such as access to paved roads, markets, health care services, and public transportation. The possibility of poverty traps and other non-linear poverty dynamics are implicit in the model as with the possible contribution of aggregate shocks and unanticipated changes in the socio-economic environment that may affect a household's vulnerability. The assumptions made are required for a vulnerability estimation method that uses only cross-sectional data. Given data limitations, we cannot identify the particular stochastic process generating β . The expected mean and variance per capita household food consumption are estimated using a simple functional form by Amemiya's (1977) three-step feasible generalized least squares (FGLS).¹⁴ Using the β_1 and Φ_1 estimates that we obtain, we directly estimate the expected log consumption and the variance of log consumption for each household h . These are our vulnerability estimates.

To facilitate further comparison of the vulnerability distribution, we estimate additional summary measures. The vulnerable fraction of the population is calculated using an arbitrarily chosen threshold. The relative vulnerability threshold is the observed poverty rate in the population. The motivation behind using this threshold is that in the absence of aggregate shocks the mean vulnerability level within a group would be approximately equal to its observed poverty rate (Chauduri et al., 2002). Thus, vulnerability levels above the observed poverty rate threshold imply that the household's risk of poverty is greater than the average risk in the population, thus making it more vulnerable. We use the official estimates of rural poverty by the Planning Commission of India as the first vulnerability threshold. According to this 28.3 per cent of the population was living below the then official poverty line in 2004 – 2005.¹⁵ The source for the poverty line was the 61st round of the National Sample Survey (NSS) and the criterion used was the monthly per capita consumption expenditure below Rs. 356.35 for rural areas.

¹⁴ For details on the statistical estimation refer to Chauduri et al., 2002.

¹⁵ Planning Commission estimates, as accessed on 22 September 2010
<http://www.planningcommission.gov.in/data/datatable/Data0910/tab%2019.pdf>

Another arbitrarily higher vulnerability threshold is 0.50. Households with vulnerability levels between observed poverty rates and 0.50 threshold are termed *relatively vulnerable* whereas those above 0.50 are considered *highly vulnerable*. Admittedly, there is some arbitrariness involved in the selection of the relative vulnerability so a comparison of the vulnerability estimates using additional vulnerability thresholds shows the sensitivity of the results to the choice of vulnerability threshold. The vulnerability to poverty ratio that measures the fraction of the population that is vulnerable to the fraction that is poor. For a given vulnerability threshold ratio, higher the vulnerability to poverty ratio the more spread is the distribution of vulnerability. Whereas, lower vulnerability to poverty ratio implies greater concentration of vulnerability amongst a few households.

5. Empirical Results

This section presents and discusses the estimation results of SHG participation on the vulnerability of the respondent's households. We begin by examining the probit and propensity score results of matching. This is followed by a brief discussion of the poverty and the estimated vulnerability for members and non-SHG members. Finally, we present and interpret the estimated average treatment on treated effect of SHG participation using different matching algorithms.

5.1 Propensity Score Matching

In correcting for the endogeneity of SHG participation using PSM, we begin by estimating a parsimonious logit equation to determine the probability of participating in the SHG program.¹⁶ The variables that likely affect both the participation in SHG and the outcome variable (real food expenditure per capita per month) were chosen and these include age, age squared, sex, education dummies, lack of cash or food 3 years ago, owned land 3 years ago, distance from bank, health care centre, marketplace, and paved road.¹⁷ We obtained very similar results with both neighbour to neighbour algorithm (with one person matching) and log linear regression method (for bandwidths 1). Table 1 in the Appendix shows the

¹⁶ Using saturated logit models as opposed to simple ones is debatable, as the purpose of logit equation is not only to predict SHG participation (as in selection models) but also for covariate balancing.

¹⁷ The variables were chosen through 'hit and miss' method while keeping in mind the balance.

propensity score estimation by logistic regression method. The model is well specified with a high Likelihood Ratio Chi-squared of 40.77 (with a p-value of 0.0001). The logistic estimations show that among the covariates land owned in 2000, lack of cash or food in 2000, and distance from the bank and market affect the probability of participating in the SHG. Other variables such as age, gender and education level of the respondent do not significantly explain SHG participation.

