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EVALUATING THE IMPACTS OF MICROSAVING: THE CASE OF SEWA BANK IN INDIA

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This paper estimates the impact of participating in the savings program of SEWA Bank in India on household income and consumption. Contrary to microcredit, microsaving has not received much attention in the empirical literature yet which can be explained by a lack of reliable household data. The paper uses panel data to account for individual unobserved effects that can lead to substantial biases when not being controlled for. I find that when controlling for self-selection, no significant impacts of the program can be observed and that naive estimates, which do not account for selection biases, severely overstate program impacts.

Keywords: Microfinance, Microsaving, Impact Evaluation, Panel Data, India
JEL classification: E21, O16

1. INTRODUCTION

The potential contribution of microfinance to the alleviation of poverty has been the focus of intense research during the last years. What has been described as the "microfinance revolution" by Robinson (2001) started with microcredit schemes directed to economically active low-income households who previously had no access to formal financial services. The change from microcredit to the broader term of microfinance was brought about by the realisation that the poor do not only need access to formal credit resources, but can also profit from possibilities to save and insure themselves against economic shocks such as illnesses or natural disasters (Morduch, 1999; Armendáriz de Aghion and Morduch, 2005).

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The availability of formal saving opportunities can have various impacts on the economic situation of the poor. First of all, the possibility to save money in a secure place while also earning interest can help low-income households to gain control over their income streams which can in turn lead to better consumption insurance against economic shocks.[1] For instance, Gertler, Levine and Moretti (2002) report findings from Indonesia that those households living closer to microsaving institutions are more likely to suffer significantly less from major illnesses. Less variability in household income, in turn, may not only lead to higher school enrolment rates but also to improved children's health (Foster (1995), Jacoby and Skoufias (1997)). Obviously, in the long run, this can have positive impacts on human capital formation and thus on economic growth as well. Secondly, microsaving can contribute positively to the future ability to self-finance investments, acquire assets which can then be used as collateral for future credit or to afford major expenditures such as schooling fees (Matin, Hulme and Rutherford (2002), Armendáriz de Aghion and Morduch (2005), among others). This, of course, can lead to positive effects on household income and consumption as well.

Without formal saving possibilities, households in developing economies usually rely on family or friends as money guards or buy assets as buffer stocks (Deaton (1991, 1992)). Furthermore, informal credit contracts among families and friends are also a common source for smoothing income over time (Rosenzweig (1988), Udry (1994), among others). Another saving possibility is provided by rotating savings and credit associations (ROSCAs) which can be found nearly universally (Bouman (1995)). In the simplest form of a ROSCA, every group member regularly contributes a fixed amount to a common pot that will then be allocated each period to one member of the group until everyone has received the pot.[2] On the one side, the rationale behind joining a ROSCA can be saving for the acquisition of durable consumption goods (Besley, Coate and Loury (1993)). Yet, on the other side, it can also be a strategy used by married women to protect household savings against claims by their husbands for immediate consumption (Anderson and Baland (2002)) or a self-commitment strategy for time-inconsistent individuals (Gugerty (2005)). Regardless of the particular reason, the microfinance literature agrees that low-income households can and do save and that there is considerable demand for formal saving opportunities (Rutherford (2001)).[3]

Unlike microcredit, microsaving has not received much attention in the empirical

[1] That low-income households are usually not able to insure themselves completely against income risk has been discussed in various contributions. See, for instance, Townsend (1994, 1995), Jalan and Ravallion (1999), Kochar (1999), and Gertler and Gruber (2002).

[2] The allocation mechanism is usually random, yet “bidding” ROSCAs in which members are allowed to bid for a certain pot as well as predefined orders of allocation are possible alternatives as well.

[3] For example, figures from Uganda reported by Armendáriz de Aghion and Morduch (2005) show that the implicit interest rate charged by a money collector can be as high as 30 percent per year just for the service of guarding money.

literature yet which can be explained by a lack of reliable household data that could be used to assess the impact of microsaving on household characteristics. However, in the context of microcredit there have only been few sound impact evaluations as well. For example, Pitt and Khandker (1998) analyse the impact of microcredit programs in Bangladesh using a quasi-experimental design with an eligibility rule to instrument for microfinance participation while also addressing the problem of non-random program placement by using village-level fixed effects. They report significant impacts of microcredit on various household characteristics and also provide evidence on higher impacts when lending to women. In particular, they find that household consumption increases by 18 taka for every 100 taka lent to a woman, while only increasing 11 taka when lent to men.[4] Various other studies followed up on the seminal contribution by Pitt and Khandker using the same or a slight variation of the dataset. For instance, McKernan (2002) finds significant impacts of non-financial services such as vocational training on self-employment profits while Pitt and Khandker (2002) analyse the effect of program participation on the seasonal pattern of household consumption. They find that consumption smoothing through smoothing income is an important motivation for joining microcredit programs.