After deriving the propensity scores, the respondents with low or high probabilities that cannot be matched to the propensity scores of the control group, are dropped. Thus, only the households on the common support are retained to assure comparability. Prior to matching, the estimated mean propensity scores (standard error) for SHG members and non-SHG member were 0.94 (0.05) and 0.89 (0.06) respectively. Figure 1 in Appendix reports the histograms of the estimated propensity scores for the two groups. Dropping the off-support households, we are left with a sample of 742 households of which 691 are SHG members and 51 constitute the non-member control group. After the matching, there was a negligible difference in the mean propensity scores of the two groups (0.93 (0.04) for SHG members and 0.89 (0.06) for non-SHG members).

5.2 Poverty and Vulnerability Profile for SHG and non SHG members

NABARD (1992) explains that the main objectives of the SHG bank linkage program was to evolve strategies that supplement the credit needs of the poor to help them secure greater economic and financial strength. SHGs are thus expected to contribute to the alleviation of rural poverty. We construct a poverty profile of the SHGs (treatment group) and the non-SHG members (control group) in 2003 using standard measures such as the headcount index, poverty gap index and the squared poverty gap index.¹⁸

¹⁸ The poverty gap is the average (over all individuals) gap between poor people's living standards and the poverty line. It indicates the average extent to which individuals fall below the poverty line (if they do). It thus measures how much would have to be transferred to the poor to bring their income (or consumption) up to the poverty line. The poverty gap however does not capture the differences in the severity of poverty amongst the poor and ignores "inequality among the poor". To account for the inequality amongst the poor we calculate the squared poverty gap index which is defined as the average of the square relative poverty gap of the poor. The squared poverty gap index (Foster-Greer-Thorbecke Index) is a weighted sum of poverty gaps (as a proportion of the poverty line), where the weights are the proportionate poverty gaps themselves.

$$P_\alpha = \frac{1}{n} \sum_{i=1}^q \left(\frac{z - y_i}{z} \right)^\alpha$$
 The measures are defined for $\alpha \geq 0$, where α is a measure of the sensitivity of the index to poverty. When $\alpha=0$, we have the headcount index, $\alpha=1$ is the poverty gap index and $\alpha=2$ is the squared poverty gap index. The headcount index is the proportion of the population for whom income (or other measures of

Table 2 presents the poverty profile of the SHG member and non-member households using standard poverty measures. Our results show that a higher proportion of the SHG members are poor (72.5 per cent as compared to 60.8 per cent for the non-members) although the depth of poverty is about the same between SHG and non-SHG households. Their aggregate poverty gap per household is Rs.123 compared to Rs 118 among non-SHGs. The FGT index shows that there is slightly greater inequality among the non-SHG poor (0.24) compared to the SHG poor (0.22).

<Table 2 about here>

Following Chauduri et al. (2002) the vulnerability estimates are obtained from the FGLS estimates¹⁹ and are presented in Table 2. The mean vulnerability level within the SHG member-household group is much lower (0.45) and statistically significant as compared to the SHG non-members (0.62). This implies that participation in SHGs can reduce the vulnerability of the households in terms of falling into poverty or becoming poorer.

We also examine the sensitivity of the vulnerability estimate to the choice of a threshold. We use three different vulnerability thresholds in our study namely: a) the observed poverty rate; b) the vulnerability threshold of lying above the observed poverty rate but with a 50 percent probability of falling into poverty at least once in the next year; and c) the highly vulnerable lying above the vulnerability threshold of 0.5 for a one year time period. The relative vulnerability estimate is based on the observed the poverty rate in the population, and identifies the proportion of the population whose vulnerability level lies above the observed poverty rate. The highly vulnerable estimate identifies the proportion of the population whose vulnerability level exceeds 0.50 and is more likely to end up poor in the future. We also report the ratio of the proportion of households that are vulnerable to the proportion that are poor. This is an indication of how dispersed vulnerability is in the population.

living standard) is less than the poverty line. The headcount index does not take the intensity of poverty into account and is insensitive to the differences in the depth of poverty of the poor. Moreover, the index does not change over time if individuals below the poverty line become poorer or richer, as long as they remain below the line.

¹⁹ The three step feasible generalised least squares (FGLS) results are presented in Appendix Table 2. The results show that SHG membership leads to a statistically significant increment in the consumption. The coefficients of the control variables have the expected signs.

The fraction of the population who are vulnerable with respect to these three thresholds is given in Table 2. Even though a higher proportion of SHG members are poor, they are relatively less vulnerable (0.55) as compared to the non-SHG (0.62). Not only are the non-SHG members more vulnerable, a larger proportion of them are highly vulnerable facing vulnerability level above 0.50, with a 50 percent probability of entering poverty in the next year. The non-members also have a higher vulnerability to poverty ratio (1.18) with a more spread incidence of vulnerability as opposed to a more concentrated vulnerability amongst relatively few SHG households (0.75).