Coleman (1999, 2002) exploits a unique characteristic of a dataset from Thailand which allows him to observe future participants prior to receiving their first loan in villages that were hitherto not served by microfinance institutions. Thus, he can employ a specific estimation strategy that allows him to control for self-selection and endogenous program placement. However, contrary to Pitt and Khandker (1998), he finds only very low impacts of the investigated microfinance programs. Furthermore, he observes that "naïve" estimates, not controlling for these potential biases, severely overstate program impact. Tedeschi (2008) uses the AIMS (Assessing the Impact of Microenterprise Services) data on Mibanco in Lima, Peru to analyse the impact of microcredit on microenterprise profits by using a similar approach as Coleman Coleman (1999, 2002) as well as by employing a fixed effects estimation strategy. She finds that not correcting for self-selection biases leads to an overestimation of program impact. Still, even when correcting for self-selection, the impact of borrowing on microenterprise profits seems to be significant.

This paper attempts to partly close the gap on the impacts of microsaving by analysing the effects of a microsaving program established by SEWA Bank in India on household income and food consumption. In the case of SEWA Bank, a participation in

[4] Morduch (1998) criticised these results arguing that the eligibility rule was not strictly enforced so that the half an acre cut-off line can not be used as a valid instrument for participation which will in turn alter the results considerably. Pitt (1999), however, uses robustness tests to show that the results are not influenced by the violation of the eligibility rule. Furthermore, Khandker (2005) uses a follow-up survey in order to analyse the effect of microcredit over time. By using panel data models, he is able to provide results that support the initial contribution by Pitt and Khandker (1998).

the savings program implies that the clients are members of SEWA Union as well. Since SEWA Union pursues collective bargaining for better working conditions for its members including negotiations for higher piece-rates and minimum wages, it can be presumed that there exist positive impacts of the program on household income. This, in turn, can lead to higher consumption expenditures as well. On the other hand, consumption expenditures can also be influenced by the improved ability of the households to manage their income streams. For the impact assessment, a dataset obtained from the AIMS longitudinal studies is employed, having the advantage of providing panel data information on microsaving clients as well as on a randomly selected control group. The design of the data allows for an estimation of panel data, and in particular fixed effects models, that can control for time-constant unobserved effects that have an influence on both, program participation and the respective outcomes of interest. Therefore, issues such as self-selection into the savings program, which could substantially bias the estimated results when not being controlled for, can be taken into account. The results of the estimation strategy are striking. When controlling for self-selection, no significant impacts on income or food consumption can be observed while naive estimates, which do not control for these biases, severely overstate program impacts.

The contribution of this paper is twofold. First, since this is the first paper that attempts to estimate the impacts of microsaving in a rigorous way, the results not only contribute to the existing evidence on the impacts of microfinance but also provide further valuable insight into microsaving and its potential effects. Second, this paper adds to the few existing impact evaluations in the context of microfinance. Due to the availability of panel data information, estimation techniques can be employed that are usually not available, yet can lead to improved estimates since selection problems can be better controlled for.

The remainder of the paper is organised as follows. Section 2 discusses the survey design as well as the AIMS data and provides some descriptive statistics on program participants and the control group. Section 3 is concerned with the estimation strategy that will be used for the impact assessment while the estimation results are presented in Section 4. Section 5 closes the argument.

2. SURVEY DESIGN AND DESCRIPTION OF THE DATA

The data on SEWA Bank that is used for the impact assessment is part of the AIMS longitudinal studies sponsored by USAID that were also carried out for Mibanco in Lima, Peru and Zambuko Trust in Zimbabwe.[5] SEWA Bank is located in Ahmedabad,

[5] For details see Barnes, Keogh and Nemarundwe (2001), Chen and Snodgrass (2001) and Dunn and Arbuckle (2001).

India, the commercial centre of Gujarat state in Western India. The bank was founded in 1974 emerging out of SEWA Union, a trade union consisting only of self-employed women working in the informal sector.[6] Since SEWA Union consists only of female members, SEWA Bank focuses exclusively on banking with women as well.[7] Contrary to Mibanco and Zambuko Trust, SEWA Bank offers its members not only possibilities to borrow but also to save and even emphasises savings over credit (Chen and Snodgrass (2001)). Therefore, for the microsaving impact assessment, the data on SEWA Bank was selected.

It should be noted that saving is not compulsory at SEWA Bank. Even though clients have to save regularly for at least one year for being eligible to apply for an uncollateralised loan, it is also possible to obtain collateralised loans which have no restriction regarding saving behaviour. Furthermore, even in the case of uncollateralised loans, not the savings accounts but guarantors serve as an alternative form of security. Therefore, saving at SEWA Bank should not be considered as a mere by-product of the credit schemes.

For each of the aforementioned studies, a baseline survey was conducted in 1997/98 followed by a second round in 1999/2000 in which the same households were interviewed again. The surveys collected detailed information on household characteristics such as demographics, education, consumption expenditures, income or economic shocks as well as on the microenterprises run by the households.

In all three studies, a stratified random sample of clients was selected from a list provided by the respective microfinance program. Subsequently, in India and Peru, a control group was identified by drawing a random sample from the nonparticipants in the same region who met the eligibility criteria of the microfinance institution. In Zimbabwe, researchers used a "random walk method" for finding an adequate control group.[8] The goal of the studies was to measure the impact of the microfinance programs on low-income households in the project cities. For this goal, mainly analyses of covariance (ANCOVA) were used. However, since these estimation strategies can not account for self-selection issues, the obtained results are likely to be biased.