The above results also indicate that there are some households whose ex-ante probability of becoming poor (vulnerability level) is high and yet they are currently observed to be non-poor. Conversely, there are a proportion of currently poor SHG members, whose vulnerability level is low enough for them to be classified as non-vulnerable. This reflects the stochastic nature of the relationship between poverty and vulnerability. In other words, while poverty and vulnerability are related concepts, there are important distinctions between the two and neither is a subset of the other. The characteristics of those observed to be poor at any given point in time may differ from the characteristics of those who are vulnerable to poverty.

5.3 Assessing Impact on Vulnerability

Table 3 presents the Average Treatment on Treated estimates (ATT) of SHG participation impact on vulnerability and average food expenditure per capita per month. We estimate the ATT using two different algorithms for propensity score matching to identify the comparison group. Nearest Neighbour matching algorithm is the more intuitive of the two as it matches each treated observation to a control observation with the closest propensity score. We employ the local linear regression (LLR) algorithm one to one person matching (bandwidth 1), which is a generalised version of kernel matching that allows faster convergence at the boundary points.

<Table 3 about here>

The results from Table 3, column 1 show that the ATT point estimates are not significant, indicating that even though the SHG members have a higher proportion and depth of poverty they are unlikely to be more vulnerable as compared to the non members. SHG participation

on the other hand does lead to an increase in its average food expenditure per capita per month using the LLR algorithm method (Table 3, column 2). A likely reason for this might be due to the provisioning of SHG loans that may be used for any purpose (including consumption) and thus helps the households cope with economic shocks. Our results show that even though the current poverty status of SHG member households show a very high proportion of poor with a higher aggregate poverty gap, their propensity to become poor in the next period (vulnerability) is not higher.

6. Sensitivity Analysis - Robustness of Results

The propensity score matching hinges on the conditional independence or unconfoundedness assumption (CIA) and unobserved variables that affect the participation and the outcome variable simultaneously that may lead to a hidden bias due to which the matching estimators may not be robust. It is not possible to directly reject the unconfoundedness assumption however. Heckman and Hotz (1989) and Rosenbaum (1987) have developed indirect ways of assessing this assumption. These methods rely on estimating a causal effect that is known to be equal to zero. If the test suggests that this causal effect differs from zero, the unconfoundedness assumption is considered less plausible (Imbens, 2004).

Building on Rosenbaum and Rubin (1983) and Rosenbaum (1987), Ichino, Mealli and Nannicini (2008) propose a sensitivity analysis. They suggest that if the CIA is not satisfied given observables but is satisfied if one could observe an additional binary variable (confounder), then this potential confounder could be simulated in the data and used as an additional covariate in combination with the preferred matching estimator. The comparison of the estimates obtained with and without matching on the simulated confounder shows to what extent the baseline results are robust to specific sources of failure of the CIA, since the distribution of the simulated variable can be constructed to capture different hypotheses on the nature of potential confounding factors.

To check the robustness of our ATT estimates, we use two covariates to simulate the confounder namely: young (respondents under the age of 26 years) and illiterate (with no education). These covariates are chosen with the intention to capture the effect of 'unobservables' like ability, entrepreneurial skills and risk aversion etc., which have an impact on the participation in SHG program and vulnerability of the household. If the ATT

estimate change dramatically with respect to the confounders, then it would imply that our results are not robust. We employ the Kernel matching algorithm with between-imputation standard error, in order to use only the variability of the simulated ATT across iterations. Since our outcome variable is continuous, the confounder is simulated on the basis of the binary transformation of the outcome along the 25th centile. The results of these two confounders²⁰ are presented in Table 4. For both the ‘young’ and ‘no education’ confounders the simulated ATT estimates are very close to the baseline estimate. The outcome and selection effect on vulnerability is positive but not very large. The results indicate a robustness of the matching estimates.

<Table 4 about here>

We further test the robustness of our results using Rosenbaum’s (2002) bounding approach in order to determine how strongly an unmeasured variable influences the selection process to undermine the implication of the matching analysis.²¹ Rosenbaum bounds calculate the bounds for average treatment effects on the treated in the presence of unobserved heterogeneity (hidden bias) between treatment and control cases. It takes the difference in the response variable between treatment and control cases and then calculates Wilcoxon sign rank tests that give upper and lower bound estimates of significance levels at given levels of hidden bias. The Hodges-Lehmann point estimates and confidence intervals for the average treatment effect on the treated are also provided.