In the case of SEWA Bank, the baseline study in 1998 included information on 900 women, 300 borrowers, 300 savers, and 300 controls.[9] The sample was chosen according to a three-step procedure. First, the geographical areas in which the survey

[6] For a detailed description of the history of SEWA Bank see Rose (1992) or Crowell (2003).

[7] Today, many microfinance institutions consider women as their predominant target group since they are assumed to be more reliable when it comes to repayment of loans (Hossain (1988), Hulme (1991)). Furthermore, some studies even report higher impacts on household outcomes such as consumption expenditures or children's nutrition and schooling when lending to women (Thomas (19900, Pitt and Khandker (1998), Holvoet (2004), Khandker (2005)).

[8] See Barnes, Keogh and Nemarundwe (2001) for details.

[9] The description of the sample design was drawn from Chen and Snodgrass (2001).

was conducted were selected. In this step, 10 out of the 43 wards of Ahmedabad City were identified in which approximately half of the clients of SEWA Bank lived. Then, in a second step, a random selection of 300 current borrowers and savers that also reflected the proportional shares of clients in the ten wards was drawn from a list of all SEWA members provided by the bank. The randomly selected women were replaced if they could not be located or were unwilling to participate in the survey. In the case of savers, new women were also selected if they were no longer actively saving or had taken out loans in the meantime while borrowers were replaced if they had already repaid their loans. Subsequently, in a third step, the non-client sample of 300 women was chosen out of a list of 15,000 households with economically active women over age 18 working in the informal sector, the target group of SEWA Bank.

The second round of the survey was conducted in January 2000. In total, 798 of the initial 900 women (89 percent) could be re-interviewed in the second period.[10] Of those, 12 borrowers were selected for case study research. Therefore, all in all there was information on 786 women, 264 borrowers, 260 savers, and 262 controls, available for both periods.

Since this study focuses on the impacts of microsaving, the two groups that are left in the sample are first the savers group which had at least one savings account and did not have a loan outstanding at the time of the first interview. And second, there are the controls who were neither members of SEWA Bank nor SEWA Union at the time of Round 1 or Round 2. Furthermore, there is a small group of new savers consisting of those members of the control group who selected themselves into the savings program between the two interviews.[11] Unfortunately, there is no information on Union members who do not save which implies that the impact of the saving program can not be separated from the Union effect. The remaining sample that is used in the following consists of 425 women, 184 women who had savings accounts in both periods, 20 women who became savers between 1998 and 2000 and 221 women in the control group.[12]

Table 1 summarises key characteristics of the three groups such as age, marital status, caste, number of household members and educational attainment at the time of Period 1. The figures show that the groups are relatively equal with respect to these parameters. Furthermore, the observable differences are not statistically significant. It is interesting

[10] Chen and Snodgrass (2001) report that drop-outs were relatively similar compared to the rest of the sample with respect to personal and household characteristics.

[11] There exists also a small group of three women who leave the program between the two rounds. However, the size is too small for obtaining reliable information on the differences compared to the other groups.

[12] These figures are lower than the total number of available data points due to the fact that income and food consumption per capita were trimmed at the top and bottom one percentile since they seemed to be relatively noisy.

to note that the percentage of scheduled castes and scheduled tribes (SC/ST) is with 40 percent relatively high in all groups. The percentage in total Ahmedabad was estimated to be 13 percent in 1991. However, as the formerly untouchables, SC and ST still often face discrimination and constitute a large part of the poorest of the poor in India (Borooah (2005)). Therefore, it is not surprising that they have a high representation among the clients of SEWA Bank. Regarding educational attainment, it can be seen that about 40 percent of all women have never received any kind of schooling.

Table 1. Demographic Characteristics

	Always Savers	New Savers	Control Group
Age			
Average Age (years)	33.8	34.4	35
Marital Status			
Married (%)	87.50	80.00	83.71
Caste			
Upper Caste (%)	17.93	10.00	23.98
Backward Caste (%)	41.30	45.00	37.10
Scheduled Caste or Tribe (%)	40.76	45.00	38.91
Educational Attainment[1]			
No Education (%)	39.67	40.00	41.63
Primary Education (%)	34.78	50.00	34.39
Secondary Education (%)	21.74	5.00	20.36
Higher Education (%)	3.80	5.00	3.62
Household Members			
Avg. Number of Household Members	5.7	6.3	5.9
Earning Household Members (average)	2.8	2.7	2.7
Observations	184	20	221

Notes: These estimates refer to the status of 425 women at the time of the first survey. [1] Defined according to the household questionnaire. Primary education refers to classes 1-7 or technical training, secondary education to classes 8-10, and higher education to classes 11-12, college or a post-graduate program.
Source: Socio-Economic Review Gujarat State: 2005-2006.