Table 5 presents the results from the Rosenbaum bounds analysis for vulnerability using different Hodges-Lehmann point estimates. The analysis is conducted on the matching procedure using local linear regression (bandwidth 1) with a random draw and bootstrapped standard errors. The estimates illustrate the sensitivity of the results to potential hidden bias. Our assumption about the potential endogeneity in assignment to treatment is given by Γ which reflects the odds of participation in treatment. Matched units have the same probability of participation only if $\Gamma=1$. If the odds of participation differ from 1 then it must be due to hidden bias.

²⁰ Both these confounders are “dangerous” confounders, since both the outcome and the selection effect are positive.

²¹ Instead of testing the unconfoundedness assumptions, the Rosenbaum’s bounds provide evidence on the degree to which any significance result hinge on this assumption.

<Table 5 about here>

The Hodges-Lehmann point estimates reflect the uncertainty in the estimated Average Treatment Effect on the Treated at increasing levels of assumed hidden bias. At $\Gamma = 1$, there is no hidden bias and the estimates are equal (upperbound=lowerbound= 0.15). The confidence interval includes zero only when we cross $\Gamma=1.5$. This means that the unobserved effect would have to increase the odds of participation in SHG by more than 1.5 before one changes the conclusions about the effect of SHG participation on participants. This indicates that the postulated effects of the SHG participation on mean vulnerability of the households due to unobservables would have to be quite large for us to doubt our results.

7. Concluding Remarks

This paper explores an important dimension of household welfare that conventional measures of poverty do not address, namely vulnerability. We examine the likely effect of Self-Help microfinance groups (SHG) on the vulnerability of participating member households using an Indian household sample survey data from 2003. We argue that a household's ability to mitigate risk and cope with shocks is enhanced through SHG participation by increasing household earnings through provision of microfinance and training, aiding the household in the face of shocks by providing consumption loans, and enhancing their resilience by strengthening social support and improving women's empowerment.

We use propensity score matching to extricate the potential selection bias that may arise due to unobservable attributes. Additionally, we empirically examine the current poverty status of households in SHG and non-SHG groups using several poverty measures and then make inferences about whether or not these households are currently vulnerable to future poverty using the Chauduri et al. approach. After matching the treated and comparison groups on the basis of their propensity scores, we estimate the average treatment on treated effect using nearest neighbour matching algorithm and local linear regression. The robustness is checked with help of sensitivity analysis and Rosenbaum bounds. Our main empirical results show that vulnerability is not significantly different among SHG member households as compared to those who are non-participants (control group), even though SHG-member households are found to be poorer than the non-SHG member (control group) households. These results are found to be robust using the sensitivity analysis and Rosenbaum bounds method.

The SHG bank linkage program is a joint liability microfinance program where the loan may be used for any purpose, be it production or consumption. Microfinance in this case provides an additional resource for consumption smoothing thus reducing the variability in food consumption levels. Finally, microfinance SHG can strengthen mutual support networks that help reduce vulnerability of members and that of their households in ways that may not be adequately captured by change in household earnings.

References

- Abadie, A. and Imbens, G. (2007) Bias Corrected Matching Estimators for Average Treatment Effects, Working Paper, Harvard University.
- Amin, S., Rai, A.S. and Topa, G. (1999) Does microcredit reach the poor and vulnerable? Evidence from northern Bangladesh. Working paper 28, Centre for International Development at Harvard University.
- Amemiya, T. (1997) The maximum likelihood estimator and the non-linear three stage least squares estimator in the general nonlinear simultaneous equation model, *Econometrica*, 45, pp. 955-968.
- Bali Swain, R. (2003) Sampling Methodology for Impact Study of Nabard's SHGs, unpublished draft, Department of Economics, Uppsala University.
- Bali Swain, R. and Floro, M. (2007) Effect of Microfinance on Vulnerability, Poverty and Risk in Low Income Households (with Maria Floro), Working Paper 2007:31, Department of Economics, Uppsala University.
- Bali Swain, R. and Varghese, A. (2009) Does Self Help Group Participation Lead to Asset Creation? *World Development*, 37(10), pp. 1674-1682.
- Bali Swain, R. and Wallentin, F.Y. (2009) Does Microfinance Empower Women? *International Review of Applied Economics*, 23 (5), pp. 541-556.
- Calvo, C. (2008). Vulnerability to Multidimensional Poverty: Peru, 1998-2002. *World Development*, 36 (6), pp. 1011- 1020.
- Calvo, C. and Dercon, S. (2005) *Measuring Individual Vulnerability*, Department of Economics Working Paper Series, 229, Oxford University, Oxford.
- Cannon, T. T, and Rowell, J. (2003) Social Vulnerability, Sustainable Livelihoods and Disasters. Report to DFID. Conflict and Humanitarian Assistance Department (CHAD) and Sustainable Livelihoods Office London.
- Cardona, O.D. (2004) The Need for Rethinking the Concepts of Vulnerability and Risk from a Holistic Perspective: a Necessary Review and Criticism for Effective Risk Management, in: Bankoff, G., Frerks, G., and D. Hilhorst (ed) *Mapping Vulnerability: Disasters, Development and People* (London, Earthscan publications), pp. 37-51.
- Carter, M., and Barrett, C. (2006) The economics of poverty traps and persistent poverty: An asset-based approach. *The Journal of Development Studies*, 42 (2), pp. 178-199.
- Carter, M., Little, P., Mogues, T., and Negatu, W. (2007) Poverty Traps and the Long term consequences of Natural Disasters in Ethiopia and Honduras, *World Development*, 35(5), pp. 835-856.
- Carter, M. and Ikegami, M. (2007) Looking Forward: Theory-based measures of Chronic Poverty and Vulnerability, CPRS Working Paper No. 94, University of Wisconsin, Madison.

Chauduri, S. Jalan, J. and Suryahadi, A. (2002) Assessing Household Vulnerability to Poverty from Cross Sectional Data: A Methodology and Estimates from Indonesia, Discussion paper 0102-52, Columbia University Dept of Economics.

De Aghion, B.A. and Morduch, J. (2006) *The Economics of Microfinance* (Cambridge, Massachusetts: MIT Press).

Dercon, S. and Krishnan, P. (2000) Vulnerability, seasonality and poverty in Ethiopia. *Journal of Development Studies*, 36(6), pp. 25-53.

Dercon, S. (2005) Vulnerability: a micro perspective, Mimeo, Oxford University.

Dercon, S. and Hoddinott, J. (2005) Health, Shocks and Poverty Persistence in: Stefan Dercon (ed), *Insurance Against Poverty*, Oxford University Press, Oxford, pp. 124-136.

Feldbrügge, T. and von Braun, J. (2002) Is the World Becoming A More Risky Place? Trends in Disasters and Vulnerability to Them. Discussion Papers on Development Policy No.46.Center for Development Research, Bonn.

Glewwe, P. and Hall, G. (1998) Are some groups more vulnerable to macroeconomic shocks? Hypothesis tests based on panel data from Peru. *Journal of Development Economic*, 56(1), pp. 181-206.

Günther, I. and Harttgen, K. (2009) Estimating Households Vulnerability to Idiosyncratic and Covariate Shocks: A Novel Method Applied in Madagascar. *World Development*, 37(7), pp. 1222-1234.

Hashemi, S.M., Schuler, S.R., Riley, A.P. (1996) Rural Credit Programs and Women's Empowerment in Bangladesh. *World Development* 24(4), pp. 635-653.

Heckman, J. and Hotz, J. (1989), Alternative Methods for Evaluating the Impact of Training Programs (with discussion). *Journal of the American Statistical Association*, 84(804), pp. 862-874.

Heckman, J., Ichimura, H., and Todd, P. (1997) Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *Review of Economic Studies*, 64, pp. 605-654. Heitzmann, K., Canagarajah, R.S., P.B. Siegel (2002) Guidelines for Assessing the Sources of Risk and Vulnerability. Social Protection Discussion Paper Series. Social Protection Unit, The World Bank. Washington.

Ichino, A., Mealli, F. and Nannicini, T. (2007) From Temporary Help Jobs to Permanent Employment: What Can We Learn from Matching Estimators and their Sensitivity? *Journal of Applied Econometrics*, 23(3), pp. 305-327.

Imbens, G. (2004) Non Parametric Estimation of Average Treatment Effects Under Exogeneity: A Review. *The Review of Economics and Statistics*, 86(1), pp. 4 -29.

Karlan, D. (2007) Impact Evaluation for Microfinance: Review of Methodological Issues November 2007, Poverty Reduction and Economic Management (PREM) Doing Impact Evaluation Discussion Paper 7, World Bank, Washington DC.