Average income and food consumption per capita are summarised in Table 2. Of the three groups, always savers had the highest average income per capita in both periods and the difference compared to the control group in 1998 and 2000 is significant at the 5 and 1 percent level, respectively. In US $, the average annual income per capita for always savers is approximately equal to \$178 in Period 1 and \$182 in Period 2.[13] Furthermore, it is interesting to note that new savers experienced a strong income rise between the two periods which could be due to the union membership. However, the sample is too small to obtain reliable information on the differences compared to the two other groups.

Table 2. Average Income and Consumption in Rupees

	Always Savers	New Savers	Control Group
Income per Capita			
Yearly Income per Capita (1998)	7,370	4,779	6,282
Yearly Income per Capita (2000)¹	7,518	6,743	6,483
Consumption per Capita			
Daily Consumption per Capita (1998)	10.96	11.02	10.05
Daily Consumption per Capita (2000)¹	11.13	11.15	10.40
Observations	184	20	221

Note: ¹ Reported income and consumption in 2000 were deflated to 1998 prices by dividing by 1.1053 and 1.0536, respectively.
Source: Consumer Price Index for Ahmedabad, Labour Bureau, Government of India.

Average food consumption per capita defined as total daily food expenditures was relatively equal for always savers and new savers, but approximately 10 percent lower for the control group.[14] The difference between always savers and the control group in Period 1 and Period 2 is also significant at the 1 and 5 percent level, respectively. Converted to US \$, average daily food consumption per capita of always savers was approximately equal to 26.50 Cents and 26.91 Cents in 1998 and 2000, respectively.

In order to provide further insight into income differences between savers and the control group, kernel densities have been estimated for 1998 and 2000.[15] Figure 1 shows that the distribution for always savers lies more to the right than the kernel for the

[13] The values were calculated using the average 1998 exchange rate of \$1 = Rs. 41.36 (Source: Federal Reserve Statistical Release (2000)).

[14] Consumption expenditures are defined as the total amount of money spent on food consumption the day before the interview. In order to derive these expenditures, all types of food items that were consumed during the previous day combined with the respective amount were collected and then multiplied by the unit price of the groceries. This procedure led to the total daily expense on food eaten at home and by adding the amount of money spent on food eaten away from home, total daily consumption expenditures were calculated.

[15] The kernel densities use an Epanechnikov kernel with an optimal bandwidth.

control group in both periods. While the difference in the upper part of the distributions does not seem to be high, the probability of low income realisations for always savers is considerably lower. The only observable difference in Period 2 compared to Period 1 is that the kernels seem to be somewhat tighter for both groups, but the difference is not high.

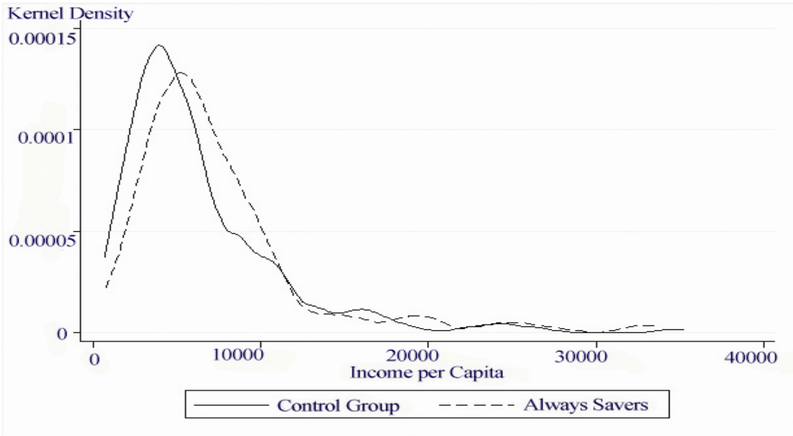

Figure 1(a). Kernel Densities for Income per Capita: Period 1

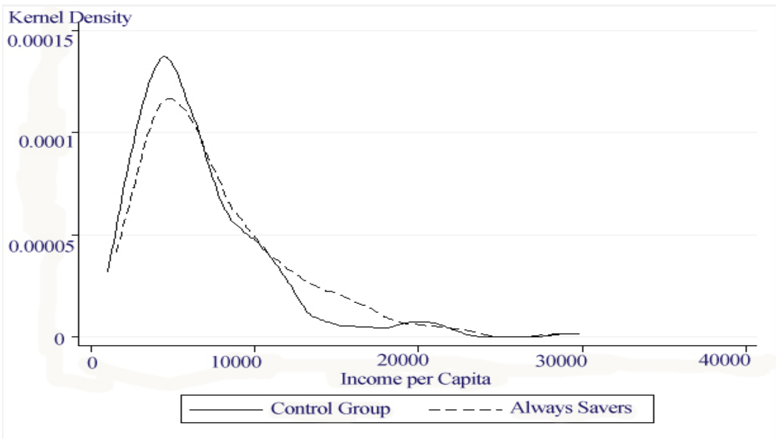

Figure 1(b). Kernel Densities for Income per Capita: Period 2

3. THE ESTIMATION STRATEGY

When evaluating the impacts of a specific program, the following equation is usually estimated