- Khandker, S. R. (1998) *Fighting Poverty with Microcredit: Experience in Bangladesh* (New York: Oxford University Press, Inc).
- Ligon, E. and Schechter, L. (2004) Evaluating Different Approaches to Estimating Vulnerability, Social Protection Discussion Paper 0201, World Bank, Washington D.C.
- Ligon, E. and Schechter, L. (2003) Measuring Vulnerability. *The Economic Journal*, 113(486), pp. 95-102.
- Ligon, E. and Schechter, L. (2002) Measuring Vulnerability: The director's cut. UN/WIDER Working Paper.
- McCulloch, N. and Baulch (2000) Simulating the Impact of Policy upon Chronic and Transitory Poverty in Rural Pakistan. *Journal of Development Studies*, 36(6), pp. 100-130.
- Morduch, J. (1999) The Microfinance Promise. *Journal of Economic Literature*, 37, pp. 1569-1614.
- Morduch, J. (2004) Consumption Smoothing Across Space: Testing Theories of Risk-Sharing in the ICRISAT Study Region of South India, in: Stefan Dercon (ed), *Insurance against Poverty* (Oxford University Press).
- Morduch, J. (2005) Consumption Smoothing Across Space: Testing Theories of Risk-Sharing in the ICRISAT Study Region of South India in: Stefan Dercon (ed), *Insurance Against Poverty*, Oxford University Press, Oxford, pp. 38-57.
- NABARD. (2006) Progress of SHG-Bank Linkage in India: 2005-06, Working Paper, NABARD.
- NABARD. (1992) Guidelines for the Pilot Project for linking banks with Self Help Groups, NB.DPD.FS. 4631/92-A/91-92, Circular No. DPD/104.
- Pitt, M. and Khandker, S.R. (1998) The Impact of Group-Based Credit Programs on Poor Households in Bangladesh: Does the Gender of Participants Matter? *The Journal of Political Economy*, 106, pp. 958-996.
- Prowse, M. (2003) Towards a clearer understanding of 'vulnerability' in relation to chronic poverty. CPRC Working Paper No 24, Manchester.
- Puhazhendi, V. and Badatya, K. C. (2002) SHG-Bank Linkage Programme for Rural Poor - an Impact Assessment, Paper, National Bank for Agriculture and Rural Development-NABARD, Mumbai, India.
- Rosenbaum, P. (1987) Sensitivity Analysis to Certain Permutation Inferences in Matched Observational Studies, *Biometrika*, 74(1), pp. 13-26.
- Rosenbaum, P. (2002) *Observational Studies*. 2nd ed. New York: Springer.
- Rosenbaum, P. and D. Rubin (1983) Assessing Sensitivity to an Unobserved Binary Covariate in an Observational Study with Binary Outcome, *Journal of the Royal Statistical Society, Series B*, 45, pp. 212-218.

Smith, J. and Todd, P. (2005) Does Matching Address Lalonde's Critique of Nonexperimental Estimators? *Journal of Econometrics*, 125, pp. 305-353.

Zimmerman, F. and Carter, M. (2003) Asset Smoothing, Consumption Smoothing and the Reproduction of Inequality Under Risk and Subsistence constraints. *Journal of Development Economics*, 71, pp. 233-260.

TABLES

TABLE 1

Descriptive statistics

	<i>Overall</i>	<i>SHG members</i>	<i>Non-SHG</i>	<i>T-tests^{††}</i>
	<i>Mean (S.D.)</i>	<i>Mean (S.D.)</i>	<i>Mean (S.D.)</i>	
N	840	789	51	---
Average Real food expenditure per capita per month	307 (442)	308 (453)	282 (194)	-0.82
Average Age of Respondent	35 (8.41)	35 (8.44)	36 (8.08)	0.80
Primary education	0.18 (0.39)	0.18 (0.38)	0.24 (0.43)	0.92
Secondary education	0.17 (0.38)	0.18 (0.38)	0.12 (0.33)	-1.23
Post-Secondary education	0.03 (0.18)	0.03 (0.18)	0.02 (0.14)	-0.65
Ave number of children	1.5 (1.27)	1.5 (1.27)	1.4 (1.25)	-0.56
Dependency ratio	0.66 (0.22)	0.66 (0.22)	0.62 (0.23)	-1.47
Average number of workers in the household	2.48 (1.24)	2.46 (1.23)	2.70 (1.40)	1.11
Average number of workers engaged in primary activity	2.49 (1.37)	2.48 (1.37)	2.55 (1.30)	0.35
Mean size of owned land in 2000(in acres)	0.85 (1.43)	0.87 (1.45)	0.48 (1.12)	-2.36**
Real value of non-land wealth years ago (in Rupees.)*	64,691 (90197)	63,708 (86775)	79,891 (132625)	0.86
Distance to Bank (kms.)	7.33 (6.87)	7.48 (7.02)	4.96 (3.16)	-4.96***
Distance to Health Care	3.55 (2.84)	3.46 (2.78)	4.95 (3.30)	3.15***
Distance to Market	5.39 (4.02)	5.38 (4.07)	5.46 (3.16)	0.1
Distance to Paved Road	3.06 (3.32)	3.03 (3.33)	3.59 (3.04)	1.30
Distance to Bus Stop	3.75 (3.55)	3.69 (3.59)	4.71 (2.76)	2.51**
Lack of cash or food in 2000	0.38 (0.49)	0.39(0.49)	0.27 (0.45)	-1.69*