$$Y_i = \gamma + \alpha D_i + X_i \beta + \varepsilon_i , \quad i = 1,..., N ,$$

where Y_i is the outcome variable of interest, D_i is an indicator for program participation of household i, X_i is a vector of household characteristics and ε_i is the error term. The problem arising with impact assessments is that α will only reflect the true impact of the program if program participation is completely exogenous given the covariates. For instance, this could be assumed if participation in the program was randomly assigned to the households. However, since randomisation of participation is rarely the case, individuals at least partly determine whether they participate in a specific program or not. A problem arises if this decision is not only based upon observable variables such as age or marital status, but on unobservables that can not be included in the estimation equation. In the case of microsaving, potential unobservable variables that influence self-selection could be, for instance, risk and time preferences, the perception of the future, or the ability to self-commit (Gugerty (2005)). Furthermore, in the case of SEWA Bank, the wish to obtain an uncollateralised loan could also be a motivation for participating in the savings program. If these variables are also correlated with the outcomes of interest conditional on the covariates, then standard estimation techniques such as OLS will not yield consistent estimates of program impact.

The standard solution to the problem of self-selection is the implementation of instrumental variables techniques. However, suitable instruments that fulfil both assumptions, namely that the instrument is uncorrelated with the disturbances, but correlated with the treatment indicator while not having an effect on the outcome variable, are rarely available. One exception in the context of microfinance is the study by Pitt and Khandker (1998).

A second solution lies in the estimation of panel data models. If panel data is available, program impacts can be consistently estimated if there exist no unobserved influential variables that change over time and have an effect on both, the participation indicator and the outcome variable of interest. It is likely that unobservables such as risk and time preferences or the attitude toward the future change over time, but as long as they are not correlated with program participation conditional on observables such as age, occupation or household size, which can probably be assumed, this effect can be captured by including these variables in the regression. Furthermore, since the intention to apply for an uncollateralised loan is likely to be time-constant if the loan has not been approved yet, this effect can be captured by using panel data models as well. Therefore, for the problem at hand it is most likely that panel data methods will yield better estimates of program impacts than OLS estimators.

The model that is estimated in the following analyses can be written as

$$Y_{it} = \alpha D_{it} + X_{it}\beta + \gamma_t + c_i + \varepsilon_{it}, \quad i = 1,...,N, \quad t = 1,...,T \ ,$$

where Y_{it} is the respective outcome variable which will either be household income or food consumption per capita. D_{it} reflects the saving status of the household which will be equal to the number of years in the savings program. X_{it} is a vector of household characteristics such as age and marital status of the respondent, household size, religion, caste, and the number of shocks experienced by the household. γ_t is a time-specific intercept term and c_i is the unobserved individual effect that is constant over time. Finally, ε_{it} is the error term. When assuming that there exists no individual unobserved effect that influences D_{it} as well as Y_{it}, standard OLS should yield consistent estimates of program impacts. The results from the OLS strategy will be compared to a fixed effects model that can eliminate the time-constant unobservables. Since this dataset consists of two periods, estimating a fixed effects model is equivalent to first-differencing. It is clear that by estimating fixed effects models, time-invariant variables in the X_{it} such as caste and religion will be dropped from the sample. Compared to a random effects model, fixed effects should be more appropriate since, when estimating random effects, c_i is treated as a random variable that is not allowed to be correlated with D_{it} and X_{it}. Yet, it is precisely the potential correlation between c_i and D_{it} that can lead to inconsistent estimates of program impacts. Whether a fixed or a random effects model is more adequate will be tested using a Hausman specification test. The idea behind this test is that random effects is more efficient if there exists no correlation between the individual-specific effects and the regressors, but it will be inconsistent if such a correlation exists while fixed effects would yield consistent estimates and would thus be the model of choice.[16]

4. ESTIMATION RESULTS

The results of the OLS regression of household income and consumption per capita on the participation indicator and the covariates are summarised in Table 3 and Table 4.

[16] The Hausman test statistic is calculated as

$$W = (\hat{\beta}_{FE} - \hat{\beta}_{RE})'\Sigma^{-1}(\hat{\beta}_{FE} - \hat{\beta}_{RE}) \ ,$$

where $\hat{\beta}_{FE}$ is a vector of fixed effects estimates, $\hat{\beta}_{RE}$ is a vector of random effects estimates and Σ is the covariance matrix of the difference vector $\hat{\beta}_{FE} - \hat{\beta}_{RE}$. The test statistic follows a chi-square distribution with *k*-1 degrees of freedom (where *k* is equal to the number of regressors).

Table 3. OLS Regression for Income per Capita

Variable	(1)	(2)
Number of Years with Savings		141.26**
		(59.49)
Household Characteristics		
Age of Respondent	16.74	17.90
	(18.11)	(18.11)
Married	1078.34**	1054.18**
	(477.39)	(476.67)
Household Size	-787.54***	-771.42***
	(98.98)	(98.73)
Active Household Members	952.86***	926.62***
	(145.16)	(146.45)
Number of Children	-385.19***	-391.10***
	(109.01)	(108.31)
Number of Economic Shocks	-79.37	-85.96
	(210.23)	(209.43)
Religion and Caste		
Hindu	-600.66	-601.96
	(414.57)	(412.94)
Backward Caste	-270.67	-321.24
	(434.76)	(435.54)
Scheduled Caste / Scheduled Tribe	32.34	-15.17
	(470.79)	(468.75)
Education of Respondent		
Primary Education	866.43***	856.10**
	(352.45)	(350.71)
Secondary Education	823.27	824.10
	(521.40)	(522.24)
Higher Education	2564.85***	2577.11***
	(974.27)	(979.22)
Principal Activity of the Household		
Piece-Rate Work	-1375.55***	-1298.72**
	(634.12)	(630.38)
Casual Labour	-1621.57***	-1547.96***
	(349.65)	(346.07)
Salaried or Contract Work	2139.24***	2120.72***
	(595.65)	(593.84)
Year 2000 Dummy	1209.43***	1066.23***
	(311.45)	(314.99)
Observations	850	850
R^2	0.2235	0.2281

Notes: OLS regression with robust standard errors. *** denotes significant at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are reported in parentheses.

The first column of Table 3 depicts the estimation results without the indicator for program participation.[17] The results suggest that marriage leads to higher household income per capita while household size and the number of children in the household have a strongly negative effect on per capita household income. Besides of the natural effect that a higher number of non-earning children in the household will lead to lower income per capita, it is likely that more children in the household will also imply that earning household members have to stay at home, thus resulting in lower income per capita as well. In this respect, it is straightforward that a higher number of economically active household members will lead to higher household income per capita.

It is interesting that the number of negative shocks experienced by a household seems to have no measurable effect on income per capita. However, the reason for this finding might be that there is only information available on the number of economic shocks experienced by a household, but not on the monetary equivalent. Thus, it is likely that the shocks differ considerably with respect to their actual severity and a mere comparison of the number of shocks might not be able to reflect the true impact on household income.

It is surprising to note that the effects of religion and caste are insignificant. The omitted categories are ‘muslim/christian’ and ‘upper caste’ which implies that household income per capita does not vary significantly between, for example, upper caste households, backward castes, and SC/ST. The effect of the respondents’ education is positive and significant suggesting that education leads to considerable increases in household income per capita confirming the human capital literature (Krueger and Lindahl (2001), among others). Furthermore, ‘higher education’ seems to have the strongest effect (the omitted category is ‘no education’). Finally, compared to ‘own account work’ as the principal activity of the household, piece-rate work and casual labour lead to significantly less income per capita while salaried and contract work imply higher household income.

In the second column of Table 3, the participation indicator - equal to the number of years with savings - is added as an additional regressor.[18] The results suggest that program participation has a highly significant and positive impact on income per capita. They indicate that one more year with SEWA savings leads to an increase in yearly household income per capita of Rs. 141.26 which is approximately equal to 2 percent of average income per capita. The sign and significance of the other variables remain relatively unchanged when including the savings indicator. However, the size of the effects changes for most of the variables, especially for caste and the principal activity of the household, suggesting that participation in the savings program is correlated with these variables.

[17] The results of a regression of monthly income per capita on the covariates are comparable to the results in Table 3 with respect to the significance of the coefficients and were therefore not reported in detail.

[18] All results remain exactly the same when using a dummy variable for saving status instead.

Table 4. OLS Regression for Consumption per Capita

Variable	(1)	(2)
Number of Years with Savings		0.0806*
		(0.0501)
Household Characteristics		
Age of Respondent	0.2553***	0.2553***
	(0.0769)	(0.0765)
(Age of Respondent)²	-0.0026***	-0.0025***
	(0.0010)	(0.0010)
Married	-0.9782***	-0.9848***
	(0.3851)	(0.3828)
Household Size	-0.4320***	-0.4270***
	(0.0868)	(0.0868)
Active Household Members	0.0510	0.0417
	(0.1142)	(0.1142)
Number of Children	-0.0970	-0.1025
	(0.1008)	(0.1003)
Number of Economic Shocks	0.1162	0.1115
	(0.1650)	(0.1654)
Income per Capita	0.0006***	0.0006***
	(0.0001)	(0.0001)
(Income per Capita)²	-1.55e-08***	-1.51e-08***
	(2.46e-09)	(2.46e-09)
Religion and Caste		
Hindu	-0.7113**	-0.7165**
	(0.3500)	(0.3511)
Backward Caste	0.1100	0.0756
	(0.3399)	(0.3402)
Scheduled Caste / Scheduled Tribe	0.1020	0.0730
	(0.3475)	(0.3476)
Education of Respondent		
Primary Education	0.1487	0.1448
	(0.2628)	(0.2621)
Secondary Education	0.0051	0.0061
	(0.3460)	(0.3443)
Higher Education	-0.7566	-0.7387
	(0.6188)	(0.6133)
Principal Activity of the Household		
Piece-Rate Work	0.0683	0.1043
	(0.5171)	(0.5158)
Casual Labour	-0.2242	-0.1878
	(0.2698)	(0.2683)
Salaried or Contract Work	0.4162	0.4167
	(0.3794)	(0.3783)
Year 2000 Dummy	0.2710	0.1963
	(0.2369)	(0.2439)

Observations	850	850
R^2	0.2834	0.2859

Notes: OLS regression with robust standard errors. *** denotes significant at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are reported in parentheses.