[†]Calculated with 2000 as the base year. ^{††}t- test for equality of means of SHG members and non-SHG members. *** Significant at 1% level. ** Significant at 5% level. * Significant at 10% level.

TABLE 2

Poverty and Vulnerability estimates for SHG members and non members†

	<i>SHG members</i>	<i>Non-members</i>	<i>T-test††</i>
<i>All Households</i>			
<i>N</i>	691	51	----
<i>Poverty Profile for SHG members and non-members</i>			
Headcount ratio (per cent)	72.5	60.8	----
Aggregate poverty gap per observation	123	118	----
Poverty gap ratio (per cent)	35	34	----
Foster-Greer-Thorbecke (sqd poverty gap)	0.22	0.24	----
<i>Vulnerability Profile for SHG members and non-members</i>			
Mean	0.45 (0.39)	0.62 (0.39)	-3.00***
Fraction vulnerability	0.55	0.72	-2.36**
Fraction relatively vulnerable	0.08	0.03	1.30
Fraction highly vulnerable	0.47	0.69	-3.03**
Vulnerability to poverty ratio	0.75	1.18	----

†The vulnerability estimates are based on the Chauduri et al (2002) method, standard deviation in parentheses. †† T-test for equality of means and proportion. *** and ** indicate significance at 10%, 5% and 1% levels.

TABLE 3

Average treatment on treated estimates of SHG participation impact on vulnerability and average food expenditure per capita per month

<i>Matching Algorithm</i>	<i>(1)</i> <i>Vulnerability</i>	<i>(2)</i> <i>Av. food exp per capita per month</i>
1 NN	0.09 (1.19)	29.04 (0.61)
LLR (bw 1)	0.11 (1.54)	68.35* (1.89)

Notes: ** Significant at the 5 % level. * Significant at the 10 % level. NN = neighbor to neighbor, t-stats in parentheses. LLR= local linear regression, p-values in parentheses standard errors created by bootstrap replications of 200. Covariates of regression same as in Appendix Table 1.

TABLE 4

Simulation-Based Sensitivity Analysis for Matching Estimators†
Average treatment on treated effect (ATT) estimation on Vulnerability with simulated confounder General multiple-imputation standard errors ††

<i>Confounder</i>	<i>(1)</i> <i>ATT</i>	<i>(2)</i> <i>Standard Error</i>	<i>(3)</i> <i>Outcome effect</i>	<i>(4)</i> <i>Selection effect</i>
Age	0.13	0.01	9.01	3.9
Education	0.14	0.01	5.2	1.1

† Based on the sensitivity analysis with kernel matching algorithm with between-imputation standard error. The binary transformation of the outcome is along the 25 centile. †† Age variable (=1 if age is less than 26 years; and = 0 otherwise) and education (=1 if no education; and zero otherwise).

TABLE 5

Rosenbaum bounds – Vulnerability †

Γ	<i>Hodges-Lehmann point estimates</i>				
	(1) <i>p-critical</i>	(2) <i>Upper bound</i>	(3) <i>lower bound</i>	(4) CI_{max}	(5) CI_{min}
1	7.3 (10 ⁻¹³)	0.15	0.15	0.12	0.17
1.1	1.1 (10 ⁻¹⁶)	0.14	0.16	0.09	0.19
1.2	0	0.12	0.17	0.07	0.20
1.3	0	0.10	0.19	0.05	0.21
1.4	0	0.08	0.19	0.04	0.22
1.5	0	0.06	0.21	0.02	0.23
1.6	0	0.05	0.21	-0.003	0.23
1.7	0	0.04	0.22	-0.03	0.24
1.8	0	0.02	0.23	-0.07	0.24
1.9	0	0.0004	0.23	-0.10	0.24
2	0	-0.02	0.23	-0.14	0.25