Table 4 summarises the results of the OLS regression of food consumption per capita on the covariates. In the first column, it can be seen that the age of the respondent has a significant and also non-linear effect on food consumption per capita. Furthermore, marriage and the size of the household seem to have a significantly negative impact and even though the number of economically active household members and the number of children in the household are insignificant, the sign of the coefficient is the same as for the regression on household income. Similar to the finding above, the number of negative economic shocks experienced by a household has only a negligible impact on food consumption per capita. That the education of the respondent and the principal activity of the household do not seem to have a significant influence on food consumption per capita is likely to be due to the fact that their impact is already captured in the income variable through which they affect consumption expenditures as well. Furthermore, even though caste does not seem to have a measurable effect, food consumption per capita is significantly lower for Hindus compared to Muslims and Christians.

The effect of yearly income per capita on food consumption expenditures per day is highly significant and also non-linear suggesting that the positive impact decreases with rising household income. The marginal propensity to consume (mpc) calculated at mean income per capita is equal to 0.1415. The mpc's have also been calculated for the 10th and 90th percentiles in order to provide further insight into consumption patterns of the different income groups. The mpc for the 10th percentile is with 0.1984 considerably higher than mpc of 0.0152 for the 90th percentile. Since consumption is defined as food expenditures only, this implies that the poorest households spend approximately 20 percent of their income on food consumption whereas the better off have consumption expenditures of around 2 percent of household income. The elasticity of food consumption with respect to income calculated at the mean values of income and consumption suggests that food consumption expenditures per capita increase by approximately 0.26 percent for a 1 percent increase in income per capita.

In column two, the program participation indicator is added to the regression. It can be seen that the effect of the savings program again seems to be significant even though controlling for income per capita. The results suggest that one additional year with SEWA savings leads to an increase in daily food consumption of Rs. 0.08 which is approximately equal to 1 percent of average daily food consumption. Similar to the finding above, the sign and significance of the other covariates seems to be relatively unchanged, but the size of the coefficients is again affected.

The OLS results suggest that there exists a positive and significant impact of having a savings account at SEWA Bank on household income and food consumption per capita. However, in order to correct for potential self-selection into the savings program, a fixed effects model has been employed as summarised in Table 5. It can be seen that program participation has now an insignificant effect on income as well as on food consumption per capita and that the impact of having a savings account is considerably lower than suggested by the OLS model. Furthermore, the household fixed effects are jointly significant at the 1 percent level in both cases, indicating that self-selection into the savings program has to be taken into account in order to reliably estimate program impact. When considering the covariates, the results indicate that only household size, the number of active household members and the dummy for salaried or contract work remain significant in the regression on income per capita. The main reason for this finding is a lack of sufficient variation in most of the other variables between the two periods. In the regression on food consumption per capita, the significance of the variables remains relatively unchanged compared to the OLS results.

Table 5. Fixed Effects Results

Variable	Income per Capita	Consumption per Capita
Number of Years with Savings	134.72	-0.0890
	(250.83)	(0.2057)
Household Characteristics		
Married	686.11	0.1731
	(1086.14)	(0.8913)
Household Size	-852.99***	-0.6212***
	(215.25)	(0.1803)
Active Household Members	649.57**	0.1419
	(276.83)	(0.2294)
Number of Children	-141.44	-0.0341
	(306.66)	(0.2520)
Number of Economic Shocks	92.62	0.1515
	(241.80)	(0.1984)
Income per Capita		0.0005***
		(0.0001)
(Income per Capita)^2		-1.66e-08***
		(3.69e-09)
Principal Activity of the Household		
Piece-Rate Work	662.76	0.3745
	(841.93)	(0.6907)
Casual Labour	-153.05	-0.3744
	(556.05)	(0.4558)
Salaried or Contract Work	1588.32*	0.8622
	(849.70)	(0.6998)
Year 2000 Dummy	926.64***	0.6111**
	(344.74)	(0.2892)

Observations	850	850
Household Fixed Effects	Jointly Significant	Jointly Significant

Notes: *** denotes significant at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are reported in parentheses.

In order to judge the results of the fixed effects estimations against a random effects model, a Hausman test has been used. The results of the random effects estimations are very similar to the OLS results. However, the effect of the savings program on food consumption per capita is not significant similar to the fixed effects results.[19] The chi-square test statistic is equal to 17.91 for the regression on income per capita and 41.74 for the regression on food consumption per capita. Thus, the null hypothesis of no correlation between the error term and the regressors can be rejected at the 10 and 1 percent level, respectively.[20] Therefore, it can be concluded that fixed effects seems to be the appropriate model for estimating the impact of SEWA Bank on household income and food consumption per capita.