Notes: † Γ : log odds of differential assignment due to unobserved factors

p-critical: lower bound of significance level

CI_{max} : upper bound confidence interval ($\alpha=0.95$)

CI_{min} : lower bound confidence interval ($\alpha=0.95$)

APPENDIX

TABLE 1
Logistic regression for Participation in SHGs†

	<i>Coefficient</i>	<i>T-Statistic††</i>
Age of Respondent	-0.13	1.05
Age square	0.001	0.85
Sex	-0.47	0.62
Primary education	-0.47	1.25
Secondary education	0.10	0.21
Post-Secondary education	0.27	0.25
Distance Bank (kms.)	0.18	2.52***
Distance Health Care	-0.26	3.93***
Distance Market	-0.001	0.02
Distance weekly market	-0.02	0.23
Land owned in 2000 (in acres)	0.31	2.02**
Lack of cash or food in 2000	0.69	2.05**

†Logistics Regression results with Nearest-Neighbor Matching algorithm.

†† Absolute t-ratios reported. *** Significant at 1% level. ** Significant at 5% level. * Significant at 10% level.

TABLE 2

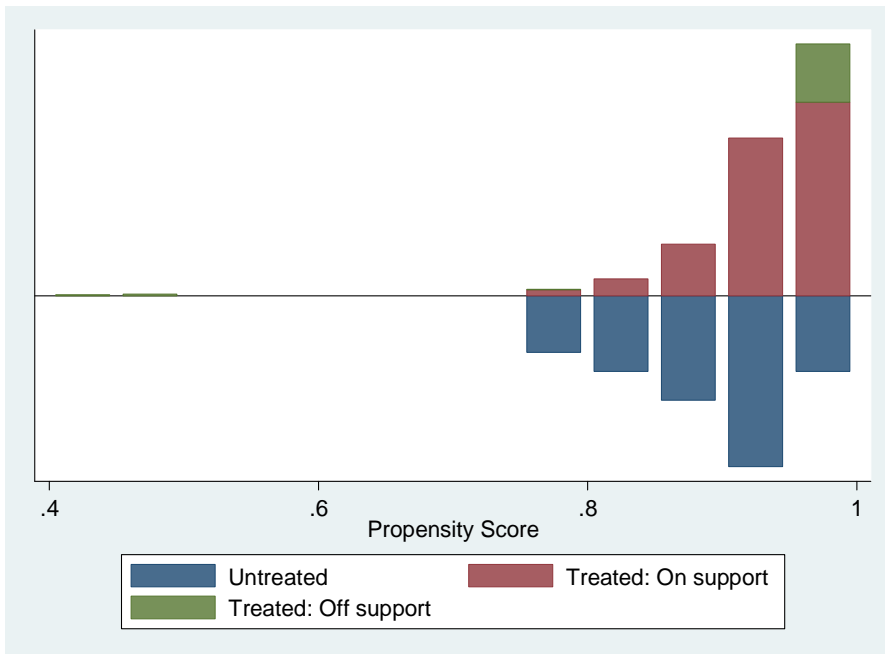
FGLS regression of per capita consumption

	<i>Coefficient</i>	<i>T-Statistic</i> [†]
Member	0.82	4.25***
Land owned in 2000 (in acres)	0.04	1.92**
Age of Respondent	0.34	18.64***
Age square	-0.004	16.93***
Primary education	-0.37	2.23**
Secondary education	0.34	3.42***
Post-Secondary education	0.59	3.59***
Number of children	0.02	0.72
Dependency ratio	-1.61	4.84***
Number of workers in the household	-0.27	5.46***
Number of workers engaged in primary activity	0.02	0.57
Real value of non-land wealth in 2000(Rs.)*	9.4e-8	0.14
Distance Bank (kms.)	-0.06	3.23***
Distance Health Care	-0.01	0.52
Distance Market	0.01	0.28
Distance Paved Road	-0.10	2.63***
Distance Bus Stop	0.16	7.26***
Lack of cash or food in 2000	0.59	8.29***

[†] Absolute t-ratios reported. *** Significant at 1% level. ** Significant at 5% level. * Significant at 10% level.

FIGURE 1

Histograms of estimated propensity scores



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