The two main findings of the analyses are that first, an estimation of a standard OLS model overestimates the impact of having a savings account at SEWA Bank on income and food consumption per capita. And second, when taking into account self-selection into the savings program, the impact of the program becomes insignificant in both cases. This suggests that those participating in the savings program differ considerably from the control group with respect to some unobserved characteristics that also cause them to have higher than average income and consumption patterns. Furthermore, the observation that the impact of the program becomes insignificant once controlling for self-selection might indicate that the difference in income and food consumption between savers and the control group is solely due to self-selection which would imply that the effect of the program is close to zero.

5. CONCLUSION

By providing formal financial services to low-income households, microfinance is assumed to have the potential for a long-lasting and sustainable effect on poverty alleviation. In this respect, not only microcredit but also microsaving plays a crucial role since low-income households demand a broad range of financial services in order to be able to afford major acquisitions, smooth consumption over time and self-insure against income shocks.

However, few microfinance programs have received rigorous statistical impact

[19] For details see Table A1 in the Appendix.

[20] The p-values are equal to 0.0565 and 0.0000, respectively.

analyses which is true even more in the context of microsaving than for microcredit. The reason is mainly that impact evaluations require reliable but rarely available information on program participants as well as on a control group. Nevertheless, since issues such as self-selection can severely bias estimated results, naive estimates, not taking into account these potential biases, might not reflect the true impacts of the program.

The estimated results on the impacts of microsaving provided new insights into an important aspect of microfinance that receives increasing attention in the literature. Due to the availability of panel data, estimation techniques such as fixed effects could be employed that can reduce potential biases since selection problems can be better controlled for. The results of the estimation strategy were striking. When controlling for self-selection, no significant impacts of the program on income or food consumption could be observed. Furthermore, it was shown that naive estimates, not controlling for these biases, severely overstate program impacts.

However, the results do not necessarily imply that there exists no impact of SEWA Bank at all. It is possible that spill-over effects due to the collective bargaining of SEWA Union have an influence on other women in the respective trade groups as well so that not only SEWA members but also women in the control group are affected by the program. This presumption remains to be tested with a dataset that allows for a more detailed differentiation between the various groups.

Furthermore, the results should not be interpreted in a way that microsaving is ineffective. First of all, the effects of a specific program will always depend on the respective context and the design of the program. Second, even though the impacts on income and food consumption per capita seem to be insignificant, long-term effects, for instance on education or a better ability to smooth consumption over time, can not be assessed with the data at hand. However, for analyzing those questions, long-run panel data with multiple observations over the course of the year would be needed. And third, even if it is indeed the case that only those are supported who have an aptitude toward saving, proving a formal savings product to them is still likely to be considerably more efficient compared to the alternative of an informal savings scheme.

Microfinance has a high potential for contributing to the alleviation of poverty, but it should be kept in mind that it can be no panacea. The impacts of a specific program are highly dependent on the characteristics of the program itself and the respective country-context. Furthermore, positive impacts should not be taken for granted. In future research, improved longitudinal data and estimation techniques are needed in order to be able to reliably judge the effects against the impacts of other programs that aim at reducing poverty. Furthermore, in order to discern what really drives the self-selection of households into savings programs, information on the potentially influential unobservable variables such as risk and time preferences would be needed. By including this information in household surveys, more light could be shed on whether these variables indeed influence self-selection. Obtaining such information would thus not only be helpful for understanding saving preferences of low-income households in developing economies but also for designing microsaving programs.

Appendix

Table A1. Random Effects Results

Variable	Income per Capita	Consumption per Capita
Number of Years with Savings	150.18**	0.0787
	(72.08)	(0.0522)
Household Characteristics		
Age of Respondent	18.05	0.2475***
	(19.11)	(0.0777)
(Age of Respondent)^2		-0.0024***
		(0.0010)
Married	1015.40**	-0.8965**
	(483.34)	(0.3723)
Household Size	-765.08***	-0.4505***
	(115.65)	(0.0905)
Active Household Members	873.88***	0.0630
	(162.46)	(0.1249)
Number of Children	-371.82***	-0.1026
	(137.90)	(0.1080)
Number of Economic Shocks	-18.31	0.1183
	(196.90)	(0.1530)
Income per Capita		0.0006***
		(0.0001)
(Income per Capita)^2		-1.54e-08 ***
		(2.52e-09)
Religion and Caste		
Hindu	-559.44	-0.7302**
	(478.24)	(0.3423)
Backward Caste	-299.30	0.0712
	(509.72)	(0.3644)
Scheduled Caste / Scheduled Tribe	-5.06	0.0711
	(527.82)	(0.3644)
Education of Respondent		
Primary Education	806.23*	0.1591
	(421.97)	(0.3031)
Secondary Education	900.18*	-0.0250
	(528.81)	(0.3808)
Higher Education	2462.59***	-0.6555
	(944.35)	(0.6821)
Principal Activity of the Household		
Piece-Rate Work	-832.83	0.1184
	(587.24)	(0.4463)
Casual Labour	-1212.64***	-0.2321
	(364.50)	(0.2767)
Salaried or Contract Work	2036.79***	0.4828
	(521.91)	(0.3950)

Year 2000 Dummy	1015.32*** (262.90)	0.2193 (0.2165)
Observations	850	850

Notes: *** denotes significant at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are reported in parentheses.

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